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The Relationship Between Ownership and English Premier League Players' Salaries

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Abstract

This paper looks into the relationship between professional soccer player wages and ownership characteristics. Previous research has shown that foreign owners invest more in their clubs but has not connected it to individual players' wages. Previous player compensation models exist but have not incorporated advanced analytics or tied in the concept of MRP. Regression models have been calculated for club output, club revenue, and expected player wage. The expected player wage was then compared to MRP. These were then regressed with ownership characteristics. This paper has found that there is a statistically significant relationship between two ownership characteristics and player wages. In the future, player compensation models should tie in financial aspects to their models.

Introduction

This paper investigates the relationship between an English Premier League club's owner and the salaries of their clubs' players. Specifically, this paper will explore three different ownership characteristics: structure, foreign/domestic status, and owner net worth. In explaining this relationship, this paper develops position-based regression models for expected wages and compares them to players' MRPs to determine whether they are over- or under-paid. This question is novel because, previously, papers have only researched ownership characteristics or player salary individually. There are papers that have explored ownership characteristics: Dobson and Gerrard (1999), Wilson et al. (2013), Rohde and Breuer (2016), and there are papers that have examined salary determination: Frick (2011), Luciflora and Simmons (2013), (Franceschi et al., 2023). However, none of these papers have linked the two concepts. This paper will, for the first time, tie these concepts together, bridging existing gaps between these ideas can lead to interesting conclusions around club owners. In doing so, this paper makes two important contributions: creating an improved model for player valuation through the inclusion of advanced analytics and identifying a potential relationship between player wages and ownership characteristics. Additionally, none of these papers tie in Scully (1974)'s concept of MRP, meaning that they do not adequately account for the financial mechanisms that drive player compensation.

Clubs like Chelsea and Manchester City have seen their fortunes dramatically and quickly turnaround after being purchased by wealthy foreign owners. These foreign owners were less concerned with profit and more concerned with winning, making them willing to spend significant sums of money to bring in talent to their clubs. Over the last 10 years, Manchester

City have the second-highest net transfer spend in the Premier League (£878 million), while Chelsea has the third-highest (£866 million), over 2.3 times higher than the average transfer spend over that period (Transfermarkt, 2024). Chelsea, which had won only 13 trophies in its first 97 years of existence, have won 21 trophies in the 18 years since their initial take over, and Manchester City, which had won only 12 trophies in its first 128 years of existence, have won 22 trophies in the 15 years since their takeover. Because these clubs have such vast financial resources at their disposal, it seems that they would overpay their players, as profit is not their goal. From 2010-2014, Manchester City lost over £350 million Transfermarkt (2024), and, more recently, Chelsea has lost £115 million in 2020 and £145 million in 2021 (Transfermarkt, 2024). These clubs seem unhesitant in paying their players premium salaries. These owners are focused on win-maximizing and having the best sporting performance for their clubs. Since 2002, there has been a dramatic increase in the number of foreign-owned clubs in the Premier League (Nauright and Ramfjord, 2010). According to Blitz et al. (2023), at the start of the 2023-2024 Premier League season, 15 of the 20 clubs have foreign majority owners. The recent influx and extent of foreign investment in the English Premier League has caused researchers to ask many questions that have not yet been answered. This paper will serve to study how different ownership characteristics are correlated with the salary of English Premier League players. This paper will address the missing gaps in the existing literature that surrounds this relationship, specifically the gaps in tying player salary de salary termination to ownership and financial aspects.

Scully (1974) provides the economic basis for papers attempting to quantify the value of a professional athlete. It introduces the concept of Marginal Revenue Product (MRP), which serves as the theoretical foundation for this paper's model of player valuation. This paper assists in quantifying player determination. Over the years, there have been many papers that have attempted to improve upon the original model presented in (Scully, 1974). Rockerbie (2010), for example, uses more sophisticated regression equations, introducing important external variables such as per capita income and state unemployment rate into the team revenue equation. The advancements provided in this paper are important because they allow for a more accurate estimation of the determinants of a team's revenue. The concepts introduced by Scully have been extended to professional soccer, with many papers investigating the valuation of professional soccer players.

There is an existing gap in the literature in the determination of salaries of professional soccer players, especially when compared to the attention that has been given to transfer fee calculation. Frick (2011) investigates the variance in player salaries, determining that this variance is explained by a discrepancy in individual performances. Similar to this paper, it used variables measuring recent performance to determine valuation. However, the paper was published in 2011, before the invention and widespread use of more advanced soccer statistics, meaning that it only uses the most rudimentary of statistics such as goals and assists. This paper attempts to improve upon Frick (2011) by incorporating the use of advanced statistics such as expected goals and expected assists, which more accurately capture a player's performance and team contribution. However, these papers do not connect a player's wages to their current club. In doing so, they ignore the business aspect of professional sports. In connecting a player's salary to their MRP, this paper will attempt to capture the financial aspect that has been excluded from previous value determination attempts. This existing gap can lead to an improper understanding of player valuation.

The second major area of study in the literature discusses the relationship between club ownership and professional soccer clubs. This literature is extensive but is yet to relate club ownership to player wages. One topic of discussion has been the relationship between owner investment and motivation and team success. As owners are utility-maximizing Rohde and Breuer (2017), they are foremost concerned with their team's success. Foreign owners, especially, have less of a profit incentive, and are willing to subsidize negative revenues in an effort for increased team success. For the owner of a professional soccer club, the way to maximize utility is to increase team investment, and an increase in additional player investment is correlated with heightened team success (Carmichael et al., 2010). Furthermore, there is evidence that there is a relationship between foreign owners (aka "sugar daddies") and increased levels in team investment Lang et al. (2011), necessitating a delineation between domestic- and foreign-owned clubs. Foreign owners have been shown to be willing to heavily invest into their teams to acquire better, more expensive talent, with English Premier League clubs that are taken over by foreign owners paying overall salaries which are 21% higher than league average (Rohde and Breuer, 2016). It is also important to note that this only factors in a club's overall wage bill; it does not account for player performance. These increases in wage bills tend to come from increased investment in the teams. If owners want to win more, they must replace their squad with better, more expensive players, leading to an increase in wages.

However, regarding this subject of increased ownership, there is an existing gap in the literature – the relationship between increased foreign ownership and individual players' salaries has not yet been studied. If professional soccer club owners are becoming more utility-focused and spending more money on their clubs, then it seems important to investigate the impact they have on player wages, as well. This paper will provide answers to important questions relating to club ownership and help facilitate a discussion on the impacts of club ownership in response to the growing trend in the English Premier League of foreign ownership and uber-wealthy private investors. While the impact of different types of ownership on club revenues and sporting performance has been investigated, there is an existing gap in the literature when it comes to salary determination. By tying the concept of MRP into the concept of salary determination, the gap between player salaries and the financial aspects of the sport, seen through the lens of club ownership, can be bridged.

