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The Marquee effect : a study of the effect of designated players on revenue and performance in major league soccer

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The Marquee Effect: A Study of the Effect of Designated Players on Revenue and Performance in Major League Soccer

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Introduction

Since its formation in 1994 Major League Soccer (MLS) has slowly been gaining the momentum to reach a level of recognition similar to that of the top four sports leagues in the United States – the National Football League, the National Basketball Association, the National Hockey League, and Major League Baseball. Major League Soccer (MLS) is the top tier professional soccer league in the United States, one of only two leagues to reach that status and the only soccer league to sustain long term success.[1] Made up of nineteen teams across the United States and Canada, the MLS is structured much differently than the other leagues both within the United States and internationally. It exists as a single entity model, meaning that the league manages the individual franchises and the players of the MLS. This unique structure has led to the establishment of a comparatively low salary cap. This low salary cap has had a major influence on the development of the MLS since its launch.

Talent and money have been two restricting factors on the growth of the MLS. With a salary cap of $3.5 million the MLS has been limited to the players who are willing to accept salary levels that keep the teams under the salary cap.[2] With no salary cap European, Asian and Latin American clubs spend hundreds of millions on their players. These clubs are able to recruit high level players from across the globe and create talented teams of superstars. Teams in the MLS have not been able to attract the highest quality players from Europe or South America to the less respected and lower paid US League or retain the talented players that develop within the United

[1] The other being the North American Soccer League which operated in the United States and Canada from 1968 to 1984.

[2] Table A in the Appendix includes the increases made to the salary cap in the years 2004-2014. $3.5 million is the number for the 2014 season. This has increased incrementally over the past decade from around 2 million in 2004 to its present value of 3.5 million. Specifically in 2007 when the Designated Player Rule was initiated the salary cap was set at 2.1 million.

States. Rather these highly valued players are lost to the professional leagues of Europe or South America, and the MLS is continually composed of second (or lower) tier players.

In 2007 an adjustment was made to the salary restrictions, in order to make the MLS more competitive on a global market. Teams were now allowed to pay a player beyond the salary cap. A portion of their salary would be charged to the team total and any amount exceeding $400,000 would be paid by the club's owner.[3] Each franchise was allowed to add two of these players, labeled "designated players (DPs)", to their roster; provided they could find the outside funds to do so. This new rule allowed MLS teams to acquire and retain higher-level local players and to attract international players. The Los Angeles Galaxy was the first team to respond - signing international icon David Beckham for the 2007-2010 seasons. More recent signings include Steven Gerrard and Kaká, who have historically been beyond the financial reach of MLS clubs.[4]

The Designated Player Rule has had a twofold effect. As clubs have grown they have had the opportunity to invest in young talented players looking to make a name for themselves in the international soccer community. However, the majority of the players recruited under this rule are seasoned soccer players who have established careers in the sport and have played a number of years in other international leagues. This study will focus on this latter group of players, those who are brought into the MLS and are already well known, with the hope that they will further the success of the team and league. Success is a complicated concept to define, and in the case of

[3] Table A in the Appendix tracks the structure of the Designated Player Rule from its initiation in 2007 through 2014.

[4] Steven Gerrard is a top level British soccer player, playing for both England's national team and for Liverpool, an English Premiere League Team, from 1998 to 2015. In 2015, at age 35, Gerrard signed an 18 month $9 million dollar contract with the LA Galaxy as a designated player. Ricardo Kaká is a professional Brazilian soccer player who has spent his career playing for top level teams Milan and Real Madrid. In 2014 at age 32, he signed a Designated Player contracted to play with Orlando City FC when it was established in 2015.

Major League Soccer and these big name players it is ambiguous whether success is defined on the field or at the box office.

My research will study the "marquee effect" of designated players within Major League Soccer. I am defining the marquee effect as whether these players have a greater impact on team performance or on team revenue: the "performance effect" versus the "revenue effect". In many cases designated players are past their prime playing years. Beckham came to the Galaxy in 2007 at the age of 32 with an ankle injury that was slow to heal and significantly limited his playing time. While the players are no doubt talented, there is a question of whether they truly make a difference in the performance of their team. Most professional soccer players peak in their mid-twenties and retire before they reach the age of 30. Joining a new club at the age of 32 is not a traditional career path. Despite extraordinary skill, players start to lose value on the field as younger competitors become available and exploit the weaknesses that come with age.

However, as players grow in popularity their marketing value can increase. People spend money to buy merchandise with the player's name on it. These players could draw greater attendance at games, expanding the market beyond avid soccer fans, to those who want to watch the big name player take the field. This "star factor" is enticing to clubs and the potential for revenue growth from these players may justify recruiting them, despite the large salary.

Performance and revenue are two major considerations of professional sports teams, and traditionally the two are interconnected. For Major League Soccer, which has struggled in gaining a foothold of popularity in the United States, both are important long term goals. In order to stay relevant, improving the level of competition is necessary so that the MLS can compete with the more popular established sports leagues. Simultaneously the teams are a business with executives, employees, and financial objectives of maximizing profit. Without revenue growth the franchises

and the league cannot continue to operate. Designated players are attractive because of their crowd appeal and consequently the money they have the potential to bring into the club.

The question this paper attempts to address is what is the ultimate objective of these teams? Do clubs sign their designated players with the ultimate goal of improving the team's performance, improving the team's bottom line because of a big name player on the roster, or do designated players help teams achieve both the athletic goal of winning and the business goal of increasing profit?

I will examine the performance records and attendance totals of the MLS teams from 2004 to 2014 in order to study the overall effects of the designated players within the league.[5] I will use the points earned by each team over the regular MLS season as the measure of performance.[6] I will also use average attendance over the season for each team in order to find a preliminary relationship between a team's designated players and that team's overall average attendance. Revenue will be estimated in an additional equation where attendance and designated players will be used as an independent variable.[7] With an analysis of the data a relationship between attendance and revenue can be established and allows me to indirectly estimate the influences that DPs have on seasonal revenue.

Based on the literature and personal knowledge of the sport, I believe there will be a large effect of DPs on MLS team revenue. Similar to the findings of Jane (2014) in the case study of

[5] Because of their business structure Major League Soccer franchises are not required to publish revenue data. This lack of data complicates a direct study of the relationship between designated players and team revenue. In order to develop an equation to estimate revenue, I will be performing the secondary regression to discover the relationship between attendance and revenue using data collected and published by Forbes in 2008, 2013, and 2015.

[6] Using each team's MLS regular season record – three points awarded for a win, one for a tie, and none for a loss.

[7] Due to the characteristics of the MLS as a smaller league within the United States, ticket sales make up a large share of revenue. Thus attendance can be used as the major factor contributing to total revenue. It can also be considered that the share of attendance revenue in total revenue is relatively proportional across the different clubs allowing for a single equation to estimate total revenue in the years where data is not provided.

NBA teams, players who are popular increase demand more than players who perform well; that is fans are enticed to attend a game more by the chance to see an iconic player than to see a team perform well. Thus the coefficient on designated players in relation to attendance will be large and significant.

Much of the literature studied introduces the idea that the presence of DPs on a team may decrease team performance. It is a logical extension that team performance will not suffer and improve as a result of DPs because of the skill they offer, but the overall effect on team performance will be small. Support of this hypothesis would show a coefficient that while positive will not be statistically significant as a variable.

Literature Review

Studies of marquee players and the relationship to performance and/or revenue is a topic that has been heavily discussed in the field of sports economics. Sports teams/leagues function differently from the traditional business model, in that they are not pure profit maximizers – "playing success is the *objective* of all the relevant participants in the club – directors, shareholders, managers and supporters' clubs. However, divergent interests and, therefore, conflict may arise over *financial constraints*."[8] With the limited amount of money available to a team and the high salary cost of holding such a player, the pros and cons of marquee players is constantly under debate. A team's roster is one of the few things it can control when going into competition; thus it is important to understand the effects of roster restrictions on team objectives.

