The Labor Market for Football (Soccer) Players: An Econometric Analysis of Transfer Fees and the Financial Fair Play Policy

Satvic Garg

Advisor: Eric Auerbach

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Abstract

In a broad sense, this paper analyzes the labor market of football players in the English Premier League and the Championship League. More specifically, my research examines two specific areas of interest within this labor market. First, by utilizing various hedonic regression models, this paper identifies key determinants of player transfer fees such as goals, assists, age, minutes per game, and clean sheets as well as the provides key information regarding the extent of their impact. Second, this paper evaluates the effectiveness of the newly implemented Financial Fair Play transfer market policy. My research provides strong evidence that though this market regulation mandate was able to achieve a reduction in overall transfer expenditure in isolation, it was completely offset by the general growth of transfer fees the last ten years in these two leagues.

Ultimately, this paper identifies many determinants of player transfer fees, illustrating the underlying valuation strategies and methodologies employed by teams. It also conducts one of the first formal investigations into Financial Fair Play policy, asserting that it resulted in sufficient effects leading to failure in accomplishing its goals.

1. Introduction

1.1 Background information on footballing industry

According to the *World Football Report* published by Nielsen in 2017, football (also known as soccer) consistently surpassed all other sports in fan popularity, with at least 40% respondents stating "interested" or "very interested" in each of the surveyed markets. This translated to an estimated 736 million people across these eighteen markets[1].With such a large and global fanbase, many countries have consequently established national football leagues. Currently, there are 210 professional football leagues around the world[2]. While the immense popularity of football has contributed to vigorous debates and discussions in sporting spheres, there is limited academic investigation and exploration into the sport, and even less studying the underlying economic behavior of the industry.

Football clubs are large businesses or firms — each team employing players, coaches, and staff. As a result, there exists a natural labor market between the teams (that demand labor from football players) and football players (that supply their labor to football clubs). It is this labor market for football players that this paper specifically examines in detail. However, prior to conducting such analysis, it is first necessary to understand the organizational structure and labor market dynamics of the sport.

The football industry is structurally organized in a four-tiered system. At the highest level, there is one overseeing, governing body called *Fédération Internationale de Football Association* (FIFA). FIFA is the central authority which is responsible for presiding over as well as regulating the sport globally. FIFA most directly controls and interacts with the professional

[1] The figures represent results from surveys conducted in the following 18 markets: Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Malaysia, Poland, Russia, Singapore, South Korea, Spain, U.A.E., U.K., and the United States.
[2] This statistic is directly sourced from the website of FIFA.

leagues, which make up the secondary tier of the footballing industry. These professional football leagues are consequently comprised with many football teams that compete within them; these football clubs/teams are the tertiary tier of the industry. Lastly, at the lowest fourth tier, there are the footballers, coaches, and staff that are hired by football teams.

As previously highlighted, the labor market being studied in this paper exists between the bottom two tiers of the industry: football teams and players. Moreover, with 210 professional leagues and each league containing approximately twenty teams, there are thousands of football teams readily competing against one another for the labor of football players. This is a very different market structure than that of sports such as American football or baseball that have large monopsonist leagues like National Football League (NFL) or Major League Baseball (MLB). Football does not have one single league that dominates the employment of the entire labor market, thus the market for football players remains more competitive and efficient than many other sports.

Additionally, the labor market mechanics of the football industry also differs from that of the traditional labor market. Simply put, football players under contract do not have the ability to resign or leave their current team, and then freely join another team[3]. FIFA has implemented a specific system of procedures for the movement of contracted players called transfers.

Transfers are defined to be the purchase or sale of players under contract. For a transfer to occur, the buying team must first make a bid to the selling team regarding the player in question. The selling club could choose to accept, decline, or negotiate the fee offered in this bid. If a transfer fee is agreed between teams, the buying club will then discuss contractual demands with the football player. It is upon a contractual agreement between the buying club and player

[3] This paper will solely examine football players which are under contract; uncontracted players are not subject to transfer fees, and thus are left out of this analysis.

that the transfer will officially go through. At this point, the buying club will pay the selling club the transfer fee previously agreed upon; the player will also now be bound by the terms of his new contract. The player will now be required serve the length contract for his new club unless transferred prior.