This paper utilizes player and team data from three English Premier League seasons, covering 2020-2023 (FBRef 2021; 2022; 2023), club revenue data from the financial postings of individual clubs' year-end accounts (Companies House), and population and income data on the cities that clubs are in (Office for National Statistics 2021; 2022; 2023). This paper ties together two central ideas, connecting the effect of club ownership characteristics to the concept of player valuation, while using a more sophisticated valuation model than similar papers like (Frick, 2011). This paper will use the framework introduced in Scully (1974), incorporating regression equations for a team output function, team revenue function, and player salary function. The paper will use the results from these regressions to investigate the relationship between club ownership and player salaries.

There are concerns with endogeneity in this paper. Because no experiment is being run, it is impossible to establish a causal relationship. Clubs are not randomly assigned to owners, so a causal relationship between owners and player wages cannot be determined.. There are external factors that affect club ownership. For example, owners can only buy clubs that are on the market, and they can only buy clubs they can afford

In section 2, *Conceptual Framework*, there will be an overview of the conceptual framework of the paper, tying it into the ideas presented by Scully (1974). In section 3, *Context*, there will be additional context for the paper, helping the reader to become more familiar with the structure and innerworkings of the English Premier League. In section 4, *Data*, there will be information about the sample data used for this paper. It will describe the different data sets that were used. In section 5, *Econometric Specification*, there will be an explanation of the econometric specifications of the paper. It will present the regression equations used in the paper. In section 6, *Results*, there will be a discussion of the results of the regression equation. In section 7, *Conclusion*, the conclusions that the paper has made will be discussed.

Conceptual Framework

This paper is going to build off of the hallmark sports economic paper (Scully, 1974), which used a two-equation model in which (1) a production function related a team's win/loss percentage to a number of team inputs and (2) a team revenue function related team revenues to win/loss percentage. This paper incorporates Scully's concept of Marginal Revenue Product (MRP), which ties player salaries to their marginal contributions to team revenues and will also be incorporating advanced analytics to quantify player contributions. The performances will then be linked to the revenues generated through the team, and then, the paper will investigate whether teams are over-paying or under-paying their players and how the structure of their team ownership relates to this. Scully (1974) lays out a model for a player's MRP that links their economic value to their team and is used to determine a player's expected wages as compared to their actual wages.

$$PCTWIN_t = \beta 0 + \beta 1 TSA_t + \beta 2 TSW_t - \beta 3 NL + \beta 4 CONT_t - \beta 5 OUT_t + \varepsilon_t$$

$$REVENUE_t = \beta 0 + \beta 1 PCTWIN_t + \beta 2 SMSA_{70} + \beta 3 MARGA + \beta 4 NL - \beta 5 STD_t - BBPCT_t + \varepsilon_t$$

The equations used in this paper to determine the revenue of a club and the team output of a club are based off of the equations used in (Scully, 1974). This paper extends these concepts from baseball to the world of soccer. The equations are also more sophisticated than Scully (1974) and go beyond the original framework. Scully (1974) did not have the ability to incorporate the advanced analytics that have been introduced in Recent years. These advanced analytics should capture a team's output more accurately than Scully (1974) could.

This paper will use the foundation for player valuation laid out by that paper, estimating MRP and building off it, to create an initial determination of a player's expected yearly wages. The player's expected yearly wages will then be compared against their actual yearly wages, looking at the difference in relation to the against different aspects of a team's ownership: owner net worth, ownership structure, and foreign/domestic owner status.

However, most research relating to player valuation in the sphere of professional soccer has been focused on the transfer market and transfer fee determination, and not wage determination. The research on transfer fee determination is helpful in selecting which variables to use in the calculation of a player's salary. Because transfer fees are another way to value a player, variables that are relevant to their determination should be linked to a player's salary. Once it has been established that there is an existing association between player characteristics and transfer fees, specific variables relating to fees can be ascertained. Dobson and Gerrard (1999) created a model of the transfer market in England that determined that certain player characteristics were associated with observed transfer fees. Barbuscak (2018) reaffirmed this, concluding that player productivity had a significant influence on transfer fees and that the fees paid were not random. Luciflora and Simmons (2003) show the importance of considering off-the-field characteristics as well, finding that there was a superstar effect, which leads players to have higher salaries than would be expected from their on-the-field performance. Another important contribution to the literature was Franceschi et al. (2023), which conducted a systematic review of the research into the determinants of the valuation of soccer players.. The most relevant finding of this paper was that 85% of papers in this field used OLS models, confirming the idea that an OLS model can be effective in determining a player's valuation Moreover, this paper is helpful because it categorizes the variables used and found some of the most commonly significant variables used in regressions were age, minutes played, goals, and assists. This is helpful in narrowing down certain statistics to use in the regression model. The existing literature on transfer market fee determination is helpful in isolating certain variables that are relevant to fee determination.

As is laid out in Wilson et al. (2013), owners of English Premier League teams do not hold profit maximization and financial return on investment to be strong motives. In 2022, only 45% of European soccer clubs were profitable, and only three European soccer leagues have generated overall profits on their current operations over the last ten years (Arrondel et al., 2023). In contrast to North American professional sports leagues, English Premier League clubs are assumed to be utility- or win-maximizing and are not run with the desire to maximize profits Dobson and Gerrard (1999). Furthermore, unlike in most professional sports leagues, in professional soccer, maximizing revenue does result in maximizing profits. Additionally, Lang et al. (2011) and Rohde and Breuer (2016) each find an association between foreign owners and increased investment in clubs. Based off of these findings, there is reason to predict that, if foreign owners are not focused on profit maximization, they will not be concerned with paying their players optimal wages that reflect their MRP. If foreign owners of Premier League clubs are not bothered with making a profit, then it seems that they will be more likely to compensate their players with higher wages, leading certain clubs to pay their players more than their MRP. Additionally, foreign owners pay higher total wages than domestically-owned clubs (Rohde and Breuer, 2016). Because of these relationships, this paper hypothesizes that foreign owners will overpay their players more. Furthermore, because Premier League club owners tend to be concerned with utility-maximization and team success, this paper predicts that owners with higher net worths will overpay their players more than owners with lower net worths. As club owners are focused on winning-at-all-costs and unconcerned with financial success, owners with deeper pockets will be motivated to pay their players more to ensure greater team success. This may lead to teams with foreign owners being willing to overpay their players. European club owners are willing to sacrifice some financial return in order to achieve better sporting performance; the fact that European football clubs are win-maximizers makes them more aggressive when competing for talented players (Solberg and Haugen, 2013). While foreign owners tend to have higher net worths than domestic owners, the financial backing of these owners differs in order of magnitude, with Newcastle United's owners, the Public Investment Fund of Saudi Arabia, being worth a staggering £810 billion while the second richest team's owners are worth £21 billion (Forbes, 2024). Because of this, it is important to differentiate net worth from foreign/domestic status.

