2019

Maximizing Wins or Profit: Designated Players in Major League Soccer

Zachary Willis
Butler University

BUTLER UNIVERSITY HONORS PROGRAM

Honors Thesis Certification

Please type all information in this section:

Applicant Zachary Anthony Willis
(Name as it is to appear on diploma)

Thesis title ~~Maximizing Wins or Profit: Designated Players in Major League~~ Soccer

Intended date of commencement May 11, 2019

Read, approved, and signed by:

Thesis adviser(s) Jennifer L. Rice 05/07/19
Date

Date

Reader(s) Courtney Hatch 5/7/19
Date

Date

Maximizing Wins or Profit: Designated Players in Major League Soccer

A Thesis

Presented to the Andre B. Lacy School of Business

and

The Honors Program

of

Butler University

In Partial Fulfillment

of the Requirements for Graduation Honors

Zachary Anthony Willis

10 May 2019

Abstract

This paper seeks to add to the existing literature regarding sports teams and whether they follow a win-maximizing or profit-maximizing strategy. Specifically, this paper seeks to analyze Designated Players (DPs) in Major League Soccer (MLS) and see if DPs contribute more toward a team's on-field success, measured as win percentage, or overall revenue. Prior studies have analyzed soccer leagues across Europe and found that most teams follow win-maximizing strategies over profit-maximizing strategies. This analysis has not yet been carried over to MLS, which is not the most prevalent sports league in its home country and features a unique DP structure. Match-specific and DP data was collected over the span of four MLS seasons from 2014 to 2017, while financial data was compiled from annual reports published by *Forbes*. The data was analyzed through a series of linear regressions. The results showed that DPs have a positive effect on both win percentage and team revenue, and that DPs can explain a larger amount of the variation in team revenues than the variation in win percentage. The results imply that teams in MLS may be signing DPs in order to maximize short-term profits over long-term on-field successes.

Maximizing Wins or Profit: Designated Players in Major League Soccer

While American football may be the biggest sport in the United States, soccer (also called association football) is the most popular and most played sport around the world. In England alone, there are over 1,000 teams that compete in a weekly league each season, ranging from professionals to college-aged amateurs (Roeder, 2014). In the U.S., professional soccer games draw in large crowds, with fans spending millions of dollars per year on tickets and merchandise (Smith, 2018). The desire to be the best soccer team in the country and thereby draw in more fans and revenue, especially in Europe, leads soccer clubs to spend large amounts of money to improve their team. The most valuable club in the world, Manchester United F.C., spent over £160 million in the 2017/18 season just on acquiring players (McMahon, 2017), justifying how soccer is more than just a game to the largest clubs in the world. In many cases, the prosperity and longevity of a soccer club can depend on the success of the team. For instance, if a team is relegated from the English Premier League, they will miss out on an estimated £100 million minimum in prize money - the amount the lowest-finishing team received at the end of the 2016/17 season (Dawson, 2017). Therefore, for a club to be financially stable, they must have the best team with the best players. Acquiring the best players, however, is an extremely costly business.

In professional soccer, players are not acquired by teams through drafts or trades, but rather bought for cash. If a player is under contract with a team and wants to move, the respective teams have to agree on a buyout price, or "transfer fee." This has seen the best players in the world sold for hundreds of millions of dollars. In the mid-2000s, Major League Soccer (MLS) realized that the salary cap it imposes on its teams would prevent world-renowned superstar players from competing in the league, as MLS franchises would not have enough salary cap space to support the wages needed to retain such a player. Thus, MLS created the Designated Player Rule, granting each team three roster spots for Designated Players (DPs) that are exempt from the salary cap. MLS teams have employed varying strategies to fill their DP roster spots. While some teams have signed up-and-coming young stars or hometown heroes as DPs, the majority have used the rule to sign some of the biggest names in European soccer, albeit at the end of their careers. Superstar athletes, however, can have a larger appeal off the field, to the point that the athlete themself is a monetized brand.

The purpose of this thesis is to analyze the players that MLS teams have signed as DPs over the period from 2014 to 2017 and determine if those players had a larger effect on a team's on-field success, measured as win percentage, or the team's total revenue. There is evidence presented in the literature to suggest that DPs have a larger effect on club revenue. The rest of this paper begins with a literature review into superstar athletes, the factors that can affect team performance, and DPs. Afterward, the empirical data and models are presented. The discussion of results follows and is enriched with tables explaining the individual effects that DPs had on wins and revenue over the period studied. The study finishes with further discussion and concluding remarks.

Literature Review

There is a growing body of literature related to the business that soccer teams conduct, including player acquisitions and team wages. Unlike most major sports in the United States, soccer teams acquire players for cash. This has resulted in a world player market that sees player values fluctuate through performance-based and comparative factors. The amount of money teams spend on player transfers has increased steadily as the years have gone on. In 1996, the largest transfer fee paid out by a soccer club was only £15 million, yet in 2017, the transfer fee record had been increased to €222 million. With no golden equation and no foreseeable limit, recent transfer fees have increased drastically. The highest transfer fees are paid to acquire superstar players.

Superstar Players

The best soccer players in the world are modern day superstars. Even if the casual sports fan does not follow soccer, they will have heard of Cristiano Ronaldo and Lionel Messi. By being one of the best players on their team or in their sport, athletes develop a superstar status which often carries over to the team itself. In today's world, the very best players in any sport are superstars, and the players become household names and brands. One major reason soccer clubs are willing to spend so much money for a player is the superstar status of that player (e.g. Kuethe & Motamed, 2010; Lucifora & Simmons, 2003). Overall, there are several underlying characteristics that help create superstars out of players, and this superstar status is why teams will spend millions of dollars to acquire them. Once a team has signed a superstar player, that player will be expected to perform well and help the team.

Team Performance

Irrespective of whether or not a player is considered a superstar, the player must be able to perform well to stay on the team and win games. Regardless of which sport or which league is being measured, the performance of the entire team is most important to the fans. Berri, Schmidt, and Brook (2004) found that a team's ability to win, not necessarily the presence of superstar players, is what maximizes attendance. While star power is also statistically significant, it is not the main factor in the relationship between winning and fan attendance.

Several studies have looked at the many factors that can influence a player or team's performance on the field (e.g. Buraimo, Frick, Hickfang, & Simmons, 2015; Hall, Szymanski, & Zimbalist, 2002; Ashworth & Heyndels, 2007). Ashworth and Heyndels (2007) looked at youth leagues that are grouped by age to determine what relationship existed between age grouping in youth soccer and later performance as a professional. Their study found a relative age effect where youth players born later in the year were more represented at a professional level, due to the players having better training growing up against older players. Weimar and Wicker (2014) tested several measures of effort on team performance. Their analysis found a positive relationship between the total distance run by players and the eventual result of the match. Their analysis concluded that effort can sometimes go undervalued in soccer and often has an insignificant effect on a player's worth.

Hall, Szymanski, and Zimbalist (2002) looked at how the characteristics of a team's payroll affected the team's performance. In regards to player wages and team performance, there are two competing hypotheses: a cohesion theory that suggests teams where all players are paid similarly will perform better, and a "theory of tournaments" which says that increased salary inequality will lead to increased worker effort and productivity (Coates, Frick, & Jewell, 2016). Hall et al. examined team payrolls in the English Premier League and Major League Baseball from 1980 to 2000 to see if large variances in team payrolls caused by superstar players affect the team's performance in their league. In the Premier League, a positive correlation was found between a team's payroll and its performance over the entire period studied. Furthermore, the study found that the direction of causality between payroll and performance starts with payroll and then flows to performance. They attributed these results to both the structural difference between the Premier League and other major sports leagues, and to the world player market in soccer, where players are acquired for a market value, compared to the regulated trading market in baseball or football.

Buraimo, Frick, Hickfang, and Simmons (2015) took this analysis to an individual level, trying to find a correlation between a player's wages and his performance on the field. Using data from the German Bundesliga, they created a performance model using several characteristics that also help determine superstar players. Their models showed that increased contract length was positively related to player performance. They explained this finding by suggesting that players will perform better when they have longer contracts because they know that their position on their current team is safe. At the same time, the player can always continue to try to attract lucrative offers from other clubs. If offers do come from other clubs, this could possibly lead to the player's current contract being restructured or his wages increased so that he will stay with his current club. Buraimo et al. found that even though a team may have strategically given a player a longer contract, the player will perform better for the club as a means to try to further improve his contract.

Player Salaries

Monks and Twomey (2011), however, felt that the results of Buraimo et al. (2015) might not carry over to MLS in the U.S. due to the differing corporate structure the league employs. Their study analyzed the effects of MLS's single entity corporate structure on player salaries, discovering that MLS devotes up to 35% less of its revenues to player salaries than comparable soccer leagues. One main reason that MLS does not pay as much money on player salaries is that MLS employs a salary cap, a concept common to American sports leagues, but not to world of soccer. Késenne (2000) looked at how a league salary cap affects the performance of the teams in the league, using an assumption that there is no minimum payroll cap. Késenne found that there is a positive relationship between a league-wide salary cap and league-wide competitive balance. This way, all teams are more evenly matched and the team with the most money can not dominate the league. MLS tries to ensure an even competitive balance among players and teams by enforcing a salary cap. At the same time, however, the league also wants to be the home of the best players in the world – players whose wages would easily exceed a team's salary cap. To combat this conflict, MLS employs a unique allowance known as the Designated Player Rule.

