Predicting Transfer Values in the English Premier League

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Abstract

This paper examines factors that affect the transfer value of players transferred into the English Premier League from 2009-2015. The analysis begins by examining what factors are significant in determining a player's projected transfer fee based on the website Transfermarkt.com as well as the actual fee that the player was sold for. The paper goes on to find that competition level and a player's form are not statistically significant in models built to determine a player's transfer value. Quantile regression is then used to illustrate that there is a superstar effect with a forward's goal's scored in the transfer market.

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I. INTRODUCTION

Sherwin Rosen (1981) argued that “small differences in talent become magnified in larger earnings differences, with great magnification if the earnings-talent gradient increases sharply near the top of the scale.” Given that true “superstars” are in short supply and in high-demand, marginal increases in talent can lead to an extraordinary increase in value. Building off this analysis, Moshe Adler (1985) believes that luck and positive social network externalities are also a big proponent of stardom. Adler expanded on Rosen’s findings, stating that even among those who have equal talent, one can be more of a star due to positive social network externalities.

While in areas such as music, talent can be hard to identify due to there being a large subjective component (Connolly and Krueger 2006), in sports, it is much more feasible to quantify talent, given the amount of individual statistics collected. Better athletes tend to put up better statistics and better teams tend to win games at a higher percentage. Players and their performances tend to regress to the mean, causing luck to average out in the long run. While studies supporting Rosen and Adler’s notions have been done in fields such as business, art, music, and sporting leagues such as the National Hockey League, this extension of the superstar effect has not made its way to English Premier League soccer, the top flight soccer division in England and arguably the world. However, Franck and Nuesch (2006) examined the superstar effect in the German Bundesliga, Germany’s top-flight soccer league, and found there to be a strong superstar effect, where a small number of top players have transfer fees much higher than other players. This paper will set out to examine if soccer players purchased by English Premier League clubs with marginally better stats than others go for a much higher transfer fee.

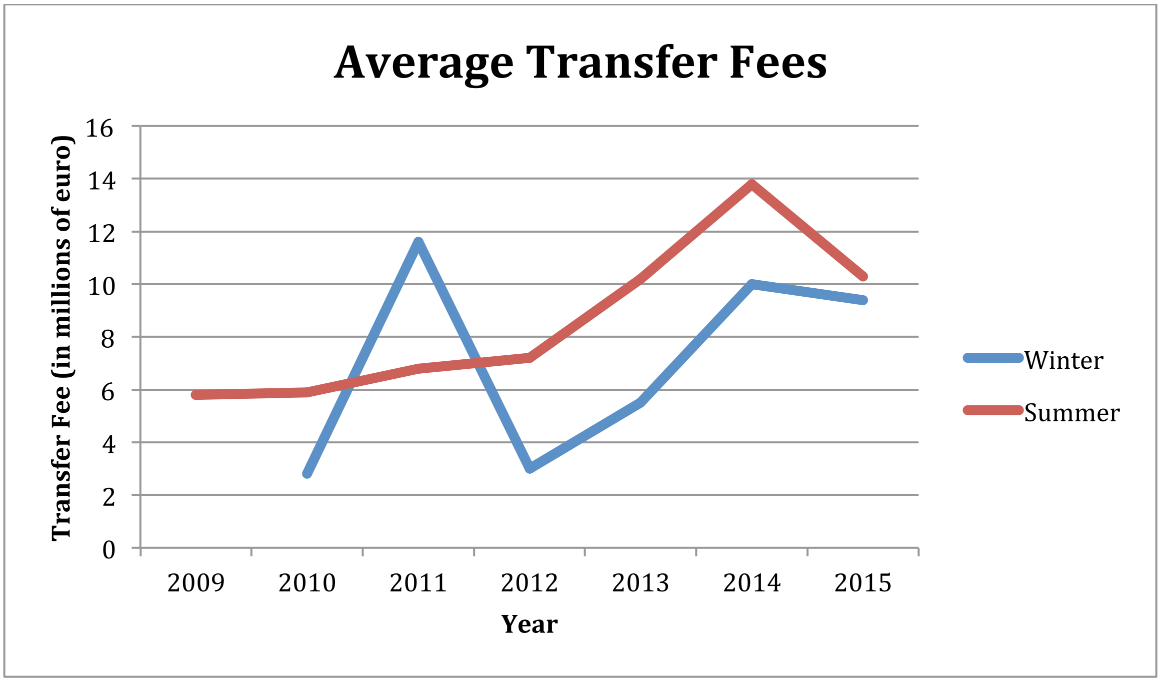
Just this summer, English Premier League clubs combined spent over 700 million euro in the transfer market. Clubs traditionally spend approximately 20% of total revenue per season in the transfer market; however, this can vary depending on team needs.[2] Most notably, this past transfer window, FC Barcelona sold Pedro for 30 million euros to Chelsea. Pedro is considered a star player who has won a World Cup and European Cup with the Spanish National Team as well as a Champions League Final with Barcelona. Meanwhile, nineteen-year-old Anthony Martail of Monaco was sold to Manchester United for 80 million euros, despite only scoring eleven goals for Monaco and having just one appearance for the French National Team. At first glance, one may wonder why the player's transfer values were as stated; however, advanced statistical analysis used by the clubs in the transfer process likely explains the difference in the two transfer fees.

Table 1: Transfer Window History

Transfer Window	Average Transfer Fee (millions of euro)	Median Transfer Fee (millions of euro)	Number of Transfers
Summer 2015	10.3	7	71
Winter 2014-2015	9.4	5	9
Summer 2014	13.8	10	47
Winter 2013-2014	10	7	10
Summer 2013	10.2	7	55
Winter 2012-2013	5.5	3.5	13
Summer 2012	7.2	6	41
Winter 2011-2012	3.0	1.4	12
Summer 2011	6.8	4.5	65
Winter 2010-2011	11.6	6	18
Summer 2010	5.9	3.5	58
Winter 2009-2010	2.8	2.5	11
Summer 2009	5.8	3.125	74

[2] Swiss Ramble. Manchester United What Difference Does it Make? September 2015.