The question of what contributes to a soccer team's objective function is addressed in the works of Sloane (1971), and Garcia-del-Barrio and Pujol (2007). Each established that utility is a

[8] "The Economics of Professional Football: The Football Club as a Utility Maximiser," Peter Sloane, pg. 135

function of both athletic success and financial stability. Sloane analyzes the English Football League studying the presence of economic activity of the league as well as the organizational characteristics. Sloane addresses the presence of star players and the paradoxical cycle of purchase of these high level players and balance of maintaining a competitive league. He finds that the traditional profit goal of a business enterprise "exerts a smaller influence on behaviour" (p. 145) as team utility is not solely based on maximizing profits but also playing success, average attendance, the health of the league, recorded profits, minimum after tax profits, and taxes. Garcia-del-Barrio and Pujol focus their research on Spanish Soccer Players and the professional leagues in Spain. They create a model which estimates what number of players with superstar abilities will be hired in order to maximize superstar inputs. This allows them to then study the relationship of monopsony rents within the league and the superstar players who benefit from this characteristic of the league. Garcia-del-Barrio and Pujol define utility as related to the potential playing success of a team which is a function of the amount of talent hired, the proportion of average skill on the team, and a binary variable which accounts for individual team characteristics. Using variables representative of the salaries, revenue-generating capabilities, superstar capabilities, and individual characteristics of each player in the Spanish professional soccer league for the season 2001/2002 the authors concluded there are two labor markets in professional soccer – a market for super stars and another for ordinary players. Their analysis goes further to indicate the existence of monopsony rents which are paid out by the ordinary players and used to reward the superstars. This explains the limited profits of the soccer teams as the superstar players, not the teams, are the ones who benefit from the monopsony rents generated by the organization of the league.

In the current literature there are two major branches of the analysis of "marquee" players – studies focusing on the effects of player salaries on performance and those that focus on the

effects of marquee players on attendance. Some research also expands upon this to consider the relationship between high-performing players and game attendance. Much of this research focuses on the costs and benefits of star athletes. All sports leagues contain iconic players and top-level performers. And with the data and information that is easily available today, the impact these athletes have on games and on the league can be measured.

Part of being a designated player in the MLS is the high salary that comes with this status, and DPs are paid well beyond what the majority of the team makes. Kuethe and Motamed (2010) study the wage determination of players within Major League Soccer. Specifically focusing on how the presence of players of "superstar status" affects the wages of the players across the entire roster. Kuethe and Motamed discovered that while salary is a function of individual performance, experience and reputation, being a designated player "yields a 928% wage premium" (pg. 575) over the average player. Studies have shown that this disparity among player salaries can lead to reduced team performance. Frey et al. (2013) observe this pay-performance relationship in a study focusing on players in the NBA and the German Bundesliga. The authors measured both the pay and performance of the athletes in these two leagues, concentrating on the relative income level of the players in relation to the rest of their team. It was determined through their research that personal performance is directly and negatively related to relative salary level.[9] Soccer is a team sport and a poor performance by a single individual directly influences the performance of the team as whole. Understanding that relative pay can adversely affect team performance is valuable if the purpose of a team is to maximize success. Sonntag and Sommers (2014) and Coates et al. (2014) each find that unequal salary distribution affects team performance in Major League Soccer. In the former, Sonntag and Sommers observed the effects of the designated player rule on

[9] The Bundesliga is the top tier German Soccer League.

the probability of a team winning over the 2011 and 2012 season. By computing a GINI coefficient representative of salary inequality on the team, the authors observed that increased inequality leads to decreased probability of winning. The latter study, Coates et al., observes points as a function of the total wage bill, the wage bill distribution, and goals scored per game over the season in the MLS. With the purpose of studying the relationship between production and the salary structure of the team with a special focus on superstars in the MLS, Coates et al. observed that the size of the wage bill and the wage inequality of a team oppositely affect the success of a team, with the final effect dependent on the size of the franchise. Each of these studies observe that when the distribution of team salaries becomes more unequal the performance of the team suffers. The presence of a single designated player significantly increases the wage disparity between players on an MLS team; and most teams have more than one player of this designation on their roster creating an even more unequal spread of salary amongst the team.

The other half of the literature is addressed in research by Jewell (2015), Lawson et al. (2008), and Jane (2014). Each of these authors examines the effect of star players on attendance. Attendance is one of the key indicators of revenue for a sports team, ticket sales make up a large portion of the money that a team makes over the course of a season. Jewell (2015) was able to measure the cumulative effect of designated players on attendance by studying attendance records in the MLS from 2007 to 2012. Jewell considered both home and away attendance in order to observe the full effect of each designated player on game attendance. He determined that having designated players increases game attendance, but with diminishing returns as the novelty of their presence wears off. Lawson et al. (2008) similarly approached the topic by focusing solely on David Beckham and the effect that he had on the 2007 season in sales and attendance across the entirety of the MLS. They found that Beckham's presence positively affected both. Beckham's

presence within the MLS increased both sales and attendance when the MLS was considered as a whole. They also looked at Beckham's contribution to his team, the LA Galaxy. Lawson et al. were able to determine that the increased profits that Beckham brought in covered six times the $400,000 reserved for him out of the salary cap. This presents an interesting perspective as one must simultaneously consider the impact Beckham had on the league as well as his team. It is possible that the final results of the "Beckham Experiment" would not equally (or even positively) affect both the MLS and LA Galaxy. Jane (2014) investigated attendance in the NBA surrounding the presence of both high performing athletes and those considered the most popular. Similar to the work of Jewell, Jane concluded that star players did increase attendance, with the demand being driven by the popular players rather than the high performing athletes.

Counter to the results of these studies, authors Berri et al. (2004) determined that in the NBA people were drawn to competitions because of the desire to see a good game rather than the presence of a star player. Through their study of gate revenue at NBA games, Berri et al. rejected the idea that star players are the driving force of revenue in the NBA.

My research advances the literature because it simultaneously studies both performance and revenue in Major League Soccer. Previously the literature has often limited itself to one of the two topics - performance or revenue. By looking at the results side by side from the same data I can examine the effects simultaneously in both outcomes. I also consider designated players and the subsequent data in the MLS into 2014. This is significant because 2013 was the first year in which each team in the MLS had at least one designated player on its roster. Including these more recent years allows the study to reach across each of the MLS teams and reflects the effects of designated players on each of the distinctive teams. By defining all players ever labeled as a designated player as marquee players I expand the sample of star players used

in previous literature. Additionally, when studying designated players in the MLS, few authors have used the entire list of players; rather they have limited the group of players they study (Lawson et al. (2008); Jewell (2015)). Having a greater number of observations will allow for more precise results measuring the effect of designated players as a whole rather than a selective group. The players that Jewell (2015) considers include solely the most recognizable players and Lawson et al. (2008) only study the influence of Beckham. The group of designated players as a whole includes many other players who exhibit different characteristics than those previously studied. The designated player rule has now been in effect for eight seasons, it has adapted and evolved over this time period. These changes have created a different culture of designated players than those inaugural players in 2007. This would allow for the effects of all designated players considered to be different than the impact of solely the most notable names.

Theoretical Model

In most for profit contexts, profit maximization is the assumed firm objective. Sports franchises, however, often have connecting objectives of profit maximization and on field success. Without success in both of these categories the club will be disbanded because of the inability to pay for players or lack of competitive contribution to the league. Major League Soccer clubs face these goals simultaneously and thus the objective function of the franchise is not only a function of profit, but also is affected by performance and other athletic characteristics.

Peter Sloane addressed the utility of the club in his study of the English Football League in 1971. Sloane introduces the concept of soccer clubs as utility maximizers rather than solely profit maximizers. The presence of management individuals that are focused on performance and monetary success leads teams to decisions that address both of these categories. Both good results

and high attendance are needed in order for a program to continue (or establish) success. Sloane adapts O. E. Williamson's (1963) utility maximization model to represent the function of a soccer club: [10]

(1) $$U = u(P, A, X, \pi_R - \pi_0 - T)$$

subject to $\pi_R \geq \pi_0 + T$

where P = playing success
A = average attendance
X = health of the league
π_R= recorded profits
π_0= minimum after-tax profits
T = taxes

Considering playing success and average attendance, in addition to profits when constructing the utility function yields different predictions that than of profit maximization. Utility maximization of this model suggests why clubs focus on maximizing their playing success while also addressing club profits.

