PLAYER VALUATION IN THIN MARKETS:

THE CASE OF EUROPEAN ASSOCIATION FOOTBALL

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Abstract

The amount of money in football is staggering and is a concern for people of all walks of life. While these concerns are valid, the money in football is justified and consumers of football as a form of entertainment, actively participate in the set-up of this labour market. Thanks to the availability of market value, wage, and transfer fee data for the most valued production workers (players) and bolstered by the emergence of data analytics firms to crunch large amounts of performance data in real time, it is possible to analyse and better understand the monetary worth of the most talented players, and the role of each stakeholder in the buildup of this value. This 3-essay series uses Mincer's (1985) human capital formulation and multilevel regression analyses to provide a complete study of the different money centers that underlie player valuation.

Essay 1 analyses player market values – values attributed by football fans via crowd-sourced open forums online. Market values (Transfermarkt values) that are used in actual transfer and salary negotiations are driven by both football and non-football related factors. From a sample of 500 offensive player observations in the big 5 European leagues for the 2017/18 and 2018/19 seasons, this essay analyses 12 data points per player observation, hence 6,000 data points in total, using a series of multilevel regression models to isolate the proportion of player market value based solely on talent (performance and demographic). Results show that the proportion of market value due to talent decreases as market value increases. For the players sampled, the mean impact of talent on overall market value is 77%.

Essay 2 analyses the transfer fee premia. The difference between the amount paid for the transfer of a football player and his crowd-sourced market valuation at the time of transfer (transfer premium) is dependent on several factors some of which are not measurable. This essay analyses 30 top transfers per season over the decade 2011 – 2020 and shows that buying clubs exhibit risk tolerance in that they spend a sizeable premium on young promising players compared to mature players with proven talent. The breach of a player's current contract and player's overall performance rating during the previous season also play significant roles in the size of the transfer premium.

Essay 3 looks at the top end of the football market valuation and shows that there are no diminishing returns on player wages as age increases. An analysis of the 90th percentile of football players in Europe's 'big 5' leagues, ranked by Transfermarkt market value, shows that mature players earn 112% more than young players, while mid age players earn 64% more than young players. Transfers in this market segment come with a wage penalty, but compared to young players, mature players get an offset. Player performance and minutes played in the preceding season do not matter much in wage determination as players in this market segment already have reputation built over the years. Player popularity has a small positive effect on the basic wage of football players compared to the impact on their bonuses and image rights.

The player labour markets shows that clubs exhibit risk tolerance in player transfers by their willingness to spend huge amounts on the transfer of young players with no proven talent in the hopes that this investment will pay-off in the future. On the other hand, when it comes to wages, clubs exhibit risk aversion as they pay much higher wages to mature players with proven talent.

Declaration

I declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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1. GENERAL INTRODUCTION

"… are you saying he will receive XAF11.5 million this Friday and then receive another XAF11.5 million next Friday and every Friday thereafter, just for playing football?"

Me: yes sir!

"LIES! come with me. You must be punished for this…"

It was a quiet afternoon in May 1996, and I was in my high school classroom holding copy of the French Football Magazine, *Onze Mondial*. The cover story was about Ronaldo (Luís Nazário de Lima) on the brink of a world record move to Spanish side FC Barcelona from Dutch side PSV Eindhoven. Dick Advocaat's reluctance to play Ronaldo in the Dutch Cup final had infuriated the young striker and his mind was made up to leave the Eredivisie outfit. I read a portion of the article to my classmates regarding the purported contract that offered an annual salary of 6 million French francs ($1.2M) to Ronaldo. I quickly converted the figure into our local currency which amounted to approximately XAF600 million, hence XAF11.5 million per week. The whole class erupted in a thunderous indignation and the noise attracted the high school disciplinary master to our classroom. When the class prefect relayed what I had said to him [disciplinary master], he confronted me, and I affirmed I had said all that was reported to him. He was not interested in checking the magazine I was holding. I ended up getting punished for propagating false claims and creating an atmosphere of disorder in classroom. The above anecdote merely illustrates that more than a quarter century ago, from the far reaches of planet earth, the astounding amounts of money in football had heads spinning in disbelief. For a high school disciplinary master earning about $400/month, the thought of a footballer earning about 58 times his monthly wage in a week was nerve wracking and outrightly enervating. Fast-forward 25 years on, the weekly wage of the highest earning footballers will surely send this disciplinary master into a coma. The rate of inflation of sports wages compared to other sectors in society is markedly higher. Also, within the sports labour market, the rate of wage inflation for the top earners has risen dramatically over the last quarter century. In 1996, Dennis Bergkamp (Arsenal FC) was the highest paid player in the Premier League earing £25,000/week[1]. Today, the highest paid player (Cristiano Ronaldo – Manchester United FC) earns £996,481/week in base salary and bonuses, a 3,884% rise in 26 years. Like wages, transfer fees have seen meteoric rises in the last quarter century as well. In 1996, Alan Shearer transfer from Blackburn Rover to Newcastle United for £15 million was the transfer fee record. Neymar's €222 million transfer from FC Barcelona to Paris Saint Germain in 2017 represents a 1,133% increase.

1.1 – Money in Football

Association football is a €25 billion industry.[2] The revenues of football clubs come from three principal sources: matchday (including ticket and corporate hospitality sales), broadcast rights (including distributions from participation in domestic leagues, cups, and UEFA club competitions) and commercial sources (e.g., sponsorship, merchandising, stadium tours and other commercial operations). The most important asset on the balance sheet of football clubs, and hence the largest expense are the players (Morrow, 1996; Tunaru *et al.,* 2005; Majewski, 2016). For the first time since 2009, the European football market contracted by 13% in 2019-20 with overall revenues falling by €3.7 billion to €25.2 billion[3]. While wages did not fall principally due to ongoing contracts, the wage to income ratio rose by 12 percentage points to 73% according to the Deloitte's Review of Football Finance for 2021. These figures paint a picture of clubs operating a dangerous tightrope well outside the recommendations of the UEFA financial rules. All major European leagues saw their operating profits decline in 2020-21 making it clear that the European football market is not immune to global economic downturns. Falling revenues have pushed clubs to borrowing to stay afloat. The Premier League clubs' net debt rose to £4 billion, an increase of £500 million pre-pandemic. Consequently, the sports business model is gradually shifting from dispersed to concentrated ownership structures. Deloitte's Review of football finance for 2021 also highlighted the increase interest from private investment firms (concentrated ownership) in sports ventures. Private investment in major US and European leagues totaled €7.8 billion, a 50% increase from 2009. Some pundits believe that the Covid-19 pandemic has triggered a set of

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[1] https://www.thesun.co.uk/sport/football/1443127/from-4-a-week-to-400000-how-wages-have-changed-in-football-through-history/
[2] https://www2.deloitte.com/uk/en/pages/sports-business-group/articles/annual-review-of-football-finance.html
[3] Deloitte Review of Football Finance for 2021

factors that would inevitably lead to the burst of the football bubble. There are troubling signs on the horizon. Andrea Agnelli, president of Italy's Juventus and chairman of the powerful European Club Association (ECA) recently painted a bleak picture of the impact of pandemic on club finances. Most leagues have been forced to pay rebates to broadcasting corporations for games cancelled because of the pandemic. Lost matchday revenues have also heavily dented the revenue streams of most clubs. The shift from dispersed ownership (exemplified by the German style of social democrats) to concentrated ownership (exemplified by US capitalist models) signals a reaction from new ownership to re-engineer their business models and ensure continued profits. The failed introduction of the European Super League (ESL) was a step in this direction. According to Professor Simon Chadwick in an interview to AL-JAZEERA[4] , the current UEFA models makes it such that when European super weights such as Real Madrid CF and Manchester United FC clash, the financial proceeds are shared amongst all UEFA members organisations including the Maltese and Faroe Islands. However, the authors of the ESL were proposing a liberal free-market capitalist model where the proceeds from such a big clash would be shared only between the participants. Despite the failed attempt, it is inevitable that capitalists will always seek growth and with the ESL looking less likely to become a reality, it would be a mistake to think that proponents of the ESL have given up entirely.

In the football player labour market, there are three principal money centers: the free market valuation of the player as a floating asset (player market valuation), the transfer of a player from one club to another (transfer fees), and the remuneration of players (wages). The free market valuation of a player by Transfermarkt as of the time of writing has a record market value of €200 million attributed to Kylian Mbappe of Paris Saint Germain in December 2018[5]. The transfer fees record is currently held by Neymar Jr. in a 2017 €222 million transfer from FC Barcelona to Paris Saint Germain[6]. The highest player salary (base + bonuses) at the time of writing is $70M[7] per year (£996,481/week) paid to Cristiano Ronaldo at Manchester United. Be it market valuation,

[4] https://www.aljazeera.com/economy/2021/4/23/what-was-behind-the-collapse-of-the-european-super-league
[5] https://www.transfermarkt.com/spieler-statistik/rekordmarktwerte/marktwertetop
[6] https://www.forbes.com/sites/bobbymcmahon/2017/07/31/neymars-move-to-psg-will-set-a-world-record-and-trigger-more-high-priced-transfers/?sh=5929a7c531f7
[7] https://www.forbes.com/sites/christinasettimi/2021/09/21/the-worlds-highest-paid-soccer-players-2021--uniteds-cristiano-ronaldo-reclaims-top-spot-from-psgs--lionel-messi/?sh=2dafcd843b7b

transfers, or wages, the amount of money in football is staggering even for well-situated persons with an above average knowledge of free market economics. As an example, in 2019/20, £17.04B was paid in wages to 10,070 players by 350 teams playing in 18 leagues across 12 countries in 8 sports disciplines (GSSS, 2019). There are 5 leagues in European Association Football denoted as the 'big 5'. These comprise of the English Premier League, the Spanish La Liga, The German Bundesliga, the Italian Serie A, and the French Ligue 1. In 2019/20, of the £17.04B in salaries, 28.7% (£4.89B) was paid by 98 teams to 2,559 players in the 'big 5' leagues. In that same year, the total revenue generated by the top 20 of the 98 teams that comprise the 'big 5' was £7.00B, a 12% drop from the previous year (Deloitte, 2021). European clubs in total spent £3.80B in player transfers in 2019, with 10% of the players (130) accounting for 90% of the amount spent on player transfers. These figures are mind-boggling, and many public figures both within and outside football have expressed concerns that big money is a threat to the 'beautiful game'. Manchester United midfielder Juan Mata (earning £144,000/week) in an interview for Spanish TV program *Salvados* said "*Football is very well remunerated at this level. It's like we live in a bubble. With respect to the rest of society, we earn a ridiculous amount*". UEFA Financial Fair Play rules have been set to curb inflation, but these do not seem to work. However, the thesis of this research is that the money in football is justified. All stakeholders (fans, players, clubs) have key roles in the fundamentals of this labour market and every stakeholder willfully participates in this labour market and makes choices freely with many other alternatives available. This 3-essay series focuses on each of these money centers and analyses each for a better understanding of the role played by each stakeholder.

Understandably, the ever-increasing amount of money in football is a concern to most people, whether directly involved in football or not - from lovers of the game who are concerned that this financial bubble will burst with serious ramifications to the game; to regulatory authorities concerned with the financial stability and sustainability of clubs; to the civil society alarmed by the apparent social injustice associated with such huge amounts. From a classroom in sub-Saharan Africa to a pub in London, peoples from different walks of life are grappling with the financial figures in football. Hence, it is not a matter of interest to sports economists only. While the concerns of those who worry about the inflation in football are understandable, it is worth noting that this inflation is not limited to football. Sports entertainment in general is witnessing increasing wages for players, and where applicable, transfer fees are also increasing. Beyond sports, the entertainment industry in general is witnessing the contracts and wages of the production workers skyrocket – from movie stars to musicians and stand-up comedians (Bakija, Cole & Heim, 2012). The superstar phenomenon is applicable in many other sectors other than sports and football (Scarfe et al., 2021) where a few individuals with slightly better skills earn exceptionally higher wages comparatively. Whether it is due to Rosen's (1981) version of superior talent, or Alder's (1985) version of network externalities, or a combination of both, technological advancements that have allowed low-cost reproduction and global availability of services via different media will result in convex earnings. Money is concentrated at the upper end of the football labour market. This market segment is the focus of this research. In the economics of labour markets, a market that is characterized by few buyers and few sellers and high price volatility is known as a thin market. Conversely, markets with many buyers and sellers, and low price volatility is a thick market. The upper end European football market has the characteristics of a thin labour market (McLaughlin, 1994; Dobson & Gerrard, 1999; Abraham et al., 2013; Bryson et al., 2013) as there are few very talented players valued at a very high price and there are a few clubs who have the resources for afford the services of such players. Price volatility in this market is very high such that when one player leaves the market, the price of close substitutes shoots up. The lower end of the market has many close substitutes (alternatives) such that it is easier and cheaper to recruit a player or get a replacement for any player, hence a thick market.

1.2 – Market Values in Football

Assigning a monetary value to a football player is a complex process. Unlike other assets such as currencies for which the values are fixed and generally accepted; the value of a player is dependent on the player's attributes that are important to the needs of a club at a point in time, and hence varies considerably from one club to another. Several third-party entities have emerged over the years with their own methods of assigning market values to football players. The top 2 most common are KPMG Football Benchmark (www.footballbenchmark.com) and Transfermark (www.transfermarket.com). The latter is founded on the principle of "wisdom of the crowds" and has gained considerable traction since its inception at the turn of the century.

New York Times sports journalist Rory Smith chronicles the history of Transfermarkt in an article titled '*Wisdom of the Crowds*' (Smith, 2021). Transfermarkt started as a one-man (Matthias Seidel) venture with a spreadsheet populated with the player details of his favourite club (Werder Bremen). Soon, Seidel started getting corrections from avid fans as to player details and later from clubs regarding actual amounts for transfer fees. These corrections, and later opinions of a wide fanbase sums up Transfermarkt's offering – *a crowdsourced guess at a valuation*, or better still, *an estimate of worth based on the work of thousands of volunteers and sifted by the site's 80 staff members*. Today, Transfermarkt serves 22 countries and has 680,000 registered members, with about 5,000 active members sharing opinions on the market values of players. The following excerpt from Smith's (2021) NYTimes article best describes Transfermarkt's place in the football industry today [*…Lintz and his colleagues are proud of how accurate their educated guesses tend to be. They take it as vindication and validation of their "wisdom of the crowd" approach when a real-life player moves for a fee similar to his value on the site. But they know, too, that there is a reason for that. Though Transfermarkt started out as — and is still, at heart, designed to be — an attempt to reflect the state of the transfer market, it has come to exert a gravity on it. A player's worth on Transfermarkt is not seen within the sport as an estimation, but, effectively, as a price tag: the starting point for negotiations on trades in which tens of millions of dollars change hands, a digital anchor for a real-world fee*]. Herm at al. (2014) detail the aggregation process of Transfermarkt and the rule of judges in their article titled '*When the Crowd Evaluates Soccer Players' Market Values: Accuracy and Evaluation Attributes of an Online Community*'.

Due to their high levels of correlation with actual transfer fees, the research community has also embraced Transfermarkt values as a proxy for transfer fees and wages, such that values taken from Transfermarkt are used in analyses published in scientific journals (Franck & Nüesch, 2012, Bryson *et al*., 2013; Herm *et al*., 2014; Müller *et al*., 2017). Transfermarkt values hence represent a reference value point from which clubs and agents can initiate negotiations to either maintain, increase, or decrease the monetary value dependent on the circumstances of the club and the player at the point in time. Transfermarkt values have shortcomings both in terms of the process through which they are derived (Müller *et al*., 2017) as well as what they conceptually represent (an arbitrary valuation based on the weighted opinions of many). While Transfermarkt values can be seen as the value attributed to a player as a floating asset in the global football market, the players valued play for clubs and their values are based in large part to the performances of the players for their clubs over the preceding season. Hence, the prestige of the club (and the league) as well as the competitions in which the club (and the player) participates also affect the player's valuation by the online community. For example, take 2 offensive players: Raheem Sterling and Florian Thauvin. During the 2017/18 season, Thauvin played 2,966 minutes in the French Ligue1 scoring 22 goals and providing 11 assists. He also played 761 minutes in the Europa League scoring 3 goals and providing 2 assists. In the same season, Sterling played 2,593 minutes in the English Premier League scoring 18 goals and providing 11 assists. He also played 497 minutes in the Champions League, scoring 4 goals, and providing 1 assist. Both players were aged 24 and both featured in their nations World Cup squads. Thauvin won the World Cup. However, in December 2018, Transfermarkt valued Thauvin at €50M and valued Sterling at €150M (threefold) on the back of near identical performances in the preceding season. It is worth noting that the European Sports Media (EUSM) that awards the Golden Boot based on a point system considers goals in the English Premier League and the French Ligue 1 on an equal point basis – 2 points[8]. This demonstrates the extent to which Transfermarkt values are affected by non-performance attributes. Additionally, the popularity (iconic status) of the player is a factor in the valuation by online communities. Herm et al. (2014) report that the most popular players get the most reviews from online fans, hence player popularity is already factored in Transfermarkt market values. This shortcoming is often noted as a limitation in the use of Transfermarkt values in scientific research, and as such, a limitation in this study. However, until such a time when better data options (both practical and conceptual) would be available, Transfermarkt values remain the best alternative.

1.3 – Gaps in the Literature

Since Rottenberg's (1956) seminal paper on the Major League Baseball (MLB) labour market in North America, several sports economists have analysed different aspects of the sports labour market. The sports market in general has 3 principal stakeholders: the employers (clubs), the workers/employees (players), and the consumers (fans). Input from all 3 stakeholders underlie

[8] https://www.eusm.eu/item/goldenshoe_winners.htm

the basic functioning of the market - Clubs employ the players who are the primary production workers, and their [players] on-field display produces paid entertainment consumed by the fans either in stadiums or via television broadcast. Labour market areas such as workforce mobility/recruitment (transfers), employee remuneration (wages), and asset valuation (market value) have been covered individually and to varying extents by extant research. Most studies analyse football labour markets as homogenous units and make generalized conclusions, except studies that aim to test the superstar theory. While testing superstar theories in the German Bundesliga, Lehmann & Schulze (2008) argue that ordinary least squares (OLS) regressions do not capture the convexities at the upper end of the sample and proposed the use of quantile regressions. Aside the wage convexities mentioned by Lehmann & Schulze (2008), what other specificities exist within this thin market? At the time of writing and to the best of my knowledge, no other study has addressed the thin segment of the market to explore how player, club, and market characteristics affect the distribution of the three valuation factors under study, and the interrelationship between these valuation factors. This is the gap that this study intends to fill.

The uppermost quantiles of the football labour market in the 'big 5' have the characteristics of thin markets, hence the focus of this thesis. The total population of the 'big 5' leagues in Europe is 2,225[9] players spread across 98 teams. In European Association Football, labour mobility (player transfers) and employee remuneration (player wages) are interactions primarily between employers and employees (mostly represented by agents). Player valuation on the other hand is primarily assigned by consumers via online fan forums that have become widely accepted as baseline for player market value, e.g., Transfermarkt. The latter has been widely accepted as a proxy for transfer fees in scientific studies (Bryson *et al*., 2013, Franck & Nüesch, 2012, Müller *et al*., 2017), quoted by reputable magazines (Bryson *et al*., 2013), and used in actual transfer negotiations (Herm *et al*., 2014).

[9] 2019 figures per GSSS.

1.4 - Research Aim and Objectives

The aim of this research is to explore how certain player characteristics, club characteristics, and market characteristics affect the distribution of player market value, transfer fees, and wages in the thin segment of the football labour market.

The relationship between player and club characteristics have been established by extant research in the general population of the football labour market. However, when considering the thin segment of the football labour market, are these relationships the same in terms of magnitude and direction? The objectives of this study are to use a series of player, club, and market variables to regress the three money centers in the football labour market (market value, transfer fees, and wages) in thin markets and show the differences compared to results that extant research has produced for the general population.

This research will follow a three-step process outlined in subsequent chapters. Firstly, the market valuation attributed to players as floating assets on a free market will be regressed against the applicable descriptive factors (player characteristics). Given that goals and assists constitute the highest number of online threads submitted by fans in the Transfermarkt forum, the first essay of this research will be analyzing offensive players only and looking at how their offensive attributes as well as demographic attributes affect the distribution of market values. This study will answer questions such as: how does player factors (age and performance) affect the distribution of market value in thin markets? How does the distribution of player market value in thin markets differ from the distribution in thick markets (based on the findings of extant research)? Secondly, to explore the distribution of transfer fee premia (difference between actual transfer fees paid for the services of the player and the Transfermarkt valuation of the player at the point in time, [Depken II & Globan, 2021]), player, club, and market characteristics are used in the analyses. Unlike the first case where club factors and market characteristics are not included in the analyses, the distribution of transfer fee premia is affected by buying club factors as well as transfer market demand/supply factors. The contribution of a player to team success is factored as well as the ownership structure of the buying club. The ranking of the buying club vis-à-vis the selling club is also analysed to see the effects of poaching versus offloading. The pressures of the winner's curse and heightened sense of speculative fever that characterizes the transfer window also affect the amount of money that clubs offer to get the services of players. Lastly, to explore the distribution of wages, player characteristics as well and club and market characteristics are analysed in a similar fashion as with the preceding case. Using the uppermost quantile of players ranked by Transfermarkt values, player wages are regressed against descriptive factors. The sample is a mix of players who have recently transferred and players who did not transfer during the window under consideration for this study. This cross-sectional analysis gives a point in time effect of descriptive factors on the wage distribution. Interactive terms are also analysed to show how the transfer status of players affects the wage distribution.

Combined, this study provides a holistic and comprehensive analyses of the thin football labour market by successively testing similar player profiles (high valued players) across the three money centers (open market valuation, transfers, and remuneration) using the most advanced and up to date variables (for which data are available).

1.5 - Research Contributions

By analyzing all three money centers, this research shows the interconnectedness of the money centers and the origins of player monetary valuation from the valuations done by football fans via crowd-sourced online platforms. The progression from how a player profile is valued by the open market, how much a club is willing to pay for the services of that player compared to the open market valuation of the player, and how much the club is willing to remunerate the player provides a clear picture of how monetary valuation is distributed in the football labour market. Individually, the essays offer the following contributions:

- The main contribution of essay 1 is that it dissects the attributed player market value into talent-based market value grounded on a player's footballing ability and 'intangibles'-based market value grounded on a player's iconic status, origin, popularity, etc.
- The main contributions of essay 2 are twofold: Firstly, this essay analyses the size of transfer fee premia using a comprehensive set of measurable variables including player characteristics, buying/selling club characteristics and the regulatory framework in place - to the best of my knowledge at the time of writing, no other study uses this approach. Secondly, this essay complements the literature on how revenue levels generally affect

transfer premia but goes beyond the league level to test if at the very top of the transfer market, certain buying club characteristics (ownership structure, change in leadership/ownership) leads to impulsive behavior (irrational exuberance) that is not informed by market information – a requirement for perfect market operation.

- The main contribution of essay 3 is that it analyses football player wages jointly as a function of age group and transfer status. Additionally, this essay innovates the measurement variables for performance and popularity as follows: firstly, this essay uses more sophisticated performance measure. Unlike previous studies that primarily use goals, assists, tackles, etc. (Lehmann & Schulze, 2005; Lucifora & Simmons, 2003), this essay uses an overall performance variable that best measures the contribution of every player to team success, hence all positions are included. Secondly, player popularity, hitherto measured by press citations and Google hits, is measured by their social media following - multi-way, immediate, and contingent medium linking fans and the player/club (Peters et al., 2013).

All 3 essays combined paint a clearer picture of how the drivers of monetary value change from valuation through recruitment to remuneration across similar player profiles and how the distributions in thin markets differ from the findings in in the overall unsegmented player labour market.

1.6 - Research Outlay

The first essay titled: ***The Market Value of Talent in Thin Markets*** focuses on the open market valuation of a player, attributed by fans. The value attributed to a player as a floating asset on the market (player market valuation) has been defined as the amount of money that a club is willing to pay to acquire the services of the player, independent of a contract (Herm et al., 2014). In this study, this value is equal to the Transfermarkt valuation of the player at a point in time. Transfermarkt values are aggregations of valuations by multiple fans, of which the final output is sampled by a panel of judges (Herm et al., 2014). Crowd-sourced market values have as shortcoming, a lack of clarity in the valuation process (Müller *et al*., 2017) as it is not possible to replicate the methods that individual fans use to assign market values. Studies have shown that iconic players (superstars) get most of the valuation input from fans and forward-leaning players also get a disproportionate share of the valuations (Herm et al., 2014). The monetary value assigned to each player by a fan is a mix of the player's footballing ability and other non-footballing attributes such as iconic status, origin, etc., otherwise coined as *intangibles*. Müller *et al*. (2017) use data-driven methods to estimate player market values and compare the results to Transfermarkt valuations in predicting the actual transfer fees that clubs are willing to pay to acquire the services of a player. They find that data-driven methods show more accurate estimates of transfer fees for the lower 90 percent of players while Transfermarkt values are better at estimating transfer fees of the top 10%.