1.2 Financial Fair Play policy

Over time, transfers have become a key factor in increasing the likelihood of team success, as it allows teams to recruit better talent and address turnover issues. Seeing the value in this, many clubs began to invest more heavily into their squad in the form of transfers. However, the transfer system in place was soon being exploited by wealthier football team[4]. Wealthier clubs started to use their deep pockets to assert market dominance over players. By bidding up transfer fees to high amount, smaller clubs struggled to compete in the labor market. As a result, these richer football teams gained a severe advantage. In response, FIFA decided to implement Financial Fair Play (FFP) regulations in 2012.

The crux of FFP regulations was in its break-even requirement, which mandated that football teams clubs can spend no more than the income generated, and they must balance their books over the course of three years[5]. This ensured that team expenditure in transfer purchases, employee wages, and other costs were balanced by revenue from sponsorship/advertising, transfer sales and prize money. Such restrictions were designed to equalize competition in the transfer market[6] by constraining the financial dominance of wealthier teams.

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[4] In his paper, Matesanz states that football has become "a money game where the clubs with the highest transfer spending achieve better sportive performance."

[5] The regulations and policy of Financial Fair Play is sourced from the website of FIFA.

[6] The labor market for football player is also referred to as the transfer market.

However, as transfer activity continues to grow year-on-year, some industry experts remain skeptical regarding the true impact of the Financial Fair Policy regulations. Thus, the effectiveness of this new market regulation policy remains a point of strong controversy and prompts formal investigation.

1.3 Goal of research

The goal of this paper is to analyze the labor market of football players by answering two important research sub-questions. First, it will identify and investigate the determinants of football player transfer fees. More specifically, it will examine which physical characteristics, individual performance metrics, and team-related characteristic are determinants of transfer fees and how they may impact the fee of a football player. Second, the paper will then begin to evaluate the effectiveness and impact of the Financial Fair Play policy in regulating the transfer market for contracted players.

2. Literature Review

2.1 Relevant literature in sports economics

There exists an extensive amount of literature and research conducted on player compensation and mobility in sports. Yet, only North American dominated sports such as baseball, basketball, and ice hockey were of interest to the academic community initially. It is speculated that this was the case due to the regulated nature of sport leagues and availability of data in the late twentieth century. However, even as the formal study of football grew in popularity, the research was centered around predicting outcomes of matches or modeling betting behavior. Consequently, there is limited existing literature that has studied player/team value and its relation to player and team performance as well as other factors.

The first models examining player and transfer valuation in football were published in the *Bulletin of Economic Research* in 1999. This paper—written by Carmichael, Forrest, and Simmons—employed a hedonic regression to determine the structure and factors of player valuation. More specifically, Carmichael et al. regressed transfer fees on three key variables: human/productivity attributes (age, goals, etc.), player characteristics (position, preferred foot, etc.), and selling team characteristics (divisional status, prestige, etc.). The dataset used in the study consisted of players in English football during the 1993-94 season. While results of the paper were consistent with factors of player renumeration in other sports, the true significance of the paper lied in its tackling of empirical challenges. Carmichael et al. highlighted the problem of self-selection bias in the football transfer market. Thus, to tackle this issue, the authors utilized the Heckman two-step method to correct for this type of bias. Lastly, the paper talked elaborately about improvements for future study such as the use of more sophisticated performance metrics.

For these reasons, this paper remains a seminal part of the literature, providing a foundational basis for future research.