Designated Players

Created in 2007 for David Beckham, the Designated Player Rule allows an MLS team to forgo their salary cap to sign a superstar player at the world market price. MLS assigns a portion of the player's salary to the team's wage bill, and the team owners are expected to cover the rest. After eleven years, every team in the league has signed at least one DP, and many have proven successful, while others have not fared well with their new teams and left after a year or two. Several studies (e.g. Parrish, 2013; Jewell, 2017; Coates, Frick, & Jewell, 2016) have looked at DPs and their impacts on their teams and MLS. Parrish (2013) looked at the effects of DPs on game day attendance, finding a significant positive relationship between the number of DPs a team has, and that team's game day attendance. Jewell (2017) also looked at teams with DPs and measured the impact on game day attendance for the team during the time the DP played. Surprisingly, Jewell only found three DPs who had a statistically significant positive impact on their team's game day attendance, and he noted that the impact diminished with each additional season the DP played. His study also noted that for foreign-born DPs, any effect on game day attendance was only present for the team's home games.

Coates, Frick, and Jewell (2016) measured the impact of DPs in a different manner, focusing instead on their impact on team performance. They based their study on player wages since a DP would be paid considerably more than most of his teammates. Their study aimed to determine the relationship between salary inequality on an MLS team, and the team's performance in the league (measured in terms of points per game). What they found is that the relationship is negative, indicating that overall team production is lower as a team's salary inequality is higher. Their findings support a cohesion hypothesis that the best production comes from workers with equal salaries.

In order to be able to sign DPs and pay out hefty wages to those players, teams in MLS must be able to make money. Like all sports teams, there is a business side of the franchise that has to make money for the team to survive.

Maximization

It would be simple to assume that the goal of every sports team would be to win as many games as possible. Yet off the field, sports teams try to maximize their revenues through multiple channels, including ticket prices, stock listings, and player acquisitions. Ferguson, Stewart, Jones, and Le Dressay (1991) hypothesized that one way a team could maximize their profits was through increasing ticket prices. Their study looked at NHL franchises and whether there was a positive relationship between a team's goal of maximizing its profits and ticket prices. The study showed that the relationship was positive and that the data supported the assumption that teams in the NHL were profit maximizers. Leach and Szymanski (2015) studied the business behavior of 16 top soccer clubs in England. These 16 clubs all had listings on the London Stock Exchange in the mid-1990s. The study wanted to see if acquiring a stock listing resulted in a club's behavior shifting towards making money for its investors, instead of winning as many games as possible. The results of the study show this relationship is not statistically significant, and that the clubs continued to be win maximizers. A franchise's decision to be more oriented toward maximizing wins or profit can also be crucial to the league.

While a soccer team can make money off the field through increased ticket prices or stock listings, some studies (e.g. Garcia-del-Barrio & Szymanski, 2009; Liu, Liu, Lu, Wang, & Wang, 2016) suggest that a team's on-field activities are also conducted so as to maximize profits. Garcia-del-Barrio and Szymanski (2009) looked into the exchanges of soccer players and focused on the teams instead of the players. As they discuss, a team at the top of the first division will do their business differently than a team at the bottom of the fourth division. Their analysis looked at teams in the Spanish and English soccer leagues to try to explain whether a team made business decisions and acquired players specifically to maximize wins or to maximize profits. Although only two nations were examined, it was determined that most clubs are oriented towards maximizing wins. The exception was teams that have a history of being successful and winning titles (i.e. Real Madrid C.F. and Manchester United F.C.), who are more driven toward profit maximizing because they know they will be able to draw in superstar players anyway since they are always competitive. Even if a team is acquiring players to try to maximize profits, a team's successes are judged by how well they did during their season and if they won any trophies. Liu, Liu, Lu, Wang, & Wang (2016) wanted to see if there was a relationship between a soccer club's transfer activities (or lack thereof) and the club's success on the field in the following seasons. There are many variables that affect the extent of a club's transfer activity, including a club's position in their league and the total value of their wealth. Their analysis showed that there is no clear relationship between transfer activities and future successes. Overall, a soccer team's means to maximize its revenues can be derived from many sources, both on and off the field. MLS, however, has one profit-maximizing source that other soccer leagues do not – Designated Players.

Hypotheses

Garcia-del-Barrio and Szymanski's (2009) analysis of win maximization versus profit maximization looked at teams in the top soccer leagues of Spain and England. However, in those leagues, DPs do not exist. This study plans on applying a similar analysis to teams in MLS to see if the presence of DPs leads teams to assume a win maximizing or profit maximizing strategy. Unlike other American sports leagues, the majority of MLS revenues are game day revenues from tickets, concessions, or jersey sales (Jewell, 2017). Parrish (2013) and Jewell (2017) found that having a DP on a team does have a positive impact on attendance, thus allowing the club to maximize their revenues. Coates et al. (2016) found a negative relationship between DPs and team performance, suggesting that DPs do not bring much of an on-field advantage. This conclusion is contrary to the common line of thought that a superstar player can improve a team's performance on the field. Despite the findings of Coates et al., a DP has led MLS in goal scoring in all but two of the seasons that the DP structure has been in place.

This study aims to answer the question regarding whether teams in MLS sign DPs in order to maximize wins or profit. As explained, there are many reasons to believe that players would have a larger impact on a team's revenues. The applied hypotheses for this study are:

H1: Designated Players increase a team's winning percentage.

H2: Designated Players increase a team's annual revenue.

H3: Teams in Major League Soccer sign Designated Players to maximize profits over wins because Designated Players have a larger effect on revenues than they do win percentage.

These three hypotheses together look at the overall effects of DPs in MLS. The first hypothesis aims to conclude that DPs have a positive effect on the team's on-field performance, measured as win percentage. Many of the players who have been tagged as DPs are viewed as superstar players, some of which have previously played in the top soccer leagues in the world. By having a DP on the team with a lot of experience, it would help the team win more games during the season. The second hypothesis aims to conclude that DPs also have a positive impact on revenue. Because some DPs are superstar athletes, they are very popular and their arrival will offer a boost that other sports teams see when they sign a new superstar to their roster. This boost is felt through increased jersey, ticket, and other merchandise sales. The empirical analysis detailed below will assist in answering the first two hypotheses, at which point a conclusion for the third hypothesis can be reached. The third hypothesis seeks to conclude that the effects brought by DPs contribute more toward increasing a team's revenue than it does increasing a team's win percentage. Using the results of the forthcoming regression analysis, it can be determined whether DPs contribute more toward maximizing the team's wins or profit. Due to a generally short average tenure with the club, the average age of former European superstar players, and the large amount of wages needed to sustain a DP, it is hypothesized that DPs contribute more toward maximizing revenues.

Data

The data collected for this thesis is from the MLS seasons from 2014 through 2017. Match-specific and DP data had been collected for the 2013 season, but was not used due to a lack of financial data for that season. This specific range of data was chosen in order to include the most recent data possible for this study. At the time of data collection, the 2017 season was the most recent completed season. Although the DP structure has been in existence since 2007, data was only collected back to 2014 due to the challenge posed by collecting financial data, as explained below. The number of teams in MLS changed several times over the observed data period. In 2014, there were 19 teams in the league. By 2017, the number of teams had increased to 22. This expansion occurred in two waves. Prior to the 2015 season, Orlando City and New York City FC joined the league while Chivas USA was folded. Atlanta United and Minnesota United then joined the league in 2017. There were three different types of data collected for this thesis: data specific to a certain match, data specific to DPs, and financial data specific to a certain team in a certain year. These types of data were collected for each team in each season.

Variables Collected

Match-specific data is data that is specific to only one match that has been played. As such, a match-specific variable will be different for every game included in the data set. Examples of match-specific data include attendance, the time the match kicked-off, the month and day the game was played, and if the match was played in a soccer-specific stadium. See Table 1 for a complete list of the match-specific variables collected and what each one represents. These variables are included in the data set because they can all have an effect on the eventual outcome of the match. Even though the main focus of this study is on DPs, and the first hypothesis relates to the effect of DPs on win percentage, these other factors can also have a role in determining the outcome of the game. For example, if a team is playing in a match and has already played two prior matches that same week, the team will be tired, which will affect their performance on the field and could lower their chances of winning that specific game, especially if they are playing a team that has played fewer matches within the prior week. Several of the match-specific variables collected for this study were also collected by Owramipur, Eskandarian, and Mozneb (2013) in their study to create a Bayesian Network to predict the outcome of soccer matches. Match-specific data for Chivas USA, Orlando, New York City, Atlanta, and Minnesota is only available for the seasons they played, due to each club joining or leaving MLS during the period studied.