This essay analyses the most prominent variables reported from the threads posted by fans on Transfermarkt for high value players and tries to dissect the attributed market values to estimate the proportion based on footballing ability and the remainder based on intangibles. Why is this dissection important? Football as a sport goes beyond the matchday displays. There are other factors (intangibles) that account for part of the monetary value attributed to players. As utility maximizers, clubs need revenues to acquire the talent needed to achieve sporting success. Hence, there is need to optimally balance the talents and 'intangibles' in a squad such that the talent's on-field prowess helps with winning games, while the 'intangibles' off-field prowess helps with revenue growth. Revenue also comes from fans who are willing to pay (for season tickets, club merchandise, and broadcast subscriptions) to consume a leisure entertainment activity (football) among other leisure alternatives available at cheaper cost, showing that they acknowledge the prices as fair. For example, as of June 2017, Transfermarkt (fans) valued Cristiano Ronaldo at €100M. How much of this value was attributed to his talent and how much to his image rights and merchandise-selling ability? This essay will help understand why 2 players with similar profiles and stats playing in the same league have markedly different market valuations, e.g. In the 2017/18 season, Sadio Mane (24) of Liverpool FC made 39 appearances in the league and UEFA Champions League scoring 20 goals and providing 8 assists. In the same season, Raheem Sterling (22) of Manchester City FC made 34 appearances in both the English Premier League and the UEFA champions League scoring 22 goals and providing 12 assists. At the end of this season, Sadio Mane was valued at €70M while Raheem Sterling was valued at €90M. Can the €20M difference in valuation be attributed to the 2 years age difference, the 2 goals difference, and the 4 assists difference? Football fans (via crowd-sourced forums) play an active role in the allocation of value to football players, especially the ‘intangibles’ that further exacerbate the valuation.

The second essay titled: ***Football Transfer Premia in Thin markets*** focuses on the distribution of transfer fee premia and the factors that influence the size of these premia. At the upper end of the player valuation chain, Transfermarkt values should more accurately reflect transfer fees (Müller et al., 2017) - Essay 1 operated on this premise. However, this is not always the case. The difference between the transfer fee paid for the services of a player and the Transfermarkt valuation of the player at that point in time has been coined the transfer fee premium (Depken II & Globan, 2021). The transfer fee premium can either be positive, zero or negative. While it has been clearly established in extant research that market values and transfer fees are influenced by the similar factors (Bandes & Franck, 2012; Bryson *et al.*, 2013; Frick, 2007) and hence conceptually similar, there are certain factors that affect transfer fees but do not affect market values such as player contractual obligations, irrational exuberance of buying clubs, transfer window demand and supply, etc. Depken II & Globan (2021) study transfer fee premia in European Association Football and show that the English Premier League pays the highest transfer fee premiums. They also show that landmark broadcasting deals with clubs coincide with highest transfer free premia. Given the current regulatory framework governing player transfers, and despite the Financial Fair Play rules, the utility maximization objective of football clubs continues to push transfer fees upwards as the biggest clubs struggle fiercely to secure the signatures of the best players. While extant research (Depken II & Globan, 2021) has shown that revenues from broadcasting deals directly affect transfer fee premia, broadcasting revenues do not constitute same proportion of club revenues across the board. While smaller clubs largely depend on broadcasting revenues, larger clubs have other sources of revenue such that broadcasting revenues makes less than half of their total revenues. For example, according to KPMG Football Benchmark, for the 2017/18 season, Liverpool FC reported a total club revenue of £514million, with £248 million (48%) coming from TV broadcasting deals. Conversely, in the same year, Stoke City reported total revenue of £144 million, with £114 million (79%) from TV broadcasting deals. This is the same trend in all ‘big 5’ leagues where broadcasting revenue makes under 50% of the club’s overall revenue of the biggest clubs (Real Madrid, 36%; Juventus FC, 50%; etc.).

Consequently, the expenditures of bigger clubs in the transfer market cannot only be influenced by their broadcasting revenues. However, while broadcasting revenue alone does not drive transfer fee premia in this market segment, other club revenue sources (ticket sales and merchandise sales) borne of fans willingness to pay for this leisure entertainment helps push the transfer premia.

Essay 2 goes beyond club revenues and the sources of these revenues and posits that club ownership structures (concentrated or dispersed), changes in club leadership/ownership, as well as the player characteristics, contractual obligations, and transfer window demand/supply, all affect the distribution of transfer fee premia. Regarding club leadership structures, this variable is very important as all the market analysis can be ignored and replaced by instinctive behavior (Irrational exuberance) on the part of concentrated owners, defying all market analyses – winner's curse. In thin markets, it is more likely that due to additional pressures from instinctive club owners, and where not adequately constrained by Financial Fair Play rules, transfer fee premia more likely be positive than negative or zero. Also, beyond the leagues, essay 2 examines the distribution of transfer fee premia across player age groups and playing positions.

Finally, essay 3 titled: ***Football Player Wages in Thin Markets*** analyses the last of the 3 money centers in the football labour market. Broadcasting deals are a major source of revenue for clubs alongside ticket and merchandise sales. Fan attendance at sports venues or paid viewership on TV supply the pipeline that feeds into these revenue streams. The players who produce the entertainment that fans pay to consume deserve a commensurate wage for their services. According to the marginal revenue productivity theory, players should earn a wage equal to their MRP (Scully, 1974). Football is a collective sport, and given the complexities associated with calculating the MRP of each production worker in collective production (Antonietti, 2006), it is no surprise that wages do not always equal MRP in football. Wages can either be equal, lower, or higher than the MRP of the player. Wages will equal MRP in an equilibrium characterized by perfect market conditions – accurate calculation of the change in revenue to the club due to the recruitment of the player. However, due to the several non-market forces that operate in the player market, a market equilibrium is rare. As a result, there are several other factors that affect the distribution of player wages – player characteristics, club characteristics, and player labour market characteristics. Extant research has shown that the factors that influence player market value and transfer fees also influence player wages (Bryson et al., 2013; Frick, 2007). Studies that focus on testing the superstar phenomenon have shown convexity of wages in the thin labour market for football (Lehmann & Schulze, 2008; Lucifora & Simmons, 2003). These wage convexities can either be attributed the Adler's (1985) network externalities theory, Rosen's (1981) slight difference in talent, or both. This essay looks at the different factors that affect the distribution of player wages in this market segment and how these factors affect the distribution across different player demographics, playing positions, and leagues. Fan purchases and broadcast subscriptions help finance the remuneration of players.

In summary, fans attribute a monetary value to the player as an asset in the open market. Fans then buy season's tickets, club merchandise, and pay for TV broadcast subscriptions that fuel the revenue streams for clubs. Clubs use the revenues at their disposal to secure the best players to achieve sporting success and please their fanbase. Players (represented by agents) negotiate fiercely with clubs to secure the most lucrative contracts (wage) they can possibly get. This makes it a free market and hence justifies the money involved.

1.7 – Conceptual Framework

Fig. 1 below is the general conceptual framework for this thesis. The solid arrows show the direction of relationship between the independent variables (outer greyscale rectangles) and the dependent variables (blue, red, and black rectangles). These solid arrows show relationships for which the data are available and included in this study. The broken arrows show relationships for which the data are not available and hence not included in this study – a noted limitation. As has been noted above, the factors that affect market values, transfer fees and wages are conceptually similar. Player demographics, performance, playing position, popularity, and participation in European Club competitions are base factors that affect all the three dependent variables of this study (market value, transfer fee premium, and wages). However, there are other factors that cannot be known *apriori* when estimating player market value, but which do affect transfer fees and wages, such as buying/selling club characteristics, irrational exuberance of buying clubs, player contractual obligations, and transfer window demand/supply. Market value (Transfermarkt) is used as a baseline for the estimation of all three dependent variables.

The solid blue lines in Fig.1 represent direct correlations between the grey rectangles (independent variables) and the blue rectangle (dependent variable). Performance is hypothesized to have a direct positive relation to market value. Demographic variable (Age) is hypothesized to have an increasing yet diminishing correlation with market value. Playing position is a dummy variable and hypothesized such that market value would increase with how forward the position of the player is: center forward > winger > attacking midfielder. UEFA Club Competition is dummied to represent participation in the UEFA Champions League (UCL), UEFA Europa League (UEL) or NIL for player who did not participate in any UEFA club competition. This variable is hypothesized such that correlation to market value will be in the order: UCL > UEL > NIL. Lastly, the broken blue line represents a relationship that is not included in this study and represents part of the 'intangibles' – non-footballing factors. Per this study, player popularity and/or iconic status though relevant to their market value do not affect their footballing abilities.

The solid black lines represent direct relationships between the independent variables in grey rectangles and the dependent variable in the black rectangle (transfer fees). The hypotheses are similar to those of the solid blue lines. Popularity, Market Value, and Contractual Obligation (number of years remaining on player's contract) are numeric variables and hypothesized to have a direct positive effect on transfer fees, and hence transfer fee premium. Club Characteristics are dummied reflect superior buying club (poaching) or inferior buying club (benefiting from off-loading). Poaching is hypothesized to lead to higher transfer fees while offloading is hypothesized to result in lower transfer fees. Additionally, Club Characteristics is also dummied to reflect the ownership structure of the club: dispersed ownership versus concentrated ownership. The hypothesis is that dispersed ownership allows for careful analyses decisions informed by market data, hence lower transfer fees, whereas concentrated ownership involves irrational decisions based on gut-feeling and hence higher transfer fees and hence transfer fee premia. Lastly, Club Characteristics are dummied to show recent changes in club leadership/ownership and hypothesized such that recent changes in leadership/ownership will result in higher transfer fees compared to stable leadership/ownership over time. The broken black lines show relationships that do exists but for which data in not available for this study – another noted limitation.

Irrational Exuberance, a 'winner's curse' could not be coded into data form and Transfer Window Demand/Supply data are not available for this study.

The solid red lines show relationships between the independent variables in grey rectangles and the dependent variable in the red rectangle (wages). The hypotheses are similar to those of the solid blue lines and solid black lines in terms of magnitude and direction. As in the preceding instances, the broken red lines depict relationships that exists but for which data are not available for this study.

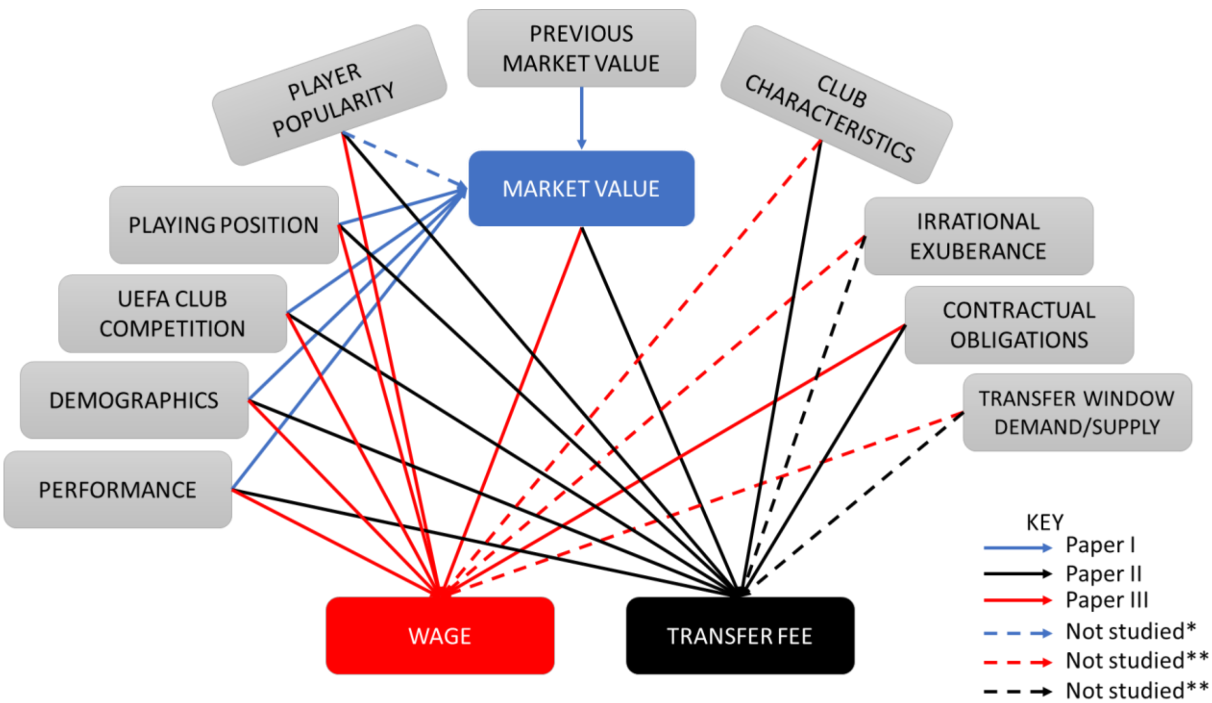

Fig. 1 Conceptual Framework

*Notes: * Not included in analysis due to inability to get reliable historical social media following on the selected platforms.*
*** Not included in analysis because data to code and measure these variables was not available at time of writing.*

The essay-specific findings and limitations are summarized at the end of each essay. The overall findings will be summarized in section 5 as well as the general limitations of this study and proposed areas for future research.

1.8 Research Assumptions / Limitations

Despite advancements in data availability for analyses in European football, there are still setbacks for which assumptions need to be stated to alleviate practical and conceptual concerns that will inadvertently arise. Some variables used across this study make use of second choice data sets simply because of the absence of better data.

Firstly, at the very core of this study is the concept of market values. Transfermarkt values are used with reservation. It is assumed that the Transfermarkt value represent point in time monetary value of a player. This value represents what the player is worth based on the demographic and performance attributes of the player. These market values are crowdsourced and research into the crowdsourcing process (Herm et al., 2014; Muller et al., 2017) shows that a portion of these values is borne of *intangibles* (factors not related to the footballing abilities of the player) such as player popularity (iconic status), the prestige of the club holding the player's registration, and the continental club competitions in which the player participated. Hence, using the Transfermarkt valuation of the player (beginning of the season) as an independent variable assumes that the intangible portion of that value is downplayed.

Secondly, a player's performance is measured while the player is operating as part of a club, and part of a league. As such, club factors and league factors impact the valuation of the player. However, designating the player as a floating asset assumes that contractual obligations between the player and the holding club do not affect the market valuation of the player. For example, a player who plays for Real Madrid CF in the Spanish La Liga and hence participates in the UCL will have a better valuation compared to a player who plays for EA Guingamp, even if the latter has a £1B release clause in his contract.

Third, player performance rating are taken from Whoscored.com (powered by Opta). Opta is a reputable sport data agency and provides data for sports analysis to major broadcasting networks, player awards including 'Man of the Match' Awards in several major leagues and football tournaments. While it is true that this metric is not an error-proof measure of contribution to team success, it is the best metric available to measure individual contributions. Whoscored ratings have been used in peer-reviewed scientific studies (Dendir, 2016). The settings that players operate in are hardly identical. This study is cognizant of the fact that players play in teams with different players and in different league. Additionally, not all players face similar opponents. As such, a comparison of performance between players in different settings may be problematic. However, absent a better measure of performance and contribution to team success, this study will use Whoscored ratings.

Lastly, a larger random sample would have been ideal to analyse and then run quantile regressions to compare against the results of the larger sample. However, due to data constraints with regards to availability and accuracy, this study makes uses the data of the most popular players and hence the data are skewed towards the upper end of the player valuation table. To curb this constraint, the results of these analyses will be compared to results of extant research that made use of larger samples and then conclusions will be drawn comparatively. It is therefore assumed that earlier research in this field of study serves as a reference of comparison for the results of this study.

2. Essay 1: THE MARKET VALUE OF TALENT IN THIN MARKETS: THE CASE OF EUROPEAN ASSOCIATION FOOTBALL.

2.1- INTRODUCTION

European Association football (hereafter referred to simply as 'football') is a billion-euro industry with 2017/18 revenues totaling €28.4 billion according to Deloitte Sports Business Group[10]. The 'big five' leagues comprising the English Premier League, German Bundesliga, Spanish La Liga, Italian Serie A and French Ligue 1 all account for €15.6 billion or 55% of this revenue. The remainder 45% is accounted for by the non 'big five' top leagues (€5.3B or 19%); FIFA, UEFA and National Associations (€4.2B or 15%); the 'big five' countries' other leagues (€2.6B or 9%); and the non 'big five' other leagues (€0.7B or 2%). The English Premier League tops the revenue chart with €5.44B revenue in 2017/18. Football revenues come from three primary sources: broadcasting rights, sponsorship/commercial deals, and match day receipts. Of the €5.44B that the English Premier League received in 2017/18, €3.21B (59%) came from broadcasting rights, €1.47B (27%) came from sponsorship/commercial deals and the remainder €0.76B (14%) came from match day receipts. The most successful teams in European football earn highest share of the revenues. There is a school of thought that says football clubs are profit-seeking entities (Storm, 2010; Szymanski, 2006; Zimbalist, 2002) - Thus, they have an incentive to secure the best talent at the right price (minimal cost) to ensure on-field success and hence financial gain. Another school of thought holds the clubs are utility maximizers looking primarily to achieve sporting success (Kesenne, 2007; Sloane, 1969, 2006; Fort, 2000). In either case, both schools of thought agree that to an extent that both ends are inextricably linked. The most important asset on the balance sheet of football clubs are the players (Morrow, 1996; Tunaru *et al.,* 2005; Majewski, 2016). The 2017/18 transfer window in Europe saw football transfer fees cross the €200 million mark with Brazilian international, Neymar Jr. joining Paris Saint-Germain from FC Barcelona for a transfer fee of €222 million. With such astronomical amounts, the greatest challenge for football

[10] https://www2.deloitte.com/uk/en/pages/sports-business-group/articles/annual-review-of-football-finance.html

managers and football clubs in general is the acquisition and remuneration of players (Herm *et al*., 2014; Müller *et al.,* 2017).

To secure the services of a player, clubs need to evaluate how much the player is worth to the club. The value of a player to a club is the amount of money that the club is willing to pay to make the player sign a contract (Herm *et al.,* 2014). The value that a club assigns to a player is dependent on the needs of the club at a point in time. This implies that there are several non-player specific factors that clubs take into consideration when attributing a value to a player, independent of the player's innate characteristics. Players are human and what the football club is interested in is the performance rights of the player (Majewski, 2016).

Aside clubs, there also exist crowd-sourced methods of player valuation from online communities like Transfermarkt[11]. A synthesis of the discussion threads of online communities reveals certain player attributes are considered more important in determining market values. Measured by the frequency of a market value indicator in discussion threads, talent variables (age, scoring, and successful passing) receive more than 500 hits each while the other talent attributes did not get half as much (Herm *et al*., 2014). While crowd-sourced methods have their apparent shortcomings as explained by Müller *et al.,* (2017)[12], they have proved to have a high degree of accuracy in determining player market values. As a result, Transfermarkt valuations have been quoted by some of the most influential newspapers and magazines in Europe (Bryson *et al*., 2013; Herm *et al*., 2014). Transfermarkt values have a good reputation in the sports industry and are used in actual transfer and salary negotiation and have been used as proxy for scientific research (Bryson *et al*., 2013, Franck & Nüesch, 2012, Müller *et al*., 2017). In this study, market value refers to the Transfermarkt valuation of a player at a point in time. Given the near accuracy of online community's predictions, it is curious as to how much variance in market values can be explained by these talent variables alone.

Human capital formulation pioneered by Jacob Mincer (1958) considers human capital a function of schooling and experience. This essay builds on the work of Lucifora & Simmons (2003) and

[11] See Herm *et al*. (2014) for a description of the Transfermarkt process.
[12] See Müller *et al.* (2017) for details of the shortcomings of crowd-sourced methods.

adapt the Mincer-type human capital formulation to estimate the market value of a player as a function of the player's innate characteristics (demographics and performance) only. First, given that the most important (per online community assessment) market value indicators are consistent with the offensive part of football (goals and passing accuracy), this essay focuses on offensive players only (center forwards, wingers and attacking midfielders). Second, in line with one of the drawbacks of crowd-sourced estimations where lesser-known players do not get as many reviews (Müller *et al.,* 2017), this study focuses on well-known players who get the highest volume of reviews from members of the online communities. In this regard, the focus is on the top valued players on the market valuation ranking. Third, to have a somewhat fair comparison between player performances (goals per game, assists per game, etc.), only players who played in the top five European Football Leagues (Spain, England, Germany, Italy, and France) during the 2017/18 – 2018/19 seasons are included.

The main contribution of this essay is that it dissects the attributed player market value into talent-based market value grounded on a player's footballing ability and 'intangibles'-based market value grounded on a player's iconic status, origin, popularity, etc.

2.2- BACKGROUND

2.2.1 – Definition of Player Market Value

As explained in section 1.2 above, player market values used for this study are taken from the crowdsourced website Transfermarkt.com. Despite the practical and conceptual shortcomings of these values, they still represent the best data set available for scientific studies at the time of writing. Herm *et al.* (2014) define the market value of a professional athlete such as a footballer as an estimate of the amount of money a club would be willing to pay in order to make this athlete sign a contract, independent of an actual transaction. Player market values represent an estimate of the transfer fees that is paid to retain the services of the player (Müller *et al.*, 2017). While player market values and player transfer fees are conceptually similar and to an extent influenced by similar factors (Frick, 2007; Brandes & Franck, 2012; Bryson *et al.*, 2013), they are different. To best understand market values, it is helpful to contrast market values with transfer fees.

Generally, market values are dependent on player-specific factors and club (and league) endogenous factors whereas transfer fees include non-player-specific factors such as supply and demand forces that operate during a transfer window, club specific exogenous factors, irrational exuberance, and player contractual obligations. These non-player specific factors cannot be known *a priori*. Hence, market values could be considered a sub-set of transfer fees. However, while it is possible to have zero transfer fees (in the case of a free transfer), this does not mean that the player in question has a market value of zero. Extant research in the area of player market valuation identifies player-specific characteristics (talent and popularity) as the main variables that account for player market value.

Talent is defined as a combination of performance and demographic variables. Performance variables are goals, assists, shots, key passes, and dibbles. The sole demographic variable used in this essay is player age. Age determines the athleticism and maturity of a player.

2.2.2 - Determinants of Player Market Value

With the liberalization of the player market in European football thanks to the *Bosman* ruling of December 1995 and the subsequent availability of data on player's performance, demographics, and financials (wages and transfer fees), several studies have looked at determinants of market values. In extant research, the variables that affect player market value are grouped differently by researchers. The underlying idea is to separate the variables into groups according to the whether the variable is an objective measure or a subjective measure. Variables such as age, height, goals, assists, etc. are player-specific and can be objectively measured. Variables such as google hits, kicker scores, social media following, crowd-pulling ability etc. constitute a subjective aspect of market value of the player. Hence, player-specific variables are demographic and performance variables – these are objective measures directly linked to the player's market value. Player popularity can be considered subjective based on how it affects the player's market value. Popularity (measured by Google hits and press citations) can either be positive (fame) or negative (infamy), hence it is not exactly clear how this affects market value. Conventionally, it is expected that positive popularity will increase market value while negative popularity will reduce market value.

Unlike the directly measurable performance variables (goals, assists, etc.) used to measure a player's contribution to team success, the *plus-minus ratings model* is used to calculate a players' contribution to team success based on how the team performs with the player on the field compared to how the team performs without the player. Hitherto applied in Ice Hockey (MacDonald, 2012a; Gramacy et al., 2013; Spagnola, 2013) and basketball (Fearnhead, Taylor et al., 2011; Still, 2010), the plus-minus ratings model has been adapted to soccer (Saebo & Hvattum, 2015; Schultze & Wellbrock, 2018; Kharrat et al., 2021) in the recent past. The application of the plus-minus ratings model in football calculates the differential based on a particular metric (goals, points, etc.). For example, using *goals* as a metric, the model calculates the number of goals scored by the team when the player is on the field less the number of goals scored by the team when the player is not on the field. Evidently, the downside of this model is that other conditions will have to be the same for the calculations to be valid. Empirical analyses using directly measurable variables (goals, assists, etc.) have the setback that these variables do not capture the entirety of a player's contribution, for example, when a player makes a move without the ball and draws opposing defenders to himself allowing a teammate to score, this act is not captured by the conventional performance variables. However, due to the complexities associated with putting in place identical settings for every player to operate and then calculate the differential of the metrics, this study does not adopt the plus-minus ratings model.