Sloane's utility function can be expanded using the research produced by Pedro Garcia-del-Barrio and Francesc Pujol in their study of the Spanish professional soccer league. They also address the idea that a team's utility is not solely focused on profit maximization but is rather based around playing success:

(2) $$U_n = U\left(\frac{\sum A_i^*}{N}, S_n, \varphi_n\right) \quad \forall\, n = 1, \dots, N$$

where $\frac{\sum A_i^*}{N}$ = the proportion of all kinds of ordinary skills that corresponds to each team
S_n= the amount of superstar talent hired
φ_n = team characteristics and peculiarities
n = number of teams

[10] Williamson, O. E. (1963). Managerial Discretion and Business Behavior. *American Economic Review*, Vol. 53, 1963.

In this model the playing success and ultimately the utility of a team is based upon the superstar talent it is able to afford, as well as how much ordinary skill they have in relation to other teams. Garcia-del-Barrio and Pujol assume that there is a positive relationship between superstar inputs and the utility. This leads to the idea that equation (2) can be maximized by increasing the number of super star players the team is able to hire (S_n). But it must also be considered that teams want to avoid running any long term financial deficit. From this assumption Garcia-del-Barrio and Pujol adjust their optimization model in order to address profits. The following constraint on utility maximization acknowledges this secondary focus of the team:

(3) $$\prod_n = \alpha_n\left(\frac{S_n}{S^*}, \varphi_n\right) \cdot \prod_{ind}^{A} + E_n(f(S_n), m(S_n), \varphi_n) - (ws^f \cdot S_n + ws^m \cdot S_n) \geq 0$$

where S_n, φ_n, n = the same as above
$\alpha_n(\cdot)$ = proportion of earnings that correspond to each team
$\frac{S_n}{S^*}$ = the special talents hired by the team with respect to the total *special* abilities in the league
$E_n(\cdot)$ = additional source of revenue
$\prod_{ind}^{A}$ = total revenues generated by the whole league
ws^f = rewards of player performance contribution for superstar players
ws^m = payments associated to merchandizing activities for superstar players

Within equation (3) φ_n is considered exogenous and the assumption is made that all extra profits are spent on superstar talent. The first element of equation (4) estimates the portion of the profits achieved by the industry as a whole that corresponds to each particular team. The second element measures the level of revenues that can be attributed to attendance and the level of support that each team draws from its fans, values dependent on individual team characteristics. It is obvious from the work of Garcia-del-Barrio and Pujol that a team's utility function is based on performance and maximized subject to the revenues of the team.

Each of the two utility models addresses the presence of both performance and revenue as a contributor to maximizing utility and thus a focus for a team. A simpler model can be developed from the previously discussed models. An additively separable objective function takes into consideration both profits and performance as contributors to a team's utility, while acknowledging the limiting nature of the salary cap that is imposed on MLS teams.

(4) $$U = \alpha \prod + \beta P$$

subject to the *salary cap*

where $\prod$ = Revenue – Cost

P = Points

Creating an additively separable model allows for teams to address profits and performance separately. While it might be possible for teams to maximize their objective function in this manner, from Sloane it can be seen that doing so could lead to the termination of a program because of the limited success in the other category. Additional the salary cap is a function of the marginal factor costs of each player (their salaries), where for each designated player only $400,000 of their salary is counted into this amount.

(5) $$salary\ cap = \sum_{i=1}^{n} MFC_i - (MFC_{DP} - Price_{DP})$$

where MFC_i = the marginal factor cost of player i

$MFC_{DP} - Price_{DP}$ = the portion of the DP's salary counted into the salary cap

n = the number of players on the team's roster

This equation addresses the relationship of the individual costs of each player and how as a whole each marginal factor cost as well as the price of a designated player plays into the salary cap which acts as a restriction on the team's utility.

From a profit side of the objective function (equation (4)) a team will sign a player so long as the marginal revenue product of that player is greater or equal to the marginal factor cost, or

salary, of that player. We consider two relationships that lead to increased revenues; an increase in points which leads to increased attendance which then increases revenue and the direct relationship between increased attendance and greater revenue. The influence of designated players on performance and attendance are important because of the implications. These players cost a great deal to the teams that sign them, if their marginal revenue product is not greater than the marginal factor cost to the team, then the team's profit will decline.

The other component of the objective function addresses the performance of a team. Players contribute to a team in different amounts, a factor which could be considered their marginal points. This contribution must be weighed against the cost of that player. A team then signs players with the highest marginal points subject to this salary constraint. This again addresses the cost of a designated player. If these players are not contributing to performance enough to balance their high cost, then utility will suffer rather than increase when these players are signed to the team.

Econometric Models and Methods

The models for performance and attendance express the dependent variables as functions of each team's wage bill, the GINI coefficient for the team salaries, and the number of designated players on a team.[11] Performance and attendance will also be affected by the characteristics of the season (year) and the team. The performance of the team in the current year as well as the previous year will be considered as an additional contributor to attendance. There will also be a binary variable included to indicate whether it is the inaugural season of a team as this will be a factor that contributes to performance. Two Ordinary Least Squared Regressions will be performed to

[11] A GINI coefficient is an economic measure of inequality. It is the area between the linear function of equal salary and the true salary values of the team. The greater the inequality the larger the GINI coefficient will be.

determine the coefficients of the two equations. This will test the proposed relationship between the independent variables and the dependent variables of performance and attendance. The estimated regressions of the points and attendance of each team will be based on the following forms:

$$(6) \qquad Pts_{it} = B_0 + \underset{(+)}{B_1 WB_{it}} + \underset{(?)}{B_2 GINI_{it}} + \underset{(+)}{B_3 DP_{it}} + \underset{(-)}{B_4 FY_{it}} + \theta_i + \gamma_t + \varepsilon_{it}$$

$$(7) \qquad Att_{it} = \delta_0 + \underset{(+)}{\delta_1 WB_{it}} + \underset{(?)}{\delta_2 GINI_{it}} + \underset{(+)}{\delta_3 DP_{it}} + \underset{(+)}{\delta_4 Pts_{it}} + \underset{(+)}{\delta_5 Pts_{i,t-1}} + \theta_i + \gamma_t + \varepsilon_{it}$$

Where Pts_{it} represents the points of team *i* in year *t*, Att_{it} represents the average attendance of team *i* in year *t*, WB_{it} represents the wage bill of team *i* in year *t*, $GINI_{it}$ represents the GINI inequality coefficient of the player salaries of team *i* in year *t*, DP_{it} is the number of designated players on team *i* in year *t*, FY_{it} is a binary indicating if it is the first year the team is playing, $Pts_{i,t-1}$ exists as a lag variable for the performance of team *i* in the previous year (*t*-1), θ_i exists to carry the fixed effects of team *i*, γ_t carries the time effects of year *t*, and ε_{it} is the error term.

Over the course of a season a team claims points based on the final result of each game they play; that is three points for a win, one for a tie, and zero for a loss. The total number of points across the season will be used as the measure of performance. The other dependent variable will be attendance. Attendance will be collected as a seasonal average of the total game attendance for each team from the posted match reports following each game.

The wage bill for each team will be measured as the total of the guaranteed compensation values for each player. Guaranteed compensation values for the year are used rather than the player's base salary because the total compensation often exceeds the base salary values. The total guaranteed compensation salaries are more representative of the total amount the teams are responsible to pay out. Using these values also leads to a GINI coefficient that is a better

illustration of the true inequality in player-to-player salary as some players receive generous additional compensation while others receive very little, if anything. One would assume that more money spent on salaries would indicate a better team with better players (all around not solely DPs). Therefore, in the points regression it is expected that the wage bill would produce a positive coefficient. One would expect to see similar results in the attendance equation for the same reasons as points.