At the end of each match, the referee submits a report to MLS and the Professional Referee Organization (PRO). Among the details included in this report are the final score, any disciplinary cards issued, and which players scored for each team. PRO then verifies this information and MLS supplements the referee's report with additional information, including reported attendance, game start time, the stadium, and weather. MLS then publishes a game summary on their website, as well as on each team's individual website, which is jointly operated by the team's administrative staff and MLS. Over the course of a given season, both the MLS and team websites will accumulate reports for all matches played during that specific season. These reports are then archived at the end of the year, and remain available even after the season has ended. As a result, on the "schedule" page of each team's individual website, any season can be selected and the website will pull the team's schedule, results, and game reports from that season. All match-specific data was collected from the official team websites because the information available on those websites came from referee reports verified by PRO and published by MLS. Sports websites like ESPN and Fox Sports also post game scores and reports of their own, however information was not pulled from those websites because their information does not come from a confirmed verified source. While it can be assumed that the information published in their game reports would be correct, ESPN and Fox Sports were not used as sources for collecting match-specific data.

The second type of data collected for this thesis is DP data. DP data is match-specific data about the DPs who played for each team in a given match and their in-game performances. MLS allows each team to have a maximum of three DPs on their roster. Examples of DP data include the number of DPs a team had for a certain match, if any of them scored, and whether the visiting team also had DPs on their roster. All DP variables collected are also included in Table 1. DP data is included in the data set to test the first and second hypotheses. The number of DPs on each team will help test the second hypothesis regarding revenue, while the goals scored by DPs will help test the first hypothesis relating to wins. While it is important to include other match-specific variables that can be factors affecting a team's win percentage, the DP data is the main focus of the first hypothesis. DP data is only listed for Chivas, Atlanta, Orlando, Minnesota, and New York City in the seasons they competed.

DP data was collected using the match-specific data collection method stated earlier. Individual game reports would include DPs in the game lineups and note if any of them scored just like any other players. Confirmation of which players were tagged as DPs was also pulled for the official MLS website. The website maintains two separate pages - one listing all current DPs in the league with their teams, and another listing all former DPs, the teams that tagged them, and the seasons they were DPs. This is especially helpful as players can transfer between seasons, and some players have served as DPs for multiple teams. In other cases, a club that already has three DPs will sign a fourth and have to remove the DP tag from one of the first three players. The DP master lists on the MLS website confirmed which players served as DPs for which teams in which seasons. From there, the appropriate DP data could be collected from game reports found on the team-specific websites.

The third type of data collected for this thesis was financial data. Financial data includes a team's yearly revenue and operating income. These variables are also included in Table 1. The financial data is not match-specific, and is listed at a seasonal level. The financial data is included in this study to measure any effects that a DP could have on their team's revenue in accordance with the second hypothesis. Financial data was collected from online articles published by *Forbes* regarding MLS teams and their finances. MLS operates in a single-entity structure with each franchise actually partowned by MLS as part of an overall “company” despite operating separately. It is for this reason that the individual teams do not release their own financial statements. Financial data, therefore, has been collected from *Forbes*. In 2008, 2013, and annually since 2015, *Forbes* has assessed the teams in MLS and ranked them by their projected value. *Forbes* uses prior year financials to assess a team for the current year. In addition to a team’s estimated worth, *Forbes* also publishes each club’s revenue and operating income from the previous season. *Forbes* defines operating income as “earnings before interest, taxes, depreciation, and amortization” (Smith, 2018). Using the 2015 through 2018 articles from *Forbes*, seasonal revenues and operating income for each team was collected from 2014 through 2017. There are, however, multiple exceptions. *Forbes* did not publish a listing in 2014. Thus, financial data for the 2013 season was unavailable. It was for this reason that 2013 match-specific and DP data was not used in this study. Additionally, Chivas USA was folded by MLS after the 2014 season, and thus was not included by *Forbes* in their 2015 rankings. With *Forbes* not completing their valuation ranking on a yearly basis before 2015, no financial data is available for Chivas USA. Also, revenue data is only available for Atlanta, Orlando, Minnesota, and New York City starting from the seasons they began in MLS. Again, this is because those four clubs joined the league during the period studied.

[Table 1]

The data presented in Table 1 was not all collected on the same basis. Match-specific and DP data was collected on a match-level basis while financial data was collected on a seasonal basis. Match-level financial data was not available from *Forbes*. Therefore, all match-level data had to be converted to a seasonal level so that it was on the same basis as the financial data. This was mostly accomplished by averaging the match-level variables to create new variables representing the average game for each team in each season. Not every variable was averaged, however. The Home Team variable was not averaged because the teams in MLS do not change within a single season. Also, a new variable was created and called “Goals Ratio.” This variable presents a ratio of the goals scored only by the home team DPs to the goals scored only by the visiting team DPs. This ratio is calculated using season totals and is not an average of individual game ratios. The seasonal data created is presented in Table 2.

[Table 2]

Descriptive Statistics

After the data was collected at a season level, it was then compiled into descriptive statistics. Descriptive statistics are used to summarize larger sets of data. For this study, the descriptive statistics represent each of the variables collected and used at a seasonal level. These statistics were used as the observations to test the hypotheses in the method presented in the next section. Table 3 shows the descriptive statistics representing the dependent and independent variables explained in the next section. These variables are presented by team as an average of the four seasons studied.

[Table 3]

In Table 3, it can be observed that not all teams in the league had the same number of DPs. Additionally, having the most DPs did not translate to having scored the most goals. As Philadelphia and Orlando show, there is no guarantee that a team’s DPs will score all of their goals. Revenue figures can also be seen in Table 3. LA Galaxy led the league in revenue with Seattle not far behind. Most of the teams were in a range from 20 to 30 million dollars, with the league average at $30.88 million.

Additional variables were collected to test the hypotheses. Table 4 presents descriptive statistics representing all of the season-level variables presented in Table 2, including the descriptive statistics already presented in Table 3. Each variable in Table 4 is presented by year, showing one averaged value representing all teams that played in MLS for that given year.

[Table 4]

Table 4 shows several trends that have formed in the league. Over the period studied, both average attendance and revenue increased each year. The number of teams with soccer-specific stadiums decreased, though this is due to league expansion and the addition of four new teams across the period studied. Recent expansion franchises have typically not had their soccer-specific stadiums completed until a few years after they began play. Additionally, the number of DPs signed by teams increased slightly over the period studied, reflecting how more teams are moving to the maximum of three DPs.

Table 5 presents an additional set of descriptive statistics representing each of the season-level variables collected. This final set of descriptive statistics condenses the variables presented in Table 4 even further to give one averaged value representing all teams in MLS from 2014 to 2017. The values presented in Table 5 represent a grand average for each variable over the period studied.

[Table 5]

Table 5 presents a healthy view of the league, with teams winning half their games and having a 50/50 chance of making the playoffs. Average attendance is over

20,000 fans per game and teams brought in an average of over $30 million in revenue. Not all teams had three DPs but the average team had at least two.

These descriptive statistics are important in testing the first two hypotheses in order to answer the third. The DP data will be used to show any extent to which DPs are able to affect their team's win percentage through goals and their team's revenue through presence. Players alone, however, are not the only factors that affect the outcome of a game. The match-specific data is included to account for other factors than can affect a match, even though they are not the main focus of this study. The financial data will be used to determine the extent that DPs are able to affect their team's annual revenue. By using these three types of data, it can be determined to what extent DPs are able to affect their team's win percentage and yearly revenue. After the first two hypotheses have been answered, the regression results generated to support them can then be used to answer the third hypothesis, which acknowledges whether DPs contribute more toward maximizing win percentage or revenues.

Method

Analysis for this study was carried out using an empirical analysis of the data collected to determine the effects of DPs on both win percentage and revenue. Multiple regressions were performed in order to determine the effect of DPs with and without additional control variables included. These additional control variables are the match-specific variables included in the data set. After testing for association and causation, four regressions were performed to establish relationships between DPs and both win percentage and revenues. Model diagnostic testing was also performed to ensure there was no correlation or bias in the results, and that variation was also unaffected.

The process of condensing the data to a season level created the observations that were used for the empirical analysis. An observation is a single point of data representing one team in one year. For each variable in the match-specific, DP, and financial data, there is an observation for every team in each year during the period studied. The total number of observations for each variable is 79. Several observations had to be dropped from the data set. This was due to the fact that financial data was not made available by *Forbes* for the 2013 season and for Chivas USA in 2014. *Forbes* did not include Chivas and their 2014 financials in their 2015 valuations because the franchise had folded at the end of the 2014 season. As a result, all match-level and DP observations that did not have accompanying financial observations were removed from the data set. As a result, every collected variable has 79 total observations associated with it, one for each team (except Chivas USA) from 2014-2017.

Dependent Variables

This study features two dependent variables. Dependent variables are the variables being tested in the study, and whose value depends on other variables. The two dependent variables used in this study are win percentage and annual revenue. These are the variables that this study aims to measure to see how much of their variances can be explained by the main independent variables. Because four equations were used for this study, win percentage and annual revenue each serve as the dependent variable for two of the four equations as explained further below.