A study by Bernd Frick also investigated determinants such as contract duration, career length, and mobility and their potential impact on player renumeration and value. It is important to note that this paper used a complex dataset with information on over 2,500 players in the top five European leagues in 2015. While Frick did not use traditional econometric models in his study, the various statistical analyses conducted yielded important findings. The results of the study illustrated that average player performance increases in the final year of contract, while the variance of player performance decreases. Additionally, the study found that the number of years left under contract is a major determinant of transfer fees. This is most relevant to my research as it provides guidance for what factors to include in the model. Furthermore, the paper addressed key gaps in current literature such as the lack of comparative studies across countries.

The most recent study of player valuation in football was conducted by Majewski in 2016. In the paper, Majewski aimed to identify the most important determinants of the market value of attackers. The paper utilized three different variations of regressions, each with 14 explanatory variables representing human capital, performance, and organizational attributes. At first, Majewski began by implementing an ordinary least squared (OLS) regression. However, due to issues with homoscedasticity and normality, the paper turned to weighted least squares (WLS) and feasible generalized least squares (FGLS) regressions. The final results of the paper found the most important influences on the market value to be Canadian classification points (goals and assists), value of the club adjusted by FIFA ranking, and the “goodwill” or “brand” factor of the player. However, it is imperative to understand that this model lacks significant strength in terms of fit, hence, eliminating any possible predictive or forecasting applications of the model. Nevertheless, these results remain one of the most recent and comprehensive attempts at examining the determinants of transfer fees in football.

Although most of the literature discussed in this review is directly focused on football, similar studies on player value and renumeration have been conducted in other sports. In his paper, Idson studies hockey player compensation with regards to player and team performance in the National Hockey League (NHL). The paper presents the final regression in three discrete stages. The first stage was a regression solely on player salary and player performance; the next was regressed on both team and player performance; the final stage was on team, player, and the interaction between both as well. By comparing the results of these regressions, the influence of the team variables becomes clear. After the addition of team variables during the second and third stages, a significant decline in player performance effects can be observed, which can be interpreted as the reduction of bias in the model. However, the real novelty of the study was in its use and interpretation of the interaction term. The interaction term proposes the notion of compounded or synergistic effects of team and player performance on player compensation. Ultimately, Idson shows the power of model specification and its ability to drive meaningful results, making it an invaluable piece of literature.

2.2 Relatedness of thesis to existing literature

The existing literature on this subject matter is especially helpful in terms of guidance and direction for my own research. While most of the papers reviewed above share similar conclusions about basic determinants of transfer fees, each reveals a specific approach or methodology that can be employed. Most importantly, the results of the past literature are indicative of the results and trends that should be expected.

This paper first seeks to identify what are the determinants of transfer fees and to quantify the nature and extent of their impact. To do so, a hedonic regression is the most appropriate method of analysis; it is also important to note this paper will compile findings from previous literature through the inclusion of various determinants deemed significant in the literature discussed. Moreover, the results of this paper will be conducted on the most contemporary ten-year dataset available, the 2008/2009 to 2018/2019 seasons. Secondly, my research will also evaluate the effectiveness of the Financial Fair Policy in regulating the transfer market by modelling the implementation of the policy as a natural experiment. Ultimately, my contribution to the current literature is threefold as my research looks to incorporate significant findings over the last two decades, use a more relevant data set, and conduct one of the first novel studies analyzing Financial Fair Play policy.

3. Data Collection and Processing

3.1 Collecting data with use of web-scraper

Comprehensive statistics on many football leagues, football players, and transfers are easily available through online sources. Yet, for the purposes of this paper, it is most appropriate to use data specifically from two leagues, the English Premier League and Championship League. This is due to two key reasons. Firstly, the data on these leagues and its players have been collected over the longest duration of time — with reliable data available after 2009. Secondly, there are considerably more information and variables collected regarding player-performance, team-performance, and the overall league statistics when compared to other football leagues. Additionally, the Championship League is not subject to Financial Fair Policy, which is critical to the second section of this paper.

Transfermarkt.de is an online database with verified information on footballer player transfers in English Premier League and Championship League. Important data include the name of player, transfer fee, year of transfer, previous team, and new team. Additionally, *footystats.org* is another online database that provides data on team performance, player performance metrics, and player characteristics on the English Premier League and the Championship League. Thus, for my research, I employed the use of a web scraper to be able to collect data from these two websites.