To properly measure the relationship between an owner and their players' salaries, it is essential to properly define different ownership structures for a team. Wilson et al. (2013) defines three different models for ownership: the stock market mode, the supporters trust model, and the foreign ownership model. However, because foreign ownership is already being accounted for elsewhere, this paper will modify Wilson et al. (2013)'s ownership structure, replacing foreign ownership with private ownership. Without this structure, it would be impossible to measure the relationship between player wages and ownership characteristics. As owners finance every aspect of their clubs, this potentially has significant implications on the way their clubs are operated. While the currently existing literature has reviewed how owners impact club investment and success, it has not studied how ownership impacts their players' compensation. This paper provides a pertinent contribution to sports economics by examining how professional soccer club owners influence player compensation, examining whether there is an association between an owners' financial resources and how they make player compensation decisions. This is additionally relevant because there has been a trend of increased foreign ownership, coming in with larger and larger bankrolls. The impact of this increased foreign ownership on player salaries has not been adequately researched. While previous papers have displayed a positive link between a club's total player wages and their resulting position, there is currently an existing gap in the link between owners and how their players are compensated. This paper will provide answers to important questions relating to club ownership and help facilitate a discussion on the impacts of club ownership in response to the growing trend in the English Premier League of foreign ownership and uber-wealthy private investors. Furthermore, there is another existing gap in the literature regarding the effect of owner net worth on player valuation. No paper currently ties this characteristic to the concept of player valuation. This paper will bridge this gap through its examination of ownership characteristics and their association with player salaries.

This paper expects that an owner with a higher net worth will overpay their players more than owners with lower net worths. It also expects that foreign owners will overpay their players more than domestic owners. Franceschi et al. (2023) shows that there are certain variables in these value determinations that tend to be statistically significant, and that OLS is a valid method to perform these regressions. There are potential difficulties in identifying ownership characteristics. A specific team structure is difficult to measure, yet, by modifying the initial structure model identified by Wilson et al. (2013) to differentiate on a basis of private, stock market, or supporters trust ownership, ownership structure should be properly distinguished.

Context

Each Premier League season is comprised of twenty clubs, who play each club once at home and once away, totaling thirty-eight matches each season. A win nets a club three points and a draw garners one point. At the end of the season, the team with the most total points wins. However, unlike American professional sports, there are further competition incentives other than simply winning the league. League finishing position has a significant impact on a club's revenues. Premier League clubs receive so-called "merit payments" based on their finishing position in the league table, with first place netting nearly £75 million last year, while twentieth netted only £3.7 million (Bosher, 2023). The three worst performing clubs, those who finish between 18h and 20th, are relegated to the second tier of the English Football League, which is known as the Championship. There is a drastic financial disparity between the first and second tier, with Championship clubs earning a cumulative revenue of £676 million in 2021/22, while Premier League clubs earned a staggering £5.5 billion in cumulative revenue (Deloitte, 2022; 2023). The four highest finishing teams qualify for the Champions League, a competition which pits the top European football clubs against each other and provides another significant revenue stream for clubs. Simply participating in the Champions League earns a club over £12.8 million, while winning a match nets £2.4 million Football Benchmark (Swiss Ramble, 2023). Qualification for the Champions League quickly adds up – in 2022-2023, the 4 EPL teams that participated in the Champions League earned on average £79 million (Swiss Ramble, 2023). Furthermore, teams that finish 5th and 6th in the Premier League qualify for the Europe League, which net teams £25 million, on average, and the team finishing 7th qualified for the Conference League, earning them £18 million (Swiss Ramble, 2023). Because of the potential for clubs to earn significantly larger sums of revenue based on league position, teams are incentivized to win.

The trend of foreign-born investors taking over English Premier League teams kicked into high gear at the turn of the millennium. In 2012, three-quarters of Premier League teams were majority owned by private investors (Rohde and Breuer, 2017). Another significant development in the ownership of Premier League clubs was the arrival of the "sugar daddy". A "sugar daddy" is simply a colloquial term for an owner who invests enormous amounts of money in their clubs (Lang et al., 2010). Typically, the term “sugar daddy” has been used with clubs such as Chelsea and Manchester City, which had little previous success before being purchased by their “sugar daddy” owners, and then became world-class clubs. The first sugar daddy to come onto the scene was Roman Abramovich, who bought Chelsea in 2003, and immediately started pumping money into the club, leading to levels of success never-before-seen for the club, winning 5 Premier League titles in a span of 15 years, after not winning any in the previous 50, and winning the club’s first-ever Champions League. Then in 2008, an unparalleled level of sugar daddy emerged, when Sheikh Mansour, a member of the royal family of Abu Dhabi, purchased then-minnows Manchester City and used the power of the nation-state to catapult the team into the ranks of the European elite. Along similar lines, the Public Investment Fund of Saudi Arabia, worth a ludicrous £490 billion, around £474 billion more than any other premier league club Summerscales (2023), controversially took over Newcastle United in 2021, bringing with them a ludicrous amount of spending power. These two purchases brought with them the newest wave of controversy facing the Premier League, sportswashing, in which foreign governments attempt to launder their international reputation through investments in sports. The rapid increase in foreign investment in the English Premier League has brought in owners with deeper pockets who care less and less about running profitable clubs. These new owners have created vast economic and financial disparities between club owners, with some clubs even having the backing of entire nation states.

It is also important to understand the nature of individual player compensation. Because players tend to switch clubs frequently, companies do not sponsor clubs because of specific players. The salaries measured only reflect the wage paid by a club to a player. Additionally, players’ salaries are not determined in relation to individual sponsorships they may earn. While players attempt to maximize their salaries, they may end up being underpaid for a variety of reasons. For example, if a player has recently signed a contract and they quickly begin outperforming that contract, they will not have the bargaining power and leverage to attempt to negotiate another new contract that reflects their newly realized abilities. Additionally, players may be underpaid in the context of advanced stats. If a player and their agent do not have an accurate grasp on their value, they may accept a lower contract.

Data

This paper gathers three different aspects of data. The sample size and population size for all the data collected is the same. The first aspect is focused on player salaries and statistics and was gathered from FBRef (2021; 2022; 2023), a football statistics and history website which tracks match-by-match data for professional soccer. The data set for this paper measures data for player statistics and salaries from the 2020-2021, 2021-2022, and 2022-2023 English Premier League seasons and is a panel data set, representing statistics from players over the span of the three seasons. The population of the player data represents data from 1,304 players who participated in either of the three seasons. Goalkeepers are excluded from the data set because of the nature of their position. Their statistics are far different from those of the outfield players, and, therefore, their salaries will be calculated in a much different way, which is outside of the scope of this paper. The data collected for the team finances spans from 2020-2023 and was collected from the clubs' individual Companies House account filings (Companies House, 2021; 2022; 2023). This data includes observations from the 60 teams that participated in the 2020-2021, 2021-2022, and 2022-2023 English Premier League seasons and is a panel data set. Additional data for team finances was collected from the United Kingdom's Office for National Statistics (2021; 2022; 2023) and includes population and GDP per capita data for each of the 60 teams included in the financial data set. The population for a club was determined by the city that their stadium is located in. For the five clubs that are located in London (Arsenal, Chelsea, Crystal Palace, Fulham, and Tottenham), population was determined by the neighborhood of London that their stadium is located in. The data for GDP per capita is used for the city that the stadium of each club is located in. For the clubs that are based in London, data for the clubs' individual neighborhood was used. Forbes (2024) was used to gather owner net worth estimates.