Figure 1: Average English Premier League Transfer Fees Over Time



In the global soccer market, teams can buy players from soccer clubs all over the world. In England, this happens during a two-month window in the summer and a one-month window in the winter. The summer window happens before the season starts, and runs from the first of July to the first of September. The winter transfer window opens roughly midway through the season, from 1 January to 1 February. Most major signings take place in the summer window, while the midseason winter transfer window tends to be used as an opportunity to purchase reinforcements incase a team realizes that they have a glaring need or have had injuries negatively affect the team.[3] In order to go about this transfer, clubs must pay the other club a fee for the value of a player, known as a transfer fee, and the player must agree to the move. This transfer fee paid is

[3] Transfer Window in European Soccer Explained. July 2014.

different than a player salary. Each year, roughly 80 players are transferred to the Premier League for a disclosed fee. Using this data, I can draw conclusions about the incremental effect of statistics on a player's market value (i.e., the incremental effect of a goal). Table 1 and Figure 1 provide descriptive statistics on the amount of players transferred to the Premier League each season as well as the median and mean values of the transfer fees. From the summer of 2009 to the summer of 2014, we see the average transfer fee rise year-to-year, presumably given the growth of club's revenue from commercial deals and broadcasting rights. Interestingly, the average transfer fee slightly declines in 2015; however, due to a new Champions League television deal, it is expected that the average transfer fee will increase in the coming windows.[4]

To analyze the effect of player statistics on transfer fees, I used the detailed statistics of STATS LLC, a sports data collecting service that collects a wide variety of advanced statistics. I examine the transfer fees of player purchased by English Premier League clubs, reported by the BBC, since the end of the 2008 season. This coincides with the last major sale of an English Premier League club, when Manchester City was sold to Sheik Mansour of Abu Dhabi. This purchase is seen by many to have disrupted the transfer market, as Manchester City began spending exuberantly and have the highest Premier League net spend on players since 2008.[5] The 2009-2015 window range also includes 466 players that were transferred into the English Premier League, including 441 outfield players.

Using these actual transfer fees as the dependent variable, and using the statistics from STATS LLC as the independent variables, I examine the relationship between player statistics and transfer values. I examine whether these to see if there is a superstar effect present in the English Premier League's transfers by using quantile regression to see the value of an

[4] The Guardian. BT Sport Champions League Exclusive Rights. 9 November 2013.
[5] Soccerlens. Manchester City Changing Face of English Football. August 2014.

incremental goal for a player who is in the top 5% of goals scored compared to a player who scores the median number of goals. In the 2014-2015 season, 977 goals were scored in the English Premier League. As each team has a senior roster of 25 players, usually consisting of 22 outfield players, this means the average number of goals scored per Premier League outfield player is 2.2. However, this is taking into consideration defenders and the members of the roster who typically do not play very frequently, both who seldom score on average.

I focused solely on transfers to the English Premier League given the complexity of each league's labor laws and homegrown quotas, where a certain percentage of players on the team must have citizenship of the country in which the league is located in. For example, the English Premier League states that there must be four players on one's 25 person roster who are English, and four more who trained with an English club for three years before their 21st birthday, regardless of nationality. The Italian Serie A states that there must be eight homegrown players, four of which are Italian and four of which are Italian and trained with an Italian club for three years before their 18th birthday, and is considering upping the quota number.[6] Furthermore, the Russian Premier League simply states that four players on each roster must be Russian, but is in talks to dramatically increase this number before they host the 2018 FIFA World Cup.[7]

No rules have been changed regarding transfer fees or nationality quotas for the English Premier League; however during my 2009-2015 window; however, television money for the Champions League (in which the top four English teams participate in), as well as for the English Premier League has massively increased over the past few years after new worldwide contract negotiations. This leads many to believe that transfer fees are increasing at a rapid rate

[6] Four Four Two. Premier League and Serie A: Radical Quota Changes Could Save Italian Football.
[7] New York Times. Russian League to Cut Back of Foreign Soccer Players. April 2015.

year over year, as club's revenues rise, which I will account for in my research.

For the rest of the paper, I go in detail about previous literature in section two, my theoretical framework in section three, the data in section four, my empirical specification in section five, my results in section six, and the overall contributions in section seven.

II. LITERATURE

In the early 2000s, the Oakland Athletics of Major League Baseball began to use a "sabermetrics," approach to better their team, as they did not have the monetary resources of other teams. In this approach, they analyzed player's statistics and found overvalued and undervalued players on the market by finding statistics that were highly correlated with win percentage. This is regarded as the first time that econometrics methods were used in sports. While the Oakland Athletics never officially released their methods to the public, many economists such as Hakes and Sauer (2006) believe that simple regressions can arrive at similar findings. Since then, many sports teams have attempted to use advanced statistics to determine optimal, undervalued players; however, many criticize this method, saying statistics cannot fully explain sporting performance or that sports other than baseball are not optimal for this statistical modeling. Baseball's individualistic nature on offense, where only one batter is up at a time, makes it easy to track, and therefore analyze, statistics for given players. Bill Gerrard, one of the founders of the "moneyball method" that the Oakland Athletics implemented, and Howard (2007) believe that the moneyball approach can be applied to other sports and leagues as well, as long as the data is present and team executives and fans are not resistant to change.

This moneyball analysis has been extended to multiple sports across the globe, from hockey to Australian Rules Football (Stewart, Mitchell, and Stravos, 2007); however the analysis seems to be under-utilized with regards to soccer, with just one major paper having been written regarding soccer. While most moneyball analyses revolve around baseball, Egon Franck and

Stephan Nuesch (2012) used empirical tests to determine what individual player statistics were most correlated with a team's win in the German *Bundesliga*, the top professional soccer league in Germany. Not surprisingly, they found goals and assists to be highly correlated with a win. They also found shots on target and cross success rate to be significantly correlated with a win, while red cards, yellow cards, and conceded penalties were highly correlated with a loss. Then, they used these findings, which statistically affect the outcome of the game, as the explanatory variables to better understand a player's market value. Their analysis shows that the aforementioned statistics and a player's media popularity, measured by a number of times a player was mentioned for non-performance reasons in popular German newspapers and magazines, can explain roughly 70 percent of a player's predicted transfer fee, as projected by *Transfermarkt*.

Both Rosen and Alder argued that the value of superstars increases exponentially compared to that of an average performer or artist. Alan Kruger (2005) examines and extends this superstar effect when it comes to musicians – people will pay a much higher amount to listen to a superstar artist than they would to listen to an average artist. This analysis is further extended to CEO pay, where it is found that companies will pay more for a "superstar" CEO. Fortune 50 CEOs make four times as much on average than an average Fortune 500 CEO.[8] Extending this, in many fields, the best are much more expensive than those who are just very good.

Using a quantile regression approach, as used by Franck and Nuesch, the incremental impact of a goal can be analyzed for different stardom levels. For example, Franck and Nuesch find that a star player at the 95% quantile sees his market value increase by 4.5% for each goal scored,

[8] "How Superstars' Pay Stifles Everyone Else." *New York Times*. New York Times, 25 Dec. 2010. Web. 5 Oct. 2015.

whereas an average player sees his value increase by approximately 1% for each goal scored. I extend this analysis to the English Premier League, where there are arguably even more superstars than the German *Bundesliga*.

I use a transfer fees as the dependent variable and have different player characteristics as the independent variables, similar to what Franck and Nuesch's analysis. While Franck and Nuesch's analysis will serve as a good template, I believe that there are potential additions and improvements that will make my analysis stronger. These improvements, such as using an actual transfer fee and examining the effect of competition level and form, will hopefully lead to having a higher adjusted r-squared, thereby explaining more of the variation in the data and being a better predictive model. In what follows, some potential improvements to the previous literature are discussed.