3.2 Data consolidation and characteristics

The web-scraper was able to successfully collect and capture the necessary information and variables from both online databases. However, this scraped dataset required additional data cleansing procedures to be accurate for further analysis. There were several types of players that needed to be removed from the dataset. The two notable data inaccuracies were the inclusion of players on loan deals as well as players with no prior data. Loaned players return to their original (parent) club, and thus, are not considered official transfers[7]. Some transferred players that did not play during the season prior did not have complete data available and were also consequently excluded. Thus, by cleaning the dataset, the new dataset will be more suitable and appropriate for the current research and analysis.

The final dataset used for analysis yielded a total of 331 observation and over 10,000 data entries, spanning from the 2008/2009 season to the 2018/2019 season. While some information captured by the scrawler was quantitative such as the goals scored, assists obtained, or age, other key information such as position and nationality were qualitative. Thus, to incorporate such qualitative information into the regression analysis, the important qualitative metrics were transformed into dummy variables. The position variable was broken into three different position types: forward, midfielder, and defender. A value of 1 if the player is considered to play that specific position, and 0 otherwise[8]. Below is a table that shows all relevant information captured by the web-scraper. Additionally, Table 1 and Table 2 show present important descriptive statistics of the quantitative and qualitative variables respectively.

[7] Football players that are loaned to other teams are not subject to transfer fees. They are not relevant to the investigation conducted in the paper, and accordingly excluded from the dataset used in the regressions.
[8] Although players can play multiple positions, players were limited to their most played position for the purposes on this analysis.

Variables Collected						
Quantitative	*Fee*	*Age*	*Goals Scored*	*Assists*	*Goals Conceded*	*Appearances*
					Clean Sheets	*Mins Per Game*
Qualitative	*Position*					

Variables Collected	
Dummy	*Forward*
	Midfielder
	Defender
	Goalkeeper

Table 1: Descriptive statistics on numerical variables

Variables	Obs.	Min	Median	Mean	Max	Std. Dev.
Fee	331	0.052	5.735	11.277	130.5	16.36676
Age	331	19	24	24.04	37	3.384506
Goals Scored	331	0	1	2.955	31	4.814919
Assists	331	0	1	1	10	2.70461
Clean Sheets	331	0	6	6.278	16	3.957513
Mins Per Match	331	3	66	66.45	90	22.57901

Table 2: Descriptive statistics on dummy variables

Variables		Frequency	Percentage
Position	*Goalkeeper*	14	4.23
	Defender	90	27.19
	Midfielder	128	38.67
	Forward	99	29.91

4. Research Methodology and Model Specification

4.1 Specification of hedonic regression model

The first section of this paper focuses on the identification of transfer fee determinants and analyzing their influence on fees. As pointed out by previous literature, such findings and inferences can most effectively be drawn by using a multivariate hedonic regression model. Mathematically, the model is represented in the following manner:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{k-1} x_{k-1} + \beta_k x_k + e$$

In this paper, the dependent variable will be the transfer fees (in millions of Euros) of players and the independent variables are various characteristics that are considered relevant. There are many different areas that could be of interest. For example, player performance statistics such as goals, assists, minutes played; player characteristics such as age, position, nationality; team performance metrics such as team rank, possession, and clean sheets. In order to select the most relevant factors, it is beneficial to lay out a few hypotheses that are based on my specific knowledge of the sport as well as previous studies so the models incorporate only relevant variables.