The data from *Table 1* gives an overview of the average Premier League Club, which makes £295,500,000 in revenue and has an owner worth £6,730,000,000. This average club scores 47.125 non-penalty expected goals and allows 51.34 expected goals against per season. Over the three-year time period measured, 46/60 clubs owners were foreign and 44/60 club owners were single majority owners. Additionally, 33/60 clubs had another first division club in their city.

The pros of the datasets are that the player data is extensive. FBRef (2021; 2022; 2023) is the best public source of data for this information. Transfermarkt has the most comprehensive dataset on player wages and transfer fees publicly available, spanning decades. The Deloitte Money League is also a trusted source of club valuations, with records going back to the late 1990s. There is a flaw in the data stemming from the dataset for the clubs' finances. The issue with this data is that it is more difficult to acquire than the player data. There is no unified data source compiling all the clubs' financial information. Clubs publish their financial data independently of each other and do not publish it in a standardized format. Clubs tend to list differing financial data. Because of this, it has been hard to compile this data. This also leaves the potential for some club revenue figures to be incorrect, which would have a significant effect on the upcoming regressions.

Econometric Specification

This paper will utilize a panel model that observes player and team statistics over three consecutive English Premier League seasons. This type of model was used because it allows for the examination of individual-specific effects. It allows for player growth and improvement to be tracked over time and can show how, as players play better, their contracts improve.

First, the club output function and club revenue functions will be calculated, and then the MRP of a player will be determined from these equations. To calculate the gross MRP of a player, a player's individual statistics are plugged into the club output equation, determining the number of points they are estimated to have won for their club. This is then tied into the club revenue equation, multiplying the points added by the revenue earned for each additional point. Costs also must be factored into the calculation of a player's MRP. Professional soccer players train in academies run by teams from the ages of 12 through 21, at the oldest. To determine this player development cost, UEFA category 1 estimates are used, which estimate a single-year of development to cost £77,250, or £695,250 overall. These costs are then subtracted from the player's gross MRP. Then, after the MRP has been calculated, it will be compared with the player salary function. This will be done on a team-by-team basis to see whether teams are over-paying, under-paying, or fairly paying their players. After this has been determined, it will be plugged into a regression equation featuring the three ownership characteristics of a team: owner net worth, ownership structure, and foreign/domestic ownership.

The MRP of a player shows what a player should be paid while the player salary function shows what a player is actually paid. When these two features have been estimated, teams will be investigated on a team-by-team basis to discover the ownership effects. It will then be determined whether certain clubs are overpaying or underpaying their players. Once this has been determined, teams will be evaluated on three ownership characteristics: ownership structure, foreign or domestic owner, and owner net worth. Thus, the impact of ownership characteristics on player salaries will be able to be evaluated. After the MRP has been calculated, the expected wages of players are calculated from their positional regression formulas. A salary difference is then measured by subtracting the expected salary from the MRP. Finally, an ownership regression equation is run to measure the relationship between player compensation and ownership characteristics.

Equation 1 is the ***club output formula***. It calculates team outpoint, measured as points by a team over the course of a season, as a function of various team-related inputs.

$$Club_{cy} = \beta 0 + \beta 1 Age_{cy} + \beta 2 npxG_{cy} + \beta 3 xGA_{cy} + \beta 4 xAG_{cy} + \beta 5 SCA_{cy} + \beta 6 GCA_{cy} + \beta 7 CmpPerc_{cy} + \beta 8 Tkls_{cy} + \beta 9 Int_{cy} + \beta 10 Clr_{cy} + \epsilon_{cy}$$

Age is the average age of players in the club. NPXG is the expected number of goals scored over a season. It is based on the probability that a given shot will result in a goal based on the characteristics of that shot and the events leading up to it, excluding penalty kicks. xA is the expected number of assists over a season. It is based on the likelihood that a pass will result in a goal assist. xGA is the expected number of goals conceded by a team over a season. It is based on the total of expected goals accrued by opposing teams. SCA stands for shot-creating actions. It is the sum of attacking actions (passes, dribbles, shots, and fouls) that directly lead to a shot on goal. Cmpperc stands for completion percentage and measures the total number of passes completed against the total number of passes attempted. Tkl stands for tackle and measures the total number of tackles won over a season. Int stands for interceptions and measures the number of times a defensive player takes possession of the ball after it has been thrown or kicked by the opposing team. Clr stands for clearances and measures the number of times a player kicks the ball away from the goal they are defending. As this equation measures club statistics, the stats used represent the sums accrued by all players on each given club.

Equation 2 is the ***club revenue function***. It calculates revenue as a function of a team's total points accrued over a season and a number of team-related inputs. As the revenue is calculated only over the last three years, revenue is stated in nominal terms.

$$Revenue_{cy} = \beta 0 + \beta 1 Points_{cy} + \beta 2 Pop_{cy} + \beta 3 Percap_{cy} + \beta 4 Atnd_{cy} + \beta 5 UCL_{cy} + \beta 6 UEL_{cy} + \beta 7 CmpPerc_{cy} + \beta 8 TeamInCity_{cy} + \epsilon_{cy}$$

Pts is the number of points accumulated by a club over an entire season. Pop is the population of the city a club is located in. Percap is the per capita income of the city/neighborhood a club is located in. Atnd is the club's average home attendance over a season. UCL is a dummy variable indicating whether or not a club participated in the Champions League. UEL is a dummy variable indicating whether or not a club participated in the Europa League. TeanInCity is a dummy variable indicating whether or not there is another Premier League team located in their city.

Equation 3 is the ***player salary function***. This function is used to calculate the expected salary of an individual player. This function is necessary because players are not paid the same wages. The difference in wages between players in the same club is based on their varying outputs. Players who contribute more to their club, through actions such as goals or assists, are expected to earn higher wages than their teammates. The equation calculates the log of an individual player's yearly wages as a function of a number of player-related inputs. A flaw with this model is that is does not include in it any sort of "superstar effect" which incorporates a player's performance outside of games, based on factors such as popularity. This could potentially understate the expected salary of a player. A potential fix for this would be to factor in whether a player features on their national team. However, the data set used did not track this.