Independent Variables

Multiple independent variables are used in this study. Some independent variables are part of the main focus of this study, while the rest are control variables. The main independent variables include the number of DPs on the home team, the number of DPs on the visiting team, and the ratio of goals scored by home team DPs to goals scored by away team DPs. These are the observations that this study aims to analyze to see what extent they influence the dependent variables. The other independent variables are control variables. These include all other seasonal observations listed in Table 2. The match-specific data was collected because it includes other variables that can also affect the outcome of a match. These control variables are also included in some of the regressions to account for additional factors beyond DPs that influence the dependent variables, especially win percentage, as explained below.

Testing the Hypotheses

The three hypotheses were tested by performing linear regressions using Ordinary Least Squares (OLS). These regressions will provide more information than correlation coefficients can about the relationships between variables. OLS is able to establish causation between the variables and develop a linear equation that best identifies the relationship between the dependent variable and the independent variables being tested. By utilizing multiple regressions, the influence each independent variable has on the respective dependent variables can be determined. This way, the influence DPs have on win percentage and club revenue can be measured while also taking all other factors into account.

A total of four linear regressions were run. The following equation was used to perform the OLS regressions:

$$Y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \mu_i \qquad (1)$$

This equation will be used in each regression, where y is the relevant dependent variable, and each x is an independent variable being tested.

The first regression will measure the effects of the three main independent variables on revenue. No other independent variables are measured in this equation. The purpose of this regression is to establish the causation each of the three main independent variables have on the dependent variable when not controlled for additional outside factors. This will help establish how much of an influence DPs and the goals they score have on a club's annual revenue, answering the second hypothesis. The relevant equation is:

$$Revenue_i = \beta_0 + \beta_1 Home\ DPs + \beta_2 Visiting\ DPs + \beta_3 Goals\ Ratio + \mu_i \qquad (2)$$

The y value for this equation is a team's annual revenue as provided by *Forbes* in their annual online reports. This variable is measured as an average of yearly revenues across the four years studied, or fewer if the home team joined the league during that time. The number of home DPs and the number of away DPs is measured as an average of the number of DPs on each team over the course of the period studied. There is less variance in the Home DPs variable as each home team does not change from game to game. The average of visiting team DPs fluctuates more because each individual game has a different visiting team with a potentially different number of DPs. As a result, the visiting DPs variable represents an average number of DPs that would be on the visiting team across the period studied. The Goals Ratio variable represents the ratio of goals scored per game by home team DPs to goals scored per game by the visiting team's DPs. This ratio was calculated using seasonal goal totals and is not an average of individual ratios.

The second regression measures the effects of the same three main independent variables on win percentage. The only difference between the first and second regressions is the dependent variable. The y value for the second regression is a team's average win percentage. Each team's win percentage is easily calculated by dividing the total number of wins, a total of the Win binary variable in Table 1, over 17 total home games each season. Each win percentage observation represents the percentage of home game victories each team had in that season. The purpose of the second regression is to measure the extent that DPs and the goals they score affect the home team's winning percentage, helping to answer the first hypothesis. This equation also does not take into effect any additional variables that can influence the outcome of a match. The relevant equation for the second regression is:

$$Win\ \%_i = \beta_0 + \beta_1 Home\ DPs + \beta_2 Visiting\ DPs + \beta_3 Goals\ Ratio + \mu_i \qquad (3)$$

By comparing the results of the first and second regressions, it can be determined whether DPs contribute more toward maximizing wins or revenue when no other factors are taken into consideration, providing a preliminary answer to the third hypothesis. Additional regressions will be run to account for additional factors that affect soccer matches.

The third and fourth regression models test the three main independent variables in addition to several control variables that can also influence matches. The purpose of adding these additional independent variables is to account for additional factors that influence match results. By understanding how much each control variable influences a team's win percentage or revenue, it can be more accurately determined the exact amounts that DPs contribute to maximizing wins and revenue. This will allow for more precise answers to all three hypotheses than what might be provided by the first two models.

The third regression tests the impact of the three main independent variables and the additional independent variables on revenue. The additional independent variables include attendance, soccer specific stadiums, the total number of seasons the team has played, the team's previous year point total, if the team made the playoffs the previous year, and a home team dummy variable to control for additional team-specific effects. The dependent variable for this model is the home team's average annual revenue. The equation for the third regression is:

$$Revenue_i = \beta_0 + \beta_1 Home\ DPs + \beta_2 Visiting\ DPs + \beta_3 Goals\ Ratio + \beta_4 Attendance + \beta_5 Stadium + \beta_6 Seasons + \beta_7 Previous\ Year\ Points + \beta_8 Previous\ Year\ Playoffs + \beta_9 Home\ Team + \mu_i \tag{4}$$

Additional betas and x variables are added to include each of the additional independent control variables. The attendance variable represents the average attendance at games hosted by the home team across the period studied. The Stadium variable represents the binary variable in Table 2 labeling whether the home team played its games in a soccer specific stadium. This variable was prepared using an average to reflect any possibility that the home team changed the location of a game or opened their own soccer-specific facility during the studied time period. In any other cases, the variable average would still reflect a simple 1 or 0. The Previous Year Points variable reflects the number of points the team earned in the season prior to the observation. This does mean that the point total of one season becomes the previous year total for the next season. This variable helps estimate the performances of the team relative to the others in the league.

Additionally, teams look to constantly improve year after year, especially if they were near the bottom of the league in a previous season. The Previous Year Playoffs variable also helps to this extent by reflecting if the home team made the playoffs in the season prior to the observation. The individual team dummy variables were generated to capture any additional team-specific effects that can also influence a match.

By testing this equation, the exact extent that DPs and the goals they score influences revenue can be more accurately measured. This equation also estimates the effects of the control independent variables and if any of them are statistically significant as well.

The fourth model tested the three main independent variables and the additional control independent variables for their effects on the home team’s win percentage. The only difference between the third and fourth models is the dependent variable. The dependent variable for the fourth model is the home team’s win percentage. The purpose of the fourth equation is to more accurately measure the effects of the main independent variables on the dependent variable when additional controls are take into account. The model used for the fourth model is:

$$Win\ \%_i = \beta_0 + \beta_1 Home\ DPs + \beta_2 Visiting\ DPs + \beta_3 Goals\ Ratio + \beta_4 Attendance + \beta_5 Stadium + \beta_6 Seasons + \beta_7 Previous\ Year\ Points + \beta_8 Previous\ Year\ Playoffs + \beta_9 Home\ Team + \mu_i \qquad (5)$$

By adding the additional control variables, the effects that DPs have on wins and revenues can be more accurately determined. At that point, the first two hypotheses relating to these effects can be answered. The results of these regressions can also answer the third hypothesis which seeks to know where DPs have a larger influence.

Model Diagnostic Testing

Before the linear regressions were performed, additional tests were performed on the data to test correlation and ensure there was no bias included in the sample, and that all variances were natural. The first test completed was to measure the correlation coefficients between the two dependent variables and the three main independent variables. These correlation coefficients are measured to establish the association between any two variables and whether there is a strong relationship between them. This relationship is shown by a value ranging from -1 to 1, with higher numbers away from 0 in either direction indicating a stronger relationship. The results are presented in Table 6.

[Table 6]

Each coefficient represents the strength of the relationship between those respective variables. As none of the coefficients were above the correlation threshold of 0.8 in either direction, it could be confirmed that there was not a strong correlation between any of the variables that would have affected the data. However, correlation coefficients are nonparametric and do not establish causation. Another model must be used to establish causation between variables.

Multicollinearity was the next condition to be tested in the sample. Multicollinearity is a condition in which two or more independent variables are highly correlated with each other. This can cause problems with the model and the model will not properly estimate each variable’s relationship to the dependent variable. By testing for multicollinearity, variables can be checked against each other to prevent redundancy in the data. By preventing redundant variables, the equation can properly estimate each variable's relationships.

Multicollinearity is measured through a calculated variance inflation factor (VIF). All independent variables used in this study were tested for multicollinearity. The VIF results showed a moderate level of collinearity with three of the additional control independent variables. The three main independent variables relevant to this study showed three of the four lowest VIF values, with none being over 2.5. These results indicate that while there may be some correlation regarding the additional control variables, there is no collinearity of significant importance between the main independent variables.

Heteroskedasticity was also tested for this model. When performing linear regressions, homoskedasticity is an assumption that the variation of the error term is always constant. Testing for heteroskedasticity ensures that all error terms in the model are kept constant. Violation of such variance can result in incorrect T statistics. Errors could also become more extreme as the independent variables shift away from the average. At that point, the OLS model will not provide an estimate with the smallest variance. In other words, there could have been a significant variable that was omitted.