For example, majority of the previous literature analyzing football player transfer fees have consistently found assists, goals, and age to be statistically significant determinants. Thus, to verify and reconcile previous findings, it is imperative to account for these quantitative variables in the regression analysis. Moreover, more sophisticated metrics in football such as minutes per game and clean sheets[9] are also thought to be play important roles in determining transfer fees. Apart from the inclusion of quantitative variables, qualitative factors such as position are considered to be key determinants that influence player transfer fees. Conversely, it is important to understand that various player characteristics, player performance statistics, and team metrics have excluded from the regression analysis such as nationality, height, preferred foot, average team possession, and number of bookings. This is because they are believed to be unrelated to player value, and thus irrelevant to the determination of transfer fees. With this information, three hedonic regressions were specified in the following way:

(I)

$$Fee = \beta_0 + \beta_1 Goals + \beta_2 Assists + \beta_3 Appearances + e$$

(II)

$$Fee = \beta_0 + \beta_1 Goals + \beta_2 Assists + \beta_3 Age + \beta_4 MinsPerGame + \beta_5 CleanSheets + e$$

(III)

$$Fee = \beta_0 + \beta_1 Goals + \beta_2 Assists + \beta_3 Age + \beta_4 [Forward] + \beta_5 [Midfielder] + \beta_6 [Defender] + e$$

[9] A team earns a clean sheet by preventing their opponent from scoring in the entire game. For example, if Barcelona wins 1-0 against Real Madrid, Barcelona obtained a clean sheet.

4.2 Specification of differences-in-differences regression model

The second section of this paper evaluates the impact and the effectiveness of the Financial Fair Play policy on the labor market for football players. This can be achieved by representing the implementation of Financial Fair Play as a natural experiment. By doing so, a differences-in-differences regression model can be used to assess and capture the effect of the policy on the transfer fees.

The critical feature of a differences-in-differences regression that allows model to quantify the effect of a natural experiment is the differentiation control and treatment group. In this case, the use of the English Premier League and the Championship League data was specifically chosen to facilitate the use of this model. The English Premier League was subject the rules and regulations of the Financial Fair Play starting in 2013[10]; however, the Championship League is not subject to the rules of this policy. As a result, the English Premier League can be modelled as the treatment group, whereas the Championship League can be viewed as control group. The model also makes use of other covariates representing possible determinants. The model can be represented mathematically in the following form:

$$y = \beta_0 + \delta_1 * [\textit{Post-Treatment}]_1 + \delta_2 * [\textit{Treatment Group}] + \delta_3 * [\textit{Treatment Group}] * [\textit{Post-Treatment}] + \beta_1 x_k + \ldots + \beta_k x_k + e$$

Similar to the regression in the first section, the dependent variable will remain fees of transferred football players[11] which occurred the 2008/2009 to 2018/2019 seasons. However, the

[10] Although the Financial Fair Play policy was passed by the FIFA in 2012, the regulations went into effect during the start of the 2013.

[11] The transfer fees in the differences-in-differences model are still denoted in millions of Euros.

most important feature in the model is the use of the dummy variables to isolate the treatment group from the control group and separate pre-policy transfers from the post-policy transfers.[12] More specifically, the "*Post-Treatment*" dummy variable will delineate if the transfer took place before or after the implementation of the Financial Fair Play regulation; the "*Treatment*" dummy variable will denote if the transfer was part of the treatment group, the English Premier League. The final dummy variable used in this regression model is an interaction term representing transfers that were both part of the treatment group and also occurred after the implementation of the regulation policy. Additionally, it is important to note that remaining covariates are possible determinants of transfer fees (spoken about in the section prior). These would be goals, assists, age, goals conceded, clean sheets, and positions. Therefore, the specification of differences-in-differences regression model is shown below.

$$y = \beta_0 + \delta_1 * [Post\text{-}Treatment]_1 + \delta_2 * [Treatment\ Group] + \delta_3 * [Treatment\ Group] * [Post\text{-}Treatment] + \beta_1\, Goals + \beta_2\, Assists + \beta_3\, Age + \beta_4\, MinsPerGame + \beta_5\, CleanSheets + e$$

[12] The dummy variables exclusive to the differences-in-differences model are denoted with delta coefficients to highlight the novel aspects when compared to the previous regressions.