The player salary function is subset into 5 positions based on FBRef data: Defense (DF), Midfield (MF), Midfield/Forward (MF,FW), Forward (FW), and Forward/Midfield (FW,MF). The position of a player is determined by the two most common positions they played in during the 2020-2021, 2021-2022, and 2022-2023 seasons. These categorizations were already present in the FBRef data. Because of the differing duties of different positions, a salary function that does not incorporate positionality is not as accurate as it could be. These subset equations are more accurate because they incorporate statistics that are more impactful based on a player's position. For example, a defender is not tasked with scoring goals, so a salary function for a defender should focus more heavily on actions they are tasked with such as tackles or interceptions.

$$LogAnnualWageMF_{py} = \beta_0 + \beta_1 Age_{py} + \beta_2 npxG_{py} + \beta_3 PlsMns90_{py} + \beta_4 SCA_{py} + \beta_5 CmpPerc_{py} + \beta_6 SoTPerc_{py} + \beta_7 KP_{py} + \beta_8 GCA_{py} + \beta_9 Tkl_{py} + \beta_{10} Lost_{py} + \beta_{11} Touches_{py} + \beta_{12} TB_{py} + \beta_{13} ForeignDummy_{py} + \beta_{15} StructureDummy_{py} + \beta_{16} NetWorth_{py} + \varepsilon_{py}$$

This equation introduces 12 new variables. Age represents the age of a player. Non-Penalty Expected Goals measures the likelihood that a goal will be scored based on the characteristics of a shot. Plus Minus Per 90 represents the difference between the amount of goals scores and conceded by a team while a player was on the pitch, per 90 minutes. Shot-Creating Actions measures the two offensive actions leading directly to a shot. Completion Percentage measures the percent of passes a player completed. Shot-on-Target Percent measures the percentage of a player's shots that were on goal. Key passes measures a pass that directly leads to a shot. GCA measures the 2 offensive actions directly leading to a goal. Tackles is the number of successful tackles a player has. Challenges lost measures the number of tackles that a player loses. Touches represents the number of times a player touches a ball. TB measures a player's number of through balls.

$$LogAnnualWageFW_{py} = \beta_0 + \beta_1 Age_{py} + \beta_2 npxG_{py} + \beta_3 PlsMns90_{py} + \beta_4 SCA90_{py} + \beta_5 Carries_{py} + \beta_6 Touches_{py} + \beta_7 SoT90_{py} + \beta_8 GxG_{py} + \beta_9 ForeignDummy_{py} + \beta_{10} StructureDummy_{py} + \beta_{11} NetWorth_{py} + \varepsilon_{py}$$

This equation introduces 1 new variable. Carries measures the number of times a player controls the ball with their feet.

$$LogAnnualWageFW,MF_{py} = \beta_0 + \beta_1 Age_{py} + \beta_2 npxG_{py} + \beta_3 xAG_{py} + \beta_4 SCA90_{py} + \beta_5 CmpPerc_{py} + \beta_6 GSh_{py} + \beta_7 ForeignDummy_{py} + \beta_8 StructureDummy_{py} + \beta_9 NetWorth_{py} + \varepsilon_{py}$$

This equation introduces 1 new variable. Goals to shots measures the number of goals a player has to their number of shots.

$$LogAnnualWageMF,FW_{py} = \beta_0 + \beta_1 Age_{py} + \beta_2 npxG_{py} + \beta_3 xAG_{py} + \beta_4 SCA90_{py} + \beta_5 Mins_{py} + \beta_6 PlsMns90_{py} + \beta_7 Touches_{py} + \beta_8 Crs_{py} + \beta_9 ForeignDummy_{py} + \beta_{10} StructureDummy_{py} + \beta_{11} NetWorth_{py} + \varepsilon_{py}$$

This equation introduces 2 new variables. Expected Assisted Goals measures the likelihood that a pass will lead to a goal. Crosses measures the number of crosses a player attempts.

$$LogAnnualWageDF_{py} = \beta_0 + \beta_1 Age_{py} + \beta_2 xAG_{py} + \beta_3 Tkl_{py} + \beta_4 Int_{py} + \beta_5 Lost_{py} + \beta_6 WonPerc_{py} + \beta_7 Mins_{py} + \beta_8 PlsMns90_{py} + \beta_9 Cmp_{py} + \beta_{10} Clr_{py} + \beta_{11} Crs_{py} + \beta_{12} ForeignDummy_{py} + \beta_{13} StructureDummy_{py} + \beta_{14} NetWorth_{py} + \varepsilon_{py}$$

This equation introduces 5 new variables. Interceptions measures the number of times a player intercepts a ball. Aerials Won Percentage measures the percentage of aerial duels won by a player. Minutes represents the total number of minutes played by a player. Completions measures the total number of passes completed by a player. Clearances measures the total number of times a player cleared the pall from their defensive area.

The variables that were chosen for the club output function and the player salary function were chosen through intuition regarding the nature of professional soccer. Different variables measuring player and team performance that were thought to have the greatest impacts were chosen based on prior, extensive knowledge of soccer and were experimented with until the chosen variables were selected.

$$SalaryDifference_{py} = \beta_0 + \beta_1 NetWorth_{py} + \beta_2 ForeignDummy_{py} + \beta_3 StructureDummy_{py} + \varepsilon_{py}$$

The salary difference is calculated by subtracting a player's expected salary from their MRP. For the Foreign dummy variable, teams with foreign owners have the value 1. For the Structure dummy, teams with single majority owners have the value 1.

One major flaw in this paper is that the regressions cannot account for the interconnectedness of a team sport like soccer. Each player is heavily dependent on the ten other players on their team that are on the pitch at the same time as them. Because of this, it is harder to measure an *individual* player's contributions to a team's output. The issue that arises here is that the regression analysis assumes that team performance is simply the sum of a team's individual player performance, which may not necessarily be the case. The major issue that this will cause with the results is that when calculating the amount of points a player contributes to their team will be significantly overestimated because player interaction is not being accounted for. One possible way to account for this flaw could be to deal with player interaction by comparing a player's MRP to the MRP of the average player. This idea could be extended by doing the MRP of the average player of the same position. Another flaw in the calculation of MRP is that, as of yet, costs are not incorporated into the equation. Because of this, a player's MRP will be significantly higher than it actually is. In the future, a way to determine a player's costs will need to be determined and factored into the calculation of the MRP. Another consideration to be made is whether it is needed to scale results based on individual player input.

However, one way to account for this and assuage this problem slightly is with the inclusion of advanced statistics. For example, only using a "simple" measure like assists puts a heavy emphasis on team quality. A player may make a perfect pass to a teammate who has a wide-open goal, but that teammate may miss. By using the more "advanced" measure, expected assists, which tracks the *likelihood* that a goal will be scored from a pass, individual contribution can be better measured.