III. THEORETICAL FRAMEWORK

a. Dependent Variable

Franck and Nuesch used *projected* market values made up by German newspaper *Kicker* as the dependent variable in their model. While the German newspaper they used solely predicted transfer values of all German players for that year, a leading soccer website also used by Franck and Nuesch, known as *Transfermarkt*, estimates the value of soccer players from around the world. These *Transfermarkt* estimates seem random at times, so I started by running correlation tests of what they say the "market value" of a player is at the time that they are transferred (what they predict the player should go for if they were transferred) with the corresponding actual transfer value paid by the Premier League club to see how good these estimated market values are. As the transfer fee rises, the correlation between the actual transfer fee and the projected transfer fee diminishes. As such, using actual transfer fees as a dependent variable should lead to better findings. Regressing the actual transfer fee with *Transfermarkt's* projected value for a player at the time that they were transferred shows an adjusted R-Squared of 73% and the slope coefficients are significantly different than one (Table 2). More so, when doing a correlational analysis, we see that *Transfermarkt's* projected values are 85.6% correlated with the actual transfer values of a player (Figure 2).

Table 2: OLS Regression with the Transfer Fee as the dependent variable and the Transfermarkt projection as the dependent variable

Transfer Fee (in tens of millions)	**Coefficient**	**SE**
Transfermarket Projection (in tens of millions)	0.883***	0.025
Constant	7.948***	0.308
N=441		
Adjusted R-Squared=0.73		

When looking solely at transfers that went for 10 million euro or higher, we see an even poorer relationship between *Transfermarkt's* projected values and the actual transfer fees paid. In this case, the adjusted R-squared is 55% and the slope coefficients are significantly different than one (Table 3). Running a correlational analysis between *Transfermarkt's* projected transfer values and actual transfer fees worth more than ten million euro in the past year saw that the values are 75% correlated. As *Transfermarkt* becomes less accurate with more expensive transfer fees, I believe the superstar effect and quantile regression will help me build a better model to predict actual transfer values.

Although using *Transfermarkt* data would allow me to have a larger sample size, I will still have an amble sample size and have a more reliable and useful model if the dependent variable is the actual transfer fee. To extend Franck and Nuesch's 2006 paper and for comparison purposes, I run an initial regression using Transfermarkt's "projected" transfer fees at the time the player was transferred for players transferred into the English Premier League before running regressions with actual transfer fees.

Table 3: OLS Regression with the Transfer Fee as the dependent variable and the Transfermarkt projection as the dependent variable, only including transfers that had a transfer fee over 10 million euro

Transfer Fee (in tens of millions)	**Coefficient**	**SE**
Transfermarket Projection (in tens of millions)	0.682***	0.025
Constant	1.253	0.308
N=133		
Adjusted R-Squared=0.55		

b. Player Characteristics and Statistics:

Player statistics are added to the model as independent variables as one would expect a player's transfer fee to be highly dependent on player's statistical performances. These statistics can be seen in Table 4.

While overall statistics are an important variable, breaking the statistics down by season would portray a more accurate picture on how the player is doing. For example, someone who scored 20 goals in his first season, two goals in his second season, and two goals in his third season is different than someone who scored two goals in his first season, two goals in his second season, and 20 goals in his third season, despite them both scoring the same number of career goals. To best capture form, I try two dummy variables, one for assists and one for goals, equal to one if the output in the respective category increased from the previous year. I also try a variable whose value is equal to the net change in goals and assists compared to the previous year.

More so, a homegrown dummy variable is also included in the regressions. In Alex Bryson, Giambattista Rossi, and Rob Simmons' "The Migrant Wage Premium in professional Football: A Superstar Effect?" (2007) it is shown that in the Italian Serie A, foreign players get paid more than domestic Italian players, when controlling for players' statistics. While examining this for the English Premier League, I would hypothesize that the opposite could be true, for transfer values, as eight players on a team's 25-man roster must be from England or have been in an English academy for three years before his twenty-first birthday. This quota artificially raises the demand for English footballers, and as a result, raises the transfer fee. Managers of Premier League clubs, such as Manuel Pellegrini of Manchester City, argue that homegrown players are too expensive given the perceived inflated fee. In my regression, I would add a variable for being an English "homegrown" player to see if, holding all else equal, being homegrown leads to a higher transfer fee. Using an OLS model, I examine what exactly the homegrown premium is, numerically speaking. Despite this "homegrown premium" being heavily talked about in the media, the extent of it has not been analyzed before.

Figure 2: *Graph Depicting Transfermarkt's Projected Transfer Values (in millions of Euro) on the x-axis compared to the Actual Transfer Values (in millions of euro) on the y-axis for players transferred to the English Premier League from the 2009 to 2015 season*