It is important to consider the effect of inequality in wages of the team salaries as there is evidence relating performance and salary distribution. The GINI coefficient for each team's player salaries will be used to represent this. The standard deviation of the salary was also considered as a factor rather than the GINI coefficient to represent the inequality of wages. However, the correlation between the salary standard deviation and the other variables was considered too significant to include that factor.[12] Despite this high correlation the standard deviation of player salaries was included in some of the equations in place of the GINI coefficient so that the relationship between this measure and points and attendance could be observed. Much of this literature finds that increased salary dispersion leads to poorer team performance.[13] If this is the case, it might be that as teams pick up designated players they end up hurting the performance of the club. Using this information it is difficult to determine the sign of the coefficient on the GINI variable in either regression.

The final common factor between the two equations is the number of designated players on the roster. The sign, significance and magnitude of these coefficients is the focus of the

[12] Table B in the Appendix includes the correlations between the wage bill, number of designated players, wage GINI and salary standard deviation variables.

[13] Sonntag and Sommers (2014) and Coates et al. (2014)

hypothesis. Excluding the years 2004, 2005, and 2006 when the rule was not in effect, the number of designated players per team ranges between zero and three.[14] As stated earlier there would potentially be a positive coefficient but not a statistically significant effect of the number of DPs on a team's record and points. Yet, due to the popularity of most designated players and the draw of seeing them in person there should be a positive and significant coefficient of DPs on attendance.

The attendance equation also considers the performance of the team in the previous season. Teams will likely gain fans following a year of success or lose fans if they produce a poor performance. The effect of a team's historical performance will be measured by this lag performance variable. This will most likely result in a positive and statistically significant coefficient on the lag points variable as well as the points variable as successful teams draw bigger crowds to their games.

Considering whether this is the first year a team is playing is also important. New teams rarely produce a successful first season as they work to build their team and their franchise. The effects of being a first year team can only be considered in the points regression because the lag variable in the attendance equation eliminates all first year teams from the sample. The coefficient on the binary will be negative and significant because a team will produce fewer points in their first season.

It is necessary to include team and year binary variables in the model because of the unique characteristics of each team and season. The team binary variable controls for differences in city demographics that can contribute to the success of a team in building a fan base.[15] The year

[14] Table C in the Appendix Lists the number of Designated Players on each team for each year from 2007 to 2014.
[15] Contributing differences between cities to MLS teams would be the make-up of the population, economic stature of the city, other professional sports teams that exist in the area, and existing soccer youth development programs.

dummy variable will cover the characteristics of the league that change year to year as well as outside factors.[16, 17]

From the estimated coefficients (B_i and δ_i) both the statistical significance and the economic significance of each of the variables will be observed. It must be taken into consideration that there is a possibility that the overall effect of a variable, though statistically significant, does not have enough economic weight to be observed as a contributing factor in the study.

Following the completion of the previous regression and study of the generated coefficients and information the significance of the relationship between attendance and team revenue will be tested. For three years Forbes Online has estimated MLS team revenues based on their own research. These years include the 2007, 2012, and 2014 MLS seasons and values for each of the teams active in that year. Using these data, as well as the attendance data an equation will be estimated to represent this relationship.[18] This will require another use of an OLS regression. This equation will be applied to the remainder of the attendance data in order to estimate the effect of the designated players on revenue.

(8) $$Rev_{it} = \alpha_0 + \underset{(+)}{\alpha_1 Att_{it}} + \underset{(+)}{\alpha_3 DP_{it}} + \theta_i + \gamma_t + \varepsilon_{it}$$

In Equation (8) Rev_{it} represents the total revenue of team i in year t, and Att_{it}, DP_{it}, θ_i, γ_t, and ε_{it} represent the same elements as in the earlier equations. From this equation the relationship

[16] For example from 2004 to 2014 the league has changed the number of games played in a season.

[17] Outside contributors could include whether the MLS season coincides with a World Cup tournament year. In a season where the World Cup takes place teams that have international teams players on their roster will lose them to preliminary international matches and have to give them a rest period following the tournament before they return to MLS play. Players that play on their national teams are often also under Designated Player status.

[18] Forbes Revenue Data Summary Statistics contained in Table D in the Appendix.

between attendance and revenue and indirectly the relationship between designated players and team revenue can be identified. It is expected that the effect of attendance on revenue will be positive because the more people that attend an event the greater the revenue from that event will be. It would also be expected that the number of designated players a team has would also positively affect revenue because the reputation and popularity of these players allows them to bring in money for the team outside of game attendance.

There are a number of potential additional influences that DPs can have that are not being considered in this research. The variables chosen provide a lower bound estimate of the effect of designated players. No positive future outcomes from signing these big name players are being considered. By limiting the study to the factors that are more directly related to designated players only the most conservative effects are displayed. Due to this limitation there is potential for other gains for clubs and Major League Soccer as a whole that are not addressed in this paper. For example these may include increased merchandise sales that contribute to revenue.[19] The exposure teams receive nationally may increase the MLS fan base leading to greater sales in the future as well as demand for higher performing U.S. players. The global recognition gained from signing big name international players could help a team recruit better players in the future.

These are interesting topics to pursue but they exist outside the scope of the objective for this research. The focus of this research is to study whether the ultimate goal of these franchises in signing designated players is that of a winning sports team, or that of a profit making business. In order to observe the significance of these players the study's model must be simple and straightforward.

[19] As earlier mentioned, Major League Soccer is not a large league and much of their revenue is derived from ticket sales. This reason, along with the lack of revenue data, is why I am not including merchandise sales in my research.

These regressions test the value of the marquee player. The effect of the presence of DP players on performance and on revenue can be observed and measured. From this research on MLS teams it can be predicted whether they hire designated players in order to improve team performance or if the ultimate goal is to increase team revenue.

Data

I have collected panel data covering the individual variables for each team active in the years from 2004 to 2014. This information was obtained from the MLS league website as well as the respective team websites.[20] The MLS expanded from ten teams to nineteen over the period from 2004 to 2014. Table E lists the teams in the sample and the years in which they are active. All nineteen teams were not formed until the 2012 season.[21]

Summary statistics for the data are presented in Table F.[22] Due to the nature of the data each statistic is organized in a panel format. In total there are 167 observations over the eleven year period. In order to simplify the summary I have taken the panel as a whole in calculating the following values rather than measuring across a year or a team.

Each of these values comes from team data from the end of the season. This is after all trades have been made and rosters are finalized for the championship tournament at the end of the season. In the summary statistics total guaranteed compensation and attendance are measured at their whole value, in the regressions they are adjusted to units of 1000 so that the regression results would produce more manageable values. Revenue is also measured per million dollars for each team.

[20] www.mlssoccer.org or www.mlsplayer.org
[21] Table E is presented in the Appendix

[22] Table F is presented in the Appendix

The number of designated players for each team lies between 0 and 3. The first year that each team had a designated player was 2013, during the 2014 season each team also had at least one designated player. LA Galaxy and the New York Red Bulls are the only two teams to roster at least one designated player each year following the creation of the Designated Player Rule. Montreal Impact and the Portland Timbers each had a designated player every year following their founding years, 2012 and 2011 respectively. There is an average of 27 players on each roster over the eleven seasons from 2004 to 2014. Additionally there was an increase of $2.5 million, from $1.9 million to $4.3 million, on average spent in salaries from the time period before the Designated Player Rule was implemented (2004-2006) and in the years following (2007-2014).

Results

These models were estimated using three fixed effects regressions, one each with points, attendance, and revenue as the dependent variable. Table G, Table H and Table I report the results of the regressions.[23] The results for the binary variables representing the years and the individual teams were not included in the results table in order to highlight the important variables under consideration.

The first variable placed under consideration was performance using the points accumulated over the season as the dependent variable. Multiple regressions were performed using a combination of the total number of designated players, total guaranteed player salaries, the GINI coefficient on player salaries, the team standard deviation on salaries, the founding year binary, as well as time effects and fixed effects for the individual teams.