5. Regression Results and Discussion

5.1 Results of the hedonic regression model

Table 3: Results of hedonic regression analysis

	Transfer Fee (mm)		
Goals Scored	1.2786*** (0.2103)	1.12375*** (0.20152)	1.6018*** (0.2236)
Assists	1.17** (0.3744)	0.8622* (0.36942)	1.1812** (0.3768)
Appearances	0.14194 (0.08837)		
Age		–1.22591*** (0.21717)	–1.1591*** (0.2177)
Minutes Per Game		0.07897** (0.0361)	
Clean Sheets		0.54832* (0.22065)	
Forward (dummy)			–8.2099* (3.9262)
Midfielder (dummy)			-3.8055 (3.8237)
Defender (dummy)			0.2455 (3.8227)
Constant	5.3462*** (0.9504)	31.13289*** (5.99477)	39.5614*** (7.2286)
R-squared (adjusted)	0.2689	0.3503	0.3498
	Regression 1	*Regression 2*	*Regression 3*

Significance level: '***' = 0.001; '**' = 0.01; and '*' = 0.05

Compared with the second and third regression models, the first model returns a lower R-squared value. This is largely expected as transfer fees were only regressed on three independent variables. However, the purpose of the first regression model was to verify previous findings and conclusions from existing literature.

Firstly, it becomes clear that goals are a critical determinant of transfer fees, as it remains strongly statistically significant across all three regressions. This relationship is also positive, implying that as goal scored increase, the transfer fee would also increase. This result is heavily discussed in the literature and is supported intuitively as well. Football itself is centered around scoring goals as means of winning, thus, a player that scores more goals in inherently increasing the likelihood of a team winning. As a result, this increased winning probability is likely reflected in a team's willingness to pay more for these specific players.

Similarly, the second covariate in the first regression is assists obtained. Assists are the most valuable pass for team as it is the pass that leads directly to a goal. Players with ability to contribute to goals through passing also enhance a team's likelihood of winning, and thus positive relationship is expected. However, the coefficients of assists were smaller and less statistically significant than that of goals in all regression results. This highlights the extent to which goals are important. As in comparison to other player performance metrics, the coefficient of goals is consistently larger than others—underscoring the strong influence of goals on the determination of transfer fees.

The second regression model also provides strong evidence against appearances[13] as a key determinant of transfer fees, due to significance of minutes per game. A possible explanation

[13] Appearances is a statistic that simply tracks number of matches the player has played in throughout the season. Regardless of the amount of time played, if a player were to feature at all (even as a substitute), the match would count as an appearance.

could be that appearances is not the appropriate statistics to capture the idea of availability and reliance. In existing research, the rationale of including an appearances variable is to account for the notion that footballers that consistently play for the team are more valuable. Conversely, if a player is often unavailable to play, the team is less reliant on player as the player cannot not make regular contributions to the team.

However, it becomes clear when comparing the first and second regression that appearances is not the correct instrument to capture this idea of player value. In fact, it is better captured by the minutes per game variable. Many times, players are simply substituted late into the game to provide valuable players rest when match outcomes are already decided. These substitutions are counted as part of appearance statistics, even though the player is not playing a consistent role for the team throughout the match. Therefore, the utilization of minutes per match alleviates this issue. The minutes per match covariate is positive and statically significant in the model, proving this metric is a more appropriate instrument to capture the idea of availability and reliance. Ultimately, the model shows minutes per game to be an important determinant influencing transfer fees in the labor market.

Additionally, the second and third model support hypothesis that age is an important determinant of transfer fees. Yet, it is necessary to note that this relationship is negative; thus, as player age increases the transfer fees generally decrease. This result could be regarded as slightly counterintuitive since scouts and coaches value experience, and this is naturally a result of age. However, the transfer market shows that is not the case. In fact, the market places a premium on players that younger. Possible explanations could be that older players have less years until they retire. Moreover, younger football players have many years left in their career and have greater potential to improve and become better. Teams could also then choose to sell these contracted for bigger transfer fees in the coming years. Thus, due to investment and improvement/growth potential, age has an inverse relationship with transfer as one of its important determinants.