Results

As seen in *Table 2*, there were 6 variables that were statistically significant at the 95% level in determining a club's points output. As is to be expected, the best way for a club to get points is by creating more expected goals, which increases a club's point total by 1.209 points. Each additional chance created, through a goal-creating action, increases a club's point total by 0.286 points. A strong defense also helps a club, with each additional expected goal against decreasing a club's point total by 0.37 points. Teams are rewarded on defense by relieving pressure, with each additional clearance increasing a club's points total by 0.024 points. Additionally, teams that possess the ball more and play less defense are not required to tackle as much. Teams that defend more are penalized, with each additional tackle a club makes reducing their points total by -0.042 points. However, an intriguing result is that for each additional expected assist a team has, their points total decreases by -1.319. This does not make sense as typically an assist would be a positive attribute, even considering that each pass, regardless of whether it is a shot-creating action, contributes to expected assists.

Table 3 shows the regression done to determine a club's expected revenue, finding 5 significant variables at the 95% level. Teams are highly incentivized to be as good as they possibly can. Each additional point a team earns nets them £3,375,299. Additionally, finishing in the top 4 positions and playing in the Champions League earns teams an additional £266,200,000 and finishing in 5th or 6th and playing in the Europa League earns teams an additional £54,155,107. Additionally, matchday revenue earned from attendance plays a small role in a team's revenue, with a 1-point increase in attendance earning a club £2,816. Finally, market size also comes into play. Teams that play in major cities with multiple Premier League teams earn £54,155,107 in revenues.

Age is the single most reliable variable in predicting a player's salary, with it being significant at the 95% level for every position. The wage structures of professional soccer clubs seem to reward seniority. Youth players will tend to be underpaid in relation to their value, as they are still on their first professional contracts. However, as they play more, earn greater bargaining power, and begin renegotiating their contracts, their pay begins to increase significantly. There is also a statistically significant constant for each position, indicating that there is a baseline wage, independent of any predictors.

Unsurprisingly, as midfielders and forwards are tasked with scoring goals for their clubs, non-penalty expected goals play a significant part in a player's expected salary. Plus/Minus Per 90, which measures how a player's team performs while they are on the pitch, is also a significant characteristic in most positions. This is not surprising – players whose teams perform best when they are on the pitch should be paid the most. Ownership characteristics also have an influence on player wages. For every position except Defense and Midfield/Forwards, there is an ownership characteristic that is statistically significant in influencing a player's salary.

Table 4 shows the results of the regression for midfielders. Midfielders are rewarded for being more balanced, well-rounded players. They need to be capable of playing in both offensive and defensive roles, with statistically significant variables including creative output (through balls, shot-creating actions) and defensive output (challenges lost). A surprising result from this regression is that an increase in shot-creating actions leads to a decrease in a player's expected wage. This follows the same trend that we saw in table 3 where expected assists also had a negative relation with expected points, implying that chance conversion could outweigh chance creation as it pertains to increasing a team's expected points.

Table 5 shows the results of the regression for forwards. Forwards are all about scoring goals and creating shots. Ownership characteristics have by far the strongest impact on a forward's salary than at any other position. Forwards whose clubs are foreign-owned see a

40.9% increase in their expected wage, while forwards who play in clubs who are single-majority owned see a 34.6% decrease in their expected wages. This significant increase could be due to foreign owners wanting to invest in "star" players to draw more attention to their clubs. Interestingly, an extra shot-creating action leads to a 12.1% increase in expected salary while an increase in non-expected penalty goals scored only leads to a 6.1% increase in expected salary. This goes against the assumption that goals are the most important attribute in calculating a forward's expected salary.

Single-Majority ownership also has a statistically significant relationship in the expected wages of Forwards/Midfielders, seen in *Table 6*, leading to 36% decrease in their expected wages. Forwards/Midfielders are the position most impacted by an increase in non-penalty expected goals, with each goal leading to a 7.7% increase in expected salary. They are also relied on for their creative skills, with an increase in pass completion percentage leading to a 2.1% increase in expected wages.

Midfielders/Forwards (*Table 7*) are one of the two positions where there is not a statistically signification relationship between expected wages and ownership characteristics. The strongest predictors of their wages are Shot-Creating Actions per 90 and Plus/Minus per 90, with a 1-unit increase leading to an 18.2% increase and a 15.3% increase, respectively.
Another interesting result is that players who cross more are penalized slightly, with each additional cross leading to a 0.6% decrease in expected wages. This reflects the tactical evolution that is underway in soccer where crosses are encouraged less and less.

Table 8 shows the regression results for the expected wages of Defenders. As is expected, defenders are rewarded for more tackles, with each additional tackle leading to a 1% increase in expected wages. Modern day defenders are required to be more technically adept than they were previously expected to be. More and more clubs are passing it out of the back, so defenders are expected to be more skilled with their feet. This trend is reflected in the fact that each additional completed pass increases a defender's expected wage by 0.3%.
Interestingly, defenders are penalized slightly for touches, with each additional touch leading to a –0.2% decrease in expected salary.

Tables 9, 10, & 11 display the t-tests that were run to determine if differences in wages were statistically significant. *Table 9* demonstrates that the difference between expected and actual wages is statistically significant. *Table 10* confirms that there is a significant difference in salaries for players owned by foreign-owned teams and domestic-owned teams, with foreign-owned teams paying salaries that are, on average, approximately £1,000,000 higher. Lang et al. (2011) and Rohde and Breuer (2016) came to similar conclusions, finding that foreign owners invested more in their teams. However, *Table 11* finds that the difference in average wages between teams owned by consortiums and teams owned by a single-majority owner were not statistically significant.

Because the t-tests confirm that there are significant differences in wages in relation to ownership characteristics, we can proceed in investigating the relationship between ownership characteristics and player wages. *Table 12* provides valuable insights on player valuation, suggesting that players may be underpaid relative to the additional revenue they generate for their teams as their MRPs (£4,853,591) are, on average, higher than their actual wages (£3,375,234.8). The regression models used to calculate players' expected wages seem to undervalue players' contributions in terms of revenue, as MRP is significantly higher than their expected wages. Furthermore, as actual wages are, on average, higher than their expected wages, this indicates that market factors such as negotiation skills or factors such as player popularity or marketability may play a role in determining a player's actual wages.

Of the three ownership characteristics tested, owner net worth had the lowest impact and was not statistically significant. The foreign/domestic status of an owner was significant at the 95% level. Foreign-owned teams had a salary difference that is £703,854 lower, meaning they overpay their players more. This finding confirms Rohde and Breuer (2016)'s idea that foreign owners are focused on utility-maximization, not profit-maximization. The ownership structure of a team was significant at the 90% level. Teams that are owned by a single-majority owner underpay their players, having a salary difference that is £318,827 higher, on average. It is important to note that the three ownership characteristics measured only account for 1.5% of the difference between the MRP and the expected wage of a player. This lends itself to the idea that ownership characteristics are not as important in determining a player's wage as player output is.