Heteroskedasticity was tested using the Breusch-Pagan test. The Breusch-Pagan test is a chi-squared test that checks whether the variances in the error terms of the regressions are dependent on the values of the independent variables. In such a case, heteroskedasticity would be present. The Breusch-Pagan test results returned a chi-squared value of 1.01 and a p-value of 0.3159. Because the p-value is not below the significance threshold of 0.05, it can be assumed that heteroskedasticity is not present in the models.

Finally, the models were tested for omitted variables. An omitted variables test is completed to ensure there is no omitted variable bias in the data. This bias would result in significant variables being left out of the model. As a result, the effects of those omitted variables might be attributed to other variables included in that data. By checking for omitted variables in the data, it can be assured that the effects attributed to certain variables by the regression analysis do belong to those variables, and that the models are not biased. The Ramsey Reset test performed on the models returned a p-value of 0.5640. Because this p-value was not below the significance threshold of 0.05, it can be confirmed that there is no bias in the model and that no relevant variables were omitted.

With confirmation that the data set was unbiased and did not include any correlated or omitted variables, the linear regressions were then performed. The results of those regressions are presented in the next section.

Results

This section presents the results gathered by the four linear regression models used to determine how much of the variation in a team's win percentage and annual revenue can be explained by DPs. Two regressions were utilized to measure the effects of DPs on win percentage while the other two regressions measured the effects of DPs on revenue. For each dependent variable, one regression examined the three main independent variables alone while another also analyzed additional control effects. Team-specific dummy variables were also included to capture any additional effects not included in the data that can affect the dependent variables. The results gathered seek to answer the three posed hypotheses. These three hypotheses guess that DPs have a positive effect on both wins and revenue, with the effect on revenue being larger than the effect on wins. The results presented below were able to support all three hypotheses, in addition to detailing specific significant variables relevant to each dependent variable.

Table 7 shows the results of the regressions below.

[Table 7]

The first regression listed in Table 7 tested the relationship between DPs and their team's annual revenue. This regression only included the three main independent variables in order to analyze how much of the variation in a team's revenue can be explained by the three main independent variables alone. Of the three main independent variables tested, the results showed that only one was significant at the 5% significance level. That variable was the number of DPs on the home team. The variable's coefficient of 0.182 shows that each additional DP on the home team increases revenue by 18.2%. This result can be explained by the fact that all game data was taken relative to the home team. Financial data was also collected this way. It should then be expected that the DPs on the home team would have some impact on the revenues of the home team, as each player's superstar effect is what the team is hoping to financially capitalize on. The other two independent variables tested were not found to be statistically significant regarding revenues. The R-squared value for this regression was 0.243. That value means that 24.3% of the variance in annual revenues can be explained by the DP variables tested in the model. This model confirms the second hypothesis, which stated that DPs would have a positive impact on revenue.

The second regression listed in Table 7 tested the relationship between DPs and their team's win percentage. Like the first regression, this model only included the three main independent variables in order to analyze how much of the variation in a team's win percentage can be explained by the three main independent variables alone. Of the three independent variables tested, the results again showed that only one was significant at the 95% confidence interval. The significant variable was the Goals Ratio. Neither of the other two independent variables returned values indicating significance. The Goals Ratio variable coefficient of 1.65 indicates that each additional goal scored by a DP on the home team has a strong positive impact on the team's chances of winning a game. Each additional goal increases the team's chances of winning by 165%. The idea that the ratio of goals scored would have a significant relationship with winning percentage does make sense for a sport in which the objective is to score more goals than the opponent. Regardless of which team member scores the goal, it will help their team increase their chances of winning the game. This result shows that with DPs especially, this relationship remains true. The R-squared value for this regression was 0.151. That value means that 15.1% of the variance in win percentage can be explained by the DP variables tested in the model. This model confirms the first hypothesis, which stated that DPs would have a positive impact on win percentage. These results also somewhat contradict the findings of Coates et al. (2016) which found that having DPs, as measured through salary inequality, had a negative effect on team production. While this study found the mere presence of DPs to be insignificant relevant to team performance, the goals they scored had a significant impact.

At this point, the third hypothesis can also be preliminarily confirmed. The third hypothesis stated that DPs would have a larger effect on revenue than on wins. Using the R-squared values of the first two regressions, the DP variables can explain a larger amount of the variation in team revenues than the variation in win percentage, when additional control variables are not factored in. The result that DPs have a larger effect on revenue presents findings contradictory to Leach and Szymanski (2015), who found that soccer teams in England and Spain, where the DP structure does not exist, behave more in line with a win-maximization strategy. Garcia-del-Barrio and Szymanski (2009) found some teams in Europe to be profit maximizers, but those clubs were among the largest and most popular in the world. Although MLS clubs would not fit that profile, European leagues do not employ a superstar player structure like the Designated Player Rule.

The third and fourth regressions listed in Table 7 also tested the relationships between DPs and both win percentage and revenue. Unlike the first two regressions, additional control variables were included. These extra variables were added to test for other factors that can affect the outcomes of soccer matches and to see if any of them diminish the effects of DPs.

The additional control variables included average attendance, if the average game was played in a soccer-specific stadium, the number of prior seasons played, the number of points the team earned in the prior season, if the team made the playoffs the previous year, and the individual team-specific dummy variables. The purpose of adding these additional variables to the third and fourth models is to not only test how much of the variation in the dependent variables can be explained by DPs, but also to determine how much of the variation can be explained by control variables. The results of these models can better estimate the effect of DPs since additional game-changing factors have been accounted for.

The third regression listed in Table 7 tested the relationship between DPs and their team's revenue. This model included the additional control and dummy variables to capture the effects of any other factors that influence win percentage. Of the three main independent variables tested, the results again showed that only one had a statistically significant relationship with revenue at the 5% significance level. The significant variable was the average number of DPs on the home team. This result mirrors that of the first regression, with the same implications as explained earlier. The variable's coefficient, however, increased to 0.563, indicating that each additional DP on the home team leads to a 56.3% increase in revenue. This large coefficient increase shows that simply having DPs on the team will have a larger effect on revenue than most other common factors.

Several of the control variables were also found to be significant at the 5% significance level. The control variables found to be significant included attendance, soccer-specific stadiums, and the number of seasons played. The attendance variable coefficient of 0.000 shows that while attendance is a significant factor in increasing revenue, the game-to-game variations in attendance have an insignificant effect. The significance of the attendance variable makes sense considering a majority of MLS revenues are game day revenues, which include ticket sales. The more tickets a team can sell to their games, the more money they will make over the course of a season. Over time, clubs have learned that DPs have a positive impact on attendance at games, as also proven by Parrish (2013) and Jewell (2017).

The significance of the variable representing the number of seasons played implies that teams that have played more seasons in the league are typically more established, more structured, and better financially set than their counterparts just joining the league. As the results show, the coefficient of 0.069 indicates a revenue increase of 6.89% for each additional season a team plays in MLS. While MLS does require a large financial investment to start up a new franchise as a means of demonstrating that the club can be self-sufficient financially, teams become more solid businesses with time. Soccer-specific stadiums and winning championships help this variable as each will bring more publicity to the club, which, in turn, helps increase game day revenues in following seasons.

Soccer-specific stadiums themselves were also found to be significant. The Stadium coefficient of 0.385 shows that having a soccer-specific stadium can increase a team's revenue by 38.5%. This result makes sense considering a majority of teams in MLS now play in their own stadiums. Building and operating their own soccer stadiums allows MLS franchises to collect all revenues form events held in their stadiums. Playing in a soccer-specific stadium also means teams do not have to share revenues with another tenant, like, for example, if they were playing in an NFL stadium. Seven of the team-specific dummy variables were also found to be significant, proving that there are still additional factors that can affect revenue. The presence of these additional factors can also be seen in the R-squared value for this model. The R-squared value for this regression was 0.932. This value means that 93.2% of the variance in annual revenues can be explained by the variables tested in the model. This model also confirms the second hypothesis, which stated that DPs would have a positive impact on revenue. When comparing the results of the first and third models, it can be seen that the control variables explain much more of the variance in revenue than the DPs alone can explain.

The fourth regression listed in Table 7 tested the relationship between DPs and their team's win percentage. Like the third regression, this model included the additional control and dummy variables. The only difference between the third and fourth models was the dependent variable. Of the three main independent variables tested, the results again showed that only one was significant at a 5% significance level. The significant variable was again the ratio of goals scored by home team DPs to visiting team DPs. The coefficient of 3.87 shows the very strong effect that scoring a goal has on the team's chances of winning. This result indicates that each additional goal that a DP scores over the opponent increases the team's chances of winning by 387%. These results were the same as in the second model, yet the extent of the effect scoring a goal has greatly increased when additional variables were added. These results again contradicted the findings of Coates et al. (2016) by finding that DPs do have a positive impact on team performance, albeit only through the goals they score. The results further prove the implications explained earlier.