[23] Table G, Table H, and Table I are available in the Appendix

Under these regressions, total guaranteed player salary and founding year proved to be significant variables each time at the 99% level. These were the only two variables that proved to be consistently significant regardless of the other variables included in the regression. This indicates that for every additional $100,000 a team spends on their wage bill a team can be expected to improve their season results by two points (or 1 point under the second regression). The coefficient on founding year indicates that a first year team would produce on average 11 fewer points than a veteran team, a result that would be expected giving the new team has no experience in the league.

In the case of each regression the coefficient on the number of designated players is negative and in every case the coefficient is insignificant. Across each of the regressions the results produced are consistent regardless of changes in the variable also included in the estimation. This indicates designated players have an adverse, albeit insignificant, effect on team performance.

The R square value for these regressions all lie between 0.315 and 0.383. It can be understood that the variables included in this regression only explain about 35% of the variation in points. Thus there must be a number of other factors that determine the success of a team that have not been considered in this regression. This could be as simple as team chemistry or the strength of their schedule to the more complicated influences such as player injuries or coaching dynamic, these variable would be much more difficult to capture and measure as contributors to team performance.

The second regression considers the relationship between designated players and attendance. Multiple regressions were performed using total number of point, the points of the previous season, total guaranteed player salaries, the GINI coefficient on player salaries, team standard deviation of salaries, as well as time effects and the team fixed effects.

Across the four regressions the coefficients on the total number of points for the season and the previous season's points were consistent, at the 99% level and 95% level respectively (excluding the fourth regression where the previous season was only significant at the 90% level under a one-tailed test). The coefficient on points of on average 0.077 indicates that each additional point gained in a season would increase average attendance by around 77 people. An additional point in the previous year would increase attendance by around 40 people. Similarly, the coefficient on GINI wage coefficient, shows that a 0.1 increase in wage inequality increases attendance by 835 people and is also significant at the 99% level in the fourth regression. Team standard deviation on salaries is included in the third regression and significant at the 99% level. The coefficient of 0.004 means that an increase of one standard deviation would increase attendance by 400 people. Total guaranteed player salaries was not consistently significant across the regressions but in the cases where the coefficients are significant they are negative, indicating that an increase in total guaranteed salaries causes attendance to decrease.

In the case of designated players the coefficient on the variable is both negative and significant when wage inequality is also considered as a contributing factor (regressions three and four). In each of the final two regressions the coefficients are significant at the 90% and 95% levels and contrary to what was expected the data shows that the presence of one additional designated player would decrease attendance by 381 and 569 people, respectively. This could be because the diminishing returns of a designated player playing for multiple years was not considered, an idea introduced by Jewell in his 2015 study of MLS attendance and designated players.[24]

[24] Jewell, R. Todd. 2015. "The Effects of Marquee Players on Sports Demand: The Case of U.S. Major League Soccer." *Journal of Sports Economics* 1–14.

This regression produces as R square values that ranged between 0.893 and 0.903. In the final regression which was most representative of the relationship of the considered variables it can be understood that 90.3% of the variation in attendance can be explained by changes in the included independent variables. This would indicate that performance (points) is a significant contributor to game attendance. The exceptionally high R^2 value can also be attributed to the team fixed effects and year effects which, in many cases, are also significant contributors to team attendance records. Understanding the significance of points on attendance is important for future analysis because of the insignificant effect that designated players have on points and performance as seen in the results above.

The final regression studies the effect of attendance on revenue. Using the average season attendance (adjusted to per 1000 people) and the revenue data published by Forbes it was determined that the coefficient on attendance was positive and significant at the 99% level. Each additional thousand attendees increased a team's revenue by $970,000. This regression also ended up with an R square value of 0.955 signifying a very positive relationship between changes in attendance and those in revenue, as well as the fixed team effects and year effects.

An additional regression was run including the number of designated players as a contributing variable to revenue. This was performed to study the affect that designated players have on revenue separate from their influence on attendance. Under this estimation average attendance was still significant at the 99% level. The number of designated players were significant at the 90% level when considered under a one-tailed test. The coefficient of 0.992 indicates that an additional designated player will increase revenue by $992,000, all other factors held constant. This is a significant increase in revenue per player, especially when considering the limited influence that designated players have on attendance and points. These influences could

come through in categories such as merchandise purchases by fans or potentially sponsorships that are created by the presence of designated players on a team's roster.

The focus of this paper is the relationship between designated players and performance and revenue. From the regression results it seems as though the relationship initially hypothesized is incorrect. Designated players seem to negatively affect both points and attendance. The implications of these results must then be addressed while considering the objective function (equation (4)) that was presented earlier. The theoretical model addresses the marginal factor cost of the designated players as well as their marginal points and marginal revenue product. The negative and insignificant coefficient on the number of designated players in the first set of regressions indicates that designated players have little to no effect on a team's performance. This would equate their marginal points to that of an average player on the team. This weighed against the high cost of the player does not justify the signing of that player to the team's roster. Additionally the positive effect of points on attendance and negative effect of designated players on attendance, where attendance has a significant and positive effect on revenue addresses the idea that designated player do not effect revenue through either of these categories. Rather the marginal revenue product of designated players is solely influenced by what seems to be external elements. It must then be addressed whether these designated players have a marginal revenue product high enough to offset the marginal factor cost.

An estimation of a designated player's marginal revenue product can be made using the results of the regressions. The third regression introduces the idea that designated players increase revenue by $992,000 through external factors. This can be weighed against their effects on performance and attendance using the following equation.

(9) $$MRP_{DP} = 992{,}000 + (-569 * 1005) + (-1.688 * 80 * 1005) + (-1.688 * 31 * 1005)$$

The first portion of equation (9) comes from the effect of designated players on revenue. The second part comes from the effect of designated players on attendance and the subsequent effect of attendance on revenue. The third and fourth measure the influence of designated players on points, the effect of points and lag points on attendance respectively, and finally the effect of attendance on revenue. This calculation takes into consideration all the different avenues through which designated players affect the final revenue of a team. The final value of equation (9) comes out to only $231,850. This is a total well below the average designated player salary of $1,802,343, the average marginal factor cost of these players. The model objective function introduced earlier in this paper presents the condition that franchises only sign designated players if their marginal revenue product is greater than or equal to their marginal factor cost. Equation (9) shows that this is not the case for designated players in the MLS today. These players are being paid beyond the additional revenue that they are bringing into the teams that they play for. The costs of these players far outweigh the benefits that they bring to their franchise.

Robustness

The relationship between designated players and performance/attendance/revenue was further examined through three alternative methods of measuring the presence of designated players[25]. Performing these additional regressions would allow greater consideration for the unique values of the designated players rather than considering each player identical. By addressing interactive effects as well between designated players and the teams they play for the differences that the presence of these players have for their individual teams can be observed rather than relying solely on the fixed team effects to capture these differences.

[25] The Summary Statistics for the variables used in this further study are presented in Table J.

The first addressed measuring designated players as a total amount of salary spent on these players rather than the number of designated players on the roster. This is valuable consideration because there are some designated players who are being paid only just beyond the $400,000 allotted to the salary cap and there are some who are paid five or six times this amount. This is a wide range of designate player salaries which also might reflect the skill and/or "star" quality of the players the teams are signing. By measuring the total amount being invested in these players rather than solely their presence, the relative value in comparison to their cost can be taken into further consideration.

Two sets of fixed effects regressions were performed for each performance and attendance – the first just adding the summation of the designated player salaries and the second using this variable to replace the variable accounting for the number of designated players on each team's roster.[26] In each of the regression where performance was the dependent variable the results were consistent with those produced previously. The founding year binary variable and the total guaranteed player salaries remained statistically significant across each of the regressions, and the number of designated players on a team remained generally insignificant when it was included in the regression. There was only one case where the wage bill of the designated players was significant and this was when there were not measures of salary or inequality included in the explanatory variables. Additionally in these regressions the coefficient on designated player wage bill was not consistently positive or negative, indicating that the true effect of this variable on team performance cannot truly be observed under these circumstances. These results were similar when the DP wage bill was also used in place of the number of designated players. Overall there were no changes to the results when this variable was included in the analysis.

[26] The results of these regressions are available in Tables K, L, M and N in the Appendix.