Conclusion

This paper originally set out to study the relationship between ownership characteristics on the wages of English Premier League players, focusing on three specific aspects:

foreign/domestic owners, single majority/consortium owners, and owners' net worth. As a function of this, the paper also aimed to establish an improved model for determining the expected wages of a player. The most significant finding of the paper is that there is a statistically significant relationship between foreign/domestic owners and single majority/consortium owners and English Premier League player wages. Foreign-owned teams pay £703,854 more than domestically owned teams, meaning that they overpay their players more, confirming one of the points in the original hypothesis. However, in contradiction with one of the original hypotheses, owner net worth does not have a significant relationship with overpaying or underpaying a player. The statistically significant relationship between foreign/domestic owner status and ownership structure implies that, in the future, when modeling player wages, ownership characteristics also need to be accounted for.

The outcome of this study is limited by the accuracy of the expected wages model. The more accurate the model is, the more accurate the relationship with ownership characteristics will be. Further research into the effects could improve the model provided by turning it into a fixed effects or random effects model. The regression could also be improved upon and made more sophisticated. There is also the potential that different variables in the position regressions could be chosen to more accurately capture a player's expected wage.

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Figures & Tables

Table 1: Club Summary

Variable	*Obs*	*Mean*	*Std. Dev.*

Revenue	60	295,500,000	201,8000,000
Points	60	52.7	17.858
Population	60	2,939,510.6	3,872,877.9
Per Capita Income	45	39,626.978	17,137.355
Attendance	60	26,707.733	22,798.914
Champions League	60	.233	.427
Europa League	60	.083	.279
First Division Team In City	60	.55	.502
Owner Net Worth	57	6,730,000,000	4,960,000,000
Foreign Owner	60	.767	.427
Single Majority Owner	60	.733	.446
Average Player Age	60	26.655	.982
Non-Penalty Expected Goals	60	47.125	12.585
Expected Goals Against	60	51.34	10.781
Expected Assisted Goals	60	36.553	10.232
Shot-Creating Actions	60	832.5	163.449
Goal-Creating Actions	60	88.5	31.84
Pass Completion Percent	60	78.28	4.732
Tackles	60	618.65	75.762
Interceptions	60	365.6	47.762
Clearances	60	735.183	130.283

Table 2: Club Output Regression

Points	***Coef.***	***St.Err.***	***t-value***	***p-value***	***[95% Conf***	***Interval]***
Age	1.197	.755	1.59	.119	-.319	2.714
Non-Penalty Expected Goals	1.209	.385	3.14	.003	.435	1.982
Expected Goals Against	-.37	.112	-3.29	.002	-.595	-.144
Expected Assisted Goals	-1.319	.426	-3.10	.003	-2.174	-.463
Shot-Creating Actions	.016	.015	1.11	.272	-.013	.045
Goal-Creating Actions	.286	.051	5.64	.000	.184	.388
Pass Completion Percentage	.41	.272	1.51	.138	-.136	.956
Tackles	-.011	.011	-1.01	.319	-.033	.011
Interceptions	-.042	.019	-2.18	.034	-.08	-.003
Clearances	.024	.011	2.23	.031	.002	.045
Constant	-35.102	38.58	-0.91	.367	-112.632	42.428

Mean dependent var	52.700	SD dependent var	17.858
R-squared	0.928	Number of obs	60
F-test	63.412	Prob > F	0.000
Akaike crit. (AIC)	379.070	Bayesian crit. (BIC)	402.108

Table 3: Club Revenue Regression

Revenue	***Coef.***	***St.Err.***	***t-value***	***p-value***	***[95% Conf***	***Interval]***

Points	3,375,299.8	882,043.66	3.83	.000	1,588,109.6	5,162,490.1
Population	-3.122	8.231	-0.38	.707	-19.801	13.556
Per Capita Income	560.542	1024.351	0.55	.588	-1,514.99	2636.074
Attendance	2816.776	512.129	5.50	.000	1,779.105	3854.447
Champions League	2.667 x 10^{8}	38,796,581	6.88	.000	1.881 x 10^{8}	3.453 x 10^{8}
Europa League	1.213 x 10^{8}	48,635,968	2.49	.017	22,726,018	2.198 x 10^{8}
First Division Team in City	54,155,107	23,384,511	2.32	.026	6,773,587.3	1.015 x 10^{8}
Constant	-74,681,680	44,512,623	-1.68	.102	-1.649 x 10^{8}	15,509,461

Mean dependent var	284553333.333	SD dependent var	210321128.494
R-squared	0.908	Number of obs	45
F-test	52.243	Prob > F	0.000
Akaike crit. (AIC)	1760.039	Bayesian crit. (BIC)	1774.493

Table 4: Midfield Wages Regression

Log Annual Wages	*Coef.*	*St.Err.*	*t-value*	*p-value*	*[95% Conf*	*Interval]*
Age	.093	.014	6.71	.000***	.065	.12
Non-Penalty Expected Goals	.115	.044	2.62	.009***	.029	.202
Plus/Minus Per Ninety	.145	.061	2.37	.019**	.025	.266
Shot-Creating Actions	-.018	.008	-2.23	.027**	-.035	-.002
Completion Percentage	.014	.011	1.24	.215	-.008	.035
Shot-on-Target Percentage	-.003	.003	-1.05	.295	-.008	.002
Key Passes	.017	.012	1.42	.157	-.007	.041
Goal-Creating Actions	.022	.023	0.95	.344	-.023	.067
Tackles	.001	.004	0.29	.773	-.007	.009
Challenges Lost	-.011	.005	-2.11	.036**	-.022	-.001
Touches	.0004	.0002	2.00	.047**	6.4 x 10^{-6}	.001
Through Balls	.057	.016	3.63	.000***	.026	.088
Foreign Owned	.385	.12	3.20	.002**	.148	.622
Single Majority Owned	-.7	.118	-0.57	.567	-.299	.164
Owner Net Worth	-4.55 x 10^{-14}	5.87 x 10^{-13}	-0.08	.938	-1.2 x 10^{-12}	1.11 x 10^{-12}
Constant	10.868	.984	11.04	.000***	8.93	12.806

Mean dependent var	14.696	SD dependent var	1.015
R-squared	0.386	Number of obs	278
F-test	10.982	Prob > F	0.000
Akaike crit. (AIC)	690.816	Bayesian crit. (BIC)	745.230

Table 5: FW Wages Regression

Log Annual Wages	*Coef.*	*St.Err.*	*t-value*	*p-value*	*[95% Conf*	*Interval]*
Age	.113	.014	8.35	.000***	.087	.14
Non-Penalty Expected Goals	.061	.021	2.92	.004**	.02	.102
Plus/Minus per 90	.125	.038	3.26	.001**	.049	.201