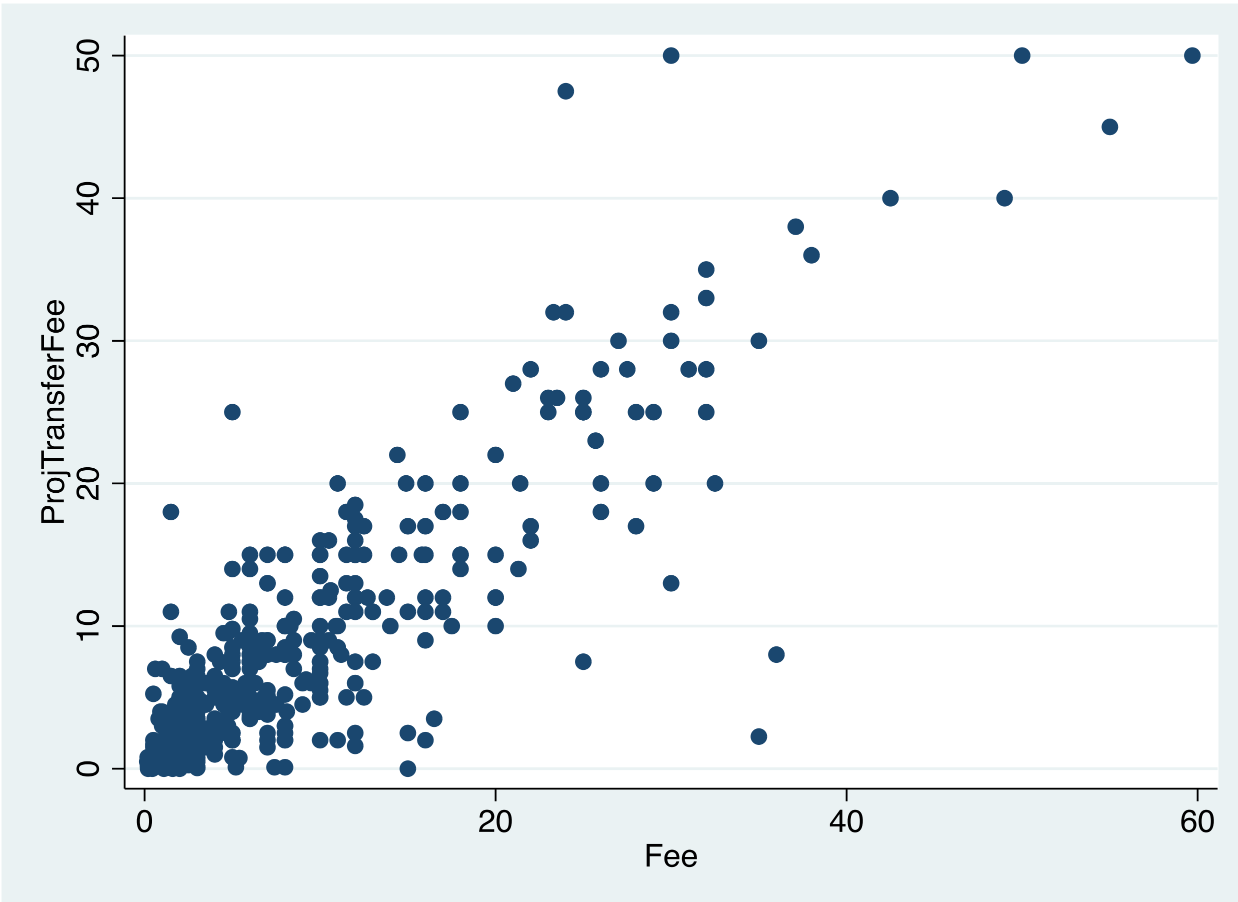


Table 4: Player Characteristics and Statistics

Variable	Description
Age	Player's age in years at the time they were transferred
Age Squared	The squared value of a player's age at the time they were transferred
Appearances	The number of matches that a player has appeared in
Matches Started	The number of matches that a player has started
Minutes Played	The amount of total minutes that a player has played in
Goals	The number of goals scored
Assists	The number of assists, passes that lead directly to a goal, that a player has
Form Dummy	Equal to one if a player has increased output in goals or assists
Form Net Change	Equal to the amount of goals and assists that the player increased their output by compared to the previous year
Homegrown Dummy	Equal to one if the player is considered homegrown in England

c. Purchasing Characteristics:

Purchasing characteristics are added to the model to control for the time that the player was purchased and who purchased the player. As there are two transfer windows each year in the English Premier League, a dummy variable will control for which time of year the player was purchased. The winter transfer window is during the middle of the season, and many speculate that this leads to higher prices as teams would want to charge a premium if they were to give away a player without proper time to get a new player accumulated to the system.

Team fixed effects were also added to the regression, including all thirty-two teams that have participated in the English Premier League since the 2009 season. The regressions include fixed purchasing team effects due to the massive differences in revenue among teams. For example, in 2014, Manchester United brought in 433 million euros, while Cardiff City brought in just 83 million euros, by contrast.[9]

Another aspect I examine is if richer teams are charged a premium to buy players. It is often brought up that more successful, richer teams always have to overpay for talent as the selling teams know that they have a lot of money. The revenues of Arsenal, Chelsea, Manchester City, and Manchester United outpace the rest of the teams in England, and are about double that of the revenue of the sixth highest club, Tottenham Hotspur.[10]

[9] Swiss Ramble. Manchester United What Difference Does it Make? September 2015. http://swissramble.blogspot.com/.
[10] Swiss Ramble. "Arsenal Searching for Hows and Whys." September 2015.

Table 5: Purchasing Characteristics

Variable	Description
Purchasing Team Fixed Effect Dummy Variables	Dummy variables for the purchasing club
Selling Team Fixed Effect Dummy Variables	Dummy variables for the selling club
Winter Transfer Window Dummy	A dummy variable equal to one if the player was purchased in the winter transfer window, rather than the summer transfer window
Rich Club Premium Dummy	Was the player bought by a team in the Champions League

d. Popularity

Popularity, as shown by Franck and Nuesch, also plays an important role in the transfer fee of a player. While I won't have time to delve through the amount of non- performance related articles that players are mentioned in, I tried to measure popularity based off of other online metrics. Unfortunately, Facebook likes do not seem to be tracked over a long period of time and Google searches are indexed to the peak of searches for that term. More so, while jersey sales would be a good proxy, many leagues around the world do not list jersey sale data for individual players. Similarly, autograph value could be a good proxy for player popularity, but it is difficult finding autograph prices at the time a player was transferred. Further, Twitter mentions seemed to be a potentially quantifiable metric; however, one can only go back three to five days for Twitter data analytics, again making this a useless statistic for transfers that have previously occurred. In short, there are many ways to measure popularity of players, but none seem to be feasible at this time, which will be one downside of my analysis compared to previous analyses.

IV. DATA

For player statistics, I use data from STATS LLC. Stats LLC is a leading data company that tracks soccer players statistics across the world throughout multiple competitions including almost every domestic soccer league, international club competitions such as the Champions League, and international country competitions such as the World Cup. For player transfer fees, I have already complied a list of transfer fees as reported by the British Broadcasting Company, a reliable media outlet in Britain. As the prices are in Euros, I have used inflation data from the European Central Bank to normalize transfer fees to a base of 2015 euros.[11]

As seen in Table 6, the mean age that a player is transferred is 24.48, implying that Premier League clubs tend to purchase players before they hit their peak, usually around the age of 27.[12] More so, the average player has scored approximately 27 goals in his career before he is transferred, but as seen, this data can vary widely from 0 goals to 165 goals. Forwards and older players would be expected to have scored more goals in their career than defenders and younger players. Similarly, matches started and minutes played vary widely due to differences in experience and age.

[11] European Union. Euro Inflation Over Time.
[12] BBC. When do footballers hit their peak? July 2014.

Table 6: Descriptive Statistics of Career Player Statistics for Players Transferred into the English Premier League from 2009-2015[13]

Variable	Mean	Standard Deviation	Minimum	Maximum
Assists	6.75	12.83	0	116
Age	24.48	3.49	17	33
Goals	27.45	31.06	0	165
Matches Played	138.13	98.3	0	602
Matches Started	115.11	87.01	0	573
Minutes Played	10230.33	7646.73	0	50381

V. EMPIRICAL SPECIFICATION

In order to best find what factors affect a player's transfer fee, I run regressions using the natural log of the transfer fee as the dependent variable and player characteristics and purchasing statistics as the independent variables, along with the intercept and error term (Formula 1).