When the designated player wage bill was included in the regressions where attendance was used as the dependent variable the results mimicked those presented earlier. Points, lag points, and wage inequality remained statistically significant and the number of designated players produced a significant and negative coefficient in one of the regressions. The wage bill of the designated players was significant in two of the cases, though there is not strong economic significance in these situations – it would take an additional $1 million spent on designated player wages in order to bring an additional 250 fans on average to a game. The coefficient on designated player wage bill was also not constantly either positive or negative, a characteristic which indicates that the true impact of this variable cannot be accurately measured.

The variation made in the regression with revenue as the dependent variable was the creation of three addition binary variables reflecting the presence of a first, second, and third designated player on a roster.[27] This was developed in order to observe the independent effects of each of the players on the revenue of a MLS franchise. These binary variables allowed for the number of designated players on a roster to have a stepwise effect on revenue rather than each being considered to have the same impact of team revenue. When these variable were included attendance remained statistically significant at the 99% level but none of these additional variables were significant in the regression. This indicates that there is no specific player that is significant in adding to a team's revenue through out a season – it is not the first or the second or third that makes a difference in the long run for franchise revenue.

A third regression was run to observe the interactive effects between designated players and the individual teams. In this regression the explanatory variables included were average seasonal attendance, the number of designated players, the number of designated players squared,

[27] The results of this regression are presented in Table O found in the Appendix.

the interaction between designated players and team, the team fixed effects, and the year time effects.[28] Under this regression twelve of the nineteen MLS teams produced significant interactive effects with the number of designated players on their roster. The coefficients were all positive and ranged from 10.568 to 36.401. This indicates that designated players at these teams have a positive impact on team revenue bringing more money for each additional designated player that they sign to their roster. This is not the case for every franchise in the MLS; all nineteen interactive effects do not result in significant coefficients. This further examination of the relationship between designated players and revenue suggests that their presence might positively impact some of the teams in the league, but overall does not change the ultimate findings of this paper.

Conclusion

It is undeniable that the best known and most respected teams are those that are both high profiting and high performing. It makes sense that a team's objective would be success in both of those categories and their objective function would be based upon those two factors. The Designated Player Rule in the MLS was created as a method through which teams could hopefully improve upon both revenue and performance. The teams are able to promote international players and raise the expectations of fans. But on the other hand, designated players are an expensive investment. The clubs spend millions on these few players, hoping that their presence will have positive effects.

The results of this paper introduce the idea that designated players do not positively affect either performance or attendance, and through those means do not affect revenue in a positive manner. The objective function is based upon these two factors, profit and performance. Both of

[28] The results of this regression are available in Table P in the Appendix.

which are influenced by a player's marginal factor cost, marginal revenue product, and marginal points. The first, the salary of a player, is given based on the skill and reputation of a player. The latter two are what must be weighed against the first in order to determine the value of signing a player. The results show that the marginal points are not consistent with the cost of a player. Designated players cannot be used as a means by which to improve performance. The results do show that designated players have an external influence on revenue, outside of performance and attendance. In order for the signing of a designated player to be justified it must be established that this marginal revenue produce from the outside sources is greater than the cost. There needs to be a way that these players bring money into the team to offset the cost of their high salaries because they are not doing so through playing success or increased attendance.

When Grant Wahl documented David Beckham's time with the LA Galaxy in his book *The Beckham Experiment*, he discovered similar results. The book highlights Beckham's first two seasons with Galaxy, 2007 and 2008. During this period of time he spent more of his time injured on the bench playing limited minutes than turning Galaxy into a soccer dynasty. Wahl establishes that overall Beckham had little impact on the playing success of the team. His only positive impact came through increased attendance from those hoping to see the legendary midfielder play and merchandise sales, both of which decreased over time as Beckham continued to sit on the sidelines and the shine was lost from his being a Galaxy player.

It can be seen through both the results of this paper and Wahl's account of "The Beckham Experiment" the dual team objectives of performance and revenue are not evenly affected, if at all, by the presence of designated players. This opens up the debate for what positive effects they bring to teams and the league. If it is the hope of Major League Soccer to grow and expand, then it needs to be determined how to use these players as a positive influence for both the league and

the teams moving forwards. The investment into a designated player is a substantial amount and the returns on these players need to be reflective of this investment.

Appendix

Table A: Designated Player Rule and Major League Salary Cap by Year[29]

Year	Salary Cap	Cost of First DP	Cost of Second DP	Cost of Third DP
2004	1.9 million[30]	N/A	N/A	N/A
2005	1.9 million	N/A	N/A	N/A
2006	2.0 million	N/A	N/A	N/A
2007	2.1 million	$400,000	$325,000	N/A
2008	2.3 million	$400,000	$325,000	N/A
2009	2.3 million	$415,000	$335,000	N/A
2010	2.6 million	$335,000	$335,000	$335,000 + $250,000 tax[31]
2011	2.7 million	$335,000	$335,000	$335,000 + $250,000 tax
2012	2.8 million	$350,000	$350,000	$350,000 + $250,000 tax
2013	2.9 million	$368,750	$368,750	$368,750 + $250,000 tax
2014	3.5 million	$387,500	$387,500	$387,500 + $250,000 tax

[29] Most of the information included in this tabled comes from a similar table included in Coates, Frick, and Jewell's *Superstar Salaries and Soccer Success*.

[30]The salary cap for 2004 is assumed to be similar to that of 2005 due to the lack of information on the subject.

[31] The tax placed on the third Designated Player was an amendment to the rule in 2010. This eliminated the option to trade Designated Player spots but allowed teams the third position if they were willing to pay the additional fee.

Table B: Correlations: Wage Bill, Number of DPs, Salary Standard Deviation, Wage GINI

		Wage Bill	Number of DPs	Salary Standard Deviation	Wage GINI
Wage Bill	Pearson Correlation	1	.613**	.899**	.679**
	Sig. (2-tailed)		.000	.000	.000
	N	167	167	167	167
Number of DPs	Pearson Correlation	.613**	1	.510**	.431**
	Sig. (2-tailed)	.000		.000	.000
	N	167	167	167	167
Salary Standard Deviation	Pearson Correlation	.899**	.510**	1	.842**
	Sig. (2-tailed)	.000	.000		.000
	N	167	167	167	167
Wage GINI	Pearson Correlation	.679**	.431**	.842**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	167	167	167	167

** Correlation is significant at the 0.01 level (2-tailed).

Table C: Number of Designated Players on Each MLS Team (2007-2014)[32]

	2007	2008	2009	2010	2011	2012	2013	2014
Chicago Fire	1	1	1	2	0	1	2	1
Chivas USA	0	0	0	0	1	1	2	3
Colorado Rapids	0	0	0	0	0	1	1	1
Columbus Crew	0	1	1	1	1	0	3	1
DC United	0	2	1	2	1	1	1	1
FC Dallas	1	0	0	1	1	1	3	3
Houston Dynamo	0	0	1	1	0	0	1	3
LA Galaxy	1	1	1	2	3	3	3	3
Montreal Impact						1	2	3
New England Revolution	0	0	0	0	1	2	1	1
New York Red Bulls	2	2	1	1	3	3	2	2
Philadelphia Union				0	0	1	1	2
Portland Timbers					1	2	2	2
Real Salt Lake	0	0	0	0	1	2	2	3
San Jose Earthquakes		0	0	1	0	0	1	1
Seattle Sounders FC			1	3	2	2	3	3
Sporting Kansas City	0	1	1	0	1	0	1	3
Toronto FC	0	0	1	2	3	3	2	3
Vancouver Whitecaps					2	3	1	3

[32] Table F begins with 2007 because that is the first year the Designated Player Rule was in effect.