Lastly, the third regression model provides interesting insight with addition of dummy variables to describe positions. The "*Forward*" dummy variable is only position that return a statistically significant coefficient (while all other non-dummy covariates remains statistically significant). The coefficient on the "*Forward*" dummy variable is also negative. This inverse relationship is unexpected and different from previous literature. This is because forward players tend to be viewed as more valuable by supporters and fans.

However, a possible explanation for this inverse relationship could be the oversupply of forward players in the observed period. In a starting squad, forward players make up the smallest percentage of outfielders, with teams often playing with one or two forwards on average[14]. This ratio is less than the number of forwards sold/bought on the transfer market. About thirty percent of all transaction in the regression analysis were forwards. Therefore, the negative coefficient could suggest that the market is oversaturated with forwards, resulting in this inverse relation. Nevertheless, the overarching result of the forward position being an important determinant of transfer fees is supported the hedonic regression model above and previous research.

[14] Typically, in a starting eleven squad, there is one goalkeeper (not considered an outfielder), four defenders, four to five midfielders, and one or two forward players.

5.2 Results of the differences-in-differences regression model

Table 4: Results of differences-in-differences regression analysis

	Transfer Fee (mm)
Goals Scored	0.62492*** (0.09581)
Assists	0.74073*** (0.19789)
Age	–1.09649*** (0.11791)
Minutes Per Game	0.08774*** (0.02065)
Clean Sheets	0.2331* (0.11244)
Post-FFP (dummy)	5.61479* 1.63588
EPL (dummy)	8.93478*** (1.33697)
*EPL*Post-FFP (dummy)*	–2.36515* (1.305)
Constant	–8.42055*** (1.71709)
R-squared (adjusted)	0.4045

Significance level: '***' = 0.001; '**' = 0.01; and '*' = 0.0.05

This differences-in-differences regressions model allows several key conclusions to be drawn about the Financial Fair Play policy as well as the overall transfer market of players. Firstly, it is important to note that the differences-in-differences model returns coefficients for the non-dummy independent variables that are strongly statistically significant and reaffirm the findings in the previous section of this paper. Furthermore, the model yields statistically significant values for each of the dummy variables as well, which specifically help examine the impact of Financial Fair Play policy on transfer market.

First, the "Post-FFP" dummy coefficient is positive. This illustrates a general time trend across the transfer data. This can be interpreted as reflection that transfer fees are growing over time. This result is not a novel result, and this pattern has been spoken extensively in recent literature and football media[15]. Next, the "EPL" dummy variable is also statistically significant and positive. These results can be interpreted to be illustrating the difference in transfer fees between the treatment and control group. The positive coefficient points to information suggesting that transfers in the English Premier League are generally higher than that of the Championship League. This result is true as the average transfer fee for the English Premier League is consistently higher for all years than the Championship League. This is because the English Premier League has much wealthier football teams and has greater financial support, whereas the Championship is made up of smaller football teams. Thus, seeing such a result on the treatment dummy is predictable and expected.

Most importantly, however, it is important to analyze and interpret the coefficient on the interaction dummy between "*Post-FFP*" and "*EPL*". This result is statistically significant at the five-percent level and is negative. In this case, the negative coefficient provides evidence that the

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[15] In his paper, Matesanz directly critiques the rapid growth of transfer expenditure in recent history and its effects on football teams.

Financial Fair Policy has a reductive effect on transfer fees in the English Premier Leagues. However, it is important to contextualize these coefficients in relation to overall model. While the Financial Fair Policy in isolation was effective in curbing transfer expenditure slightly. There will be little observable evidence in transfer market transactions to demonstrate this reduction. This is largely due to the trends of the general transfer market. Fees have been increasing rapidly during the ten-year period. As a result, the reduction in transfer fees were almost completely offset by this time-trend. This shows that while Financial Fair Play policy in insolation has been slightly effective in reducing transfer fees and regulating the market, the general growth and trends of the market have counteracted any effects of the policy.