Research into player market values using conventional demographic and performance variables has produced consistent results over the years. A player's *age* (Bryson *et al.,* 2013; Brandes & Franck, 2012; Franck & Nüesch; 2012; Frick, 2011; Garcia-del-Barrio & Puyol, 2007; He *et al.,* 2015; Herm *et al.,* 2014; Kiefer, 2014; Lehmann & Schulze, 2008; Medcalfe, 2008; Ruijg & van Ophem, 2014) has been found to have a positive yet decreasing influence on market values. In most studies, age is included in quadratic terms *(*age^2) to ensure a linear relationship. Market values start increasing as the young player gains experience up to the mid-twenties and starts decreasing as the player's athleticism declines. A player's *height* (Bryson *et al.,* 2013; He *et al.,* 2015; Ruijg & van Ophem, 2014) which influences his ability to score or prevent goals has been found to positively affect market values. Taller players are more valuable. A player's *position* (Brandes & Franck, 2012; Bryson *et al.,* 2013; Franck & Nüesch; 2012; Frick, 2011; Garcia-del-Barrio & Puyol, 2007; He *et al.,* 2015; Herm *et al*., 2014; Kiefer, 2014; Lehmann & Schulze, 2008; Medcalfe, 2008; Ruijg & van Ophem, 2014) reflecting his flexibility shows that midfielders and forwards have more market value compared to defenders and goalkeepers. Also known as degree of specialization, midfielders have the least specialization and hence are most flexible. Midfielders can play defensive roles as well as offensive roles. Goalkeepers are the most specialized and least flexible and can only play in goal. The player's *footedness* (Bryson *et al.,* 2013; Herm *et al.,* 2014; Ruijg & van Ophem, 2014) that represents his ability to play with both feet has been found to have a positive effect on market value. Players who are dual footed tend to have a higher market value compared to single-footed players. *Nationality* (Bryson *et al.* 2013; Frick, 2011; Lehmann & Schulze, 2008) which denotes the player's country (continent) of origin has received mixed results with some studies showing that European and Latin American players are more valued than Eastern European, African, and Asian players. Other studies (Medcalfe, 2008) find no discrimination based on nationality. *Playing time* (Brandes & Franck, 2012; Bryson *et al.,* 2013; Franck & Nüesch; 2012; Frick, 2011; Garcia-del-Barrio & Puyol, 2007; He *et al.,* 2015; Herm *et al.,* 2014; Kiefer, 2014; Medcalfe, 2008; Ruijg & van Ophem, 2014), measured as the number of appearances in club and international games, just like age has been found to have a positive yet decreasing effect on market value. *Goals* (Bryson *et al*., 2013; Franck & Nüesch; 2012; Frick, 2011; He *et al.,* 2015; Herm *et al*., 2014; Kiefer, 2014; Lehmann & Schulze, 2008; Medcalfe, 2008; Ruijg & van Ophem, 2014), *assists* (Franck & Nüesch; 2012; He *et al*., 2015; Herm *et al.,* 2014; Kiefer, 2014; Lehmann & Schulze, 2008; Medcalfe, 2008), *passing accuracy* (Franck & Nüesch; 2012; Herm *et al.,* 2014; Medcalfe, 2008) *successful dribbles* (Franck & Nüesch; 2012; He *et al.*, 2015; Medcalfe, 2008) and *dueling* (Franck & Nüesch, 2012; Medcalfe, 2008) were found to positively affect player market values. Poor disciplinary attributes like *reds card* and *yellow cards* Müller *et al.,* 2017) have a negative effect on market values.

2.3 – METHODOLOGY

2.3.1 - Empirical Specification

Using a mincer-type human capital equation, expected market value is a function of player innate factors (demographics, performance, playing position and participation in a UEFA competition). The resulting Mincer-type human capital formulation is:

$$\mathrm{Ln}\left(MV_{i,c,l}\right) = \beta_0 + \beta_1 \mathrm{Ln}\left(MV_{i,c,l\,(s-1)}\right) + \beta_2 DEM_{i,c,l} + \beta_3 PERF_{i,c,l} + \beta_4 MPOS_{i,c,l} + \beta_5 UEFAComp_{i,c,l} + \varepsilon_{i,c,l} \quad (1)$$

Where the dependent variable $\mathrm{Ln}\left(MV_{i,c,l}\right)$ is the natural log of the end of season market value of player i playing for club c in league l. β_0 is a constant (intercept). $\mathrm{Ln}\left(MV_{i,c,l\,(s-1)}\right)$ is the natural log of the Transfermarkt valuation of the player at the end of the previous season (or the beginning of the current season). DEM is a vector of demographic variables and captures the player's age. $PERF$ is a vector of the offensive performance statistics of the player during the season under consideration. These performance statistics are total goals scored (*GOAL*) and this is transposed into number of goals per 90-minute period (duration of a game) to get a comparative statistic with which to compare players with different playing times. Total assists *(ASST*) are also transposed to a ratio per 90-minutes period to make it comparable with other players with varying playing times. The other performance statistics; key passes per game (*KEYP*), shots per game (*SHOT*) and successful dribbles per game (*DRB). $MPOS$* is a dummy variable representing the main position of the player; center forward *(CF)*, left/right winger *(WG)* or attacking midfielder *(AM)*. $UEFAComp$ is a dummy variable to capture the UEFA competition in which the player participated. This can either be the UEFA Champions League *(UCL)*, the UEFA Europa League *(UEL)* or *NoUEFA* if the player did not participate in a UEFA Competition. Finally, ε is an error term to capture any other effects that have not been specified among the list of predictor variables.

2.3.2 - Data Collection and Description

Football is a goal-oriented game. A positive goal margin determines the winner in a football match. While it is a collective game with defenders and goalkeepers tasked with stopping the opposing team from scoring, this study focuses only on those team members whose primary objective is offensive - to score goals and/or assist in scoring goals. The offensive part of play is consistent with the most important attributes in Transfermarkt valuations per Herm *et al.* (2014), hence, only center forwards, left and right wingers and attacking midfielders in the sample. Consistent with the goal-oriented nature of football, the most popular players in football are offensive players. European association football lags US team sports in data availability. While it is ideal to use a large random sample for such analyses, complete and accurate data are mostly available only for high profile players (most popular and valuable players). This makes the dataset skewed towards the upper end of the football player market. Additionally, while defense is an equally important aspect of football, defensive attributes do not number half as much compared to offensive statistics in the threads via which the community of fans share their opinions on Transfermarkt forum (Herm et al., 2014), hence the reliance on offensive players. Lucifora & Simmons (2003) use a sample of 124 forward players in the Italian Serie for test for superstar effects. In football, offensive players can play in more than one forward position and depending on the position, the player is more likely to be able to score or provide an assist, hence this essay considers the main position each player. For this essay, players whose main position is listed as second striker are classified equally as center forwards. This essay involves the top five leagues in Europe (English Premier League, Spanish La Liga, German Bundesliga, Italian Serie A and French Ligue 1), each league has 20 teams but for the German Bundesliga with 18 teams, hence 98 teams in total for the five leagues. Each team has averagely 10 players listed on the team roster in the offensive positions under consideration. For the 98 teams playing at the highest divisions in the top 5 leagues included in this study, the total population is approximately 980 players. The sample for this study is the uppermost quartile based on the season's market values ranking, hence 250 players for each season – 500 player observations in total. The seasons under consideration for this study are the 2017/18 and 2018/19 season. Most of the players who were in the top 250 ranking in terms of market value during the 2017/18 season also feature in the 2018/19 season ranking. For each of the 500 player observations in this sample, 12 variables per player observation are included in this study making a total of 6,000 observations being analysed. Table 1.1 below has a summary of the descriptive statistics.

The market value variable is taken from Transfermarkt.com and are point in time valuations at the start and the end of the season. The market values considered are the Transfermarkt valuation of player i at the beginning of the season under consideration ($MV_{(s-1)i}$) and the Transfermarkt valuation of player i at the end of the season under consideration, (MVi). The Transfermarkt valuation at the start of the playing period ($MV_{(s-1)i}$) has a minimum of €0.40 million and a maximum of €180 million. The mean of this variable is €24.89 million, and the standard deviation is €27.28 million. The Transfermarkt valuation at the end of the playing period (MVi) has a minimum value of €0.70 million and a maximum value of €200 million. The mean is €32.95 million, and the standard deviation is €32.34 million.

While previous research has used a series of demographic variables such as height, footedness, ethnicity, country/continent of origin etc., this essay focuses on the one demographic variable that has consistently shown to significantly affect market value- age. The age of the players is taken from Transfermarkt.com and this is the age of the player at the time the market valuation was done. Given the non-linear relationship between age and market value established in previous research, the quadratic age term is used (as in previous studies), hence age squared *(AGESQD).* The youngest player in the sample is 17 years old Kai Havertz (Bayer 04 Leverkusen)

Table 1.1.
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
MVi (in millions)	500	.70	200.00	32.9485	32.34368
$MV_{(s-1)}$ (in millions)	500	.40	180.00	24.8879	27.28438
Age	500	17	34	25.10	3.388
Games Played	500	10.17	48.00	26.3524	8.22085
Goals per Game	500	.00	1.22	.3580	.20135
Assists per Game	500	.00	.70	.1917	.12102
Shots per Game	500	.30	6.50	2.0335	.82038
Key Passes per Game	500	.20	3.94	1.2264	.60665
Dribbles per Game	500	.10	7.15	1.2345	.83458

Valid N (listwise)	500

while the oldest are 34 years Cristiano Ronaldo (Juventus FC) and Fernando Llorente (Tottenham Hotspur). The mean age of the sample is 25.10 years, and the standard deviation is 3.39 years.

All performance variables are taken from whoscored.com (powered by Opta). Whoscored.com ratings have been used in previous research (Dendir, 2016). Performance variables are computed on a per game basis. To compute the number of games played, the total appearance in minutes is divided by 90 (number of minutes in a game). Only players who played at least 900 minutes (10 games) during the season are included in the sample. The maximum number of games played in the sample is 48 games while the minimum is 10.17 games. The mean number of games is 26.35 games, and the standard deviation is 8.22. The competition games considered include the local league games and the UEFA Champions League (UCL) and the UEFA Europa League (UEL). Local cup games are not included as lower division teams do participate in local cup games. For the UCL and UEL games, teams from outside the top 5 leagues do participate. However, given that the participating teams from outside the top 5 leagues are within the top 3 of their league tables from the previous season, this study assumes that a game against any of such teams will be comparable to a game against a team in the top 5 leagues in terms of uncertainty of outcome – for example, performance data for a player from Liverpool FC (English Premier League) in a UCL game against Spartak Moscow (Russia) is comparable to a performance statistics of the same player against another EPL team such as Watford FC. The raw data on Whoscored.com has *GOAL* and *ASST* statistics as totals while *SHOT*, *KEYP*, *DRB* and *MOTM* statistics are provided as ratios per game for each competition. The minimum number of competitions a player participated in is 1 (local league) and the maximum is 4 (loaned/transferred from one club playing in the UCL to a club in another league playing in the UEL within the same season). In the sample, 6 players participated in 4 competitions representing 1.2%. Thirty-nine players participated in 3 competitions representing 7.8% of the sample. The 3 competitions could either be 2 local leagues and 1 continental club competition or 1 local league and 2 continental club competitions. Majority of the players participated in 2 competitions, 236 players representing 47.2 percent of the sample. The 2 competitions could either be a local league and a continental club competition or loan from one local league to another. Most fall in the former scenario. The remainder 219 players in the sample, resenting 43.8% participated in 1 competition – the local league.

To compute the per game ratio for goals and assists, the total for all competitions in which the player participated is divided by the number of games played. To obtain a single ratio for the other variables provided on Whoscored.com as ratios per game (*SHOT, KEYP, DRB*) for players who participated in more than 1 competition, the weighted percentage of playing time per competition is computed and multiplied to the ratio for each statistic using the below formula:

$$SR_k = \sum_{i=1}^{n}(PR_i \times WR_{ik}) \qquad (2)$$

Where SR_k is the season's ratio for variable k, PR_i is the participation ratio in competition i and WR_{ik} is the WhoScored.com ratio of variable k in competition i.

For example, to calculate the season *KEYP* ratio for Kylian Mbappé who played 2344 minutes in the French League 1 (*FL1*) with a *KEYP* ratio of 1.6 key passes per game and 701 minutes in the UCL with a ratio of 2 key passes per game.

$$PR_{UCL} = \frac{UCL\,mins}{(FL1\,mins\ +\ UCL\,mins)}$$

$$PR_{UCL} = \frac{701}{(2344\ +\ 701)}$$

$$= 0.23$$

$$PR_{FL1} = 1 - PR_{UCL} = 1 - 0.23 = 0.77$$

$$SR_{KEYP} = (WR_{KEYP})(PR_{KEYP,UCL})\ + (WR_{KEYP,FL1})(PR_{FL1})$$

$$= (2)(0.23)\ + (1.6)(0.77)$$

$$= 1.69$$

Goals per game *(GOAL)* has a maximum of 1.22 goals per game and a minimum of 0 goals per game. Five players; Cristiano Ronaldo (Real Madrid), Lionel Messi (FC Barcelona), Kylian Mbappé (Paris Saint-Germain), Paco Alcácer (FC Barcelona) and Ciro Immobile (SS Lazio) scored more than 1 goal per game during the period under consideration while 4 players (Loïs Diony, Max Meyer, Patrick Herrmann, and Oscar Melendo) did not score a single goal in 10 games or more. The mean goals per game ratio is 0.36 and the standard deviation is 0.20. For assists per game *(ASST)*, the maximum is 0.70 assists per game by Michael Gregoritsch (FC Augsburg) while the minimum is 0. For shots per game *(SHOT)*, the maximum is 6.50 shots per game and the minimum is 0.30 shots per game. Cristiano Ronaldo (Real Madrid, Juventus FC) holds the top 2 spots while Lionel Messi (FC Barcelona) holds the third and fourth spots in this category. In the key passes per game *(KEYP)* category, the maximum is 3.94 key passes per game by Alexis Sanchez (Arsenal FC) while the minimum is 0.20 key passes per game. The mean is 1.23 key passes per game with a standard deviation of 0.63. In the successful dribbles *(DRB)* category, the maximum is 7.15 successful dribbles per game by Neymar (FC Barcelona) while the minimum is 0.10 successful dribbles.

Depending on the formation of the line-up or the playing style of the team coach, the offensive players can play in different forward positions. The position variable $(MPOS)$ is categorized as dummies to represent Center Forward (CF), Left/Right Winger (WG) and Attacking Midfielder (AM). Players with main position listed as Second Striker are considered as Center Forwards in this study. There are 217 Center Forwards accounting for 43.4% of the sample, 216 Left/Right Wingers accounting for 43.2% and 67 Attacking Midfielders making up 13.4%. Everything being equal, Center forwards will be expected to have a higher goal per game and shots per game ratio compared to Attacking Midfielders and Wingers. Attacking Midfielders and Wingers will be expected to have a higher assists per game and key passes per game ratio than Center forwards.

The performance abilities of a player in a collective sport are heavily dependent on the abilities of his team mates as well as the style of play. Forwards depend on midfielders and wingers to provide assists from which they can score, midfielders depend on other team mates to play their role so as open spaces for the midfielder to be creative. As a result, there is a correlation between the performance of a player and the quality of his teammates. To avoid omitted variable bias and include these correlations in this study, random effects are added to capture the team in which is player plays as well as the league. A center forward nested in a team that has a very creative midfielder will certainly have a higher supply of quality passes and hence higher goal tally. In the same vein, an attacking midfielder nested in a team with a top-class center forward will have a high number of assists given that a top-quality center forward can score from a mediocre pass. The 500 players observations in this study are nested within 95 teams. Also, since teams are nested within leagues, leagues have their general style, for example, the Italian Serie A is well-known for a defensive style of football while the Spanish La Liga is well known for creative offensive play. Consequently, the goal tally of forwards in the Spanish La Liga will be generally higher than those of forwards in the Italian Serie A. The English Premier League has the highest number of players in this sample, 142 representing 28.4 % of the sample, followed by the Spanish La Liga with 103 players representing 20.6%. The German Bundesliga, the Italian Serie A and the French League 1 have 99, 86 and 70 players respectively representing 19.8%, 17.2% and 14% of the sample.

Aside the local leagues under study, there are also two European club competitions included in this study – the UEFA Champions League (UCL) and the UEFA Europa League (UEL). The former is more prestigious and hence players are attracted to teams that play in the UCL. The UCL is considered the grand stage of European football and performances on this stage are not comparable to performances at local league level. For this study, dummies are included to capture the effect of participating in each of these tournaments. In this sample, 174 players participated in the UCL, representing 34.8% of the sample while 123 participated in the UEL, representing 23.6% of the sample. It is worth noting that after the group stages in the UCL, the first 2 teams qualify for the knock-out stages while the third placed teams transferred to the draws of the knock-out stages of the UEL. Hence, it is possible for a player to feature in both competitions in the same year. There are 20 players who participated in both the UCL and UEL in the same year. To best capture the effect of participating in either or none of the European club competitions, this essay takes into consideration only the UCL participation for the 20 players who participated in both the UCL and UEL. 223 players or 44.6% of the sample neither participated in the UCL nor the UEL.

2.3.3 - Model Specification

Working from the empirical specification above, a simple OLS regression would suffice given the assumptions in place. However, given that football is a collective game with several interdependencies and given the clearly hierarchical nature of the data, it makes sense to analyse the data using a fitted regression. The data for this study is hierarchical in nature as players are nested within teams and teams are nested within leagues. While the innate abilities of the player are at the core of this study, the collective nature of football makes for dependencies on performance among players. The performance of each player depends to a reasonable extent on the performances of his teammates. This means that there is a likelihood of variance at the level of teams. Also, leagues are different in that in some leagues, there are a few title contenders with effective squads and a larger number of fairly good and average teams such as in the Spanish La Liga where the top 3 spots on the league table revolves amongst at most 5 teams. Conversely, in the English Premier League, there are about 8 teams in contention for the top 4 spots. This means that a forward in the Spanish La Liga has a higher chance of getting better performance statistics given he has more mediocre opponents compared to the English Premier League. Additionally, leagues have a characteristic play style that is widely accepted by the local fans, e.g., Spanish La Liga is known for free-flowing offensive football while the Italian Serie A is well known for a more defensive style of play. This also means that an offensive player stands a better chance getting superior performance statistics in the Spanish La Liga compared to the Italian Serie A. Hence a model that takes into consideration the hierarchical nature of the data structure is warranted. This study uses Hierarchical Linear Model (HLM) otherwise known as multilevel models to analyse the data. There are three levels: the League at level 3 (the highest level), the Clubs at Level 2 and the Players at Level 1 (the lowest level).

In multilevel modelling, it is generally recommended to have a sample size of at least 20 at each level. In this study, there are just 5 leagues and that is the total population of the top 5 leagues in Europe. Both a 3-level model with random intercepts at League, Club and Player levels as well as a 2-level model with Club level and Player level are run. To build the model, a random intercept-only model (null model) is run in which only the intercept (constant) and the random variables are added. Since players are the baseline and the predictor variable (Log of *MVi*) is a level 1 variable, the random intercepts are specified as *Club* and *League*. The null model will test whether there are significant variations in the intercepts across levels. If there is significant unexplained variation between levels, then a multilevel model is warranted. Additionally, the Chi Squared difference which is the difference between the Iterative Generalized Least Square (IGLS) Deviance (hereafter referred to as deviance) of the null model and a simulated single level model (Level 2 removed) will help justify if a multilevel model or a single level (simple regression) best fits the data. Also, the differences in deviance scores, log likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as each block of explanatory variables are added will show goodness of fit of the models.

An OLS regression and a quantile regression are also run to compare the coefficients. A quantile regression at the 25th, 50th and 75th quantiles will test heterogeneity in the sample given the dependent variable (*MVi*) ranges from €0.7M to €200M. The idea is to see if the independent variables have the same relationship with the dependent variable across the board, in line with the arguments of Lehmann & Schulze (2008) that there are wage convexities at the upper end of the player valuation chain. It would have been ideal to use a large enough sample size such that a quantile regression would clearly capture the differences at the upper end of the market. However, data availability is a noted constraint. Since wages and market values are influenced by similar set of factors, this check is necessary. Individual regressions across the 5 leagues and 3 positions are also run to compare the relationship and magnitude of the coefficients. A comparison of the coefficients of the variables between players at different positions will show which performance attributes are more important given the position in which the player plays. As for the leagues, the coefficients of the variables will show how much weight each performance variable carries in each league.

2.3.4 - Results

The intercept-only model (null model) shows the random effects have the following variances and standard deviations respectively; Residual level .394 and .628, Club level .457 and .676. This means that 39.4% of the variance is unexplained at Club level and 60.6% of variance is unexplained at the player level. This shows that multilevel models fit this data better than single level models (simple linear regression). Additionally, the deviance score of the null model is

1121.8. The deviance score of a null model with only one level (simple linear regression) is 1172.8. The Chi-Squared difference of 51 at 1 degree of freedom is statistically significant at p < .001, hence multilevel models fit the data better. Model 1 adds the market value at the start of the playing period, model 2 adds the demographic variable (*Age*), Model 3 adds the performance variables (goals, assists, shots, key passes, and successful dribbles), model 4 adds the categorical variables (main position and UEFA competition). Table 1.2 below summarizes the results and shows the estimated coefficients, standard errors, and p-values of the fixed effects. The lower part of the table displays the standard deviations of the random effects and the model fit parameters. Likelihood ratio tests confirm again that these improvements are significant at p<001.

The dependent variable in the regression equation (Market Value at end of period) is log transformed so the coefficients of the predictor variables are interpreted as percentage changes. For example, in model 4, a 1% increase in Goals per Game ratio increases the market value by

Table 1.2.
2-Level Multilevel regression results.

Dependent variable: Log of Market Value at End of Season	Null Model	Model1	Model2	Model3	Model 4
Fixed Effects					
Intercept	16.657*** (.078)	7.151*** (.433)	7.699*** (.404)	5.482*** (.398)	5.510*** (.363)
Log of Market Value at Start		.590*** (.026)	.662*** (.026)	.524*** (.023)	.516*** (.025)
Age			-.069*** (.007)	-.084*** (.007)	-.081*** (.007)
Goals per Game				1.232 *** (.150)	1.325*** (.157)
Assist per Game				.830*** (.229)	.801** (.233)
Shots per Game				.116** (.038)	.116*** (.038)
Key Passes per Game				.268*** (.052)	.227*** (.055)
Successful dribbles per Game				.036 (.033)	.025 (.034)
Attacking Midfielder					.141*

					(.068)
Winger					.082
					(.051)
UEFA Champions League					.149***
					(.062)
UEFA Europa League					-.046
					(.059)
Random Effects					
CLUB	.457	.044	.037	.033	.013
Residual	.394	.293	.251	.161	.168
Model Fit					
AIC	1127.8	863.9	787.3	590.6	586.1
BIC	1140.4	880.7	808.4	632.8	645.1
Log Likelihood	-560.9	-427.9	-388.6	-285.3	-279.0
Deviance	1121.8	855.9	777.3	570.6	558.1
df. Residual	497.0	496.0	495.0	490.0	486.0

Notes: '***'= p < .001, '**'= p < .01, '*'= p < .05; standard errors are in parentheses. Number of observations: 5,500. Number of groups: Players, 500; Clubs, 96.

1.03%, holding all other variables constant, while a 1% increase in Assists per Game ratio increases the market value by .73%, holding all other variables constant. Participating in the UEFA Champions League increases market value by 16.1%, holding every other variable constant. Model 4 also shows that on average, holding all other variables constant, Attacking Midfielders are 15.1% more valuable than Center Forwards and Wingers are 5.23% more valuable than Center Forwards.

Model 2 adds the demographic variable. *Age* has a coefficient of -.069 and is significant at p<.001, while the *Market Value* at the start of season is still significant at p < .001 and has a coefficient of .590. Model 3 adds the performance variables. Start of season *Market Value* is still significant at p < .001 and has a coefficient of .524 and is significant at p<.001. *Age* has a coefficient of -.084 and is still significant at p<.001. *Goals per game* has a coefficient of 1.232 and is significant at p < .001; *Assists per game* has a coefficient of .830 and is significant at p < .001; *Shots per game* has a coefficient of .116 and is significant at p<.01; *Successful Dribbles per Game* has a coefficient of .036 but is not significant. In model 4, categorical variables (main position and UEFA Competition) are added. The positional dummy variable denoting *Attacking Midfielder* is significant at p<.05 and has a coefficient of .141 while the positional variable of *Winger* is not significant and has a coefficient of .082. *Center Forward* is the reference category. For the UEFA Competition variable. *UEFA Champions League* participation (*UCL*) is significant at p<.001 and has a coefficient of .149 while *UEFA Europa League* participation (*UEL*) is not significant and has a coefficient of -.046. $MV_{(s-1)}$ is still significant at $p < .001$ and has a coefficient of .516; *Age* is significant at $p < .001$ and has a coefficient of -.081; *Goals per Game* is significant at p<.001 and the coefficient increases to 1.325; *Assists per Game* is significant at p<.01 and coefficient drops to .801; *Shots per Game* is significant at p<.001 and the stays at .116; *Key Passes per Game* is significant at p<.001 and the coefficient drops to .227; *Successful Dribbles per Game* is still not significant and its coefficient drops to .025.

Looking at the best fit model (Model 4), the $MV_{(s-1)}$ has a positive coefficient meaning that there is a direct relationship between $MV_{(s-1)}$ and *MVi*. The coefficient of $MV_{(s-1)}$ is .516 and this is in logarithmic scale. Thus, a 1 unit increase in $MV_{(s-1)}$ will increase the *MVi* by 51.6% holding all other variables constant. This coefficient of the $MV_{(s-1)}$ variable is significant at $p < .001$ meaning there is strong enough evidence to reject the null hypothesis (there is no relationship between $MV_{(s-1)}$ and *MVi*). This result is in line with extant research though there is a caveat since it is a biased estimator (Müller *et al.,* 2017) - it is used as a substitute to train the regression model because of unavailability of other reliable sources of data. The *Age* variable has a negative coefficient denoting diminishing returns. When *AGE* and *AGESQD* are included in the regression equation, both variables have a negative coefficient but are not statistically significant. When *AGESQD* is dropped, *AGE* becomes statistically significant and vice versa. The magnitude of the coefficient is -.081, meaning that when all other variables are held constant, an increase of 1 year in age of a player leads to a 8% reduction in Market value. The *AGE* variable is statistically significant at the 99% level meaning we can reject the null hypothesis that there is no relationship between age and market value. This result is in line with previous research as it has been shown severally that increased age leads to diminishing athleticism and hence reduced market value.

As for the 5 performance variables, all but *Successful Dribbles per Game* are statistically significant at 95% level, leading to the conclusion that the null hypotheses for *Goal, Assists, Key Passes* and *Shots* can be rejected whereas the alternative hypothesis for *Dribbles* can be rejected. All 5 performance variables have positive coefficients showing a positive relationship between these variables and market value. The magnitude of the coefficients shows that holding all other variables constant, a one percent increase in goal per game ratio will increase the market value of the player by 1.325%, a one percent increase assist per game ratio will increase the market value by .80%, a one percent increase in shot per game ratio will increase market value by .12%, a one percent increase in the key pass per game ratio will increase market value by .28%, while a one percent increase in the successful dribbles per game ratio increases market value by .03%. These results in line with existing literature. Football is a goal-oriented game hence goals and assists have a very strong positive relationship with the market value of a player.