Table D: Forbes Revenue Data Summary Statistics

Statistic	Number of Observations	Mean	Median	Std. Dev.	Min.	Max.
Team Revenue (Rev_{it})	50	22.224	21	10.645	5	50
Team Revenue 2007	13	12.769	10	7.886	5	36
Team Revenue 2012	19	25.484	23	9.625	15	48
Team Revenue 2014	18	25.611	23.5	9.605	13	50

Table E: MLS Club Active Years

MLS Club	Active Years
Chicago Fire	2004 – 2014
Chivas USA	2005 – 2014
Colorado Rapids	2004 – 2014
Columbus Crew	2004 – 2014
DC United	2004 – 2014
FC Dallas	2004 – 2014
Houston Dynamo	2006 – 2014
Los Angeles Galaxy	2004 – 2014
Montreal Impact	2012 – 2014
New England Revolution	2004 – 2014
New York Red Bulls	2004 – 2014
Philadelphia Union	2010 – 2014
Portland Timbers	2011 – 2014
Real Salt Lake	2005 – 2014
San Jose Earthquakes	2004-2005, 2008 – 2014
Seattle Sounders FC	2009 – 2014
Sporting Kansas City	2004 – 2014
Toronto FC	2007 – 2014
Vancouver Whitecaps	2011 - 2014

Table F: Descriptive Statistics

Statistic	Number of Observations	Mean	Median	Std. Dev.	Min.	Max.
Total Number of Designated Players Rostered (DP_{it})	167	1.006	1	1.067	0	3
Total Number of Points (Pts_{it})	167	43.545	43	10.228	16	67
Lag Number of Points ($Pts_{i,t-1}$)	157	43.045	43	9.982	16	67
Total Guaranteed Player Salaries (WB_{it})	167	$3,891,272	$2,983,033	$2,945,282	$847,715	$16, 712, 603
Team Std. Dev. on Salaries ($StdS_{it}$)	167	$242,506	$104,909	$338,176	$32,557	$1,611,533
GINI Coefficient on Player Salaries ($GINI_{it}$)	167	0.45286	0.41247	0.13543	0.29319	0.80390
Average Seasonal Attendance (Att_{it})	167	17,239	16,638	5,589	7,063	44,038
Founding Year (FY_{it})	167	0.0599	0	0.238	0	1
Year (t)	11	2009	2009		2004	2014

Table G: Regression Results – Performance

Variable	Points as Dependent Variable					
R^2	0.315	0.377	0.333	0.385	0.331	0.383
Adjusted R^2	0.163	0.233	0.179	0.238	0.177	0.236
Total Number of Designated Players Rostered (DP_{it})	-0.936 (-0.776)	-1.931† (-1.618)	-1.298 (-1.051)	-1.688 (-1.412)	-1.024 (-0.785)	-1.417 (-1.122)
Total Guaranteed Player Salaries (WB_{it}) [per $1000]		0.001*** (3.663)	0.002*** (2.867)	0.002*** (3.048)	0.002*** (3.394)	0.002*** (3.591)
GINI Coefficient on Player Salaries ($GINI_{it}$)					-13.022 (-1.126)	-13.032 (-1.169)
Team Std. Dev. on Salaries ($StdS_{it}$)			-0.009 (-1.280)	-0.009† (-1.359)		
Founding Year (FY_{it})	-10.795*** (-3.120)	-11.119*** (-3.356)		-11.161*** (-3.379)		-11.120*** (-3.361)

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table H: Regression Results - Attendance

Variable	Attendance as Dependent Variable			
R^2	0.893	0.894	0.901	0.903
Adjusted R^2	0.867	0.867	0.874	0.877
Total Number of Designated Players Rostered (DP_{it})	-0.204 (-0.757)	-0.270 (-0.972)	-0.381 (-1.398)	-0.569** (-2.015)
Total Number of Points (Pts_{it})	0.078*** (3.983)	0.072*** (3.434)	0.077*** (2.794)	0.080*** (3.948)
Lag Number of Points ($Pts_{i,t-1}$)	0.040** (2.056)	0.041** (2.100)	0.046** (2.396)	0.031† (1.609)
Total Guaranteed Player Salaries (WB_{it}) [per $1000]		0.00008961 (0.983)	-0.000332* (-1.950)	-0.000148 (-1.299)
GINI Coefficient on Player Salaries ($GINI_{it}$)				8.349*** (3.291)
Team Std. Dev. on Salaries ($StdS_{it}$)			0.004*** (2.901)	

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table I: Regression Results - Revenue

Variable	Revenue as Dependent Variable	
R^2	0.955	0.958
Adjusted R^2	0.921	0.923
Total Number of Designated Players Rostered (DP_{it})		0.992† (1.393)
Average Seasonal Attendance (Att_{it}) [per 1000 people]	0.979*** (3.719)	1.005*** (3.881)

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table J: Robustness Summary Statistics

Statistic	Number of Observations	Mean	Median	Std. Dev.	Min.	Max.
Wage Bill of Designated Players ($WBDP_{it}$)	133[33]	$1,864,220.25	$650,000	$3,116,680.50	$0	$13,885,000.00
A First Designated Player ($DP1_{it}$)	167	0.56	1	0.498	0	1
A Second Designated Player ($DP2_{it}$)	167	0.26	0	0.442	0	1
A Third Designated Player ($DP3_{it}$)	167	0.13	0	0.339	0	1

[33] These statistics were only taken over the years 2007-2014 after the implementation of the Designated Player Rule.

Table K: Robustness Regression Results – Performance

Variable	Points as Dependent Variable					
R^2	0.386	0.384	0.355	0.380	0.332	0.333
Adjusted R^2	0.233	0.231	0.207	0.233	0.172	0.174
Total Number of Designated Players Rostered (DP_{it})	-1.825 (-1.445)	-1.319 (-1.028)	-2.119* (-1.705)	-1.590 (-1.279)	-0.931 (-0.702)	-1.437 (-1.101)
Wage Bill of Designated Players ($WBDP_{it}$) [per $1000]	0.001 (0.348)	-0.000498 (-0.477)	0.001*** (2.903)	-0.001 (-0.920)	-0.000466 (-0.430)	0.001 (0.340)
Total Guaranteed Player Salaries (WB_{it}) [per $1000]	0.002** (2.242)	0.02** (2.305)		0.002** (2.354)	0.002** (2.161)	0.002** (2.101)
GINI Coefficient on Player Salaries ($GINI_{it}$)		-10.590 (-0.861)			-10.736 (-0.842)	
Team Std. Dev. on Salaries ($StdS_{it}$)	-0.00001202 (-1.053)					-0.0000119 (-1.001)
Founding Year (FY_{it})	-11.159*** (-3.368)	-11.135*** (-3.356)	-10.999*** (-3.264)	-11.145*** (-3.362)		

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table L: Robustness Regression Results – Performance (cont.)

Variable	Points as Dependent Variable					
R^2	0.376	0.379	0.341	0.373	0.329	0.327
Adjusted R^2	0.227	0.231	0.196	0.229	0.175	0.173
Wage Bill of Designated Players ($WBDP_{it}$) [per $1000]	-0.000173 (-0.108)	-0.001 (-0.651)	0.001** (2.464)	-0.001 (-1.361)	-0.001 (-0.553)	-0.000010 (-0.006)
Total Guaranteed Player Salaries (WB_{it}) [per $1000]	0.002** (2.561)	0.002** (2.506)		0.002** (2.622)	0.002** (2.313)	0.002** (2.362)
GINI Coefficient on Player Salaries ($GINI_{it}$)		-13.684 (-1.148)			-12.936 (-1.048)	
Team Std. Dev. on Salaries ($StdS_{it}$)	-0.000009 (-0.806)					-0.0000095 (-0.818)
Founding Year (FY_{it})	-10.722*** (-2.236)	-10.827*** (-3.276)	-10.441*** (-3.092)	-10.755*** (-3.250)		

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table H: Robustness Regression Results - Attendance

Variable	Attendance as Dependent Variable			
R^2	0.896	0.897	0.902	0.903
Adjusted R^2	0.869	0.869	0.875	0.876
Total Number of Designated Players Rostered (DP_{it})	-0.358 (-1.262)	-0.409 (-1.426)	-0.288 (-1.011)	-0.587** (-2.049)
Wage Bill of Designated Players ($WBDP_{it}$) [per $1000]	0.000151† (1.627)	0.000375* (1.723)	-0.000414 (-1.104)	0.000098 (0.418)
Total Number of Points (Pts_{it})	0.070*** (3.420)	0.075*** (3.587)	0.077*** (3.795)	0.080*** (3.946)
Lag Number of Points ($Pts_{i,t-1}$)	0.042** (2.145)	0.042** (2.138)	0.048** (2.494)	0.032† (1.635)
Total Guaranteed Player Salaries (WB_{it}) [per $1000]		-0.000242 (-1.138)	-0.000198 (-0.945)	-0.000220 (-1.060)
GINI Coefficient on Player Salaries ($GINI_{it}$)				7.851*** (2.793)
Team Std. Dev. on Salaries ($StdS_{it}$)			0.000007** (2.559)	

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† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table N: Robustness Regression Results – Attendance (cont.)