Formula 1:

$$\text{Ln(Transfer Fee)} = \boldsymbol{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon}$$

Where $\boldsymbol{X_1}$ *consists of player characteristics and statistics and* $\boldsymbol{X_2}$ *consists of purchasing characteristics*

The dependent variable in the regression is the natural log of the transfer fee. The natural log was used in order normalize the distribution of transfer fees. The list of independent variables

[13] Data from STATS LLC. Copyright 2016.

used throughout the models can be found above in Tables 4 and 5. While one may question why a player's wage is excluded from this analysis, after a lot of research, there does not seem to be any reliable website that lists wages for all Premier League players over time. Some star player's rumored wages are readily available, but I could not find wage data for a majority of players in my dataset.

While it is common to analyze data through Ordinary Least Squared (OLS) regressions, OLS estimates do not capture behavior at the tails as OLS approximates a mean of a conditional distribution. As such, OLS estimates will not show whether or not there is a superstar effect. In order to test for this effect, I can analyze the data using quantile regression, similar to the analysis of Franck and Neusch. Quantile regression allows one to examine the entire distribution, rather than solely the mean that OLS allows us to examine. This quantile regression approach gives the possibility of testing for a superstar effect and examining the difference between the effect of a goal on the transfer fee for a player who had a transfer fee in the 50^{th} percentile and a player who had a transfer fee in the 95^{th} percentile. In my analysis below, I begin with OLS regression and then use quantile regression to test for a superstar effect.

VI. RESULTS

a. Dependent variable of Projected Transfer Fees

To begin the analysis, the methods of Franck and Neusch's German Bundesliga study (2006) were used in order to extend their analysis and see how the results of the determinants of projected transfer fees in the English Premier League compares with that of the German *Bundesliga*. I began with making the dependent variable the logarithm of the projected transfer fees of players at the time they were transferred, according to *Transfermarkt*. I also used many of the same variables that Franck and Neusch analyzed in the regression, including goals, assists, shots, red cards, yellow cards, age, age squared, appearances, fixed teams effects, and position fixed effects. Of the aforementioned, Franck and Neusch found goals, assists, age, age squared, and appearances to be significant in an Ordinary Least Squares regression with an adjusted r-squared of 0.70. The coefficients for goals, assists, age, and appearances were al positive, while the coefficient on age squared was negative. In their quantile regression of the 95% quantile, they found goals, assists and age to be significant at the 1% level with a positive coefficient, and age squared to be significant at the 1% level with a negative coefficient with an adjusted r-squared of 0.56.

Table 7: OLS Regression using Projected Transfer Fee (in Euros) as Dependent Variable[14]

In(ProjectedTransferFee)	**Coefficient**	**SE**
Age	1.252***	0.138
Age Squared	-0.023***	0.003
Matches Played	0.002***	0.001
Goals	0.002	0.002
Assists	0.001	0.005
Shots	0.002***	0.001
Yellow Cards	0.002	0.002
Red Cards	0.055*	0.029
Constant	-2.641	1.795
N=441		
Adjusted R-Squared=0.54		

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

[14] Data from STATS LLC. Copyright 2016.

Regressing the *Transfermarkt* projected transfer fees against goals, assists, red cards, yellow cards, age, age squared, and appearances against fixed team effects and position effects led to an adjusted r-squared of 0.54 (Table 7). Age and age squared both had a p-value of 0.000, meaning that they are statistically significant at the 1% level. Age had a positive coefficient of 1.25, which means that for each increase in age the projected transfer fee increased by 125%, while age squared had a negative coefficient of -0.023, meaning that for each increase in age squared the projected transfer fee decreased by 2.3%. While the increase of age on the projected transfer fee seems high, it is important to note that the negative age squared variable is rising much faster, mitigating much of age's positive effect on the transfer fee. These effects happen as there is a decreasing returns to age, due to teams wanting players who have physically developed with more experience, but at the same time, wanting a player who is not too old given that players tend to hit their peak in their late twenties and retire by their mid thirties (BBC). Matches played was also statistically significant at the 1% level with a positive coefficient of 0.002, meaning that for each match played one's transfer fee increases by 0.2%.

Strangely, in the model, both goals and assists are incredibly insignificant with p-values of 0.822 and 0.873, respectively. While no justification for this is apparent, especially given the fact that Franck and Neusch found both to be statistically significant at a 1% level in their study of the German *Bundesliga*, it is important to remember that these are just projected transfer fees based on an undisclosed algorithm by *Transfermarkt.* More so, the Franck and Neusch study used data from the 2004-2005 season, and perhaps *Transfermarkt* has changed their algorithm since then. Also interesting was that red-cards were statistically significant at a 10% level with a positive coefficient of 0.054, meaning that for each additional red card one receives the projected transfer value increases by approximately 5%. This again does not make much sense, however perhaps controlling for matches played is not enough and another measurement, such as minutes played, should also be controlled for, as players who play more will probably receive more red cards.

Franck and Neusch's study analyzes the results at the 90%, 95%, and 98% quantile to examine if there is a superstar effect present in the transfer market. In their study, they found that at the 90% quantile, the incremental effect of a goal leads to a 9% increase in the transfer value, which is statistically significant at the 1% level. This is compared to a 9.5% increase at the 95% quantile and a 9.6% increase at the 98% quantile, both of which are statistically significant at the 1% level. In my extension of this analysis to the English Premier League, goals were not found statistically significant until the 98% quantile, where each incremental goal increased the transfer value by 0.8%. From this, we can weakly see a super star effect with the effect of goals projected transfer values, but it is noteworthy that goals become insignificant at the 98% quantile. Assists were also found to be statistically significant at the 1% level with a positive coefficient. The coefficient was 0.017 at the 90% quantile, 0.25 at the 95% quantile, and 0.029 at the 98% quantile. In my extension to the English Premier League, assists are not statistically significant and the coefficient has no clear pattern (Figure 6). It was also interesting to see shots significant at the 90% quantile and the 95% quantile, but insignificant at the 98% quantile. However, shots as a metric does not help that much, as teams would be looking for quality shots, which are probably reflected well by the amount of goals that a player takes, over a quantity of shots, as shots are really only beneficial to the team if they go in the net to score a goal.

The results of the English Premier League extension have the same signs that Franck and Neusch's analysis had and find the same variables statistically significant. However, as previously mentioned, to truly determine how the player's market values are affected by their statistics, looking at the actual transfer fees is a better predictor than looking at projected transfer values by *Transfermarkt* and other news outlets.