Neither of the other two main independent variables returned values indicating significance. Additionally, none of the control variables or the team-specific dummy variables were found to be significant. The Goals Ratio was the only variable found to have a significant relationship with win percentage. This further shows that the players on the field are what win games for the team. While DPs can certainly help the team tactically, it is the goals they and other players score that matter. The R-squared value for this regression was 0.503. That value means that 50.3% of the variance in win percentage can be explained by the variables tested in the model. This R-squared value also implies there are many additional factors not captured in this model that can affect win percentage, further demonstrating the minimal impact simply having a DP has. This model also confirms the first hypothesis, which stated that DPs would have a positive impact on win percentage. Both the second and fourth models found the first hypothesis to be true through the goals that DPs score. When comparing the second and fourth models, it can be seen that the control variables can explain more of the variation in win percentage than the DPs alone are able to.

The results of the third and fourth regressions can also confirm the third hypothesis, which predicted that DPs would have a larger effect on revenue than on win percentage. The results of the first two models were able to preliminarily confirm this hypothesis when additional controls were not accounted for. The coefficients and R-squared values of the third and fourth models can confirm those preliminary findings. The confirmation of the third hypothesis again presents findings opposite those of Leach and Szymanski (2015) and Garcia-del-Barrio and Szymanski (2009), as mentioned earlier.

Additional discussion of these results and the implications they present is given below.

Discussion

The results of the OLS regressions concluded that DPs in MLS can explain a larger impact on their team's revenue than they do on their team's win percentage. These results concur with the findings of other studies to show the effects of DPs off the field. On the field, however, a DP's influence is only felt through goals. This result should bear no real significance since the aim of soccer is to score more goals than your opponent and any of the eleven players on the field can score for their team. With that being the case, DPs essentially show no major on-field differences than any other players a team could sign. Perhaps this is why some teams in MLS have begun shifting their DP strategies away from superstar players.

The conclusion that DPs explain a larger influence on a team's overall revenue would not be seen as shocking by those who follow MLS. Many teams in the league have been using their DP positions on superstar players who will bring in excess revenues to their team through jersey sales and increased attendance. The players may have an impact on the field, but the more lasting effect long-term will be in the business office. What is more fascinating is the amount of money a team is willing to invest in a DP just to reap a few years' worth of rewards. DPs routinely have the largest wages on their teams, in addition to the transfer fees their teams pay to acquire the players. Coates et al. (2016) had previously concluded that teams with larger salary discrepancies perform worse on the field and acquire less points during a season. Although not all teams employ the same strategy when it comes to their DP roster slots, the majority choose a strategy that easily explains why DPs have such a larger effect on revenue than wins. This revenue-oriented strategy is also contrary to what MLS has recently set out to accomplish over the next few years.

There have been positives to employing the Designated Player Rule in the first place, and its effect on giving MLS and soccer in the U.S. more prominence in a crowded sports market has been massive. Today, fans and pundits will point to David Beckham joining the LA Galaxy as a rebirth of the league. Prior to 2007, MLS was struggling to gain traction and barely making money. The excitement of a newly-formed sports league had worn off. Two franchises were folded after the 2001 season and an argument could be made that the league would not still exist today without the United States' run to the quarterfinals of the 2002 FIFA World Cup, their best result in the modern era of the tournament. That World Cup gave MLS a popularity boost to sustain it for another few years. Beckham's arrival in 2007 and the creation of the Designated Player Rule to accompany it, signaled the beginning of MLS's third chapter.

Despite the obvious business implications, the tactical reasons that teams sign most DPs is because they are proven winners at some of the best teams in the top leagues of Europe. A club's tactical goal is that the player will bring a wealth of experience and knowledge and that they can help the rest of the players on the squad improve, benefitting the team as a whole as they try to win a championship. This has happened in the past but there is never a guarantee and, as this study has shown, DPs only produce tactical benefits if they score goals. As with any sport, not all player acquisitions yield the same results. Over the years, we have seen examples of DPs who have made major impacts for their teams, and other DPs who have barely left a mark. Wayne Rooney joined D.C. United in the summer of 2018, at a time when the team was last in the Eastern Conference. Over the second half of the 2018 season, Rooney led the team on a stellar comeback, only losing four games and earning a home playoff game. Rooney can be seen as the best case scenario, unlike Rafa Marquez, who joined New York Red Bulls in 2010. Marquez's tenure at the club was marred by injuries, suspensions, off-field tirades, and scuffles with his teammates. Before long, fans had turned on the player who was supposed to be their superstar. In total, Marquez only featured in just over 30 games across two and a half seasons.

This shows the wide range of effects a DP can have on the field. To be fair, any player can have similar impacts for their team, and the fact that Rooney and Marquez were DPs is essentially superficial. In soccer especially, transferring from one club to another can be a big risk for any player due to changes in play style, coaching, teammates, and the general culture of the league the player is competing in. There are plenty of examples of soccer players in Europe who leave their club to compete elsewhere and find it hard to adapt to a different play style. The same can be said for some players who have signed DP contracts, including Rooney and Marquez. What connects these two players, though, is their superstar value - Rooney, the longtime captain of English giant Manchester United, and Marquez, then-captain of the Mexican national team.

Rooney and Marquez are two of the many superstar players to sign DP contracts with their teams. These superstar players usually need no introduction, as the casual sports fan will typically know their name and that they're a famous soccer player. Superstar players have long been the type of players that MLS has been chasing and trying to get to sign for their teams. The logic behind the idea is relatively simple. A superstar player joining an MLS team will generate new local interest in the team, the sport, and the league. The team can then market themselves around this player, and use the fact that they have a world-famous athlete on their team to increase attendance and jersey sales. Teams will sacrifice the fact that the superstar DP is at the end of their career in order to benefit financially before congratulating the player on their retirement a few years down the line. Over eleven years, this tactic has not disappointed.

One of the most well documented effects a DP can have is on attendance. The results of this study proved that fact, with attendance shown to be a statistically significant variable in the third regression. Other studies (e.g. Parrish, 2013; Jewell, 2017) have looked at DPs and their impacts on attendance. While Jewell (2017) only found three instances where DPs had a statistically significant positive impact on their team's attendance, Parrish (2013) found DPs as a whole have a significant positive relationship. No matter how big the effect, it can be shown that DPs do have the ability to attract more fans to games. Higher attendances lead to more interest in the club, more merchandise sales, concessions, and repeat attendees, all of which financially benefit the club.

The financial benefits of DPs has also been seen in jersey sales. Jerseys are the most commonly bought merchandise item in sports, and especially in soccer. According to MLS, 19 of the 25 top selling jerseys in 2018 belonged to DPs, continuing a trend that has been growing over the years prior ("Major League Soccer Unveils," 2018). DPs commonly make up most of that list, with newer acquisitions usually taking the higher spots. It has become common for soccer fans to buy jerseys of DPs regardless of which team they play for. During the prime of a DP's career, they become well known and followed by fans across the globe. This would include fans in the U.S., who commonly watch European League games on weekend mornings before MLS matches begin. Because of this, soccer fans develop their favorite European-based players. If that player were to transfer to MLS, their jersey sales would soar even outside the home team's market. Such was the effect when Zlatan Ibrahimovic joined LA Galaxy in 2018. Ibrahimovic's jersey was top seller for 2018 despite him only playing half of the season, and LA Galaxy not qualifying for the playoffs.

This also brings a reminder that signing a superstar player does not automatically mean the team will find instant success, like making the playoffs for example. Teams will always hope that is the case and, for the most part, it does happen that way to some extent. There are, however, plenty of examples in soccer and in other sports of teams not reaching their goals despite having the best players. Ibrahimovic's LA Galaxy provide the best recent example of this sobering fact. Outside of MLS, the French club Paris Saint-Germain have spent over €1.1 Billion on superstar players since 2011 with the intentions of winning the UEFA Champions League. Despite their ambitions and all that money, the club still have not reached even the semi-finals. In 2016, the small English club Leicester City won the Premier League handedly over teams like Manchester United, Chelsea, Arsenal, and Liverpool who all had better and more expensive squads on paper. These examples remind us that what matters is not who has the most money, but rather the performances by the eleven players on the field, and that teams do not need superstars to be successful. Perhaps this is why a small group of MLS clubs are using their DP slots not on international superstars, but on instrumental squad players.

There are a small number of teams who are forgoing the possibility of signing a well-known DP and instead using the DP roster slot to sign a lesser-known player that the team believes can tactically fill their biggest needs. It can be argued that teams who engage in this strategy are clearly prioritizing wins over revenues. They are clearly looking for a player than can make their squad better, regardless of how popular that player is. This tactic has worked to varying effects as well and some of these "unknown DPs" have used their team's successes to catapult their own stardom. Chicago Fire finished both the 2015 and 2016 seasons at the bottom of MLS. Before the 2017 season, they made headlines by signing the World Cup-winner Bastian Schweinsteiger as a DP. Schweinsteiger was not the only DP on the team, however. Chicago had two unknown DPs on their roster, Nemanja Nikolic and David Accam. Neither of those names would be familiar to any soccer fans outside of Chicago. Despite Schweinsteiger receiving all the headlines and press due to his popularity, it was Nikolic and Accam who respectively scored the most and second-most goals for the team that season. The trio of DPs led Chicago to finish 3rd in MLS in 2017 and showed that signing unknown DPs can be a successful strategy. The following year, that strategy produced a championship team.