6. Limitations and future opportunities

There are various limitations regarding research methodology used in this paper, as many important characteristics of the transfer market and footballing industry are often unaccounted for and difficult to quantify. However, these drawbacks also provide opportunities for further research to keep exploring the labor market in the football.

Firstly, the results of the regressions may be revealing problems of homoscedasticity and normality when examining market value of players, likely due to self-selection bias. This self-selection bias exists because of the transfer process itself. Players have a choice on whether they move to a team. After the selling club accepts the bid from the buying club, the player can then decide if they want to continue with the move. Therefore, it is not a perfect market — a perfect market would allow all transaction to occur if buyer and the seller chose to trade. As a result of this self-selection, the results of the ordinary least squares regression model used in this paper could be biased. Future opportunities could utilize some of the econometric techniques spoken suggested in recent literature to alleviate such biases.

Next, all the regression models in this paper return very low R-squared values. While this may not severely undermine the findings of this paper, it prompts future work to attempt to better model the transfer market and its determinants. By reducing the R-squared values, future models will better fit the data, possibly enabling the model for predictive use.

It is also important to note that both the English Premier League and the Championship League take place in the United Kingdom. The data for both leagues are also from the most recent ten-year period. As result, the small sample size may be impacting the results in this paper. Thus, an exploration across different leagues could help navigate these data challenges, while also allowing for investigation into possible geographical and cultural differences in labor market for football players.

Lastly, FIFA has mandated a new labor market regulation policy regarding loan players. Under the new mandate, a football club will only be able to conduct eight loan deals per season, both incoming and outgoing. This new player loan system will restrict labor supply of football, forcing many players to stay at their parent club. Possible future work could attempt to predictive or later even measure the material impact of such regulation on the labor market.

7. Conclusion

The sport of football has experienced an expanding global fanbase and increased financial investment in the last two decades; however, these significant changes did not occur without profound impact on the footballing industry. With greater economic support, many teams looked to the labor market of football players to increase their chance of success. This in turn drastically impacted dynamics and behavior of the market, prompting the need for further investigation into transfer fees and the role of their determinants.

The first section of this paper highlights that player-performance metrics, team-performance statistics, and individual player characteristics together play a role in the determination of a player transfer fee. More specifically, when examining player productivity measures, the hedonic regressions employed find that goals, assists, and minutes per game to be influential determinants of transfer fees. Moreover, the paper also finds that age to be an important factor. With regards to team-performance statistics, the model indicates that clean sheets play a role as well. In the end, the hedonic regression models provide key information into how teams value players in the transfer market. It is through understanding that implicit or explicit valuation strategies and methodologies used by teams that we can develop a greater understanding of the labor market and create effective regulation and policy.

The second section of the paper evaluated the impact and effective of the Financial Fair Play policy implemented by FIFA in 2012. While the differences-in-differences model in the paper displays promising signs that the market regulation policy had its intended effects of reducing transfer fees, this is negligent of other information and observations. To elaborate, the model simultaneously describes prominent growth of the transfer fees over the period of analysis. This growth in fees of the transfer markets is much larger in magnitude than the reduction provided by the Financial Fair Play policy. So, even though the market regulation policy was effective in minutely curtailing transfer spending by teams in isolation, it is counteracted by the greater market trends of the labor market. Thus, while Financial Fair Play may have impacted the transfer market in football, it did not effectively achieve its goals set by the governing board of FIFA.

In the end, as an avid football fan, my research was designed to illustrate the growing economic complexities that exist in the footballing industry. With limited recent academic investigation into the sport, I hope that my paper encourages further exploration into the football industry whether through the examination of player numeration/compensation or the transfer market or an investigation of other policies and regulations in the sport. Additionally, such research in these areas will provide important perspective into market dynamics and team behavior within the sport, ultimately helping policy makers regulate and govern the industry in more effective manner.

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