Table 8: Chart depicting the corresponding Transfermarkt and actual market value, in Euros, that corresponds with the respective percentile

Percentile	Transfermarkt Value (Euros)	Actual Market Value (Euros)
1%	0	252,567
5%	299,250	1,011,330
10%	1,105,500	1,628,685
25%	2,645,313	2,751,000
50%	5,972,500	6,069,000
75%	11,784,250	11,612,700
90%	20,930,000	21,924,200
95%	29,6800,000	30,232,800
99%	43,310,000	42,685,470

Note: Figures adjusted for inflation to 2015 euros

Table 9: Quantile Regression Results using Projected Transfer Fee as Dependent Variable[15]

Estimation approach	**90% Quantile**		**95% Quantile**		**98% Quantile**	
In(ProjectedTransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Age	0.756***	0.196	0.698**	0.272	0.661**	0.286
Age Squared	-0.015***	0.005	-0.014***	0.005	-0.013**	0.006
Matches Played	0.001**	0.001	0.001*	0.001	0.001	0.001
Goals	-0.001	0.001	0.002	0.002	0.008***	0.003
Assists	0.006	0.005	0.002	0.008	0.005	0.008
Shots	0.001**	0.001	0.002*	0.001	0.001	0.472
Yellow Cards	0.002	0.004	0.002	0.004	0.003	0.004
Red Cards	0.008	0.026	0.012	0.021	0.014	0.016
Constant	6.104**	0.017	7.139**	3.495	7.539**	0.040
Fixed Team Effects	Yes		Yes		Yes	
Fixed Position Effects	Yes		Yes		Yes	
N=461						
Pseudo R-squared	48%		50%		54%	

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

b. Actual Transfer Fees used as Dependent Variable

To begin my analysis, I used an Ordinary Least Squared regression model with the log of the actual transfer fees paid, in 2015 euros, as the dependent variable. In order to determine what statistics helped explain the most variance in player's transfer fees, I looked at player statistics from the previous season prior to the transfer, the past three years prior to the transfer, and

[15] Data from STATS LLC. Copyright 2016.

player's career statistics prior to their transfer. The adjusted r-squared values increased when more years of player statistics were added. The adjusted r-squared values increased from .59 when statistics for the year prior to the transfer were used to .64 when statistics for the player's career prior to the transfer were used (Tables 10 through 12).

Continuing the analysis, I regressed the actual transfer fee against career statistics (Table 10). Using interaction terms, breaking goals and assists out by position, results in a similar r-squared of 0.60 as lumping all position's goals and assists together. In the first regression, without the interaction terms, goals scored were statistically significant at the 1% level with a coefficient of 0.004, meaning that each goal scored increased the player's transfer value by 0.4%. Forward and midfield interaction terms with goals and assists are present in the second regression, with defense omitted to avoid multicollinearity. In the regression with the position interaction terms, goals were only statistically significant for forwards, with each goal scored increasing the player's transfer value by 0.3%. As forwards are the most attacking players and score the most goals, this result does make sense, as the role of forwards is to score goals while midfielders and defenders have other primary responsibilities, such as creating goal-scoring opportunities and defending.

Table 10: OLS Regression using Statistics from Previous Season Prior to Transfer[16]

OLS Regression	(1)		(2)	
In(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**
Goals	0.025***	0.005		
Forward Goals			0.027***	0.008
Midfield Goals			0.016*	0.010
Assists	0.021**	0.008		
Forward Assists			0.016	0.018
Midfield Assists			0.031***	0.011
Age	0.878***	0.122	0.865***	0.123
Age Squared	-0.017***	0.002	-0.017***	0.002
Minutes Played	0.000**	0.000	0.000	0.000
Fixed Purchasing Team Effects	Yes		Yes	
Fixed Selling Team Effects	Yes		Yes	
Fixed Window Effects	Yes		Yes	
Constant	3.973**	1.551	4.134	1.555
N=441				
Adjusted R-Squared		.59		.61

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

[16] Data from STATS LLC. Copyright 2016.

Table 11: OLS Regression using Statistics from Previous Three Seasons Prior to Transfer[17]

OLS Regression	(1)		(2)	
In(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**
Goals	0.009***	0.002		
Forward Goals			0.011**	0.004
Midfield Goals			0.002	0.004
Defense Goals			0.016**	0.008
Assists	0.021***	0.004		
Forward Assists			0.003	0.010
Midfield Assists			0.014***	0.004
Defense Assists			-0.008	0.011
Age	0.802***	0.119	0.771***	0.010
Age Squared	-0.016***	0.002	-0.016***	0.002
Ln(Minutes Played)	0.035	0.440	0.016	0.003
Fixed Purchasing Team Effects	Yes		Yes	
Fixed Window Effects	Yes		Yes	
Fixed Selling Team Effects	Yes		Yes	
Constant	4.493***	0.094	4.809***	1.559
N=441				
Adjusted R-Squared		.61		.61

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

[17] Data from STATS LLC. Copyright 2016.

Table 12: OLS Regression using Career Statistics Prior to Transfer[18]

OLS Regression	(1)		(2)	
In(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**
Goals	0.004***	0.001		
Forward Goals			0.003**	0.098
Midfield Goals			0.003	0.226
Assists	0.010***	0.003		
Forward Assists			0.018**	0.010
Midfield Assists			0.008***	0.004
Age	0.742***	0.119	0.771***	0.010
Age Squared	-0.016***	0.002	-0.016***	0.002
Ln(Minutes Played)	0.130***	0.440	0.016	0.003
Fixed Purchasing Team Effects	Yes		Yes	
Fixed Selling Team Effects	Yes		Yes	
Fixed Window Effects	Yes		Yes	
Constant	4.468***	1.456	4.692***	1.459
N=441				
Adjusted R-Squared		.64		.64

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

Career assists are also statistically significant in the regression. For each assist a player has, his transfer value increases by 1%. Adding in interaction terms to the regression, we see that assists are statistically significant for forwards and midfielders. This again makes sense, as forwards and midfielders are primarily responsible for creating goal-scoring opportunities. An

[18] Data from STATS LLC. Copyright 2016.

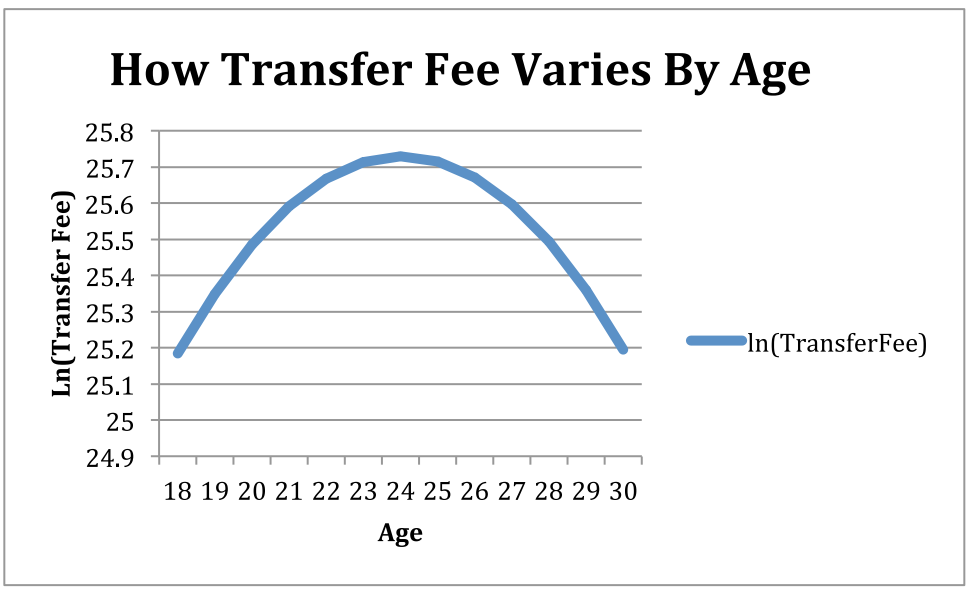
incremental assist by a forward leads to a 1.8% increase in the transfer value, while an incremental assist by a midfielder leads to a 1% increase in the transfer value. It is interesting to see that the coefficient on the assist variable is greater than that on the goal variable. Perhaps English Premier League clubs value play-making ability and players who create goal-scoring opportunities and the assist variable is a good proxy for this.