The positional dummy variables use *Center Forward* as reference category. The coefficients for *Attacking Midfielder* (.141) and *Winger* (.082) are both positive indicating that Attacking Midfielders and Wingers are more valuable than Center forwards. Everything else being equal, Attacking Midfielders are 15.1% more valuable than Center Forwards and Winders are 8.5% more valuable than *Center Forwards*. Only the categorical variable denoting *Attacking Midfielders* is significant at p<.05, hence we can reject the null hypothesis for this variable. The categorical variable denoting *Wingers* is not statistically significant; hence we reject the alternative hypothesis. Compared to *Center Forwards*, *Attacking Midfielders* and *Wingers* have a higher positional flexibility (can play on multiple positions) and are hence more valuable. This is in line with existing literature. The categorical variables representing participation in continental competitions has mixed results. Participation in the UEFA Champions League has a positive and statistically significant coefficient (.149). This shows that UCL participation positively affect market value and holding everything else constant, participation in the UCL increases the player's market value by 16.1%. As for UEFA Europa League participation, the coefficient is negative (-.046)and not statistically significant.

Table 1.3 shows the results of the OLS and quantile regressions. The signs of the coefficients of the OLS regression and the statistical significance levels are similar to the results of Model 4 in the HLM in Table 1.2. However, the magnitudes of the coefficients are slightly different. A comparison between the OLS regression coefficients and the quantile regression coefficients shows as expected that the OLS regression coefficients compare favorably with the 50th quantile (median). The signs of the coefficients for both the OLS and quantile regression coefficients are similar. However, the magnitudes of the coefficients show that the $MV_{(s-1)}$ and *Goals per Game* variables at the 25th quantile are statistically different from the OLS regression coefficients. This means that the $MV_{(s-1)}$ of the upper quartile has more weight in the MVi compared to the lower quartiles. The *Goals per game* coefficient of the upper 25% has a significantly lower coefficient that the rest of the quartiles. This means that everything else held constant, the upper 25% do not need to score as many goals per game as the lower 75% to get the same percentage increase in MVi.

The demographic, performance and UEFA Club Competition variables show the same statistical significance across all quantiles. However, for the positional variables, the statistical significance increases as we move from the 25th to the 75th quantiles. While not statistically significant at the 25th quantile, at the 75th quantile, holding everything else constant, Attacking Midfielders are 21.8% more valuable than Center Forwards and this result is significant at $p<.001$. This means for the 75th quantile, we have very strong evidence to suggest that *Attacking Midfielders* are more valuable than *Center Forwards* and hence can reject the null hypothesis. The comparison between *Attacking Midfielders* and *Wingers* shows statistical significance at $p<.05$ with *Attacking*

Table 1.3.
OLS and Quantile regression results.

Dependent variable: Log of *MVi*	OLS Regression	25th Quantile	50th Quantile	75th Quantile
Intercept	8.3073***	5.5083***++	8.1773***	9.1056***
Log of $MV_{(s-1)}$	0.5252***	0.6730***++	0.5346***	0.4954***
Age Squared	-0.0015***	-0.0013***	-0.0017***	-0.0017***
Goals per Game	1.1511***	0.8934***++	1.0106***	1.0161***
Assist per Game	0.7194***	0.3578	0.7783**	0.9741***
Shots per Game	0.0881**	0.0799**	0.0722*	0.0723***
Key Passes per Game	0.1772***	0.1662***	0.1955***	0.1993***

Successful dribbles per Game	0.0193	0.0478	0.0439	0.2541
Center Forward	-0.1583*	-0.0390	-0.2406**	-0.1969***
Winger	-0.0646	-0.0529	-0.1860*	-0.1277*
UEFA Champions League	0.1862**	0.1506**	0.1897**	0.1756**
UEFA Europa League	-0.0540	-0.0539	-0.0913	-0.0374

Notes: '***'= p < .001, '**'= p < .01, '*'= p < .05, '°'= p< .1, '++'= significantly different from OLS Regression.

Midfielder 13.6% more valuable than *Wingers* when every other variable is held constant. Again, these results are in line with existing literature regarding the position of the player and the flexibility of the player to play in more positions.

The results of the regressions by position (see Table A.1 in Appendix A) shows that *age* has the same impact of market value across all positions. *Goals* and *shots* have more weight on the market value of *Center Forwards* followed by *Wingers*. *Assists* and *key passes* have more weight on the market value of *Attacking Midfielders*. *Successful dribbles* is not significant and the variation per position is minimal. For the regressions by league (Table A.2), age has the same weight across all leagues. *Goals* have more weight in the French Ligue 1 followed by the German Bundesliga and Italian Serie A. *Assists* have more weight in Spain, followed by Italy and France. *Key passes* have more weight in France, Spain, and England while *shots* are more significant in England. *Successful dribbles* show little variation between leagues.

2.3.5 - Model Evaluation

The aim of this study was to empirically determine the market value of football players based solely on their talent: demographic and performance variables. The performance variables were collected for forward-leaning players in Europe's big 5 leagues during the 2017/18 and 2018/19 seasons. To train the model, Transfermarkt values were used given their high reputation both in academia and industry as they have proven to be the closest to transfer fees (Bryson *et al.*, 2013;

Herm *et al.,* 2014). The values generated by the empirical methods would then be compared to Transfermarkt values to see what proportion of the market values was due to football-related factors. Model results show an overall average of 13% disparity in the values across the board. That is, 13% of the market value reported by Transfermarkt is not related to footballing factors and could be a result of other factors not included in this study such as popularity, defensive ability, disciplinary records, ethnic origin, error term, etc. 79% of the players analysed in this study have their modelled market values lower than Transfermarkt values. 21% have their market values equal to or higher than Transfermarkt values. For the upper median of the sample, the difference between modelled market values and Transfermarkt values is 33% while the difference in the lower median is 1%. This falls in line with the findings of Muller *et al*. (2017) that the market values of lower valued players are more accurately estimated using data driven models while the market value of high valued players are better estimated by crowd-sourced methods given the 'intangibles' that are difficult to be estimated by data-driven methods.

Based on position, model results show the mean market value for *Center Forwards* is €20,152,485. The mean market value for *Attacking Midfielders* is €22,899,036 while for *Wingers*, the value is €27,632,731. This shows that on average, *Attacking Midfielders* are 12% more valuable than *Forwards* and this is in line with the coefficient of the categorical variable *Attacking Midfielders* (.124, significant at the 5% level), hence 13.2% in Model 4. There is a consensus in previous research (Brandes & Franck, 2012; Bryson *et al*., 2013; Franck & Nüesch; 2012) that midfielders are more valuable because they have a lower degree of specialization and hence can be used in multiple positions compared to *Center Forwards*. *Wingers* are 27% more valuable compared to *Center Forwards* as per the model calculations. While this does not correspond to the coefficient of .082 (8.6%) from Model 4 (which was not significant), *Wingers*, can play in more positions compared to *Center Forwards*.

For the performance variables, given that football is a goal-oriented game, *Goals* have the highest impact on the market value of offensive players (Bryson *et al*., 2013; Franck & Nüesch; 2012; Frick, 2011; He *et al*., 2015; Herm *et al*., 2014; Kiefer, 2014; Lehmann & Schulze, 2008; Medcalfe, 2008; Ruijg & van Ophem, 2014), followed by *Assists* (Franck & Nüesch; 2012; He *et al.* 2015; Herm *et al.,* 2014; Kiefer, 2014; Lehmann & Schulze, 2008; Medcalfe, 2008). For on-field players in general, *Successful Dribbles* has a significant positive relationship to market value (Franck & Nüesch; 2012; He *et al.,* 2015; Medcalfe, 2008). However, this model shows that for offensive players, *Successful Dribbles* is not a very important value trait. *Shots* and *Key passes* (Franck & Nüesch; 2012; Herm *et al.,* 2014; Medcalfe, 2008) are also positively correlated in line with existing literature.

Participation in Europe's elite club competition (*UEFA Champions League*) has a significant positive effect on market values. Success at the UEFA Champions League comes with a large financial compensation. Most clubs recruit players that can help them on the Champions League stage. A good reputation in the Champions League is a great boost for a player's market value. Example is the move to Juventus FC by Cristiano Ronaldo. However, participation in Europe's tier 2 competition (*UEFA Europa League*) has a small negative coefficient and is not statistically significant.

2.4 – DISCUSSION

Football players' value to their clubs extends beyond their on-field capabilities. An understanding and measure of the attributes that influence on-field success of a team is vital to club management. Young energetic players who can win games are essential to help advance the club's league standings and success in European continental club competitions. While players' popularity and image rights are a great source of income for football clubs in today's football market, clubs need to strike a balance between players of iconic status (superstars) and lesser-known players with good footballing abilities. The upper end of the market for football talent is thin (McLaughlin, 1994; Dobson & Gerrard, 1999; Abraham et al., 2013; Bryson et al., 2013) and the financial fair play rules makes it more pressing for clubs to be able to identify and recruit lesser known but equally talented players. Using the human capital formulation pioneered by Jacob Mincer (1958), this study focuses on the offensive players within the big 5 European leagues for the 2017/18 and 2018/19 seasons empirically calculates the market value of talent. Player market values range from €.7M to €200M with a standard deviation of €32.949M. When the best fit regression equation is substituted with values of the coefficients and variables, on average, market values based on talent are 13% lower compared to the overall market values. This implies that for the sample of players analysed in this study, on average, their talent account for 87% of their market values. For the upper median of this sample, their talent accounts for 67% of their market value. The trend in existing literature shows that for the smaller set of very valuable players at the top, the proportion of their market value due to talent gets smaller (Herm *et al.,* 2014) – the superstar phenomenon (Adler, 1985 & Rosen, 1981). The sample used for this study is the uppermost quartile of offensive players ranked by market value and the results fall in line with extant research showing the proportion of talent reduces as market value increases.

There are some limitations to this study. First, due to the absence of alternative sources of data, the $MV_{(s-1)}$ used to train the regression models are values based on both talent and other non-talent factors taken from Transfermarkt, hence the resulting values are influenced by non-talent. Secondly, while football is a goal-oriented game, defensive as well as disciplinary abilities of all players on the pitch also help to secure victories. This study does not include the defensive and disciplinary statistics for the players in this sample and hence, these are not accounted in the derived market values. Third, this study focuses on the top 5 leagues in Europe. While this population is ideal for identifying superstars, it is not ideal for the lesser-known players with great footballing talent. This is because all clubs have a restricted number of players on their roster listed as forwards. Lesser-known players with great talent will be easier to find outside the big 5 European leagues. Fourth, the sample size used for this study is small and this is due to data availability. Given that data is readily available only for high profile players, it is difficult to get a large enough sample that will include lesser-known players from outside the European big 5 leagues. Lastly, superstars are found in every position of the field. While most superstars are forwards, recent transfer activities make believe that midfielders (Paul Pogba), defenders (Virgil van Dijk) and goalkeepers (Alisson Becker) are newly minted superstars. Further research could add the midfield, defense, and goalkeeping positions. Also, one variable which is very important for forward players but for which data are still mostly absent is *pace*. When one considers the market values of players like Kylian Mbappé (2019/20) and Gareth Bale (2013/14), it is very evident that their speed on the pitch is an important part of their game. In the English Premier League this (2019/2020) season, Adama Traore (Wolverhampton Wanderers) is making headlines as a potential target of a high value transfer mainly because of his pace.

Having isolated the proportion of market values due to talent, further research could investigate the proportion of market values due to non-talent factors. An analysis of the external factors and what drives these external factors would give football managers and clubs a complete toolkit with which to value their most important asset.

2.5 – CONCLUSION

The value associated the with aptitude and skill that a football player displays on matchday is just a proportion of his total market value. From a sample of 500 offensive players observations in the big 5 European leagues for the 2017/18 and 2018/19 seasons, this study analysed 12 data points per player, hence 6,000 observations in total, using a series of multilevel regression models to isolate the proportion of player market value based on talent (performance and demographic factors) only. Results showed that the proportion of market value due to talent decreases as market value increases. For the players sampled, the mean proportion of talent on market value is 87%. With new methods of gathering, storing, and analyzing data thanks to big data techniques, larger amounts of player statistics measures will become available and empirical methods such as the one applied in this study will be able to fine-tune the valuation of players.

Appendix A. OLS Regressions per Position and League

Using the demographic variable (age squared) and performance variables (goals, assists, key passes, shots, and successful dribbles), I segregate the data per position and run OLS regressions for each position. The resulting coefficients per position are displayed in Table A.1 below. Additionally, I segregate the data per league and run individual regressions per league. The results are summarized in Table A.2 below.

Table A.1
Coefficients of OLS regressions by player position.

Dependent variable: Log of MVi	Attacking Midfielder	Center Forward	Winger
Intercept	6.8701***	7.1998***	8.0999***
Log of $MV_{(s-1)}$	0.6332***	0.5695***	0.5430***
Age Squared	-0.0020***	-0.0014***	-0.0014***
Goals per Game	0.9361	1.4463***	1.1787***
Assist per Game	1.4044°	0.7453*	0.6365*
Key Passes per Game	0.1941	0.1329	0.1337*
Shots per Game	0.0777	0.1071*	0.0598
Successful dribbles per Game	-0.0622	0.0584	0.0348

Notes : '***'= p < .001, '**'= p < .01, '*'= p < .05, '°'= p< .1

Table A.2
Coefficients of OLS regressions by league.

Dependent variable: Log of MVi	England	France	Spain	Italy	Germany
Intercept	5.9277***	9.1503***	6.8414***	8.3524***	9.1618***
Log of Begin MV	0.6719***	0.4416***	0.6293***	0.5000***	0.4735***
Age Squared	-0.0016***	-0.0017**	-0.0018***	-0.0015***	-0.0019***
Goals per Game	0.8681***	1.3813**	0.7803*	1.0467**	1.0732**
Assist per Game	0.7791**	1.1002	1.2437°	1.1270*	0.9368*
Key P per Game	0.2176***	0.2966°	0.2303°	0.0515	0.2004°
Shots per Game	0.1350**	0.0863	0.0721	.02224**	0.0796
Successful dribbles	-0.0074	0.0782	-0.0777	0.0542	0.0996

Notes: '***'= p < .001, '**'= p < .01, '*'= p < .05, '°'= p< .1

3. Essay 2 : FOOTBALL TRANSFER FEE PREMIA IN THIN MARKETS : An Analysis of the European Association Football Transfer Market.

3.1 – INTRODUCTION

Studies on the economics of European Association football (hereafter 'football') have long lagged North American major sports (baseball, basketball, ice hockey and American football) due to lack of statistical data from which analyses could provide insights into the individual contribution of players (Sloane, 1969, 1971, 2006). Notwithstanding the collective nature of football compared to North American sports, the advent of super computers and big data analytics software has given rise to a new collection of agencies able to crunch large amounts of data in real time. Sports data agencies such as Opta Sports collects tons of granular data in real time and feeds into systems that in turn provide assessed performance results for each player. For example, an attempted dribble (event) in the opposition's final third (area of pitch) that is successful (outcome) will have a positive effect on a player's rating. This has led to better measurements of players' all-round contribution to team success, as offensive, defensive, controlling, and disciplinary statistics of every player are analysed. Additionally, the availability of data regarding player contract length, club ranking by coefficients from the European Football governing body UEFA and ownership structure for football clubs offers more variables with which the football transfer market can be better analysed.

In football, a transfer happens when a player leaves one club and joins another. There are two basic transfer types: loan (temporary) transfer and permanent transfer. There are four possible scenarios for a permanent player transfer; a free transfer where an out-of-contract player leaves his club and joins another with no payments made - 62.5% of transfers in 2020 globally (FIFA, 2020), a player exchange where two or more contracted players switch clubs with no payments, a swap plus cash transfer where two or more contracted players switch clubs and one of the clubs offer player(s) plus additional payment, and a player for cash exchange where a contracted player moves from one club to another with the engaging club paying a cash amount to the releasing club. In 2020, 17,077 international transfers were recorded globally, down from 18,047 in 2019 (FIFA, 2020). Of this number, only 2,273 (13%) involved a cash payment. The total global expenditure on international football transfers in 2020 was $5.63B, down from $7.35B in 2019. Of the 2,273 monetary transfers of 2020, only 130 (10%) involved sums upward of $10M. European clubs accounted for 90% of the monetary transfers ($5.04B) and $4.47B of the money spent was between European clubs.

A transfer fee is the amount of money paid by an engaging club to a releasing club for the services of a player. Transfer fees can be fixed, conditional (sell-on) or release (buy-out). Release or buy-out transfer fees are the rarest and happens when the engaging club (usually at the request of the player) offers to trigger a clause in the player's contract to release the player. Conditional (sell-on) transfer fees are for cases where the releasing club stands to benefit from future performance targets or transfer of the player to a third party. The most common is the fixed transfer fee where an amount is agreed and paid upfront for the player's contract. In this study, transfer fee will represent latter type (fixed transfer fees). Several studies that analyse the player labour market find that similar factors affect player wages, market values and transfer fees (Brandes & Franck, 2012; Bryson *et al*., 2013; Frick, 2007). Market values have been used as estimates of transfer fees and researchers have found high correlations between crowd-sourced market values (from Transfermarkt) and actual transfer fees (Müller et al., 2017). Hence, Transfermarkt values are used as proxy for market values in scientific research and are also used in actual wage and transfer negotiations (Herm et al., 2014). This study uses the Transfermarkt valuation of a player at the time of his transfer as the baseline to model transfer fees.

As with wages and market values, there is a small percentage of players that command the bulk of the total transfer expenditure. This is in line with the 'superstar' literature (Franck & Nüesch, 2012; Lucifora & Simmons, 2003). In 2020, the top 80 (3.5%) international transfers accounted for 50% of the total global transfer expenditure, i.e., $2.52B (FIFA, 2020). This segment of the transfer market has characteristics of a 'thin' market, with very few selling clubs possessing high caliber players and very few buying clubs with the means to afford such players (McLaughlin, 1994; Dobson & Gerrard, 1999; Abraham et al., 2013; Bryson et al., 2013). Therefore, buying and selling club characteristics carry much weight in this market segment. While previous studies embrace either a competitive (bidding) approach or a bargaining (negotiating) approach to reach a transfer agreement, this study embraces both approaches in that the process starts as an open bid and ends as a bargain between the selling club and the buying club with the most attractive bid (sometimes contingent on the preferences of the player). In this case, monopoly (monopsony) rents are depicted as premia which can be positive, negative or zero. In the current regulatory era after the Monti agreement, buying club characteristics carry more weight as transfers can be 'forced' if the player sides with the buying club.

A transfer fee premium is defined as the difference between the actual transfer fee and the crowd sourced (Transfermarkt) valuation of the player at the time of the transfer (Depken II & Globan, 2021). While several studies hold that transfer fees and crowd-sourced market valuations (Transfermarkt) are influenced by a similar set of factors (Brandes & Franck, 2012; Bryson *et al*., 2013; Frick, 2007), and have found high correlations between both (Müller et al., 2017), the two are conceptually different in that there is a sub-set of factors that influence transfer fees but cannot be known *apriori* when determining market values, e.g., buying/selling club characteristics, player contractual obligations, transfer window demand/supply forces, etc. Consequently, transfer fee premia can largely be attributed albeit theoretically to this sub-set of factors. With growing popular interest in the inflation of transfer fees and attempts by regulatory authorities to level the playing field (Financial Fair Play), increasing transfer fee premia is seen as a threat to the beautiful game. Transfermarkt valuations can be likened to the intrinsic value of the player based on past performances and current form, whereas transfer premia will hence be considered speculative over(under)valuation characteristic of the winner's curse in an open bidding process (Kagel & Levin, 2002). Transfer fees premia are most prevalent in high value transfers (superstars) as most clubs that participate in this market segment operate within a soft budget constraint which paves the way for overbidding to secure the services of the best players (Andreff, 2018). Additionally, while there have been positive strides in data availability in football, complete and accurate data are mostly available for high value players with the most visibility. Hence, to better study transfer premia in football, the upper end of the player market value classification is the best dataset available as of the time of writing.

Using the top 30 football transfers per season for the decade between 2011/12 through 2020/21, this study analyses a total of 300 transfers using more sophisticated and reliable player performance ratings, player contractual obligations variables as well as buying/selling club characteristics that affect behavior in the transfer market. The main contributions of this study are twofold: First, this study analyses the size of transfer fee premia using a comprehensive set of measurable variables including player characteristics, buying/selling club characteristics and the regulatory framework in place - to the best of my knowledge at the time of writing, no other study uses this approach. Second, this study complements the literature on how revenue levels generally affect transfer premia but goes beyond the league level to test if at the very top of the transfer market, certain buying club characteristics (ownership structure, change in leadership/ownership) leads to impulsive behavior (irrational exuberance) that is not informed by market information – a requirement for perfect market operation.

3.2 - BACKGROUND AND RELEVANT LITERATURE

3.2.1 – Regulatory Framework in Football

Transfers happen when two clubs reach an agreement for a player to move from one club to another. While the negotiations take place between the clubs involved, all transfers are governed by the regulatory framework in place. The regulatory landscape in European football has two major landmarks: the December 1995 European Court of Justice ruling in the case of Belgian footballer Jean Marc Bosman[13] vs Belgian league club RFC Liege, and the March 2001 compromise between the European commission led by Commissioner Mario Monti (Monti Commission) and international football associations (FIFA and UEFA).

Prior to the Bosman ruling, the club holding the player's registration (holding club) had the final say in transfer matters for both contracted and out of contract players. The main argument of the clubs was that they had to protect their investment in training young talented players and smaller clubs were worried that their best talents will be incentivized to leave, and this would resort to a few rich clubs having the best players in the league. The Bosman ruling had two main implications; first, all out of contract players were free to leave their clubs without a transfer fee being paid for their release; second, the restriction on the number of foreign players on a team roster was

[13] See Court of Justice of the European Communities, Case 415/93.

uplifted, hence the transfer of players to clubs outside the league was henceforth allowed. While there has not been a surge in the number of transfers as expected, the number of expatriate players in the UEFA leagues have increased by 36.8% in general and 60.4% in the English Premier League (Poli *et al*., 2014). As expected, the only mechanism left for clubs to protect their investments in the training of young players was to offer longer term contracts (Simmons, 1997; Antonioni & Cubbin, 2000) and to renegotiate these contracts before they were due. The Bosman ruling primarily dealt with out of contract players only.

The Monti compromise of 2001 further relaxed the rules governing contracts and made it easier for contracted players to leave their holding clubs. The Monti compromise allows players or buying clubs to trigger a release by paying a fee for breach of contract and, depending on the age of the player, a fee for compensation of educational expenses. Given that this fee will be lower compared to a negotiated transfer, it forces the holding club into a negotiation for the transfer of the player. Additionally, the Monti compromise restricts contracts for periods of one to five years[14]. With transfer systems already relaxed, restricting contract duration, and allowing a player to pay a lower amount to breach the contract, clubs are resorting to using exclusivity clauses (Segal & Whinston, 2000). Exclusivity rights give clubs the ability to recoup benefits even when a player is transferred. These are often linked to the future performances of the player at the new club. Release clauses place a predetermined monetary amount which must be paid to breach a player's contract.

3.2.2 - Literature Review

Extant literature on transfer fees in football have centered around two main areas: the determinants of transfer fees and the process of deciding a monetary value for a transfer. Determinants of transfer fees broadly involve player characteristics (demographics, talent, contractual obligations, and international caps) and selling/buying club characteristics *(*previous season league position, stadium capacity, attendance records sponsorship revenues and international competitions), while the process of deciding the monetary value of a transfer

[14] See the ''FIFA Regulations for the Status and Transfer of Players''.

follows two routes: the bargaining approach (negotiation between two clubs) and the competitive approach (an open bidding process).

The bargaining approach holds that the amount paid for a transfer is the result of a negotiation between two clubs (Carmichael &Thomas, 1993; Dobson & Gerrard, 1997; Reilly & Wit, 1995; Speight & Thomas, 1997; Feess & Muehlheusser, 2003). The earliest study that deals directly with the determination of transfer fees in European football is Carmichael & Thomas (1993) analyses of 214 transfers in the English League for the 1990/91 season. Using the Nash Bargaining Solution (NBS), they operationalize the football transfer negotiation process based on three constructs relating to which party (buying/selling club) benefits if the negotiation succeeds or fails. They show that depending on which party initiated the negotiation, the alternatives available to each party and the risk averseness of the parties involved, the Nash model identifies important variables that influence the result of the negotiations. They also find that buying clubs and selling clubs have differing attributes that are important to them and hence determining what constitutes their bargaining strengths. Reilly & Witt (1995) build on the work of Carmichael & Thomas (1993) by adding a racial dimension to test if race plays a part in the determination of transfer fees in England and find that Black players command lower prices compared to their White counterparts. Medcalfe (2008) reexamines the work of Reilly & Witt (1995) by adding player productivity statistics into the analyses and find no evidence of racial discrimination.