Atlanta United joined MLS in 2017 and employed the unknown DP strategy from the beginning. The club used their three DP slots to sign three South American players, Hector Villalba, Miguel Almiron, and Josef Martinez, to partner with a South American coach, “Tata” Martino. The move formed the attacking core of the team and also established the heavy South American influence that has driven the culture associated with the team today. All of Atlanta United’s DPs to date are South American. Atlanta made the playoffs in their first-ever season and won the MLS Championship the following year. The previously unknown trio of DPs soared in popularity and were three of the five Atlanta United players to feature on the 2018 best-selling jerseys list. Almiron was able to capitalize on his new popularity and secure a move in January 2019 from Atlanta to Newcastle United of the English Premier League. Atlanta United have provided a sort of inverse DP story. The team has found success bringing in unknown South American players in as DPs who then shine for the club. In the end, the club has financially benefited even more than those who pay large transfer fees for European-based DPs, due to the fact that Atlanta has managed to send a player to Europe instead of buying one. The strategy of sending players to Europe is one that MLS Commissioner Don Garber would like to see more of, though it would require a lot more clubs to buy in.

On the heels of Atlanta’s recent triumph, Don Garber has expressed his desire for MLS to transition and become more of a “selling league.” Using Almiron and Canadian teenager Alphonso Davies (sold by Vancouver Whitecaps to Bayern Munich) as examples, Garber wants to see MLS clubs developing more up-and-coming players and to see more players rise from MLS academies to eventually play in Europe. This desire to shift focus comes as a response to the most common criticism of DPs - that MLS has become a “retirement league.” Critics of the DP system say it allows European players who are past their prime to move to a league where they can still be among the best, since the overall talent level in MLS is not at the level of the best leagues in Europe. It allows the player to play for a few more years and take one last big payday before they retire a few years after they arrive. While there are examples to validate this criticism, there are also examples to challenge it. Rooney, Ibrahimovic, and David Villa (New York City FC), despite being in their 30s, have all managed to provide success to their teams at a high level while also giving their clubs the financial boost they were hoping for. The three have all transitioned smoothly to their new teams and continue to play, expressing a desire to win more trophies in the U.S. What this does however, is provide potential problems for Garber’s vision, and put MLS at a crossroads.

As long as MLS clubs are able to profit financially (and somewhat tactically) from bringing in European superstars, they will be willing to take the risk. For a league that receives most of its revenue from game day operations, teams will do anything they can to bring more fans to games. This includes superstar players. If Garber really wants more teams in his league to pivot from the superstar approach and invest more in player development, he will need a convincing argument. Every team in the league has DPs, and most still use those roster slots on superstar players. There is nothing to suggest a drastic shift away from that strategy will happen anytime soon. Thus, MLS finds itself at a crossroads, yet potentially at the brink of starting the fourth chapter in its history. Teams like Atlanta have shown that it is possible to be successful and win championships in MLS without investing heavily on a European superstar player. MLS now wants more of its clubs to follow Atlanta's lead and shift their priorities. To do so, however, would require teams to move away from the very structure that allowed the league as a whole to grow in popularity, to become profitable, to raise the profile of soccer in America, and to add eleven clubs to the league over the past ten years (with more rapid expansion in the lower leagues of American soccer).

The answer here is not clear. DPs have become an established part of MLS, and they can have a positive impact on their clubs, as shown in this study and other works. It still is not a guarantee and over time, both the superstar approach and the unknown DPs approach have yielded championship-winning teams. MLS could change the Designated Player Rule again to further limit the number of DPs a club can sign, or they could adjust salary caps to change the way teams are able to sign their players. They could force teams to change their strategy or play more of an advisory role. With the league adding another three teams by 2021, DPs will continue to be the main attraction at MLS games. As long as DPs continue to score goals for their clubs, MLS and its franchises will continue to score dollars and reap the financial rewards that superstar athletes bring.

Further Research

Further research on this topic would allow for the additional collection of data to see if results change or if trends continue to develop over time. The data for this thesis was collected from only four MLS seasons, while the Designated Player Rule has been implemented for eleven complete seasons. The limitation on this data set was the financial data, which is not made public by MLS teams. *Forbes*' financial evaluations, which were used to collect the financial data, were not carried out on a yearly basis before 2015. These financial valuation rankings also include the team's revenue and operating income for the prior year. Now that *Forbes* is conducting these valuations every season, it is possible to add more seasons to the data set going forward. With each MLS season, teams buy and sell players and DPs will leave, retire, or be replaced. This study hopes to include match-specific, DP, and financial data from 2018 and beyond to continue evaluating the effects of DPs.

The goal in continuing this research is to see if the results change over time or if new trends develop. Now that MLS is a financially stable league and its commissioner wants the teams to change their player strategies, it will be interesting to see if the teams follow through. Perhaps in four or five years, DPs will not have as much of an effect on revenues than they do currently. It is possible that teams could change their transfer strategies and how they sign their DPs. With additional expansion franchises due to join the league in future years, these new franchises may find creative new ways to utilize their DP roster slots. For example, FC Cincinnati signed a former MLS Cup winner as their first DP instead of a European-based superstar. This presented a new strategy of recruiting talent that is already proven in the league. If expansion teams create new DP strategies, the effects of each could be compared to one another going forward.

If teams in MLS begin adjusting their transfer strategies, the effects of these changes could be evaluated over time and strategies could be compared to one another. Using the respective types of data, this study could evaluate these changing strategies through OLS regressions to see the shift in a DP's effects on their teams over time, if there is one at all. Perhaps, we would see the behaviors of MLS teams shift back from maximizing revenues to maximizing wins, the common goal for sports franchises, and most soccer teams worldwide.

References

Ashworth, J., & Heyndels, B. (2007). Selection bias and peer effects in team sports: The effect of age grouping on earnings of German soccer players. *Journal of Sports Economics, 8(4)* 355-377.

Berri, D., Schmidt, M., & Brook, S. (2004). Stars at the gate: The impact of star power on NBA gate revenues. *Journal of Sports Economics, 5(1)*, *33-50.*

Buraimo, B., Frick, B., Hickfang, M., & Simmons, R. (2015). The economics of long-term contracts in the footballers' labour market. *Scottish Journal of Political Economy, 62(1)* 8-24.

Coates, D., Frick, B., & Jewell, T. (2016). Superstar salaries and soccer success: The impact of designated players in Major League Soccer. *Journal of Sports Economics, 17(7)*, 716-735.

Dawson, A. (2017, May 22). This is how much prize money every Premier League club won in the most lucrative season ever. Retrieved from https://www.business insider.com/total-prize-money-each-premier-league-club-won-in-lucrative-season-2017-5

Ferguson, D. G., Stewart, K. G., Jones, J. C. H., & Le Dressay, A. (1991) The pricing of sports events: Do teams maximize profit? *Journal of Industrial Economics, 39(3)*, 297-310.

Garcia-del-Barrio, P., & Szymanski, S. (2009). Goal! Profit maximization and win maximization in football leagues, *International Association of Sports Economics,* 6-21.

Hall, S., Szymanski, S., & Zimbalist, A. (2002). Testing causality between team performance and payroll, *Journal of Sports Economics, 3(2) 149-168*.

Jewell, R. T. (2017) The effect of marquee players on sports demand: The case of U.S. Major League Soccer. *Journal of Sports Economics, 18(3)*, 239-252.

Késenne, S. (2000). The impact of salary caps in professional team sports. *Scottish Journal of Political Economy, 47,* 422-430.

Kuethe, T., & Motamed, M. (2010). Returns to stardom: Evidence from U.S. Major League Soccer. *Journal of Sports Economics, 11(5), 567-579*.

Leach, S., & Szymanski, S. (2015). Making money out of football. *Scottish Journal of Political Economy, 62(1) 25-50.*

Liu, X. F., Liu, Y., Lu, X., Wang, Q., & Wang, T. (2016). The anatomy of the global football player transfer network: Club functionalities versus network properties, *PLOS One, 11(6).*

Lucifora, C., & Simmons, R. (2003). Superstar effects in sport: Evidence from Italian soccer. *Journal of Sports Economics, 4(1) 35-55*.

Major League Soccer unveils 2018 top-selling jerseys (2018, October 22) Retrieved from https://www.mlssoccer.com/post/2018/10/22/major-league-soccer-unveils-2018-top-selling-jerseys

McMahon, B. (2017, November 17) Manchester United's financial records show record revenue flowing in and record costs flowing out. Retrieved from https://www.forbes.com/sites/bobbymcmahon/2017/11/17/latest-financial-results-for-Manchester-united-show-record-revenue-but-same-goes-for-operating-costs/#7aa0498b3fc0

Monks, J., & Twomey, J. (2011). Monopsony and salary suppression: The case of Major League Soccer in the United States, *The American Economist, 56(1), 20-28.*

Owramipur, F., Eskandarian, P., & Mozneb, F. S. (2013). Football result prediction with Bayesian network in Spanish league-Barcelona team. *International Journal of Computer Theory and Engineering, 5(5), 812-815*.