Both “Age” and “Age squared” are statistically significant with 0.000 p- values in both regressions. In the non-interaction term regression, the coefficient on “Age” illustrates that, for every yearly increase in a player’s age, the transfer fee increases by 74.2 percent. However, the coefficient on “Age squared” is -0.016, meaning that there is a 1.6 percent decrease in the transfer value for every increase in the “age squared” variable. In the model with interaction terms, an increase in the player’s age leads to an increase in the transfer fee by 77.1% and an incremental increase in the age squared variable leads to a 1.6% decrease in transfer value. However, a one-unit increase in the age-squared variable will not occur. For example, an increase in age from 25 to 26 will lead to a 51-unit increase in the age-squared variable, leading to an 81.6 percent decrease in transfer value. When combined with the 77.1% incremental increase in transfer value per year, from the interaction term model, the net effect for the age variables sees a 4.5% decrease in transfer value.

While seemingly counterintuitive, it is reasonable to believe that there are diminishing returns to age. Although age can also be considered a proxy for experience, which can be a good thing, as a team would like someone in the prime of their career, there is a drawback to the purchase of older players. At the same time, teams do not want to pay for someone who is too old to play at a highly competitive level. For example, I analyzed the effect that age has on a player using the OLS regression model in Figure 2. I analyzed the variables at their mean, and used a forward who was purchased by Arsenal for the team and position dummies. The figure illustrates the effect, and shows a peak of value at approximately 24 years old. After this age, there is a negative effect on the transfer fee. A BBC study showed that players tend to reach their peak form at approximately 27 to 29 years old.[19] A purchasing club would want to maximize the amount of time that they have their players in peak form, so the maximum transfer value occurring around the age of 24 years old, all else equal, seems reasonable.

The natural log of career minutes played variable was interestingly significant in the non-interaction term model, but was not significant when interaction terms were included. A one-percent change in the natural log of minutes played is associated with a 0.13% increase in a player's transfer value. This variable serves as a proxy for experience and talent, as a player who has played frequently with their previous teams would most likely be talented, or else they would have not been selected to play as much as they were.

Figure 2: Illustrating the Effect of Age on Transfer Fee



[19] BBC. When Do Footballers Hit Their Peak? July 2014.

Table 13: Quantile Regression of Transfer Fees with Career Statistics[20]

Estimation approach	**50% Quantile**		**75% Quantile**		**90% Quantile**		**95% Quantile**	
ln(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Age	0.771***	0.193	0.765***	0.181	0.684***	0.162	0.696***	0.174
Age Squared	-0.016***	0.004	-0.016***	0.004	-0.015***	0.003	-0.015***	0.004
Assists (Forwards)	0.014	0.001	0.014	0.021	0.004	0.019	0.006	0.003
Assists (Midfield)	0.008*	0.005	0.007*	0.004	0.006	0.004	0.007*	0.003
Goals (Forwards)	0.003	0.002	0.005**	0.002	0.006**	0.003	0.007**	0.003
Goals (Midfield)	0.001	0.001	0.004	0.003	0.002	0.002	0.005	0.003
ln(Career Minutes)	0.110***	0.027	0.095***	0.037	0.045	0.045	0.000	0.040
Constant	4.817**	2.453	5.50***	2.267	7.036***	2.001	7.849***	2.714
Purchasing Effects	Yes		Yes		Yes		Yes	
Selling Effects	Yes		Yes		Yes		Yes	
Window Effects	Yes		Yes		Yes		Yes	
N=441								
Pseudo R-squared	47%		50%		54%		55%	

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

[20] Data from STATS LLC. Copyright 2016.

c. Quantile regression

Quantile regression estimates a conditional quantile of a response variable given covariates using bootstrap replications. This allows one to examine the incremental impact of different statistics, such as goals, at different percentiles to determine if there is a superstar effect present in the English Premier League transfer market and if so, what that impact is. In the model, we primarily see the superstar effect present with regards to forward goals, which is similar to the results that Franck and Neusch found in their 2006 study. In the model, we see that for a forward at the 50% quantile, an incremental goal increases their transfer value by 0.3%. However, for a forward at the 95% quantile, an incremental goal increases his transfer value by 0.7%. This effect increases throughout the model, illustrating the superstar effect for goals scored by forwards. It is noteworthy that this magnitude of this effect is smaller than the magnitude that Franck and Neusch saw in the German *Bundesliga* of approximately nine percent; however, it is once again important to note that they used projected transfer fees instead of actual fees. However, other statistics do not exhibit a clear superstar effect in the model. Franck and Neusch did not separate goals and assists out by position, but found that total goals was the only statistic that exhibited a Superstar effect in the German Bundesliga.

The downward trend on the coefficient of the natural log of minutes is also noteworthy. From the regression, it appears that there is a backwards superstar effect, where having played less minutes increases the transfer fee by the most in the lower quantiles. However, the variable is not statistically significant at the 90% and 95% levels, making this a harder trend to read. On a similar note, the coefficients on age decrease from the 50% quantile to the 75% quantile to the 90% quantile, but slightly increase from the 90% quantile to the 95% quantile. I plan on examining these trends closer in the coming weeks to see if anything can be extracted.

It is also interesting to note that the psudeo r-squared increases throughout the model. As previously noted, *Transfermarkt* poorly predicts larger transfer fees; however, an increase in the psudeo r-squared throughout the model illustrates that the above model in Figure 11 explains more of the variation among larger transfer fees than it does with smaller transfer fees.

d. Addition of Homegrown Variables in Model

When added to the regression, homegrown variables have p-values that are not statistically significant at a 10% level. Neither a homegrown dummy nor homegrown position interaction dummies are significant at any reasonable level, which is surprising given the artificial eight person homegrown quota that all clubs must fulfill. In regression one, seen in Table 12, where a homegrown dummy is added to the regression, the p-value is 0.167, making it an insignificant variable. Similarly, when interaction terms are formed, between homegrown status and position, the variables are also not significant at a 10% level. The p-value for the homegrown forward variable is 0.263 while the p-value for the homegrown midfield variable is 0.011.