Where the bargaining process does not result in an agreement, arbitration is needed. Speight & Thomas (1997) analyse 404 transfers of which 217 are arbitrated settlements reached via Football League Appeals Committee (FLAC) decisions. They find arbitrated settlements results in lower transfer fees compared to negotiated settlements between clubs, hence buying clubs have more of an incentive to stall negotiations and refer for arbitration. Dobson & Gerrard (1999) use the Team Performance – Club Profits (TP-CP) framework to derive a model where player characteristics, buying and selling club characteristics as well as time effects determine transfer fees. They find an 11.6% inflation rate for 1,350 transfers in the English professional league from 1990-96. They also conclude that the market for players is segmented with markedly different characteristics between segments. At the upper end, the market is ‘thin’ with a few supply of highly talented players and few clubs able to afford such talent, thus offering more monopoly rents to selling clubs, whereas, at the lower end, there are many alternatives making the market ‘thick’ with lesser options for monopoly rents to the selling clubs. Outside professional leagues, Dobson, Gerrard & Howe (2000) analyse 114 semi-professional and non-league transfers in English football from 1988 - 1997 and find that similar factors affect transfer fees determination as in the professional league.

The competitive approach holds that transfer fees are determined via an open bidding process (Carmichael, Forrest & Simmons, 1999; Szymanski & Smith, 1997). Szymanski & Smith (1997) differ with description of the transfer market as a bargaining process between two clubs and describe it as a bidding process with more than two clubs involved. They contend that transfer fee falls between the minimum price that the selling club is willing to accept (selling club’s reservation price) and the maximum price that the buying club is willing to offer (buying club’s reservation price) and any positive difference between the two reservation prices. Carmichael, Forrest & Simmons (1999) add to the existing literature by factoring in player mobility in the analyses of transfer fees. Using the Heckman (1979) two step procedure to correct for selection bias in the English transfer market in the 1993/94 season, they argue that some players are more prone to be transferred than other, hence it makes sense to first model the probability of transfer as a subsidiary equation to be factored into the transfer fee equation. Their results show that players who will command a high transfer fee are more likely to be transferred. Ruijg & van Ophem (2015) extend beyond the sample selection bias where player mobility probability is measured. They use ordered probit estimates to overcome the selectivity issue in the case questionable randomness of a sub-sample of transferred players for which the transfer fee is known.

The literature on the determinants of transfer fees has been consistent. Most of the determinants of transfer fees also affect market values and player wages in a similar manner. Player characteristics that affect athleticism over time such as *age*, *number of games played* and *international caps* (Carmichael & Thomas, 1993; Reilly & Wit, 1995; Speight & Thomas, 1997; Dobson & Gerrard, 1999; Carmichael, Forrest & Simmons, 1999; Dobson, Gerrard & Howe, 2000; Frick & Lehman, 2001; Feess, Frick & Muehlheusser, 2004 and Eschweiler & Vieth, 2004) are recorded to have a positive yet decreasing (*quadratic form*) impact on transfer fees. Player talent characteristic such as *goals scored* (Reilly & Wit, 1995; Speight & Thomas, 1997; Dobson & Gerrard, 1999; Carmichael, Forrest & Simmons, 1999 and Frick & Lehman, 2001) show a positive effect on transfer fees. The playing *position* (Eschweiler & Vieth, 2004; Feess, Frick & Muehlheusser, 2004) of the player also affects the transfer fees with forwards commanding a premium compared to other positions. The *FIFA-coefficient of the player's country of origin* (Eschweiler & Vieth, 2004) also has a positive relation to transfer fees. Feess, Frick & Muehlheusser (2004) also find that players with *South America as continent of origin* also have positive effects on transfer fees. The *number of previous clubs* (Dobson & Gerrard, 1999; Reilly & Wit, 1995) has a negative effect on transfer fees as players considered as 'journey-men' seem to have difficulty settling in and would most likely be on the move again. Non-professionals and *semi-professional player* (Feess, Frick & Muehlheusser, 2004) status negatively affect transfer fees. The *number of years remaining on the player's contract* (post-Bosman) positively affects transfer fees as clubs strive to mitigate the possibility of a free transfer at the end of the contract period (Feess, Frick & Muehlheusser, 2004). Lastly, studies on the superstar phenomenon show that the iconic status of a player or his *popularity* also positively affects transfer fees (Lucifora & Simmons, 2003; Franck & Nüesch, 2012).

The characteristics of buying/selling clubs affect transfer fees depending on whether the buying/selling club is bargaining/bidding from a position of strength/weakness. The *revenues* and *attendance* (Eschweiler & Vieth, 2004; Dobson, Gerrard & Howe, 2000; Speight & Thomas, 1997) of the buying club, the *leagues position* (Dobson, Gerrard & Howe, 2000; Speight & Thomas, 1997; Carmichael & Thomas, 1993) of the buying club in the previous season, the *divisional status* (Reilly & Wit, 1995; Speight & Thomas, 1997) of the selling club, whether or not the buying club *qualified for a European competition* (Eschweiler & Vieth, 2004; Feess, Frick & Muehlheusser, 2004) and the *goal difference* of the buying club in the previous season (Dobson and Gerrard, 1999; Speight & Thomas, 1997; Carmichael & Thomas, 1993) have all been factored into transfer fees regression equations and results are consistent with bargaining/bidding positions of the buying/selling clubs. Where the bargaining position is strong, for example a buying club that has a larger market, or finished high in the league table, the selling club will be able to secure a higher transfer fee (including monopoly rents) for the targeted player, everything else held constant.

Depken II & Globan (2021) find evidence that English clubs pay a higher transfer fee premium compared to the other clubs in the big 5 European leagues. They link this willingness to pay higher fees to the revenue windfall from broadcasting deals signed by English Premier League clubs.

3.2.3 - Determinants of Transfer Fees

3.2.3.1 - Player Characteristics

Previous studies have factored player performance characteristics as variables in the regression equation to model transfer fees. To the best of my knowledge at the time of writing, all previous studies that model transfer fees use a single offensive metric (goals scored) as player performance variable (Reilly & Wit, 1995; Speight & Thomas, 1997; Dobson & Gerrard, 1999; Carmichael, Forrest & Simmons, 1999 and Frick & Lehman, 2001). While offensive players, primarily judged by their goal scoring ability have commanded the highest transfer fees in the past, the trend is evolving and players in other positions are getting transferred for large sums, e.g., on August 8, 2018, goalkeeper Kepa Arrizabalaga broke the record for the most expensive goalkeeper transfer in history when he moved from Spanish side Athletic Bilbao to Chelsea FC for €80million. A year later, central defender Harry Maguire broke the record for the most expensive defender in history with an €87million move from Leicester FC to Manchester United. The most expensive midfielder, Paul Pogba was transferred for €105million from Juventus FC to Manchester United in the summer of 2016. This means that goal scoring ability alone does not suffice as a measure of player performance. Other studies have used 'Kicker' overall ratings in analyses of player remuneration and contract length (Frick, 2011). The novelty of this study is that it uses a comprehensive measure of player performance metrics (overall rating) that incorporates all the contributions of a player in every aspect of the game; offensive, controlling, defensive and disciplinary.

Other non-performance player characteristics such as age, appearances, international caps, position, etc. are readily available and frequently used metrics in regression equations.

3.2.3.2 - Player Contractual Obligations

After the Bosman ruling of December 1995, all out of contract players can leave their club to another without a transfer fee paid by the new club. Clubs are thus incentivized to offer longer term contracts and renegotiate contracts before the expiry of the contract. In cases where the club and the player cannot reach a new deal for renegotiated terms or where player is not willing to renegotiate his contract early enough, the club has an incentive to sell the player before his contract expires. Hence, the remaining number of years on a player's contract is an important determinant of transfer fees. In extant literature relating to transfer fees, only one study uses this variable in the analyses (Feess, Frick & Muehlheusser, 2004). There are other studies that analyse contract length with regards to player remuneration (Frick, 2011) and to test for moral hazard in the final year of the contract (shirking). The Monti compromise further relaxed the rules governing contracted players and the latter can now trigger a release and pay for the breach of contract. This has led clubs to embrace legal instruments like release clauses and exclusivity contracts as a protection mechanism for their interests (Feess, Gerfin & Muehlheusser, 2015). It is commonplace to find exorbitant release clauses[15] in players' contracts nowadays. The most prominent case in football transfer history is the release clause added to Neymar Jr.'s contract by his then club FC Barcelona[16]. The fee associated with a release clause, or the existence thereof is not public and only known when it is triggered.

3.2.3.3 - Buying/Selling Club Characteristics

The upper segment of the transfer market is 'thin' with few clubs having the caliber of talent to offer and even fewer clubs having the resources to acquire this talent (McLaughlin, 1994; Dobson & Gerrard, 1999; Abraham et al., 2013; Bryson et al., 2013). Of the top 300 transfers of the last decade, all but 50 transfers (18.5%) were between clubs in the first division of the 'big five' leagues in European football (England, Spain, Italy, Germany, and France). 39 of the 50 came from outside the 'big five' and 11 left for clubs outside the 'big five', particularly Russia and China. Extant literature shows that transfer fees corelate positively with the revenues of the buying club. (Speight & Thomas, 1997; Dobson, Howe & Gerrard, 2000; Eschweiler & Vieth, 2004; Depken II & Globan, 2021) and negatively with the status (lower division or from outside the 'big five') of the selling club (Speight & Thomas, 1997; Carmichael, Forrest & Simmons, 1999; Frick & Lehmann, 2001). Over the last decade or two, broadcasting deals and private investors have surged the

[15] https://www.thesun.co.uk/sport/football/13107117/football-biggest-release-clauses-barcelona-real-madrid/
[16] https://www.forbes.com/sites/bobbymcmahon/2017/07/31/neymars-move-to-psg-will-set-a-world-record-and-trigger-more-high-priced-transfers/?sh=5929a7c531f7

finances of most clubs in Europe. Given that clubs are more utility maximizers than profit maximizers (Sloane, 2015), it can be assumed that most of the money is used strengthen the squad as a means to enhance team performance and hence, club status. For example, FC Barcelona received €222million in August 2017 for the sale of Neymar Jr. and spent €275million to buy Phillipe Coutinho and Ousmane Dembélé as replacement. Hence, given that most of the clubs operating in this segment (81.5%) are clubs from the top divisions of the ‘big five’, and local league success is a pre-requisite for continental club competitions, the UEFA club coefficient[17] is an appropriate measure of club success. The UEFA club coefficient is based on the results of clubs competing in the five previous seasons of the UEFA Champions League and UEFA Europa League. When a more successful club signs a player from a comparatively less successful club, this is operationalized as ‘poaching’ by the buying club and when the reverse happens, it is considered ‘offloading’ by the selling club. Poaching leads to higher transfer fees and hence higher transfer premia while offloading deflates transfer fees and transfer premia.

3.2.3.4 - Buying Club Ownership Structure

The ownership structure of football clubs has a direct effect on the transfer market process and prices. Ownership structure in corporate settings can be broadly identified as either ‘dispersed ownership system’ or a ‘concentrated ownership system’ (Coffee, 2005). Football clubs are traditionally owned by a large group of members (dispersed ownership) and managed by a board of directors. The board elects a President/Chairman, and the latter has limited authority in matters of scouting, recruitment, and remuneration. There are several major European clubs that operate under this ownership structure, e.g., FC Bayern is the largest with 290,000 members[18], Real Madrid CF is owned by 90,000 members[19] (called *Socios*) while FC Barcelona is owned by 144,000 members[20], SL Benfica in Portugal operates in the same way. In recent years however, there has been a steady influx of capital from wealthy oligarchs and private or state-owned consortia into several European football clubs, thus taking majority or complete ownership of the

[17] https://www.uefa.com/memberassociations/uefarankings/club/about/
[18] https://www.bundesliga.com/en/news/Bundesliga/why-bayern-munich-are-the-best-supported-club-in-world-football-467212.jsp
[19] https://www.forbes.com/teams/real-madrid/?sh=374a88206ed4
[20] https://www.forbes.com/teams/barcelona/?sh=441c3aca1d9b

clubs (concentrated ownership). Notable examples are Sheikh Mansour bin Zayed Al Nahyan's Abu Dhabi United Group that owns Manchester City among other clubs under its City Football Group subsidiary[21], Sheikh Tamim bin Hamad Al Thani's Qatari Sports Investment (QSI) that owns French club Paris Saint Germain[22], Glazer Family that owns majority shares of Manchester United FC, Roman Abramovich who owns Chelsea FC, etc. In the traditional dispersed ownership structure, financial decisions are reached after careful analyses of market information. Studies show that football clubs in the EPL with the dispersed ownership model show better financial health and are more likely to conform to Financial Fair Play rules compared to clubs with the concentrated ownership model (Wilson *et al.,* 2013). In concentrated ownership structures, there is the possibility of overreach based on instinct or subjective preference. This is comparable to what Boorah & Mangan (2012) called irrational exuberance (IE), loosely defined as a heightened sense of speculative fever. Instinct or subjective preferences on the part of individual or majority owners usually leads to positive premium payments (winner's curse) for transfers when the market valuation of the player is much less. Depken II & Globan (2021) show that the influx of money from broadcasting rights resulted in English clubs paying the highest transfer fee premia compared to the other European leagues. Hence, it can be deduced that excess money in general leads to higher transfer premia and more so, excess money with lesser restrictions in the case of individual or majority ownership structures.

Additionally, a recent change in club leadership/ownership can also lead to a massive expenditure on transfers. For dispersed ownership clubs, it is commonplace for aspiring club presidents to make promises about star signings to boost their campaign and would eventually engage in high value transfers to make good on such promises. For example, at the close of the 2008/09 season, aspiring Real Madrid CF president Florentino Perez promised to sign Manchester United star Cristiano Ronaldo if he got elected[23]. This resulted in a new world record transfer fee. Most clubs move from dispersed to concentrated ownership due to financial difficulty (Leach & Szymanski, 2015). In the case of concentrated ownership clubs, new ownership would most likely result in

[21] https://www.cityfootballgroup.com/our-clubs/manchester-city/
[22] http://www.qsi.com.qa/investments/paris-saint-germain/
[23] https://www.dailymail.co.uk/sport/football/article-1189500/Im-Real-thing-Perez-promises-bring-glory-days-Madrid.html

star signings to raise the club profile. Chelsea FC owner Roman Abramovich took over the club in 2003/04 and spent £121.3M on new signings in his first year as owner[24], while Sheikh Mansour is reported to have spent half a billion pounds in his first 2 seasons as owner of Manchester City FC[25].

3.2.3.6 - Transfer Window Demand and Supply

Transfer window demand and supply forces also influence the transfer market. The upper end of the transfer market is characterized as 'thin' due to the scarcity of highly talented players, the value of these players and the few number of clubs with the means to secure the services of these players(McLaughlin, 1994; Dobson & Gerrard, 1999; Abraham et al., 2013; Bryson et al., 2013). During the transfer window when clubs are searching and negotiating for new recruits, the announcement of an agreement between a club and a player further squeezes supply while keeping demand constant (at the very least to the other clubs still searching). In a free market, when *supply* decreases and *demand* remains constant, price is expected to increase (Adam Smith, 1776). This most often results in 'panic' buys as clubs scramble to reach agreements before the transfer window deadline. This is most acute in the case of players regarded as close substitutes. For example, if there are several clubs looking for a world class goalkeeper and only two goalkeepers have shown interest in a move, the announcement of a deal with one of the available goalkeepers will push up the price of the remaining available goalkeeper. For example, during the 2018 summer transfer window, Chelsea FC goalkeeper Thibaut Courtois had just one year left on his contract when he requested a move to Real Madrid CF[26]. With Courtois set to leave, and with just few options available, Chelsea needed a replacement before the transfer window closed and they were forced to break the goalkeeper transfer fee record with the signing of Kepa Arrizabalaga from Athletic Bilbao for €80million when his market value was €20million[27] at the time, resulting in a €60 million transfer fee premium.

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[24] https://bleacherreport.com/articles/1654557-charting-chelseas-year-by-year-transfer-spend-under-roman-abramovich

[25] https://www.forbes.com/2009/04/08/manchester-city-mansour-business-sportsmoney-soccer-values-09-citeh.html?sh=12b040be7993

[26]https://www.bbc.co.uk/sport/football/45122644#:~:text=Goalkeeper%20Thibaut%20Courtois%20officially%20signed,Kovacic%20had%20joined%20on%20loan.

[27] Kepa still had 6 years 10 months on his contract with Spanish side Athletic Bilbao.

Table 2.1.
Hypotheses (Dependent variable is Transfer fee Premium)

Predictor Variables	Expected Coefficient Sign
Age	-
Contract Years Remaining	+
Overall Rating Previous Season	+
Ownership Structure (Concentrated)	+
Change in Leader/Ownership	+
Successful Buying Club	+

3.3 – METHODOLOGY

***3.3.1** – Data Collection and Description*

The data used for this study are the top 30 transfers per season in monetary terms for the last decade (2011/12 – 2020/21) where the player moved to or from at least one European 'big 5' club. The dependent variable is the Transfer Premium (TP) defined as the difference between the actual transfer fees (TF) and the Transfermarkt valuation of the player at the time of the transfer (MV). Only transfers based on the payment of a fee are considered. Transfers that include exchange of players are not included in the sample. The independent variables are; the age of the player at the time of the transfer (AGE), number of years left on the players' contract at the time of the transfer (CTR_{YL}), the overall performance rating of the player in the previous season (RAT_{S-1}), club success which is the delta of the UEFA club coefficients of the buying and selling club dummied to reflect poaching or offloading ($CLUBSUCC$), a dummy to capture the ownership structure of the buying club (OWN_{BUY}), a dummy to reflect if any ownership/leadership change within 2 years preceding the transfer ($CHAN_{L/O}$) and a dummy variable to capture the main position of the player ($MPOS$). Also included in this study are year dummies to capture the rate of inflation. Variables to capture participation in European competitions; UEFA Champions League (UCL) and UEFA Europa League (UEL) are also included as well as a dummy variable to capture the window during which the transfer occurred; summer transfer or winter transfer. The numerical variables are summarized in Table 2.2 below.

There are 262 transfers that took place during the summer transfer window and 38 transfers during the winter window. 175 of the 300 players traded participated in the UEFA Champions League, 36 in the UEFA Europa League and 89 in neither of the European competitions. The playing positions of the players are distributed as follows: 128 forwards, 107 midfielders, 59 defenders and 6 goalkeepers.

The transfer fee *(TF)* and the market value at the time of transfer *(MV)* are both taken from Transfermarkt, likewise the age *(AGE)* of the player, the main playing position of the player *(MPOS)* and the number of years left on the player's contract at the time of the transfer *(*CTR_{YL}*).* The performance rating of the player in the previous season *(*RAT_{s-1}*)* is taken from WhoScored.com (powered by Opta). According to WhoScored.com, ratings are based on a unique, comprehensive statistical algorithm calculated live during a game. There are over 200 raw statistics included in the calculation of a players rating, weighted according to their influence on the game. Every event of importance is considered, with a positive or negative effect on ratings weighted in relation to its area on the pitch and its outcome. This overall rating is the weighted average of several summary, performance (offensive, controlling, and defensive) and disciplinary statistics for each player for the season prior to the transfer. Statistics included in the Overall Ratings variable are:

- Summary statistics: *number of appearances, minutes played*, *man of the match awards*.
- Offensive statistics included: *goals scored*, *assists provided, shots per game, shots from inside, the six-yard box, shots inside the penalty area excluding the six-yard box, shots from outside the penalty area, pass success percentage, aerial duels won per game, number of times fouled per game, number of times dispossessed per game, offsides per game, bad controls per game, successful dribbles per game*.
- Defensive statistics included: *fouls per game, dribbled past per game, tackles per game, offside won per game, outfielder blocks per game, interceptions per game, clearances per game, own goals per game, saves per game, number of clean sheets.*

- Game controlling statistics included: *through balls per game, long balls per game, crosses per game*.
- Disciplinary attributes included: *yellow cards*, *red cards*.

The overall rating is on a scale of 6 through 10. This rating regime makes it possible to evaluate players in all positions on a single numeric scale, hence the sample includes all players including goalkeepers. Other player demographic variables that have been used in previous studies and shown to be important determinants of player's market value such as height and footedness are essential to help the player's performance. For example, tall players will have better stats for scoring or defending aerial through balls while dual footed players would have better passing stats. Hence, this study considers the previous season's overall rating variable (RAT_{s-1}) as a comprehensive measure of a player's marginal contribution to team success. Apart from player's age (affects his athleticism over time), every other demographic or talent variable is incorporated in the RAT_{s-1} variable.

The UEFA club coefficients are based on a point aggregate[28] of a club in the last 5 seasons of the UEFA Champions League *(UCL)* and UEFA Europa League *(UEL).* These data are taken for the UEFA website (uefa.com). Participation in the UCL and UEL is based on league standing in the previous season. Since league position is measure of team success within the local league, participation in UEFA club competitions and thus the UEFA club coefficient is an acceptable yardstick to measure club successes at the continental level. In this study, this variable (UEFA club coefficient) is thus a vector of sporting and financial success. All but 13 clubs (0.03%) in the sample are UEFA clubs. There are 5 non-UEFA buying clubs in the sample, all from the Chinese Super League and they are each attributed a weighted UEFA club coefficient to account for their financial power and success in their league. There are 9 non-UEFA selling clubs, one from the Chinese Super League the remainder 4 from Latin America (Brazil and Argentina). The variable (*CLUBSUCC*) is the difference between the UEFA club coefficients of the buying club and the selling club. A positive delta indicates that the buying club is more successful, and this transfer can be characterized as poaching and hence it is hypothesized to positively correlate with transfer fee premium, while a negative delta indicates offloading from a more successful to a less

[28] See https://www.uefa.com/memberassociations/uefarankings/club/about/ for point system explanation.

successful club and hence hypothesized to be negatively correlated with transfer fee premium. Out of the total 300 transactions in this sample, 134 (44.6%) have English Premier League clubs as the buying party, 54 from the Spanish La Liga, 44 from the Italian Serie A, 25 from the French Ligue 1, 21 from the German Bundesliga and the remainder 22 from Russia, China, Brazil, the Netherlands, and Portugal combined. 193 (64.3%) of the transactions in this sample are considered 'poaching', while the remainder are considered 'offloading'.

The ownership structure of the buying club variable (OWN_{BUY}) is a dummied as 1 or 0 to reflect concentrated ownership (1) or dispersed ownership (0). Club ownership information is taken from Forbes magazine (www.forbes.com) and other reputable online sources. In the case of concentrated ownership, this study hypothesizes that irrational decisions based on instinct and not backed by market information will result in higher transfer fee premium. Most EPL clubs are owned by individuals or entities (concentrated ownership). The same applies for the French and Italian clubs in this sample. German clubs on the other hand are mostly owned by numerous members and the German football authority forbids individual majority ownership, except for Bayer Leverkusen and VFL Wolfsburg who have been handed special dispensation by the Bundesliga's 50+1 rule [29] and now have individual/entity majority shareholder. Spanish clubs are a mix of the two ownership models. Of the 300 transactions, 245 of the buying clubs have concentrated ownership structures while the other 55 dispersed ownership structures.

Lastly, a change in leadership/ownership of the buying club in less than 2 years before the transfer ($CHAN_{L/O}$) is dummied with 1 representing cases where ownership/leadership changed in less than 2 years preceding the transfer and 0 where there was no change in ownership/leadership. Changes in club leadership or ownership do not necessarily follow the transfer window calendar, hence a 2-year period is set to ensure at least one summer transfer window after the new leader/owner settles in. Data on new leadership/ownership of clubs is gleaned from online sources. There was a change in leadership/ownership of the buying club (within a 2-year period) in 75 of the 300 transactions.

[29] https://www.bundesliga.com/en/news/Bundesliga/german-soccer-rules-50-1-fifty-plus-one-explained-466583.jsp

Table 2.2.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Transfer Premium (€ million)	300	-36.00	122.00	8.04	15.60
Age	300	17	34	24.28	2.96
Contract Years Remaining	300	0.42	6.83	2.65	0.99
Overall Rating Previous Season	300	6.04	8.52	7.30	0.40

Data shows that the English Premier League has the highest number of top transfers (Figure 2.1) and pays the total highest transfer premium (Figure 2.2) compared to the other 'big 5' leagues. This is line with the findings of Depken II and Globan (2021). However, on average, the French Ligue1 pays the highest transfer premium (Figure 2.3), and this can be attributed to PSG's €222million signing of Neymar resulting in a transfer premium of €122million in 2017.

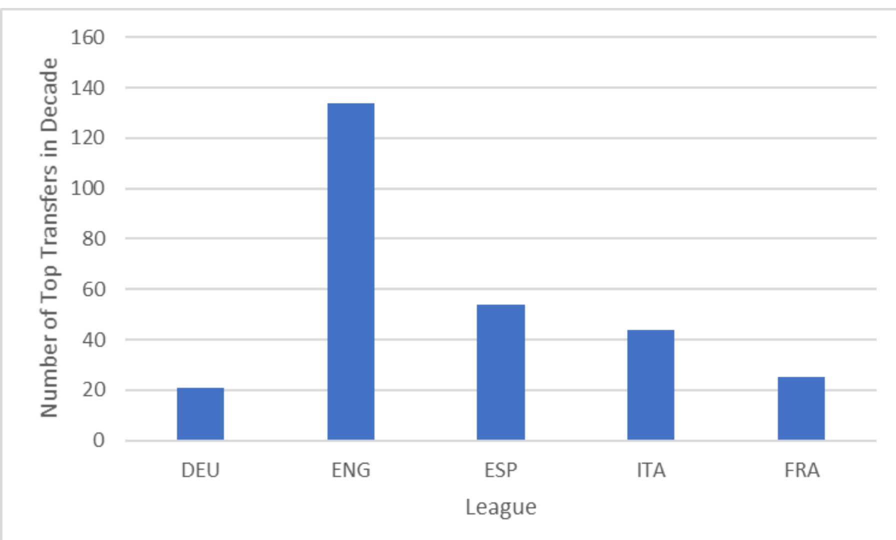

Figure 2.1.
Total number of top transfers across 'big 5' leagues over 10-year period (2011-2020).