Variable	Attendance as Dependent Variable			
R^2	0.894	0.895	0.901	0.900
Adjusted R^2	0.896	0.868	0.875	0.873
Wage Bill of Designated Players ($WBDP_{it}$) [per $1000]	0.000112 (1.276)	0.000288† (1.371)	-0.001 (-1.468)	0.000024 (0.100)
Total Number of Points (Pts_{it})	0.073*** (3.650)	0.078*** (3.762)	0.080*** (3.948)	0.084*** (4.094)
Lag Number of Points ($Pts_{i,t-1}$)	0.038** (1.980)	0.038* (1.950)	0.046** (2.393)	0.028† (1.433)
Total Guaranteed Player Salaries (WB_{it}) [per $1000]		-0.000195 (-0.923)	-0.000162 (-0.786)	-0.000159 (-0.763)
GINI Coefficient on Player Salaries ($GINI_{it}$)				6.571** (2.367)
Team Std. Dev. on Salaries ($StdS_{it}$)			0.0000069*** (2.766)	

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table O: Robustness Regression Results - Revenue

Variable	Revenue as Dependent Variable
R^2	0.959
Adjusted R^2	0.919
A First Designated Player ($DP1_{it}$)	0.260 (0.164)
A Second Designated Player ($DP2_{it}$)	0.667 (0.332)
A Third Designated Player ($DP3_{it}$)	1.779 (0.838)
Average Seasonal Attendance (Att_{it}) [per 1000 people]	0.999*** (2.737)

******* indicates significance at the 99% level, ** at the 95% level, and * at the 90% level

† indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2004 and Chicago Fire as the comparison group

Table P: Robustness Regression Results – Revenue (cont.)

Variable		Revenue as Dependent Variable	
	R^2	0.981	
	Adjusted R^2	0.922	
Total Number of Designated Players Rostered Squared $(DP_{it})^2$	-3.072** (-2.081)	Montreal Impact & DPs	13.142* (2.097)
		NY Red Bulls & DPs	20.920** (2.514)
Average Seasonal Attendance (Att_{it}) [per 1000 people]	0.833** (2.231)	Philadelphia Union & DPs	14.615** (2.533)
		Portland Timbers & DPs	27.559*** (3.156)
Chicago Fire & DPs	36.401** (2.679)	Seattle Sounders & DPs	18.317** (2.235)
Dallas FC & DPs	12.039* (1.952)	Sporting KC & DPs	12.476** (2.716)
Houston Dynamo & DPs	8.948* (1.951)	Toronto FC & DPs	10.568** (2.254)
LA Galaxy & DPs	11.942* (1.876)	Vancouver Whitecaps & DPs	18.666** (2.310)

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[†] indicated significance at the 90% level when considered under a one-tailed test

The t-statistics for each coefficient are included in parenthesis beneath the value of each coefficient.

Not included are the binary variables representative of year and team characteristics

Excluded from the Fixed Effects regressions are the data from 2014 and Chicago Fire as the comparison group

The only interaction effects that are presented in this table are those that were statistically significant in the results.

References

Badenhausen, Kurt and Peter Schwartz. "Major League Soccer's Most Valuable Teams." Available from http://www.forbes.com/2008/09/09/mls-soccer-beckham-biz-sports-cz_kb_0909mlsvalues.html. Internet.

Berri, David J., Martin B. Schmidt, and Stacey L. Brook. 2004. "Stars at the gate: The Impact of Star Power on NBA Gate Revenues." *Journal of Sports Economics* 5(1): 33–50. February.

Coates, Dennis, Bernd Frick, and Todd Jewell. 2014. "Superstar Salaries and Soccer Success: The Impact of Designated Players in Major League Soccer." *Journal of Sports Economics* 1–20.

Fey, Bruno S., Markus Schaffner, Sascha L. Schmidt and Benno Torgler. 2013. "Do Employees Care About Their Relative Income Position? Behavioral Evidence Focusing on Performance in Profession Team Sports." *Social Science Quarterly* 94(4): 921–932. December.

Garcia-del-Bario, Pedro and Francesc Pujol. 2007. "Hidden Monopsony Rents in Winner-take-all Markets – Sport and Economic Contribution of Spanish Soccer Players." *Manaerial and Decision Economics* 28: 57-70.

Houston Dynamo. "Standings." Available from http://www.houstondynamo.com/standings/mls/2004/. Internet.

Jane, Wen-Jhan. 2014. "The Effect of Star Quality on Attendance Demand: the Case of the National Basketball Association." *Journal of Sports Economics* 1–22.

Jewell, R. Todd. 2015. "The Effects of Marquee Players on Sports Demand: The Case of U.S. Major League Soccer." *Journal of Sports Economics* 1–14.

Keuthe, Todd H. and Mesbah Motamed. 2010. "Returns to Stardom: Evidence From U.S. Major League Soccer." *Journal of Sports Economics* 11(5): 567–579.

Lawson, Robert A, Kathleen Sheehan, and E. Frank Stephenson. 2008. "Vend It Like Beckham: David Beckham's Effect on MLS Ticket Sales." *International Journal of Sports Finance* 3: 189–195.

Mayers, Joshua. Sounders FC Blog. "A quick look at Sounder FC's history with designated players." 2013. *The Seattle Times*. November 19. Available from http://blogs.seattletimes.com/soundersfc/2013/11/19/a-look-at-sounders-fcs-history-with-designated-players/. Internet.

MLS Players Union. "Player Salary Information." Available from https://www.mlsplayers.org/salary_info.html. Internet.

MLS Press Box. “Designated Players.” Available from http://pressbox.mlssoccer.com/content/designated-players#overlay-context=content/media-resources. Internet.

MLS Press Box. “Roster Rules and Regulations.” Available from http://pressbox.mlssoccer.com/content/roster-rules-and-regulations. Internet.

MLS. “Designated Players in MLS: Every club has a DP for the first time in league history.” 2013. Available from http://www.mlssoccer.com/post/2013/08/16/designated-players-mls-every-club-has-dp-first-time-league-history. Internet.

Sloane, Peter J. 1971. “The Economics of Professional Football: The Football Club as a Utility Maximiser.” *Scottish Journal of Political Economy* 121-146. June.

Smith, Chris. “Major League Soccer’s Most Valuable Teams 2015”. Available from http://www.forbes.com/sites/chrissmith/2015/08/19/major-league-soccers-most-valuable-teams-2015-2/2/. Internet.

Smith, Chris. “Major League Soccer’s Most Valuable Teams.” Available from http://www.forbes.com/sites/chrissmith/2013/11/20/major-league-soccers-most-valuable-teams/. Internet.

Sonntag, Schooner J. and Paul M. Soomers. 2014. “Work Incentives and Salary Distributions in Major League Soccer.” *International Atlantic Economic Society* 471–472. October 15.

Thornton, Tweed. “DP is the Answer; Fire May Not Know How to Wield the Tool.” 2013. *SB Nation*. August 6. Available from http://www.hottimeinoldtown.com/2013/8/6/4590380/dp-is-the-answer-fire-may-not-know-how-to-wield-the-tool. Internet.

Wahl, Grant. *The Beckham Experiment: How the World’s Most Famous Athlete Tried to Conquer America*. New York: Crown, 2009. Print.

Zimbalist, Andrew. 2010. “Reflections on Salary Shares and Salary Caps.” *Journal of Sports Economics* 11: 17–28.