Table 14: OLS Regression using Career Statistics Prior to Transfer and Homegrown Variables[21]

OLS Regression	(1)		(2)	
In(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**
Goals	0.006***	0.002	0.007***	0.0013
Assists	0.006***	0.003	0.007***	0.003
Age	0.701***	0.105	0.661***	0.107
Age Squared	-0.015***	0.002	-0.014***	0.002
Ln(Minutes Played)	0.126***	0.021	0.135	0.021
Fixed Purchasing Team Effects	Yes		Yes	
Fixed Selling Team Effects	Yes		Yes	
Fixed Window Effects	Yes		Yes	
Constant	4.350***	1.490	4.917***	1.512
English Homegrown	0.105	0.076		
Homegrown Forwards			0.162	0.145
Homegrown Midfielders			0.181	0.121
N=441				
Adjusted R-Squared		.64		.64

*Note: * signifies significance at the 10% level, ** signifies significance at the 5% level, and *** signifies significance at the 1% level.*

[21] Data from STATS LLC. Copyright 2016.

e. Addition of Competition Level Variables to Model

Another variable that was hypothesized to be statistically significant was the competition level. In order to analyze competition level, I used two separate variables, an English Premier League dummy if the player was transferred from a Premier League club as well as a Top Five League Dummy variable if a player was transferred from a top five league in the world, based on historical UEFA league coefficients.[22] The top five league variable includes the English Premier League, the German *Bundesliga*, the French *Ligue 1*, the Italian *Serie A*, and Spain's *La Liga*. As seen in Table 13, the p-value for the Premier League sale is .333 in regression one while the p-value for the top five sale is 0.350 in regression two, making both variables insignificant at the 10% level. One potential reason that these competition level variables are statistically insignificant is that due to increased international competitions, such as the Champions and Europa Leagues at the club level, and continental and world tournaments such as the European Championship and World Cup at the country level, scouts are able to see players perform against quality sides. More so, there is a subjective quality to scouting that statistics do not fully track, such as ball control, which is why scouts are constantly sent to games to scout players instead of solely relying on their statistics.[23] Another explanation could be that talented young players tend to move to somewhat less competitive leagues where they can have a significant amount of playing time rather than sitting on the bench for a team in a top league. Examples of this can be seen by Gedion Zelalem's loan from Arsenal of the English Premier League to Rangers of the Scottish Championship, Michael Bradley's transfer from Roma of Serie A to Toronto FC of

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[22] UEFA. UEFA Rankings.
[23] LA Times. Europeans Continue to Tap US Soccer Pool. April 2012.
Harvard Sports Analysis. Team Form Recency Bias and Regression to the Mean. August 2015.

MLS, and Adnan Januzaj's loan from Manchester United of the English Premier League to Borussia Dortmund of the German *Bundesliga*.

Table 15: OLS Regression using Career Statistics Prior to Transfer with Competition Level Variables[24]

OLS Regression	(1)		(2)	
In(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**
Goals	0.006***	0.001	0.006***	0.001
Assists	0.006***	0.003	0.006**	0.003
Age	0.707***	0.106	0.684***	0.186
Age Squared	-0.015***	0.002	-0.015***	0.002
Ln(Minutes Played)	0.122***	0.022	0.132***	0.022
Constant	4.306***	1.492	4.532***	1.052
Competition Level				
Top Five League	0.071	0.076		
England			0.072	0.072
Fixed Purchasing Team Effects	Yes		Yes	
Fixed Selling Team Effects	Yes		Yes	
Fixed Purchasing Window Effects	Yes		Yes	
N=441				
Adjusted R-Squared		.64		.64

[24] Data from STATS LLC. Copyright 2016.

f. Addition of Form Variables to Model

In order to test whether or not a player's form was significant prior to the transfer, two sets of form variables are tested in the regression. In the first regression, assist and goal difference variables are included interacted with a player's position. These variables represent the net change in goals and assists in the season prior to the transfer compared to the season two years prior to the transfer. These can be positive or negative, depending on how the player's performance was compared to two years before he was transferred. These variables are all statistically insignificant at a 10% level. In regression two of Figure 14, simple dummy variables are added to the regression that are equal to one if a player increased his output in forwards or assists and equal to zero if that was not the case. Again, these variables are insignificant at the 10% level. While one would expect form to play a component in a player's transfer fee, it is possible that teams take a more holistic approach to the transfer to insure that a player's run of form is not a fluke. More so, players and teams typically regress to a mean, as shown by Harvard Sports Analysis, so teams may not want to base a decision off of just eight months of play.[25]

[25] Harvard Sports Analysis. Team Form Recency Bias and Regression to the Mean. August 2015.

Table 16: OLS Regression using Career Statistics and Form Variables[26]

OLS Regression	(1)		(2)	
In(TransferFee)	**Coefficient**	**SE**	**Coefficient**	**SE**
Goals	0.006***	0.001	0.006***	0.001
Assists	0.007**	0.003	0.006*	0.003
Age	0.695***	0.106	0.699***	0.106
Age Squared	-0.015***	0.002	-0.015***	0.002
Ln(Minutes Played)	0.126***	0.021	0.126***	0.021
Constant	4.439***	1.496	4.351***	1.501
Form				
Assist Change (Forward)	0.012	0.014		
Assist Change (Midfield)	0.004	0.011		
Goal Change (Forward)	0.059	0.009		
Goal Change (Midfield)	0.008	0.009		
Assist Increase Dummy (Forward)			0.018	0.124
Assist Increase Dummy (Midfield)			0.078	0.095
Goal Increase Dummy (Forward)			0.058	0.125
Goal Increase Dummy (Midfield)			0.024	0.0944
Fixed Purchasing Team Effects	Yes		Yes	
Fixed Selling Team Effects	Yes		Yes	
Fixed Purchasing Window Effects	Yes		Yes	
N=441				
Adjusted R-Squared		.64		.64

[26] Data from STATS LLC. Copyright 2016.

VII. OVERALL CONTRIBUTION AND FURTHER EFFECTS

The regression model built gives fans, players, clubs, and the media a better picture as to what certain players are worth in today's market in the English Premier League, a study that has not been publicly completed before. In the base OLS regression model we see that goals, assists, age, and minutes played have a positive coefficient and are statistically significant, while age-squared has a negative coefficient due to the fact that players hit a performance peak in their late twenties. We see that a superstar effect is evident in the soccer market, as goals scored by forwards are worth more to a player's transfer value when they are scored by elite players, rather than average players. While the study explains much of the variation in transfer fees of English Premier League players, it is missing a popularity factor to compensate for the popularity of a player. As the sport has become more global over the past ten years, and can now be easily seen on television in countries such as Chia, India, and the United States, I would imagine that popularity matters more than ever to give teams a boost in merchandise sales and television ratings. With more time, analyzing the popularity of a player should be beneficial in determining transfer values of players, but the model at the current state illustrates the impact of on-field performance on the transfer value of outfield players.

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