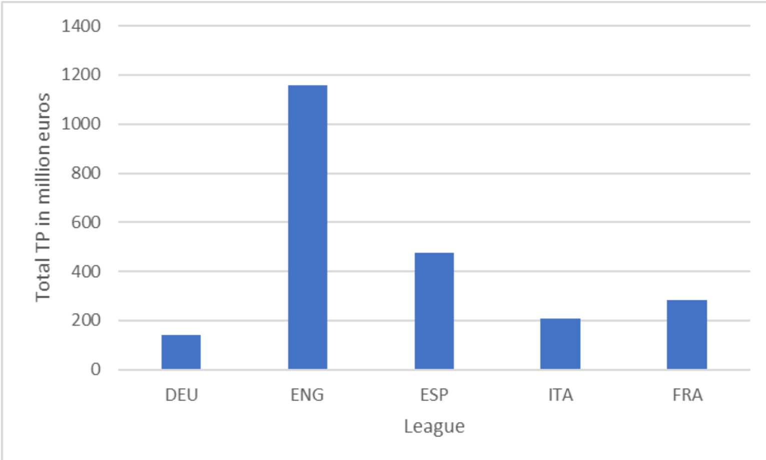

Figure 2.2.
Total transfer premium (in million euros) across ‘big 5’ leagues over 10-year period

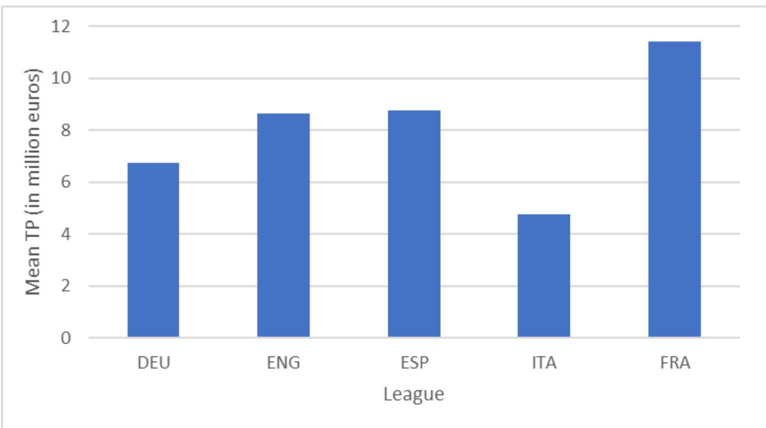

Figure 2.3.
The mean transfer premium (in million euros) across the ‘big 5’ leagues over 10-year period (2011-2020).

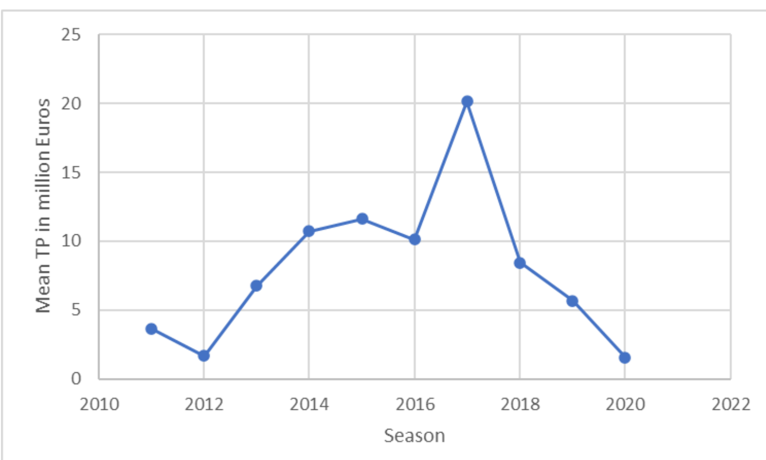

Figure 2.4.
Average Transfer Premium (in million euros) over the 10-year period (2011-2020).

Compared to the first season (2011), the transfer premium for 2014 is €7.52million, for 2015 is €7.90million and for 2017 is €16.10million higher (Figure 2.4). The rate of inflation is 9.6% in the transfer market up until 2019 and then dips in 2020 (Figure 2.5). This dip can be attributed to COVID-19 global pandemic that suspended all sporting activities for a while.

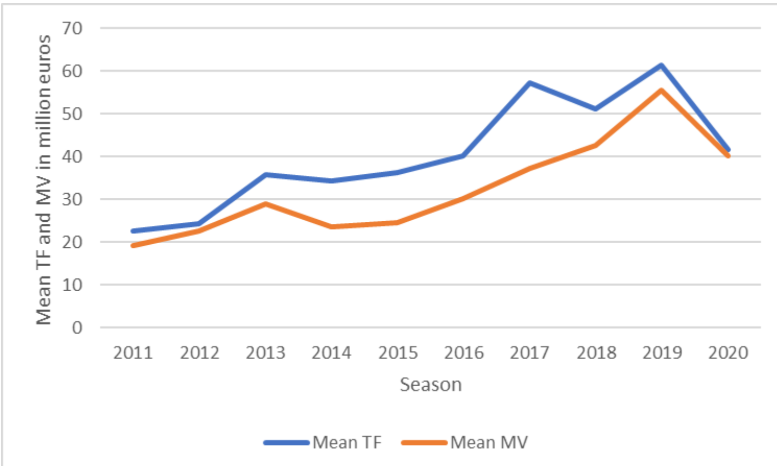

Figure 2.5.
The mean transfer fee and mean market value over 10-year period 2011-2020).

3.3.2 *- Empirical Specification*

Market values from Transfermarkt are used in actual transfer fees and salary negotiations (Herm *et al.*, 2014). Several studies have shown that similar factors influence market value and transfer fees (Bryson *et al.*, 2013, Franck & Nüesch, 2012). There are several exogenous factors that influence transfer fees and hence transfer fee premia that cannot be known *ex ante* when determining market value, such as buying/selling club characteristics and player contractual obligations (Essay 1). Transfer fee premium (TP) is the difference between the transfer fee paid and the Transfermarkt valuation of the player at the time of the transfer (Depken II & Globan, 2021).

$$TP = TF - MV \tag{1}$$

This study posits that Transfermarkt valuation of a player at the time of the transfer (MV) is the starting point. Then, the contractual obligation of the player is considered. If the number of years remaining on the player's contract (CTR_{YL}) is zero, the transfer fees (TF) equals to zero per the Bosman ruling.

$$if\ CTR_{YL} = 0; \quad TF = 0 \tag{2}$$

This study deals only with player transfers for which the number of years remaining on the player's contract is greater than zero ($CTR_{YL} > 0$). Transfer fee can thus be considered as the amount paid for the breach of contract. The Transfer fee premium (TP) is influenced by the number of years left on the player's contract (CTR_{YL}), the age of the player (AGE), the overall whoscored.com rating of the player in the preceding season (RAT_{s-1}), the main playing position of the player ($MPOS$), the ownership structure of the buying club (OWN_{BUY}), any change in the leadership/ownership of the club in the last 2 years preceding the transfer ($CHAN_{L/O}$), and the difference in the UEFA club coefficients of the buying and selling clubs ($CLUBSUCC$). In line with previous studies, a linear relationship is assumed, and the resulting least squares specification is:

$$\begin{aligned} TP_i = \ & \beta_0 + \beta_1(AGE)_i + \beta_2(CTR_{YL})_i + \beta_3(RAT_{s-1})_i + \beta_4(MPOS)_i + \beta_5(CLUBSUCC) \\ & + \beta_6(OWN_{BUY}) + \beta_7(CHAN_{L/O}) + \varepsilon_i \end{aligned} \tag{3}$$

Where TP_i is the transfer premium for player i paid by the buying club, ε_i is the error term. All other variables are as described above.

3.3.3 – Results

OLS regression results of the base model (model 1) show that there is a negative correlation between player age and transfer premium. This result is statistically significant at $p < .001$ and hence the null hypothesis is rejected. Holding everything else constant, a one-year increase in a player's age will reduce the transfer premium by €1.42million. This is in line with previous research that shows athleticism declines with age and hence, player market value and the transfer fees they command. The overall rating of the player in the preceding season is positively correlated with transfer premium. This is in line with previous research, though limited to goals and assists only. A 1-point increase in the overall rating of a player increases the transfer premium paid for the player by €6.67million, holding everything else constant. The number of years left on a player's contract has a positive correlation with transfer premium. An additional year on the contract of a player with his holding club amounts to a €2.05million increase in the transfer premium paid for breaching the player's contract, everything else held constant. This result is in line with Feess, Frick & Muehlheusser (2004) in their analysis of transfer fees. Season dummies show significant results for 2017 only. This can be attributed to the record-breaking Neymar Jr. transfer to French Ligue 1. The results for league dummies are not statistically significant. Previous research shows that broadcasting deals result in windfall revenues into leagues and this in turn leads to higher transfer premia (Depken II and Globan, 2021). However, the broadcasting deals in the English Premier League in 2012 and 2016 does not show any statistical significance in this market segment and there is no evidence on the other 'big 5' leagues.

Model 2 breaks the age variable into age brackets and adds buying Club factors. Interestingly, when players are placed into age brackets; under 23 (young), 24 – 27 (midage) and over 28 (mature), compared to mature players, young players command a transfer premium of €11.12million, everything else held constant. This result is statistically significant and shows that buying clubs are risk-tolerant due to their willingness to pay significant premia for young players compared to mature proven talents. Surprisingly, the buying club variables included in this study when run together do not show statistical significance. However, Club success alone is significant at $p < .05$. Given the theoretical formulation of the club success variable and mindful that English Premier League clubs are financially more successful compared to other 'big 5' clubs with UEFA Europa League success, an interaction is tested between the English League and the $CLUBSUCC$ variable. There is no statistical significance. The league and season dummies remain the same.

Model 3 adds Player Position variables. The player position variables are not statistically significant, even though the coefficients are in line with previous research regarding degree of specialization which shows midfielders are the least specialized and goalkeepers are the most specialized.

Table 2.3.
OLS regression results.

Dependent variable: Transfer Fee premium	Model1	Model2	Model3
Factors			
Intercept	-14.775*	-40.933*	-43.485*
Age	-1.422***		
Contract Years Left	2.052*	2.094*	1.950*
Overall Rating	6.670**	5.509*	6.118**
Buying Club Factors			
Leadership Change		-2.618	-2.596
Ownership Structure		3.358	2.891
Club Success		0.704	0.111
Dummies			
Season	Yes	Yes	Yes
League	No	No	No
Mid Age (24 – 27)		-2.951	-3.013
Mature (28 +)		-11.105***	-11.413***
Midfielder			-2.454
Defender			0.086
Goalkeeper			6.494
R-Squared	.232	.157	.157

Notes: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '°' 0.1
Number of observations: 2,700. Number of groups: Age groups: 3. Playing Positions: 4. Seasons: 10. Leagues: 5

3.3.4 *- Model Evaluation*

In essence, the number of attributes that buying clubs value in a player and the degree to which these attributes are important to buying clubs vary considerably. This study tries to test some of the most important factors that influence player purchase decisions. The dependent variable in the model (Transfer Premium) is calculated as a difference between actual transfer fees and Transfermarkt valuation of a player at the time of the transfer. Transfermarkt valuations are used as proxies for transfer fees in scientific studies (Bryson et al., 2013, Franck & Nüesch, 2012, Müller et al., 2017) and both have been found to be influenced by a similar set of factors (Bandes & Franck, 2012; Bryson et al., 2013; Frick, 2007). Hence, transfer premium would conceptually result from factors that influence transfer fees, but not Transfermarkt valuations (Essay 1), i.e., factors that cannot be known *a priori* when determining Transfermarkt valuations e.g., player contract obligations, buying club characteristics, etc. Hence, using player age and previous season performance ratings factors as independent variables which are already present in the right side of the regression equation is a concern. However, the inclusion of the age and performance ratings is meant to capture the variation in value attributed by buying clubs versus the valuation attributed by the Transfermarkt community.

Second, to test how poaching (offloading) affects transfer premium, club success is measured as the positive (negative) delta between the UEFA Club coefficients of the clubs involved in the transaction. In this study, club success is theorized to cover both sporting and financial success. Most English Premier League clubs rarely participate in UEFA competitions but occupy 17 of the top 20 clubs in terms of TV broadcasting revenues (UEFA, 2020). Hence, and interactive term with $CLUBSUCC$ and $LeagueENG$ was tested but yielded no statistically significant result.

Standard OLS tests show that the model meets the basic assumptions of multiple regression. The Variance Inflation Factor (VIF) for all models shows values ranging from 1.029 to 1.189, hence no multicollinearity. The models generally showed heteroskedasticity with studentized Breusch-Pagan test having p-values lower than the .05 threshold. To correct for heteroskedasticity, White's HC3[30] adjustment is used. There is a very slight change to the coefficients and p-values remain the same. As a final robustness check, from model 1 to model 3, the magnitude, direction and statistical significance of the core variables do not change significantly, and when the coefficients of the variables are entered into the regression equation, the resulting values though not exact, are in line with the actual TP values. Mindful that the factors that buying clubs consider when buying players are not exhaustive and cannot be completely coded, a complete dataset of factors is unrealistic and hence the regression equation cannot provide exact values as the dependent variable.

[30] $HC3 = \frac{e_i^2}{(1-h_i)^2}$

3.4 - DISCUSSION

The result of this study shows that clubs are willing to pay a significant premium for younger players with promising talent as compared to mature players with proven talent, hence depicting a risk tolerance behavior on the part of buying clubs. This is understandable given that athleticism declines with age and so does the market value of the player. Player recruitment is an investment on the part of the buying club. While mature players are at their peak or have passed their peak such that the return on investment for this segment is considerably low, young players still have many years ahead of them (barring injuries) during which the club can recoup its investment and there is also a sell-on value in the future. Younger players also have an added advantage that they may develop into superstars, thus a windfall for the buying club. Accordingly, the performance rating of the player in the preceding season is also a significant variable as it indicates the individual contribution of the player to the clubs sporting success. Hence, clubs are willing to pay a high price to breach the contract for a young player with a good recent performance record. Another plausible explanation for the premium price on young players could be that young players are awarded longer term contracts compared to mature players, and results show contract duration positively affect transfer premium.

This study further hypothesizes that this risk tolerance of clubs is further exacerbated by the ownership structure of the buying club; with concentrated ownership structures centralizing power to a single or few individuals, thus making irrational and speculative decisions more likely. However, based on the analysed sample, the result not statistically significant. However, the coefficient of the regression shows that everything else held constant, concentrated ownership clubs spend €2.98 million more in transfer premium compared to clubs with no single majority shareholder. Also, while not statistically significant, estimates show that poaching leads to a slightly higher transfer premium compared to offloading. Surprisingly, the variable depicting a recent change in club leadership/ownership is not just statistically significant, the coefficient suggests that everything held constant, clubs that had a recent change in leadership/ownership pay a lower transfer premium compared to clubs that experienced no leadership/ownership change. This is contrary to the theoretical specification and line of argument that new owners/leaders are more likely to increase spending to raise club profile. One possible explanation for this result is that the sample size is small and for every major club that had a change in ownership/leadership and splashed cash in the transfer market (PSG, Manchester City, etc.), there are other major clubs that experienced no leadership/ownership change yet spent considerably in the transfer market (Manchester United, Liverpool FC, Real Madrid, etc.). Hence, further research is needed to study a larger sample size that represents the cross-section of the football market (not just the top end) to analyse the effects of changes in leadership/ownership on buying behavior and hence, transfer premia.

Additionally, this study tested the effect of the major TV broadcasting deals signed with the ‘big 5’ leagues with transfer premia and found no statistically significant effect. While revenues from broadcasting deals makes up a substantial part of the revenues of most football clubs, this is not the case for the few clubs operating in the ‘thin’ market that is the focus of this study. For example, according to KPMG Football Benchmark, for the 2017/18 season, Liverpool FC reported a total club revenue of £514million, with £248 million (48%) coming from TV broadcasting deals. Conversely, in the same year, Stoke City reported total revenue of £144 million, with £114 million (79%) from TV broadcasting deals. This is the same trend in all ‘big 5’ leagues where broadcasting revenue makes under 50% of the club’s overall revenue (Real Madrid, 36%; Juventus FC, 50%; etc.). Hence, while TV broadcasting revenue will not have a significant effect on the buying behavior of clubs operating in thin markets. However, total revenue in general shows significant effects in 2017 for the French Ligue1 and Spanish La Liga. The purchase of Neymar Jr. for €222 million into the French Ligue1 (Paris Saint Germain) had a multiplier effect as the proceeds of this sale showed a significant effect on the transfer premium with the purchase of Dembele and Coutinho for €275 million in the Spanish La Liga (FC Barcelona).

Playing positions do not show statistical significance for the sample under study and this can be attributed to the recent hikes in the value of non-offensive players. Goalkeepers, defenders, and midfielders are currently valued upwards of €80 million. Thanks to the availability of granular data that enables individual contributions to be calculated with more accuracy, goal-scoring does not carry as much weight as before and this has led players in controlling and defensive positions to emerge as superstars of the game.

3.5 - CONCLUSION

The football transfer market is a mix of a bidding process involving more than two clubs and a bargaining process between the highest bidder from the bidding phase and the selling club (contingent on the preferences of the player). As a result, there is no fixed formula for determining exact price as it falls in a continuum between the maximum that the buying club is willing to offer and the minimum that the selling club is willing to accept. The factors that influence the reservation price of selling club and the maximum offer of the buying club vary in number, importance to each party, and whether they are measurable. Using a set of player characteristics and selling club characteristics to analyse the top 30 transfers per season in the last decade (2011-12 – 2020/21) in Europe's 'big 5' leagues, this study shows that under the current regulatory framework, clubs operating at the top end of the transfer market are risk tolerant as they spend a significant premium on young promising players compared to mature players with proven talent. The number of years remaining on a player's current contract and the overall performance rating of the player in the previous season both strongly affect the transfer premium commanded by the player. The direct positive relationship between number of years left on the players contract and the and the transfer fees that the player commands on the transfer market is evident of the current regulatory framework where there are no transfer fees when the remaining number of years on the player's contract is zero. Additionally, given that clubs exhibit utility-maximization behavior, there is a multiplier effect as proceeds from player sales are reinvested in the transfer market to secure the services of replacement players.

Regarding buying club characteristics, poaching leads to high premia compared to offloading. Clubs usually offload to make room for new recruits on both the field of play and on the club's wage bill and hence are more likely to set a favorable reservation price that can be met by potential buyers. Conversely, poaching forces the buying club to meet the minimum asking price of the selling club, hence the tendency to pay above the market value of the player, resulting in high transfer fee premia. While the other tested buying club characteristics do not show statistical significance for the sample under study, for example, the ownership structure of buying clubs, evidence shows that while the theoretical specifications are grounded, the sample population under study is not ideal to provide statistically significant results for such analyses. A simple explanation is that for every amount spent by a club with a concentrated ownership structure (Manchester City, Paris Saint Germain, Manchester United, Liverpool FC, etc.), there are there are clubs with dispersed ownership structures that spent as much in the transfer market (Real Madrid CF, FC Barcelona, Bayern Munich, etc.). Hence, the spending power of the concentrated ownership clubs is cancelled out in this sample. Future research with a larger sample that represents the entire football transfer market is needed to better analyse club ownership structure as a variable affecting transfer fee premia. Further research is also needed to code the transfer market demand and supply variable to empirically calculate how much the value of a player goes up/down when a close substitute is removed/added from/to the transfer market. Lastly, Financial Fair Play restrictions also play a key role in the ability of clubs to recruit new players. Lionel Messi’s move from FC Barcelona to Paris Saint Germain on a free transfer is due to FC Barcelona’s inability to keep Messi (given his wage) and still meet the guidelines of UEFA’s financial fair play rules. Hence, this is an important variable that future research can include for a much-detailed analysis.

Finally, the emergence of the influence wielded by player agents in the football transfer market of recent necessitates the inclusion of this factor in the analyses of the distribution of transfer fees and transfer fee premia. The best of these agents, coined ‘super agents’ are known to negotiate mouth-watering deals for their clients. Agents like Mino Riola who represents the interests of Paul Pogba, Zlatan Ibrahimovic, Mario Balotelli, etc.; and Jorge Mendez who represents Cristiano Ronaldo, Jose Mourinho, etc. have proven to be important variables in the determination of transfer fees. Hence future research should factor in player’s agents.

4. Essay 3 : FOOTBALL PLAYER WAGES IN THIN MARKETS: An Analysis of the European Association Football Labour Market.

4.1 - INTRODUCTION

Player remuneration in European Association football (hereafter referred to simply as *football*) has been skyrocketing in the recent past thanks to increasing revenues for clubs (Bernardo et al., 2021; Ribiero & Lima, 2019; Frick, 2011). Club revenues come from three principal sources: matchday (including ticket and corporate hospitality sales), broadcast rights (including distributions from participation in domestic leagues, cups, and UEFA club competitions) and commercial sources (e.g., sponsorship, merchandising, stadium tours and other commercial operations). The global lockdown of sporting activities in response to the COVID-19 pandemic slightly affected the revenues of most clubs. The top 20 European clubs in revenue terms saw their total revenue fall by 12% from €9.2B in 2018/19 to €8.3B in 2019/20 according to Deloitte Football Money League 2021[31]. Contrary to North American sports leagues where the aim is to pursue profit maximization, European football clubs aim for utility maximization (Kesenne, 2007; Sloane, 1969, 2006; Fort, 2000). To achieve this goal, top clubs in Europe engage in fierce battles to secure the services of the best players on the market (Bernardo et al., 2021). With no regulation on salary caps in place, market forces keep pushing wages up. According to Global Sports Salary Survey[32] (GSSS) for 2019, European football clubs hold the top 3 positions for average wage per player, FC Barcelona in top spot with £188,993/week, Real Madrid CF with £171,611/week and Juventus FC with £155,487/week. The subsequent 8 spots are occupied by North American (NBA) teams.

There are many player characteristics that affect the contract amount and hence, wage. Player demographics and performance have long stood out as major determinants of player wage (Frick, 2006; Garcia-del-barrio & Pujol, 2005; Lucifora & Simmons, 2003). The iconic status of a handful of players, borne of their popularity and/or superior talent has led to the former earning exceptionally high wages compared to the rest of the pack (Franck & Nüesch, 2012; Christiansen

[31] https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/sports-business-group/deloitte-uk-deloitte-football-money-league-2021.pdf

[32] https://www.globalsportssalaries.com/GSSS%202019.pdf

& Sievertsen, 2008; Lucifora & Simmons, 2003). This phenomenon is grounded in the superstar theory (Alder, 1985; Rosen, 1981). The fame and popularity of these iconic players give a massive profit boost to the clubs they represent in terms of merchandise sales, commercial sponsorships, and broadcasting rights (Rohde & Breuer 2016; Kucharska et al., 2018). For example, Juventus FC signed Cristiano Ronaldo from Real Madrid CF in 2018 for a weekly base wage of £501.000. The player has more than 200 million followers on social media (Badenhausen, 2016). According to Financial Times[33], the club's share price more than doubled, raising its market capitalization to €1.5bn even before the player set foot on the pitch. Juventus increased ticket prices by 30% and all tickets were sold out. Clubs understand the financial windfall of having an iconic player on their roster. In the MLS, this phenomenon was crystalized in North America with the introduction of the Designated Player (DP) rule to allow teams to circumvent the salary cap and lure high earning superstars (Coates et al., 2016).

An important aspect of player wages is the type and duration of the contract signed with the club. Players employ the services of agents to help in the negotiation process (Bernardo et al., 2021). The compensation package of football players in Europe is usually includes a base salary (spread over the contract duration), performance bonuses, image rights, sign-on bonus, etc. The weekly wage of a football player is the quotient of his gross basic annual contract value divided by 52 weeks. Since contracts span several playing seasons, there is debate as to whether it makes sense for players to sign long term contracts, given the volatility of the player labour market and ever-increasing contract values (Frick, 2011). On the one hand, player agents argue that short term contracts give players the ability to renegotiate their pay to market levels, the caveat being that the player could suffer from injury or a dip in form. On the other hand, clubs would love to secure a long-term commitment from the player at present market rates, the caveat being moral hazard (shirking - performance below the expected level following a newly signed long-term contract) on the part of the player (Buriamo et al., 2015; Krautmann & Donley, 2009; Feess et al., 2004). In a nutshell, a new contract usually offers a wage boost, everything else being equal.

[33] https://www.ft.com/content/cc72b6a6-b5b9-11e8-b3ef-799c8613f4a1

Player mobility has a major effect on wages. Movement between clubs (transfer) usually comes with a new contract. Transfers will indicate an appreciation of the talent (move to a superior team – poaching) resulting in a wage premium or it may indicate off-loading due to deteriorating performance (move to an inferior team/league) resulting in a wage penalty (Ribiero & Lima, 2019). Contract agreements with players are expected to represent the present value of the player to the club.