Parrish, C. (2013). Soccer specific stadiums and designated players: Exploring the Major League Soccer attendance assumption, *International Journal of Sport Management, Recreation & Tourism, 12, 57-70.*

Roeder, O. (2014, September 19). Beneath the Premier League stands the great football pyramid of England. Retrieved from https://fivethirtyeight.com/features/beneath-the-premier-league-stands-the-great-football-pyramid-of-england/

Smith, C. (2015, August 19). Major League Soccer's most valuable teams 2015. Retrieved from https://www.forbes.com/sites/chrissmith/2015/08/19/major-league-soccers-most-valuable-teams-2015-2/#391a42e83911

Smith, C. (2016, September 7). Major League Soccer's most valuable teams 2016: New York, Orlando thrive in first seasons. Retrieved from https://www.forbes.com/sites/chrissmith/2016/09/07/major-league-soccers-most-valuable-teams-2016-new-york-orlando-thrive-in-first-seasons/#484b266a270d

Smith, C. (2017, August 16). Major League Soccer's most valuable teams 2017. Retrieved from https://www.forbes.com/sites/chrissmith/2017/08/16/major-league-soccers-most-valuable-teams-2/#42acdf4bb815

Smith, C. (2018, November 14). Major League Soccer's most valuable teams 2018: Atlanta United debuts on top. Retrieved from https://www.forbes.com/sites /chrissmith/2018/11/14/mls-most-valuable-teams-2018/#24e5d612ee99

Weimar, D., & Wicker, P. (2014). Moneyball revisited: Effort and team performance in professional soccer, *Journal of Sports Economics, 18(2), 140-161*.

Appendix:

Table 1: Definitions of Match-Level Variables

Match-Level Variable	Definition
Year	Categorical variable from 0 to 3.
Game Number	Ranges from 1 to 34.
Home Team	Categorical variable from 0 to 21.
Away Team	Categorical Variable from 0 to 21.
Game Result	=0 if win =1 if draw =2 if loss
Win	=0 if win =1 if not a win
Month	Categorical variable from 0 to 11.
Day of Week	Categorical variable from 0 to 6.
Attendance	Reported attendance for match
Kickoff	=0 if before 2pm =1 if 2pm to 4pm =2 if 4pm to 6pm =3 if after 6pm
Last Match - Home	=0 if win =1 if draw =2 is loss
Last Match - Visiting	=0 if win =1 if draw =2 if loss
Prior Week - Home	Number of games in prior six days.

Prior Week - Visiting	Number of games in prior six days.
Stadium	=0 if soccer-specific stadium =1 if not soccer-specific stadium
Seasons	Total number of seasons in MLS
Previous Season Points - Home	Total number of points earned in previous season.
Previous Season Points - Visiting	Total number of points earned in previous season
Previous Season Playoffs - Home	=0 if team made playoffs =1 if team did not make playoffs
Previous Season Playoffs – Visiting	=0 if team made playoffs =1 if team did not make playoffs
Designated Player Variable	**Definition**
DPs - Home	Number of DPs on home team
Offensive	Number of Forward and Midfield DPs
Defensive	Number of Defensive and Goalkeeper DPs
DPs - Visiting	Number of DPs on visiting team
DP Goals - Home	Number of goals scored by home DPs
DP Goals - Visiting	Number of goals scored by visiting DPs
Financial Variable	**Definition**
Revenue (Millions)	“In-stadium revenue streams like tickets, sponsorships, luxury seating, and non-MLS events.”
Operating Income (Millions)	“Earnings before interest, taxes, depreciation, and amortization.”

Table 2: Definitions of Season-Level Variables

Season-Level Variable	Definition
Home Team	Categorical variable from 0 to 21
Win %	Percentage of home matches won
Attendance	Reported attendance for match
Stadium	=1 if soccer-specific stadium =0 if not soccer-specific stadium
Seasons	Total number of seasons in MLS
Previous season points	Total number of points earned in previous season
Previous season playoffs	=1 if team made playoffs =0 if team did not make playoffs
Designated Player Variable	**Definition**
DPs - Home	Number of DPs on home team
DPs - Visiting	Number of DPs on visiting team
Goals Ratio	Ratio of goals scored by Home DPs to Visiting DPs
Financial Variable	**Definition**
Revenue (Millions)	"In-stadium revenue streams like tickets, sponsorships, luxury seating, and non-MLS events."

Table 3: Descriptive Statistics by MLS Team (2014-2017)

Home Team	Seasons Played	DPs - Home	DPs - Visiting	Goals Ratio	Win %	Revenue (Millions)
Atlanta	1	3	2.18	5	64.71	47
Chicago	4	2.09	2.24	2.30	44.12	24.25
Chivas USA	1	2.65	2.35	0.60	35.29	N/A*
Colorado	4	2.19	2.41	1.32	44.12	17
Columbus	4	1.40	2.38	0.82	52.94	23
D.C. United	4	0.97	2.38	0.80	54.41	23.75
Dallas	4	2.5	2.42	1.83	66.18	28.25
Houston	4	2.54	2.29	1.35	50	26.5
LA Galaxy	4	3	2.53	4.54	51.47	57
Minnesota	1	0	2.53	0	41.18	24
Montreal	4	1.94	2.29	1.93	47.06	23.75
New England	4	1.75	2.23	1.11	58.82	26.75
NYC FC	3	2.59	2.21	2.10	47.06	37.33
NY Red Bulls	4	2.37	2.26	3.36	64.71	28.75
Orlando	3	2.78	2.37	0.76	39.22	37.67
Philadelphia	4	2.07	2.16	0.22	45.59	25
Portland	4	2.74	2.5	3.01	52.94	41.5

Salt Lake	4	2.76	2.43	4.05	51.47	21
San Jose	4	2.37	2.54	1.86	44.12	28.5
Seattle	4	3	2.44	2.09	64.71	51.75
Sporting KC	4	2.75	2.34	1.03	54.41	34.75
Toronto	4	3	2.07	4.23	57.35	41.25
Vancouver	4	2.79	2.59	1.63	47.06	20.75
All		**2.35**	**2.36**	**2.03**	**51.92**	**30.88**

*Chivas USA folded after the 2014 MLS season.

Table 4: Descriptive Statistics for MLS Teams across Seasons (2014-2017)

Variable	2014	2015	2016	2017
Win %	48.30	53.53	49.71	55.61
Revenue (Millions)	25.61	30.10	32.20	34.68
Attendance	19,116.93	21,534.36	21,693.89	22,031.24
Soccer-specific Stadium	0.79	0.70	0.70	0.68
Seasons	12.95	12.75	13.75	13.5
Previous Season Points	46.68	42.35	47.40	41.5
Previous Season Playoffs	0.53	0.50	0.60	0.55
DPs – Home	2.11	2.42	2.45	2.41
DPs - Visiting	2.13	2.41	2.46	2.40
Goals Ratio	1.85	2.11	1.87	2.25
Number of Teams	19	20	20	22

Table 5: Descriptive Statistics for MLS Teams

Variable	Mean
Win %	51.92
Revenue (Millions)	30.88
Attendance	21,242.65
Soccer-specific Stadium	0.72
Seasons	13.25
Previous Season Points	44.38
Previous Season Playoffs	0.54
DPs - Home	2.35
DPs – Away	2.36
Goals Ratio	2.03

Table 6: Correlation Coefficients for Dependent and Main Independent Variables

	Win Percentage	Revenue (Millions)	Ratio of Goals Scored	Average # of DPs - home	Average # of DPs - visiting
Win %	1.0000				
Revenue (Millions)	0.1850	1.0000			
Goals Ratio	0.4178	0.3088	1.0000		
DPs - home	0.2200	0.4668	0.4665	1.0000	
DPs - visiting	0.1021	0.1805	0.0194	0.0507	1.0000

Table 7: OLS Regression Results

Variables	Model 1 (Y=Revenue)	Model 2 (Y=Win %)	Model 3 (Y=Revenue)	Model 4 (Y=Win %)
DPs - Home	0.182 (0.000)	2.058 (0.238)	0.563 (0.047)	3.276 (0.294)
DPs - Visiting	0.206 (0.186)	4.774 (0.254)	0.070 (0.429)	13.887 (0.165)
Goals Ratio	0.015 (0.464)	1.651 (0.001)	-0.001 (0.904)	3.865 (0.001)
Attendance			0.000 (0.002)	-0.001 (0.342)
Soccer-specific Stadium			0.385 (0.023)	-7.584 (0.683)
Seasons			0.068 (0.000)	0.143 (0.932)
Previous Season Points			-0.000 (0.909)	-0.190 (0.363)
Playoffs Previous Season			0.042 (0.368)	2.364 (0.648)
Home Team			7 of 22	0 of 22
N	79	79	79	79
R^2	0.243	0.151	0.932	0.503

p-values in parenthesis