Shot-Creating Actions per 90	.121	.05	2.45	.015**	.024	.219
Carries	.002	.001	1.67	.096*	-.0004	.004
Touches	-.001	.001	-1.47	.143	-.003	.004
Shots-on-Target per 90	.048	.118	0.40	.687	-.185	.28
Goals – Expected Goals	.03	.027	1.10	.271	-.023	.083
Foreign Owned	.409	.149	2.75	.007**	.116	.703
Single Majority Owned	-.346	.131	-2.63	.009**	-.605	-.086
Owner Net Worth	-3.86×10^{-13}	3.58×10^{-13}	-1.08	.281	1.09×10^{-12}	3.19×10^{-13}
Constant	11.262	.42	26.79	.000***	10.432	12.091

Mean dependent var	14.949	SD dependent var	1.025
R-squared	0.461	Number of obs	203
F-test	14.876	Prob > F	0.000
Akaike crit. (AIC)	481.428	Bayesian crit. (BIC)	517.873

Table 6: Forward, Midfield Wages Regression

Log Annual Wages	***Coef.***	***St.Err.***	***t-value***	***p-value***	***[95% Conf***	***Interval]***
Age	.09	.019	4.66	.000***	.052	.128
Non-Penalty Expected Goals	.077	.037	2.09	.038**	.004	.15
Expected Assisted Goals	.003	.052	0.06	.952	-.1	.106
Shot-Creating Actions Per 90	.123	.082	1.50	.136	-.04	.286
Completion Percentage	.021	.011	1.95	.054*	-.0003	.043
Goals/Shots Ratio	.445	.871	0.51	.611	-1.277	2.166
Foreign Owned	.24	.145	1.65	.101	-.047	.528
Single Majority Owned	-.36	.145	-2.48	.014**	-.647	-.073
Net Worth	8.01×10^{-13}	9.65×10^{-13}	0.83	.408	-1.11×10^{-12}	2.71×10^{-12}
Constant	10.354	.844	12.27	.000***	8.685	12.023

Mean dependent var	14.656	SD dependent var	0.940
R-squared	0.307	Number of obs	151
F-test	6.942	Prob > F	0.000
Akaike crit. (AIC)	371.385	Bayesian crit. (BIC)	398.541

Table 7: Midfield, Forward Wages Regression

Log Annual Wages	***Coef.***	***St.Err.***	***t-value***	***p-value***	***[95% Conf***	***Interval]***
Age	.127	.021	6.17	.000***	.086	.167
Non-Penalty Expected Goals	.07	.054	1.29	.2	-.037	.177
Expected Assists	.06	.106	0.56	.574	-.151	.271
Shot-Creating Actions per 90	.187	.075	2.48	.015**	.038	.336
Minutes	-.00019	.0002	-0.93	.354	-.001	.00022
Plus/Minus per 90	.153	.092	1.67	.098*	-.029	.335

Touches	.001	.0004	1.98	.05**	-1.60×10^{-6}	.002
Crosses	-.006	.003	-2.02	.046**	-.013	-.00012
Foreign Owned	-.139	.191	-0.73	.467	-.517	.238
Single Majority Owned	.052	.179	0.29	.771	-.303	.407
Owner Net Worth	-2.80×10^{-14}	7.28×10^{-13}	-0.04	.969	-1.47×10^{-12}	1.41×10^{-12}
Constant	10.576	.595	17.79	.000***	9.398	11.753

Mean dependent var	14.614	SD dependent var	1.099
R-squared	0.472	Number of obs	125
F-test	9.191	Prob > F	0.000
Akaike crit. (AIC)	319.409	Bayesian crit. (BIC)	350.520

Table 8: Defender Wages Regression

Log Annual Wages	*Coef.*	*St.Err.*	*t-value*	*p-value*	*[95% Conf*	*Interval]*
Age	.088	.011	8.16	.000***	.067	.109
Expected Assists	.044	.076	0.58	.563	-.105	.192
Tackles	.01	.005	2.15	.032**	.001	.019
Interceptions	.002	.005	0.30	.766	-.009	.012
Challenges Lost	-.005	.008	-0.67	.503	-.022	.011
Touches	-.002	.001	-2.25	.025**	-.004	-.0003
Aerial Duels Won Percentage	.003	.003	1.13	.259	-.002	.008
Minutes	-.0002	.0002	-1.24	.217	-.001	.0001
Plus/Minus per 90	.117	.035	3.35	.001**	.048	.186
Passes Completed	.003	.001	3.09	.002**	.001	.005
Clearances	.004	.002	1.45	.149	-.001	.008
Crosses	.004	.002	1.62	.105	-.001	.008
Foreign Owned	.141	.09	1.57	.118	-.036	.319
Single Majority Owned	.065	.092	0.70	.483	-.117	.247
Net Worth	8.97×10^{-14}	4.16×10^{-13}	0.22	.829	-7.28×10^{-13}	9.08×10^{-13}
Constant	11.755	.326	36.05	.000	11.114	12.396

Mean dependent var	14.553	SD dependent var	0.980
R-squared	0.295	Number of obs	465
F-test	12.519	Prob > F	0.000
Akaike crit. (AIC)	1167.468	Bayesian crit. (BIC)	1229.599

Table 9: Expected vs. Actual Wages T-Test

	obs	*Mean1*	*Mean2*	*dif*	*St Err*	*t value*	*p value*
Expected – Actual Wages	1222	2,904,352.8	3,552,845.018	-648,492.26	81,429.288	-7.95	0

Table 10: Foreign Ownership T-Test

	obs1	*obs2*	*Mean1*	*Mean2*	*dif*	*St Err*	*t value*	*p value*
Actual Wages by Foreign Ownership	373	1163	2,634,214.477	3,612,896.5	-978,682.01	192,836.63	-5.1	.000

Table 11: Ownership Structure T-Test

	obs1	obs2	Mean1	Mean2	dif	St Err	t value	p value
Actual Wages by Structure	419	1117	3,291,911.217	3,406,490.4	-114,579.21	18,7181.6	-.6	.54

Table 12: MRP vs. Expected Wages vs. Actual Wages

Variable	Obs	Mean	Std. Dev.
Marginal Revenue Product	1638	4,853,591	1,681,810
Expected Wages	1282	2,824,189.3	2,371,829
Actual Wages	1536	3,375,234.8	3,266,724.9

Table 13: Ownership Characteristics Regression

Salary Difference	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
Net Worth	-9.35×10^{-7}	6.98×10^{-7}	-1.34	.181	-2.31×10^{-6}	4.34×10^{-7}
Foreign Dummy	-703,853.65	173,167.66	-4.06	.000***	-1,043,578.8	-364,128.52
Structure Dummy	318,827.02	170,915.27	1.87	.062*	-16,479.298	654,133.34
Constant	2,418,613.3	197,404.19	12.25	.000***	2,031,340.3	2,805,886.3

Mean dependent var	2104802.230	SD dependent var	2654250.063
R-squared	0.017	Number of obs	1278
F-test	7.530	Prob > F	0.000
Akaike crit. (AIC)	41418.859	Bayesian crit. (BIC)	41439.471