There are 98 teams in Europe's 'big 5' leagues for the 2020/21 season – England (20), Spain (20), Germany (18), Italy (20), and France (20). Each team roster for the season has approximately 25 players, hence the total of 2,450 players. To regress player wages, Lehmann & Schulze (2008) argued that a quantile regression is best to capture the convexity of wages at the top end of the sample. This study focuses on the 90th percentile. Using cross sectional data for the most valuable players for the 2020/21 season (ranked by Transfermarkt market value), this study empirically analyses player wages using their demographic, performance, and popularity metrics. This study samples the wage distribution between transferred players (new contract) compared to players that were not transferred during the season under study, and hence operated under an existing contract, as well as wage distribution between age groups. These two facets are then regressed against the performance and popularity variables to check for differences. To the best of my knowledge and at time of writing, no other study analyses football player wages jointly as a function of age group and transfer status. Additionally, this study innovates the measurement variables for performance and popularity as follows: firstly, this study uses more sophisticated performance measure. Unlike previous studies that primarily use goals, assists, tackles, etc. (Lehmann & Schulze, 2005; Lucifora & Simmons, 2003), this study uses an overall performance variable that best measures the contribution of every player to team success, hence all positions are included. Secondly, player popularity, hitherto measured by press citations and Google hits, is measured by their social media following - multi-way, immediate, and contingent medium linking fans and the player/club (Peters et al., 2013).

4.2 – BACKGROUND

4.2.1 *– Review of the Relevant Literature*

Rottenburg (1956) laid the groundwork for research into sports labour market focusing mainly on American Baseball (MLB). Institutional arrangements and the regulatory framework such as reserve clause and draft system, though lauded for preserving competitive balance and incentivizing training of young talent, gave monopsonist power to teams (employers) at the detriment of players (employees). The era of free agency and revenue sharing brought some gains for the players but still, the salary cap restrained players from earning the full economic rent in free markets. Kahn (2000) studied player remuneration in the major US leagues over several periods characterized by changes (mergers and breakups) that led to monopsony powers for team owners. He noticed that where rival leagues were absent and players had fewer options (lesser bargaining power), salaries dropped. In effect, the monopsony powers of the teams prevented players from earning their marginal revenue product.

Bernardo et al. (2021) analyse salary setting among the top earners in the Italian Serie A and find evidence that the popularity of players on social media has significant role in their salary determination. They show that amongst the highest earners, while popularity measured by Google trends and international reputation positively affects wages, social media following and the player’s off-field image can be monetized and have the potential of offering the player more earnings than the basic contract for on-field performances. This additional earnings potential can be gained through endorsements and merchandize placements using player’s image primarily amongst fans with lower club affiliation. Scarfe et al. (2021) study the determinants of superstar wages in the Major League Soccer (MLS) to determine whether productivity-based arguments or popularity-based arguments are more appropriate, and their results find support for the latter. Ribiero & Lima (2019) study player wages in the Portuguese league as a function of player mobility and find that movement from an inferior(superior) league/club to a superior (inferior) league/club is associated with a salary premium (penalty), everything else being equal. Walters et al. (2017) analyse the wage and contract structure in the MLB labour market and find risk aversion on the part of clubs as they prefer long term contracts to secure the services of players at current market rates as opposed to year-on-year contracts in a volatile market. Yaldo & Shamir (2017) estimate football players wages using computation estimations by application of pattern recognition algorithms to performance, behavior, and ability and find a 77% Pearson's correlation between estimated and actual salaries. Coates et al. (2016) study wage structure in the MLS with the "Designated Player" (DP) rule that allows teams to circumvent salary cap regulations and sign star players for high wages. They find support for cohesion theory as there is evidence that wage inequality has a negative relationship with team performance.

Earlier studies on determinants of wages in sports, particularly football have principally focused on player demographics and performance attributes and to a lesser extent, player popularity. Player *age* has been found to have a positive yet decreasing effect on wages as athleticism declines over time (Frick, 2006; Lehmann & Schulze, 2005; Feess et al., 2004; Lucifora & Simmons, 2003; Huebl & Swieter, 2002). Like *age, career games* (appearances) have also shown positive yet declining effect on wages (Frick, 2006; Feess et al., 2004; Lucifora & Simmons; Huebl & Swieter, 2002; Lehmann, 2000; Lehmann & Wiegand, 1999). Performance *(goals and assists*) have been shown to positively relate with wages (Bernardo et al., 2021; Yaldo & Shamir, 2017; Christiansen & Sievertsen, 2008; Montanari et al., 2008; Lehmann & Schulze, 2005; Lucifora & Simmons, 2003; Lehmann, 2000; Lehmann & Wiegand, 1999). *Position* variables have shown that *forwards* get paid a premium compared to other positions, with *goalkeepers* being the least paid (Frick, 2006; Lehmann & Schulze, 2005; Feess et al., 2004; Huelb & Swieter, 2002). Player's *country of origin* (Nationality) has shown a premium for South American exports (Frick, 2006). Participation in continental club competitions has also shown a positive relationship with wages (Garcia-del-Barrio & Pujol, 2005; Feess et al., 2004; Huelb & Swieter, 2002; Lehmann & Weigang, 1999).

Regarding player popularity as a determinant of wage, earlier studies used Google Hits as a measure of popularity and found significant positive effects (Garcia-del-Barrio & Pujol, 2006; Lehmann & Schulze, 2005). More recent studies have used social media following (Facebook, Twitter, and Instagram) as a measure of player popularity. In the Ultimate Fighting Championship (UFC), social media has been shown to positively affect wages (Gift, 2019; Ream & Shapiro, 2017); in major League Baseball (MLB), Watanabe et al. (2017) found similar positive effects as well as in the NBA (Prinz et al., 2012).

4.2.2 – *Description of the Variables and Hypotheses*

The determinants of player wage are many and varied. Extant research has mainly focused on measurable performance and popularity variables as well as demographic variables. There are several subjective variables that are difficult to quantify and hence impossible to get a measure, for example perks that clubs use to induce players to sign a new contract, players who chose to take a pay cut to play for a club based on a particular affinity, the abilities of the agent that represents the player's interests during transfer and wage negotiations, etc. As for the measurable variables, some are not made public and hence difficult to analyse, e.g., the amount paid in sign-on fees especially for players arriving on a free transfer. Therefore, researchers are left with the publicly available quantifiable set of variables. This study uses the following variables to explain variations in player wages:

4.2.2.1 – Player Market Value (MV)

The market value (Transfermarkt valuation) of a player is 'an estimate of the money a club will be willing to pay for the services of a player' (Müller et al., 2017; Herm et al., 2014). Transfer fees, market values, and wages are determined by a similar set of factors (Bryson et al., 2013; Frick, 2007). While conceptually different, in the absence of previous wage information, market values at the beginning of the period under consideration can be used as a baseline in the regression equation for wages, same as for transfer fees (Essay 2, Müller et al., 2017). The sample under study is the 90th percentile based on Transfermarkt rankings. Transfermarkt values have a good reputation in the sports industry and are used in actual transfer and salary negotiation (Herm et al., 2014) and have been used as proxy for scientific research (Müller et al., 2017; Bryson et al., 2013, Franck & Nüesch, 2012). This study uses Transfermarkt valuation of player as a baseline for the regression equations. Wages are expected to correlate positively with market values given both are influenced by the same set of factors.

4.2.2.2 – Player Age (AGEGRP)

The sole demographic variable used in this study is the age of the player at the beginning of the 2020/21 season. Age is an important variable as it reflects the player's athleticism and experience (Bernardo et al., 2021; Ribiero & Lima, 2019; Yaldo & Shamir, 2017; Montanari et al., 2008; Frick, 2006; Lehmann & Schulze, 2005; Feess et al., 2004; Lucifora & Simmons, 2003; Huebl & Swieter, 2002). Football is a physically demanding game and fitness is a very important attribute needed to excel in the sport. Hence, younger players are still vibrant and more performant than older players, everything else being equal. This study groups players into age brackets to reflect the point in their careers. A recent study using Kruskal-Wallis tests to determine the age at which EPL footballers are at their peak performance, showed that wingers and strikers peak at 25 (Jamil & Kerruish, 2020). A historical analysis of player performance at the world cup from 1930 – 2010 shows that 27.5 is the ideal performing age for players in all positions. Using playing time as a proxy to measure performance in the Premier League, results show that players peak between the ages of 24 – 28 (Caley, 2013). Dendir (2016) uses player ratings from Whoscored.com for five seasons (2010/11 to 2014/15) in the Premier League, La Liga, Bundesliga, and Serie to show that the average professional player in Europe's top leagues peaks between the ages of 25 – 27. Since player ages usually range from 17 – 36 and extant research has shown that player value increases with age at a decreasing rate (quadratic terms), this study sets the general peak performance age between 24 – 27. Hence, young players (YNG) are all players under the age of 23 in the sample. Mid-Age players $(MIDAGE)$ are those between the ages of 24 – 27, while mature players $(MATURE)$ are all player above the age of 28. In line with the findings by previous studies that show wages to increase with age at a decreasing rate and coupled with peak performance results that points to 25 as being the most performant age, this study puts forth the hypothesis that mid-age players will command a superior wage compared to young and mature players.

4.2.2.3 - Transfer Status (TRF)

Players who were transferred at the end of the 2019/20 (beginning of 2020/21) season have new contracts whereas, players who were not transferred and did not renegotiate their contracts still have their existing contracts in force. Players with new contracts have their performance ratings of the preceding season taken into consideration in their new or renegotiated contracts, whereas those players on an existing contract do not have their performance ratings for the 2019/20 season taken into consideration. In this study, all players who were transferred at the end of the 2019/20 season are considered to have a new contract. While it is possible that some player renegotiated their contract with their existing clubs, this study does not take this into account for lack of data. Everything being equal, a transfer (TRF) of a player from an inferior (superior) club/league to a superior (inferior) club/league will result in a salary premium (penalty) as recognition for improved (dwindling) performance (Ribiero & Lima, 2019). Given that the sample for this study is the top 10% valued players playing for the best clubs in Europe, upward mobility (transfer to a better club) is rare. Hence, in this market segment, transfers will most likely signal that the player is considered a surplus, hence offloading. Bernardo et al. (2021) find that players who stay longer at their clubs earn a higher wage in average. Studies on player performance in the final year of contract show evidence of shirking (moral hazard) as players increase their performance with the aim of being rewarded with better terms in a new contract (Frick, 2011). Other studies show that 'selection effect' is more predominant than shirking for players with long term contracts (Buriamo et al., 2015). This study therefore hypothesizes that in this market segment, where clubs have aim for on-field success and retaining the best players is a primary objective, a transfer will negatively affect wages.

4.2.2.4 - Overall Performance Rating in Preceding Season (RAT)

Player performance is a major determinant of wages in extant research (Bernardo et al., 2021; Yaldo & Shamir, 2017; Christiansen & Sievertsen, 2008; Montanari et al., 2008; Lehmann & Schulze, 2005; Lucifora & Simmons, 2003; Lehmann, 2000; Lehmann & Wiegand, 1999) and shown to positively affect wages. Unlike the cited studies that use individual player performance metrics such as goals, assists, dribbles, tackles, etc., this study uses the overall rating of the player in the preceding season. The overall rating of the previous season (RAT) is taken from Whoscored.com (powered by Opta). Whoscored.com ratings have been used in previous research (Dendir, 2016). According to WhoScored.com, ratings are based on a unique, comprehensive statistical algorithm calculated live during a game. There are over 200 raw statistics included in the calculation of a players rating, weighted according to their influence on the game. Every event of importance is considered, with a positive or negative effect on ratings weighted in relation to its area on the pitch and its outcome. This overall rating is the weighted average of several summary, performance (offensive, controlling and defensive) and disciplinary statistics for each player during the playing season. Overall rating measures the contribution of each player to team success, thus offering a single yardstick to rate all playing positions on the field, hence making it possible for all playing positions to be included in the analyses. This study hypothesizes that overall rating will have a positive relationship with wages (albeit for players who transferred).

4.2.2.5 - Minutes Played (MINS)

Minutes played *(MINS)* is a measure of the total time spent by the player on the pitch in the preceding season. This variable is a measure of the availability and fitness (form) of the player in the preceding season. This is different from career appearances statistics which, like age, measures player experience and hence has a positive yet decreasing effect on wages. Extant research has shown that appearances in the preceding season has positive effect on wages (Scarfe et al., 2021; Christiansen & Sievertsen, 2008; Lucifora & Simmons, 2003; Lehmann, 2000). This variable is a measure of a player's ability to maintain a form and fitness level and feature in as many games as possible. It could also indicate player adaptability to several play styles implemented by the coach during the season, player's indispensability to the squad, discipline of the player to avoid sanctions and suspension from games, or simply the work ethic of the player. High number of minutes played in the preceding season signals a fit and adaptable player and hence will relate positively with wages (albeit for players who transferred).

4.2.2.6 – Player Popularity (POP)

Unlike previous studies that measure player popularity (a determinant of wage) as an aggregate of Google hits and press citations (Franck & Nuesch, 2012; Garcia-del-Barrio & Pujol, 2006; Lehmann & Schulze, 2005), player popularity *(POP)* in the context of this study is the positive appeal that a player's image brings to the club's digital marketing efforts. The downside of using press citations and Google hits is that infamy could affect the data as some players could have high popularity measures based on press citations and Google searches due to unsportsmanlike behavior (Luis Suarez biting incidents) or legal proceedings (Adam Johnson criminal case). Social media following provides a better alternative. Recent studies using Instagram followers shows that player's off-field image have wage setting effects that can surpass the base income from on-field performances (Bernardo et al., 2021). There has been an exponential growth in the use of social media in the sports industry of late (Pedersen, 2014). Star athletes are social actors idolized in many countries worldwide (Chuang & Ding, 2013). Professional clubs and athletes use Facebook and Twitter to connect to fans (Haugh & Watkins, 2016). The importance of social media following for football clubs' economic success is further made evident by the inclusion of this metric in the Deloitte Football Money League (Deloitte, 2019). Hence, to best capture the positive popularity of players, their following on social media is considered a better measure of their appeal among the fanbase that can be transferred to the club's brand. This study uses 2 of the most popular social media platforms - Facebook and Twitter. Evidence of the superstar phenomenon has been shown in football (Adler, 1985) where network externalities result in extremely high wages for a select few. Case in point, David Beckham's move to the MLS increased attendance at games and his wage was the highest in the league (Jewell, 2017). This study therefore expects high social media following to positively affect player wages.

4.2.2.7 - Player Position (POS)

Football is a goal-oriented game and hence scoring a goal provides high visibility for forwards. In terms of contribution to team success, scoring goals and providing assists (last pass before a goal) carries more weight than most other on field actions. Evidence of the importance of offensive actions can be seen by the euphoria of fans when their team signs a new top rated offensive player (Montanari et al., 2008). The most coveted individual prize in football – the Golden Ball, has been awarded to offensive players at a highly disproportionate rate (the last 11 editions have been won by 2 wingers and an offensive midfielder), signaling the appreciation of offensive play by both spectators, analysts, and sports journalists. Extant research has shown that forward positions get higher wages (Frick, 2006; Lehmann & Schulze, 2005; Feess et al., 2004; Huebl & Swieter, 2002). Additionally, midfielders have a low degree of specialization and can play in multiple positions as compared to defenders and goalkeepers (Garcia-del-Barrio & Pujol, 2007) and earn a higher average wage comparatively. Hence, this study posits that forward-leaning positions will get a higher wage compared to the other positions.

4.2.2.8 - Participation in European Club Competitions (UEFACOMP)

The grand stage of European Club football is the UEFA Champions League. Held every season between the months of September and May, this club championship brings together to best clubs in European football. Qualification for a UEFA Champions League *(UCL)* spot is based on the position of the club in the local league in the previous season. There is also the UEFA Europa League *(UEL)* which brings together second-best clubs from standings in the local leagues in the previous season and the third-place teams at the end of the knock-out stages of the Champions League. Hence, the best players (teams) in Europe take part in these championships annually. For a club to participate in the UEFA club competitions, the club will have secured the services of quality players good enough to finish in the top spots of the local league. Working on the premise that clubs are utility maximizers (Kesenne, 2007; Sloane, 1969, 2006; Fort, 2000) and are willing to spend huge sums to secure the best talent, the huge sums will translate into higher remuneration for the players. Previous studies have shown that participation in these European Club Championships positively affects player wages (Garcia-del-Barrio & Pujol, 2006; Feess et al., 2004; Huebl & Swieter, 2002; Lehmann & Wiegand, 1999). In line with previous research, this study posits that UCL and UEL participation will have a positive effect on the player's wage.

4.3 – METHODOLOGY

4.3.1 - Theoretical Framework

Building on the human capital formulation pioneered by Jacob Mincer (1958), this study estimates the wage of a player as a function of the Transfermarkt market value of the player plus demographic, performance, transfer status, and popularity variables. The resulting regression equation is:

$$ln(WAGE_i) = \beta_0 + \beta_1 MV_i + \beta_2 AGEGRP_i + \beta_3 TRF_i + \beta_4 RAT_i + \beta_5 MINS_i + \beta_6 ln\,(POP)_i + \beta_7 POS_i + \beta_8 UEFACOMP_i + \varepsilon_i$$

where $ln(WAGE_i)$ is the natural log of the wage of player i, and β_0 is the intercept. β_1 to β_8 are vectors of the parameters being estimated and ε_i is the error term.

The current Transfermarkt market value of the player (MV) is used to as a base determinant for the regression equation. Transfermarkt values signal the quality of the player and how much clubs are willing to pay for the services of the player. Transfermarkt values are in millions of euros (€M). The age of the players is set in years and grouped *(AGEGRP)* into 3 age ranges: less than 23 (young), 24 – 27 (mid age), and 28 and above (mature). The transfer status *(TRF)* is dummied with 1 representing players who were transferred and 0 to represent players who were not transferred. The overall performance rating *(RAT)* is set on a scale of 6 – 10. The number of minutes played *(MINS)* are normalized per 1000, i.e., MINS/1000 to make for easier interpretation of the coefficients. The popularity variable *(POP)* is log transformed to match the scale of the rest of the variables. The position *(POS)* variable is dummied and referenced to the goalkeeper (GK) position. Participation in UEFA club competitions *(UEFACOMP)* is dummied and referenced to player who did not participate in any UEFA club competition (NIL). Since the data are from five leagues (the 'big 5'), to understand if there are any variation across leagues in terms of age group and wage distribution within age groups, Chi-Squared tests of independence are performed using a 2x2 cross tabulation for wage bin and age group, and a 2x3 crosstabulation for wage bin, age group, and league.

4.3.2 – Data Collection and Description

The data for this study is the 90th percentile of players during the 2020/21 season in Europe's 'big five' leagues (England, Spain, Germany, Italy, and France) ranked by market value as of June 2021. The market values are taken from the online crowd-sourced platform Transfermarkt.co.uk. The playing position, age, and transfer status are also taken from Transfermarkt. Transfermarkt values have a good reputation in the sports industry and are used in actual transfer and salary negotiation (Herm et al., 2014) and have been used as proxy for scientific research (Bryson et al., 2013, Franck & Nüesch, 2012, Müller et al., 2017). There are 270 player observations in total, of which forwards and midfielders each sum up to 100 (37.04%), defenders total 63 (23.33%) and goalkeepers make up the remaining 7 (2.59%). Players are placed into 3 age groups; below 23 years belong to the young category (YNG) making up 30.74%, between 24 to 28 years belong to the middle-aged category (MIDAGE) making up 45.19% and above 28 years belong to the mature category (MATURE) constituting 24.07% of the sample. The youngest player in the sample is 17 years old Jude Bellingham of Borussia Dortmund while the eldest is Cristiano Ronaldo of Juventus FC. The mean age of the sample is 25.03 years and the standard deviation of 3.25 years. General descriptive statistics are summarized in Table 4.1a below. Table 4.1b below shows the dispersion of wage and playing position per age group.

Table 4.1a.
Descriptive Statistics.

Variable	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Weekly Wage (£)	1,625.00	650,250.00	97,946.50	93,295.86
Market Value (€M)	10.80	160.00	46.00	20.23
Age	17.00	36.00	25.03	3.25
Ratings	6.29	8.52	7.08	0.30
Minutes played	217.00	4,500.00	2,632.00	804.39
Popularity	0	181,237,660	3,776,691	14,086,179

N = 270

Table 4.1b.
Position and Wage dispersion per age group.

Age Group	**Sample Count**	**Position Count**				**Weekly Wage (£)**			
		FW	*MF*	*DF*	*GK*	*Mean*	*Std. Dev.*	*Min*	*Max*
Young	83	34	29	19	1	58,397	42,869	1,625	405,875
Mid Age	122	38	48	35	1	90,600	65,399	4,500	354,000
Mature	65	28	23	9	5	162,238	133,032	16,300	650,250
Total Sample	270	100	100	63	7	97,946	93,296	1,625	650,250

Note: FW = Forwards, MF = Midfielders, DF = Defenders, GK = Goalkeepers
Young = Players under 23 years, Mid Age = Players between 24 – 27 years, Mature = Players 28 years and above

There have been major improvements in recent years regarding wage transparency in European football. Germany and Italy are still ahead of the pack when it comes to official reporting of basic wage information for all players in the league. In England, Spain, and France, most of the wage information is not reported officially. However, there are ways of checking the reported information to make sure it is accurate. The sample consists of high value players most of whose wages are subjects of news headlines, discussions on most football shows, and commentary during games. Information that leaks from the negotiation talks between clubs and football agents regarding player remuneration is also a major source for newscasters. The wages of the players are taken from reputable online magazines and websites; notably, *Gazzetta dello Sport* for Italian Serie A, *Welt am Sonntag* for the German Bundesliga, www.spotrac.com/epl/ for English Premier League, *L'Équipe* for French Ligue 1, and *Marca* for Spanish La Liga. Other web sources such as news websites and discussion forums were also used in the search and verification of the wage information. The wage information used for this study is the basic wage. However, some sources report wage information inclusive of bonuses (Forbes Magazine, Deloitte Football Money League, Global Sports Salaries Survey) and hence several other web sources such as news outlets were consulted to verify the wage information. Wages remain fixed during the duration of the player's contract. Wage information may change when a player renegotiates his contract with his current club (not accounted for in this study) or when the player gets a transfer and signs a new contract with a different club.

Players who were part of a transfer (TRF) at the close of the 2019/20 season are in the first year of a new contract. There are 52 players in the sample who were transferred, representing 19.26%. The transfer status is dummied with 1 representing a player that were transferred and 0 representing players that were not transferred. Regarding European club competitions $(UEFACOMP)$, 60.74% of the players participated in the UEFA Champions League (UCL), 20% participated in the UEFA Europa League (UEL) and the remaining 19.26% of players in the sample did not participate in any European club competition. Popularity (POP) metrics taken from Facebook and Twitter in mid-June 2021 shows that 221 (81.85%) of the sample have an official social media site (Facebook or Twitter). 164(60.74%) of the players have both Facebook and Twitter followers. The popularity variable is hence the sum of followers on the platforms under study. While it is very likely that same fans may follow a player on both platforms, and that some of the followers maybe fake (generated by bots), this is a dilemma for sampling and polling on online platforms in general (Khaled et al., 2018), and hence a limitation of this study.

The overall rating of the previous season (RAT) is taken from Whoscored.com (powered by Opta). According to WhoScored.com, ratings are based on a unique, comprehensive statistical algorithm calculated live during a game. There are over 200 raw statistics included:

- Summary statistics: *number of appearances, minutes played*, *man of the match awards*.
- Offensive statistics included: *goals scored*, *assists provided, shots per game, shots from inside, the six-yard box, shots inside the penalty area excluding the six-yard box, shots from*

outside the penalty area, pass success percentage, aerial duels won per game, number of times fouled per game, number of times dispossessed per game, offsides per game, bad controls per game, successful dribbles per game.

- Defensive statistics included: *fouls per game, dribbled past per game, tackles per game, offside won per game, outfielder blocks per game, interceptions per game, clearances per game, own goals per game, saves per game, number of clean sheets.*
- Game controlling statistics included: *through balls per game, long balls per game, crosses per game*.
- Disciplinary attributes included: *yellow cards*, *red cards*.

The overall rating is on a scale of 6 through 10. This rating regime makes it possible to evaluate players in all positions on a single numeric scale, hence the sample includes all players including goalkeepers. Other player demographic variables that have been used in previous studies and shown to be important determinants of player's wage, market value, and transfer fees such as *height* and *footedness* are essential to help the player's performance. For example, tall players will have better stats for scoring or defending aerial through balls while dual footed players would have better passing stats. Hence, this study considers the previous season's overall rating variable (RAT) as a comprehensive measure of a player's marginal contribution to team success. Apart from player's age (affects his athleticism over time), every other demographic or talent variable is incorporated in the overall ratings variable (RAT). The total time on the pitch in minutes ($MINS$) is taken from Whoscored.com and represents the number of minutes the player was on the pitch during a league games and European club competition games. Local cup games are not included in this study.

4.3.3 - Results

The Chi-squared tests show a p<.001 and a Pearson Chi-squared value of 28.271, meaning that age distributions are statistically different between the 5 leagues. Also, regarding age distributions within wage bins, Chi-squared tests show a p<.001 and a Pearson Chi-squared value of 60.482, meaning that wages between the age distributions are statistically different across the 5 leagues. The English Premier League has the highest pay in all age groups compared to other leagues. The variations in wages between age groups are also different across leagues.

Regression results are summarized in Table 4.2 below. The base model (model 1) regresses wages using Transfermarkt market value *(MV)* and player age groups *(AGEGRP).* Statistically significant at p<.001, model 1 shows that everything else held constant, mature players earn 206% more than young players, while mid age players earn 90% more than young players. Previous research found that wages increase with age at a decreasing level (Frick, 2006, Lehmann & Schulze, 2006, Lucifora & Simmons, 2003). Age grouping however does not show decreasing returns when regressed with player wages in this market segment. However, in this market segment, younger players are valued at a premium compared to mid age and mature players in terms of the transfer fee premium that clubs are willing to pay (Essay 2). When transfer status *(TRF)* is added to the mix (model 2), holding everything else constant, across the board, players who transferred suffer 25% wage penalty across all age groups compared to players who did not transfer. This is in line with the theoretical expectation that transfers in general in this market segment signals offloading of players that are considered a surplus to the team's needs. This supports findings that players who spend more years in their club and players who are on loan tend to earn more than their colleagues (Bernardo et al., 2021). Between age groups, using young players as a reference, model 3 shows that the overall penalty for players who transferred increases to 57%. As for players who transferred, looking at the penalty for having been transferred, mature players get an offset of the penalty and enjoy a boost of 74%, compared to a 20% boost for mid age players. In model 4 and 5, compared to young players who get a penalty for being transferred, mid age and mature players get a boost.

Table 4.2.
Multiple OLS Regression results.

Dependent variable: Weekly Wage (WAGE)	Model 1	Model 2	Model 3	Model 4	Model 5
Factors					
Intercept	9.736***	9.628***	10.399***	11.490***	11.696***
Market Value (£m)	.018***	.019***	.019***	.018***	.014***
Age Group					
Mid Age (MIDAGE	.644***	.631***	.058	.091	.126

Mature (MATURE)	1.118***	1.092***	.401	.392	.378
Transfer: Age Interaction					
Transfer0		-0.289*	-0.841***	-0.709**	-0.640**
Mid Age: Transfer0			.677*	.689**	.603*
Mature: Transfer0			.836**	.841**	.725*
Performance					
Overall Rating				-0.131	-0.203
Minutes Played/1000				-0.249***	-0.190**
Popularity					
Facebook + Twitter				.022***	.021***
Dummies					
Position (w.r.t GK)					
Forward (FW)					0.054
Midfielder (MF)					-0.164
Defender (DF)					-0.217
UEFA Comp (w.r.t. NIL)					
Champions League					.559***
Europa League					.360**
R-Squared	.343	.357	.375	.485	.536
Adj. R-Squared	.336	.347	.361	.467	.511
AIC	626.768	623.023	619.146	573.015	554.861
BIC	644.760	644.613	647.934	612.598	612.436
Lk'hood Ratio Test	-	5.745*	7.877*	52.131***	28.154***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '°' 0.1 ' ' 1
Number of observations: 2,160. Number of groups: Age groups: 3. Playing positions: 4. Leagues: 5.

Previous seasons performance *(RAT)* does not show any statistical significance across all models. When modelled as an interaction term with transfers, strangely, there is still no statistical significance. Appearance during the season *(MINS)* shows statistical significance at p<001. However, the coefficient is very small, and the relationship is surprisingly inverse. Previous research using longitudinal data has found *appearance* (like *age*) to increase wages at a decreasing rate (Frick, 2006; Feess et al., 2004; Lucifora & Simmons, 2003). However, given this study used cross-sectional data for one playing season, this result, though small, is contrary to expectation. Also, when modelled as an interaction term with transfers, there is no statistical significance. When the *MINS* variable is transformed in quadratic terms, the coefficient reduces but the direction of relationship is still negative (perversely). The popularity variable *(POP)* is statistically significant and shows across models 4 and 5 that 1% increase in social media following increases the wage of the player by .022%. This is in line with previous research that social media following has a positive effect on wages (Bernardo et al., 2021). Positional dummies *(POS)* with respect to the goalkeeping position do not show any statistical significance. Participation in European Club Competitions *(UEFACOMP)* shows that holding everything else constant, players who participated in the Champions League (Europa League) earned a 75% (43%) over players who did not participate in any European Club Competition. This result is in line with extant research (Feess et al., 2004; Huebl & Swieter, 2002; Lehmann & Weigand, 1999).

4.3.4 - Model Evaluation

The human capital model employed in this study was pioneered by Jacob Mincer (1958). This model has been used in player remuneration analysis in the football labour market in Europe (Lucifora & Simmons, 2003). The premise of this model is that a player's wages will be dependent on his current market valuation as well as several other demographic, performance, and popularity variables. This model is used to analyse a player's basic gross weekly wages, which is the quotient of his annual wage divided by 52 weeks. The annual wage is the quotient of the total contract amount divided by the contract duration (in years). The weekly wage is hence fixed over the contract duration, which could last several playing seasons. Since the sample data for this study is cross-sectional data with observations for a single playing season (2020/21), the sample has a mix of players who transferred and hence, are in the first year of contract and players who did not transfer and hence, still on existing contracts for which the weekly wage is fixed. As a result, the transfer status *(TRF)* of the player is an essential variable to understand the variance in wages for players who transferred and players who did not transfer. To capture this effect, interaction terms between transfer status performance variables *(RAT, MINS)* expected to affect wages due to the expected effect of new contracts. Initial results show no statistical significance.

As a robustness check, only players who transferred at the end of the preceding season are analysed. All dependent variables meet the conditions of linear regression and although market value *(MV)* and overall rating *(RAT)* show a statistically significant Pearson's correlation of .384, the variance inflation factor (VIF) is well below the acceptable level. Given the correlation between RAT and MV, dropping the latter from model 5 to see how it affects the goodness of fit, the adjusted R squared drops slightly from .511 to .509, signaling that the inclusion of the RAT variable slightly helps in explaining the variance. However, the AIC (BIC) drops to 554.675 (608.651) signaling that dropping the RAT variable helps the goodness of fit. A simple correlation test between wages and overall ratings shows a statistically significant positive correlation of .315. This supports the overall theory that players with higher ratings get higher wages. In a similar vein, the $MINS$ variable is positively correlated with the AGE variable (.198) and statistically significant. Like the RAT variable, this correlation has a VIF well below the acceptable threshold. Dropping the $MINS$ variable worsens the goodness of fit on all fronts, i.e., adjusted R squared drops and AIC and BIC both increase. A simple Pearson's correlation test between wages and the minutes played shows a Pearson's correlation value is .032 and this is not statistically significant. Transforming the $MINS$ variable into quadratic form as in Lucifora & Simmons (2003), further perversely reduces the coefficient to -0.036. Lastly, testing the interaction between the AGE and $MINS$ variables to see if there is variation across age groups shows no statistical significance. The interaction between transfer status and the demographic variable *(AGEGRP)* shows statistical significance and highlights the inverse disparity between the relationship between age groups and wages compared to age groups and transfer fee premia (Essay 2).

Regarding the goodness of fit across the regression models, R-squared and Adjusted R-squared values increase from model 1 through model 5 as new variables are included in the regression equation. Increasing values for R-squared and Adjusted R-squared shows a reduction in the unexplained variance in wages, hence model 5 with the largest adjusted R-Squared value is the best model to explain the variance in player wages. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) both reduce from model 1 through 5 (the BIC slightly increases from model 2 to model 3) showing that the added variables help better explain the dependent variable when added than when omitted. Likelihood ratio tests (LRT) compare the Chi-squared differential between each model and the preceding model and given the degrees of freedom (based in the number of variables), results show that the LRTs are significant across the board. In summary, looking at all the indicators of good fit, model 5 is the best fit model.

The regression model used Transfermarkt market values as a baseline variable to determine plater wages. Transfermarkt values have a good reputation in the academia and industry (Bryson et al., 2013, Franck & Nüesch, 2012, Müller et al., 2017). Caution is needed when using Transfermarkt values given that they do not capture club specific factors such as enticements used by clubs to lure star players, which could be well above the market level wage. Additionally, it is not uncommon for a player on a free transfer to get a sign-on bonus added to his contract amount, hence wages. This sign-on bonus is usually the equivalent of the cost of a comparable player in the transfer market. In the sample of the top 270 players in 2020/21 used for this study, only 1 player moved on a free transfer (James Rodriguez, from Real Madrid CF to Everton FC) and got a pay cut. Hence, the model estimations were unaffected.

4.4 – DISCUSSION

Market value (Transfermarkt) data are used as a baseline given that wages and market value are affected by the same set of variables. Normally, previous wage data would be ideal to serve as a basis for the wage regression. However, there are 2 main issues to consider. First, credible complete data for the 5 leagues under study is not available. Second, while cross sectional data are best to guard against inflation and market supply/demand forces, the drawback is that wages are fixed for the duration of contracts, the latter signed for multiple years. Hence, while the determinants of wages change every season, the wage itself is fixed for the contract duration, making it more appealing to use time series data for transferred players only. Further research could use time series data and correct for inflation and demand/supply forces.

Previous research (Essay 2) has shown that clubs exhibit risk tolerance and pay a high transfer fee premia for young players. Signing young players without proven experience is a risky future investment on the part of the club. However, wages represent the present value of the player to the club and hence, clubs would be expected to show risk aversion when it comes to wages for younger players. A summary of wage distribution for the 2019/20 season in the big 5 leagues by position and age, published by 21st Club's Omar Chaudhuri in GSSS 2019 (www.sportingintelligence.com) as shown in Figure 4.2a below supports this theory. It is not a foregone conclusion that mature players will earn more than younger players. The results of this study are based on a sample (the 90th percentile ranked by market value) of the player population in the 5 leagues under study. Focus on the 90th percentile is intended to show trends within thin markets. It is no doubt that if the sample size is increased, the results and statistical significance of some key findings will be diminished. In a similar vein, given there is no fixed entry age into football, there are some players in the young category who have a wealth of experience because the rose to the limelight at a very young age, and hence earn a wage outside the threshold of their age category, e.g., Kylian Mbappe. Looking at the average wage per age group across leagues (Figure 4.2b), figures show a more than 100% increase in average wage from the young category to the mid age category. In England, the mid age players on average earn higher than the mature players. This points to variations across leagues as shown by the Chi-squared test reported in the results section above. The performance (overall ratings) variable for the whole sample does not show any statistical significance. Surprisingly, when interacted with players who transferred, there is no statistical significance either. However, there is a positive Pearson's correlation between performance and wages when a simple correlation test is performed. There are two possible explanations for this. First, the log transformation of the wage variable affects

COUNTRY	LEAGUE	AGE BRACKET	GK	DF	MF	FW	TOTAL
England	Premier League	Up to 23	£843,143	£1,832,629	£2,115,750	£3,037,273	**£2,129,750**
Spain	La Liga	Up to 23	£503,425	£646,403	£1,004,163	£2,273,109	**£1,149,710**
Italy	Serie A	Up to 23	£1,053,241	£987,202	£1,037,311	£961,982	**£1,004,783**
Germany	Bundesliga	Up to 23	£420,625	£792,430	£1,090,518	£1,046,339	**£895,737**
France	Ligue 1	Up to 23	£182,049	£405,659	£432,564	£843,505	**£498,332**
England	Premier League	23-29	£3,212,182	£3,005,443	£3,819,563	£4,032,261	**£3,521,556**
Spain	La Liga	23-29	£1,826,392	£1,489,928	£2,253,666	£2,117,644	**£1,908,790**
Italy	Serie A	23-29	£1,111,820	£1,678,972	£1,803,992	£2,447,385	**£1,817,017**
Germany	Bundesliga	23-29	£1,378,327	£1,659,948	£2,046,790	£1,612,373	**£1,774,016**
France	Ligue 1	23-29	£1,000,095	£1,020,252	£980,542	£1,859,236	**£1,199,863**
England	Premier League	30-plus	£2,197,000	£2,918,933	£4,632,000	£4,573,833	**£3,278,035**
Spain	La Liga	30-plus	£1,551,282	£2,016,120	£2,533,964	£6,432,656	**£2,963,852**
Italy	Serie A	30-plus	£1,298,701	£1,880,631	£2,342,033	£4,749,589	**£2,576,631**
Germany	Bundesliga	30-plus	£1,343,508	£1,880,733	£1,751,063	£3,766,579	**£2,135,075**
France	Ligue 1	30-plus	£1,514,713	£1,320,250	£1,895,000	£3,189,727	**£1,752,085**
England	Premier League	ALL AGES	£2,407,770	£2,751,537	£3,555,354	£3,839,875	**£3,173,264**
Spain	La Liga	ALL AGES	£1,514,951	£1,479,128	£2,066,977	£3,090,194	**£2,037,648**
Italy	Serie A	ALL AGES	£1,156,775	£1,536,945	£1,743,234	£2,625,975	**£1,785,497**
Germany	Bundesliga	ALL AGES	£1,074,167	£1,440,928	£1,748,059	£1,836,067	**£1,583,710**
France	Ligue 1	ALL AGES	£863,615	£894,835	£891,896	£1,573,857	**£1,038,759**

Figure 4.2a. (Taken from GSSS 2019)

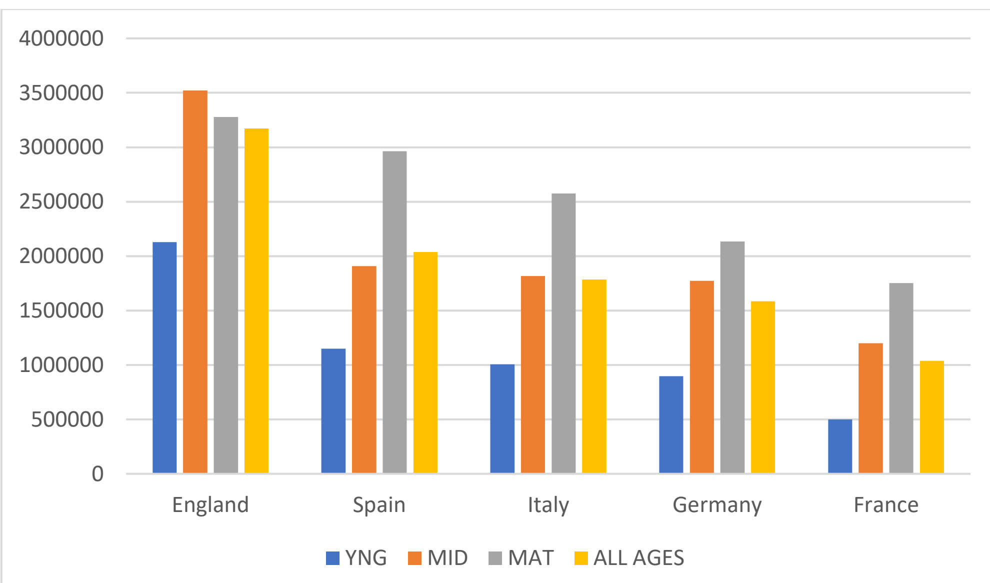

Figure 4.2b. Chart overview on the TOTAL column of Figure 4.2a.

the relationship and coefficient interpretability – a simple correlation test between $LNWage$ and RAT gives a much lower coefficient (.169) and a reduced p-value. Second, the positive correlation between MV and RAT also affects the statistical significance of the RAT variable when both are included in the regression equation. Additionally, it is possible that for players at this high level, much is already known about their ability such that the stats of the previous season alone do not carry as much weight as for lesser-known players still breaking into the limelight, e.g., if Cristiano Ronaldo, Messi, Neymar Jr., or Mbappe had a poor season, their valuation will not drastically change given that they have had many good seasons in the past. The same will apply for minutes played. A player who featured less due to injury or style of play of the coach will not suffer a wage penalty as appearances in other seasons still carry weight. A good example is Eden Hazard and despite his current fitness woes at Real Madrid CF, his market valuation has not fallen drastically.

Player popularity on social media platforms has a small effect on the base wage. Understandably, player popularity will mostly affect the image rights of the player and bonuses. Between June 2014 and June 2015, an average of 64 percent of the income for the top 20 most endorsement earning athletes came from endorsement (Forbes, 2015a). Hence, same as with tournament prize money for individual sports, the winners' cash prize will be unchanged irrespective of the popularity of the winner. However, a popular winner can earn a windfall in image rights.

Lastly, the regulatory framework in Europe puts no cap on wages. While Financial Fair Play tries to limit club spending on wages, it falls short of placing a cap on player wages as is the case in the North American leagues. Consequently, clubs will continue to increase the wages of superstar players beyond what observable market rates predict. Like transfer fees, there is irrational exuberance when it comes to player wages as clubs use wages as a tool to lure the best players to achieve on-field success. This is evidenced by the fact that all the measured variables account for just over half of the variance. This means that about half of the variance in the distribution of player wages in this market segment is driven by factors that have not been coded into measurable variables or simply cannot be measured.

4.5 – CONCLUSION

The market for highly talented footballers is a thin market with a very small number of players in this segment and very few clubs with the means to procure and remunerate these players. With clubs aiming for sporting success (utility maximization) in European football, the costs associated with the procurement and remuneration of the most talented players keep soaring. To better understand the variance in the wage distribution of players in this market segment, this study analysed the 90th percentile of players ranked by Transfermarkt valuation at the beginning of the 2020/21 season. The sample for this study consisted of 270 players from the 'big 5' European leagues. Using the demographic, performance, and popularity variables for a period of one playing season, this study applied the human capital equation formulated by Jacob Mincer (1958) to regress the wages with player market value as the baseline.

This study found that mature players earn more than double compared to young players, with mid aged player earning a wage premium of 64% higher in comparison to young players. This finding contrasts with how transfer fee premia are distributed across age groups, with the younger players having the highest transfer fee premium (Essay 2). Player transfers in this market segment most often signal off-loading, hence, a wage penalty as upward mobility is limited given this is the upper end of the talent market and clubs operating in this market are the best in the world. Performance statistics and amount of playing time in the previous season do not have much of an impact on wages in this market segment as most players already have a reputation built from previous playing seasons. The popularity of the player on social media platforms provides a slight boost on the player's basic wage. Understandably, popularity in sports mostly counts towards bonuses and image rights from merchandise sales and endorsements.

The variables (Market value, demographic, performance, and popularity) used in this study to analyse the distribution of player wages only account for 51% of the variance. This means that there is a 49% unexplained variance in the distribution of player wages in this market segment. Like with transfer fee premia (Essay 2), there are some sophisticated variables that will similarly affect wages, such as irrational exuberance - where a team owner decides to offer a player exorbitant wage that defy market logic (further exacerbated by the absence of a wage cap), and transfer window demand/supply forces – where the absence (presence) of close substitutes in the market will inflate (deflate) the wage offer for a player being considered. Football agents have also become a powerful force in the football labour market and wield a great deal of influence. The best of them, coined ‘*super agents*’ are able to negotiate moves for players between clubs and contract mind-boggling wages for their clients. Consequently, agents have become a very important variable that needs to be accounted when analyzing wage and transfer fee distribution among players. As more data becomes available and rules on wage disclosure loosen, future research can build more complex models that will encompass these sophisticated variables and help explain more of the variance that is still unexplained.

5. GENERAL CONCLUSION

Extant research in the football labour market has some generalized and widely accepted conclusions as to the relationships between player characteristics and valuation (market value, transfer fee premium, and wage) variables. However, the directions and magnitude of relationship effects between the explanatory and predicted variables are not similar across the board as there are peculiarities within different segments of the football player labour market. The aim of this 3-essay series is to provide a comprehensive view of the thin segment of the labour market in European Association football as it pertains to player valuation, acquisition, and remuneration. To achieve this, 3 different essays; each focusing on a single valuation factor, used the human capital formulation pioneered by Mincer (1958) to empirically regress each predicted variable (market value, transfer fee premium, and wage) as a function of a particular set of explanatory variables. A series of regressions are run to show how the variables relate.

5.1 – Main Findings

The main findings show that the player demographic variable (age) is a very important variable in this market segment and its effect differs in magnitude and direction compared to the rest of the football labour market, particularly with regards to acquisition and remuneration. First, in relations to player acquisition (transfers), clubs pay a significant transfer fee premium for young players compared to mature players with proven talent – a risk-tolerant attribute in the transfer market. It is worth noting that in the general football labour market, extant research has shown that transfer fees (hence transfer fee premia) will increase with age at a decreasing rate. Conversely, when it comes to remuneration, mature players earn more than double what young players earn in this market segment and wages show no diminishing returns as age increases. This is kind of a balancing-effect as the risk-tolerance in the transfer market is countered by risk-aversion in remuneration. Clubs also exhibit risk-aversion by willingness to offer longer term contracts in a bid to avoid the volatility of thin markets. Like transfer fees, extant research shows that in the general football labour market, wages increase with age at a decreasing rate.

Next, transfers (new contracts) come with a wage penalty in this market segment. This penalty is highest for young players whereas for mature players, the wage premium compared to the younger players offsets the transfer penalty. The penalty resulting from a transfer can be explained by the higher likelihood of downward mobility given that the clubs operating in this segment are the top clubs, making upward mobility unlikely. In the general football market, transfers can either signal upward mobility (wage boost) or downward mobility (wage penalty), hence the higher likelihood of downward mobility is a key feature of this segment. Also, playing position, hitherto shown to be a significant determinant of transfer fees and wages in the general football labour market, is not a significant in this market segment. There is not much disparity in the transfer fees and wages for players in all positions. Goalkeepers and defenders have been transferred for huge sums and they earned huge amounts in this market segment – another deviation from the general football labour market.

Lastly, this study shows that in the thin football labour market, footballing ability (the aptitude and skill displayed on the field of play) accounts for averagely 77% of the market value of the player. This percentage reduces as the market value increases, hence giving credence to the superstar phenomenon.

The significance of these findings is that the peculiarities of this market segment go beyond the argument of the appropriateness of quantile regression compared to OLS regression laid out by Lehmann & Schulze (2008) with regards to convexity of wages in thin markets. Without outrightly challenging the existing notion of the player labour market and how to best analyse the latter, this study adds to the literature on the need for market segmentation and cautions the generalization of results across the board. The idea of segmenting the football labour market is not new. Dobson & Gerrard (1999) analyse the English transfer market and show that segmentation is required to better understand distributions of transfer fees. Müller et al. (2017) use data-driven methods to estimate player market value and find that same estimation technique does not provide same accuracy levels across the board, hence segment specificities. Lehmann & Schulze (2008) as well as Lucifora & Simmons (2003) estimate player wages and acknowledge the need for segmentation of the player labour market. Consequently, studies that treat the football labour market and a single unit will find that results are not generalizable. For example, Depken II & Globan (2021) analyse 5760 transfers over a 14-year period within the 'big 5' and conclude that landmark broadcasting deals correlate with high transfer fee premia. While this is true for the mid to low level clubs (thick market) for which broadcasting revenues make up over 50% of their revenues, this does not apply to the top clubs for which broadcasting revenues are less than half of their revenues. In a similar light, extant research has shown that playing position is a key determinant of transfer fees and wages. Again, while this true for thick segment of the player labour market, results from thin market analyses does not show significance for this variable. While no statistical significance in analysis of this type could have several reasons, one plausible reason supported by a simple observation of the data are that there is no marked difference in the transfer fees and wages of defenders and goalkeepers compared to forwards and midfielders in this market segment. For example, Harry Kane (FW, Tottenham Hotspur) and Mo Salah (FW, Liverpool FC) each earn £200,000/week while Jan Oblak (GK, Atletico Madrid) and Marquinhos (DF, Paris Saint Germain) earn £294,000/week and £255,000/week respectively. With regards to transfer fees, Harry Maguire (DF, Manchester United), Virgil van Dijk (DF, Liverpool FC), Matthijs de Ligt (DF, Juventus FC), and Kepa Arizabalaga (GK, Chelsea FC) all transferred for sums greater than €80 million. The differences in wages and transfer fees between the different playing positions are not that marked in this market segment.

In a nutshell, the objectives of this study have been met as results clearly show that the magnitude and direction of the relationship observed by extant research and generalized to the football labour market as a whole does not apply in the thin segment. Compared with results of extant research carried out on the general population:

- Age does not show diminishing returns in transfer fees and wages

- transfers come with a wage penalty across all age groups in this segment

- playing position does not show a premium transfer fees or wages for offensive positions.

5.2 - Limitations

The limitations of this study are all related to data availability (shown by the red and black broken lines in the Conceptual Framework on page 15). Compared to North American sports, European Football still has the issue of data transparency with respect to the financial data around wages.

While several strides have been made in this regard, there is still a long way to go. Analyzing transfer fees and wages of the top earners without invoking the superstar phenomenon seems like an obvious exclusion. However, wage convexity can best be estimated if the complete earnings of the players are available. Earnings data from image rights, bonuses from merchandise sales and product endorsement is not readily available and this is the core earnings that justify superstar effects. In a similar vein, superstardom due to network externalities (Adler's version) can best estimated if the complete earnings are available. However, this research deals only with basic wages. The inclusion of social media following in Deloitte's Football Money Review in 2019 onwards signals the importance of social media following as a revenue-generating factor. However, knowing that social media following mostly affects image rights via endorsements and remuneration for the latter is capture in bonus for which the data are not readily available, this is a major limitation of this study.

There are also significant data gaps regarding important market forces that affect player transfer fees. The transfer window demand/supply factors, though very significant are not included in this research as they cannot be coded in data form. Also, with the steady move from dispersed to concentrated ownership of clubs and more billionaire owners taking over clubs, ownership structure of clubs is an important variable. While this study modelled this variable as a dummy, there are better ways of factoring in this variable if adequate information is present. All ownership styles do not operate in similar fashion, as we have notable dispersed owners (Real Madrid CF, FC Barcelona) who spend comparable to concentrated owners. Hence, irrational exuberance, though an important factor that affect both wages and transfer fees, is not included in this study for lack of data.

5.3 – Areas for Future Research

Future research could go deeper and wider to gain more insight into the football labour market. Deeper analysis would entail coding more variables and building more sophisticated models to explain the variance in both wages and transfer fees. The amount of unexplained variance is still too large to be left to error. Factors such as the effect of player agents in the representation of the player, the club manager (coach), etc. need to be included in analyses as these have a profound bearing on the value of a player. A wider analysis on the other hand would cover other areas of the football market. Several studies have used the European top tier leagues as samples for analyses. Spreading into lower tier leagues and non-European leagues (where information is available) would provide a more complete labour market analyses against which we can compare the results of existing research.

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