THE SUPERSTAR CODE - DECIPHERING KEY CHARACTERISTICS AND THEIR VALUE.

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ABSTRACT

The purpose of the presented research is to advance the superstar literature on the aspect of superstar's characteristics and value. Typically, superstar research is faced with one problem: They apply the same criteria to determine who their superstars are as to describe them later because they lack "an objective measure of star quality" (Krueger, 2005, p.18). To avoid this complication, the author chose to study Major League Soccer's (MLS) designated players as this setting present a unique, as discrete, assignment of star status. MLS has formally introduced stars in 2007 under the designated player (DP) rule which delivers over 100 star-observations in the last ten years to investigate MLS strategy of star employment. The insights from this data set demonstrate which characteristics are relevant, whether MLS stars can be categorized as Rosen or Adler stars, and what the MLS pays for and in this sense values most. A cluster analysis discovers a sub group of ten stars that stand out from the others, in this sense superstars. A two-stage regression model confirms the value stemming from popularity, leadership qualities, previous playing level, age and national team experience but refutes other typical performance indicators like games played and goals scored or position. Overall, evidence for Rosen and Adler's theory is found, and an over the time change from hiring old and popular stars to younger but still leadership-prone stars.

***Keywords**:* Superstar, Major League Soccer, designated players, superstar salary, popularity.

***JEL Classification**:* Z22, J44, L83

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1 Introduction

Fame and fortune are two attributes that are instantaneously associated with superstars. Today, superstardom is ubiquitous in the music, movie and sports business. Interestingly, some sources suggest that the origins of the term superstar stem from sports[1]. In economics, star research is popular since Rosen (1981) and Adler (1985) laid out substantial theories to explain the emergence of superstardom. In sports, Hausman and Leonard (1997) have been the first to demonstrate superstar effects. They found a positive impact of sport superstars on TV ratings for the team that hired the superstar but also positive externalities for other teams (i.e., smaller market teams "free-ride" on large market teams that hire the superstars). But why does superstardom make a difference? With regard to Akerlof (1970), soccer enthusiasts use accessible, diagnostic cues to avoid the risk of purchasing a ticket to a soccer game equivalent of a "lemon". Instead of a ticket purchase, we can also think of the decision to watch a game on TV or online or simply show interest in a league at all. In all cases, stars of known quality with a certain level of popularity can work as cues and reduce uncertainty for the consumer. If this works, accumulating stars is an effective way of boosting the interest in a league, get people to come to games and increase viewership on the TV and online. The professional North-American soccer league, Major League Soccer (MLS) recognized the fact that stars can have a considerable impact on the popularity of the league and in turn on profits. Therefore, they introduced the Designated Player Rule in 2007. This rule allows clubs to employ a certain number of players, today up to three, whom they could not have afforded before with the strict salary budget caps in place. Designated players can be paid as much as the club wants to and only count with a maximum salary charge to the cap. Subsequently, MLS has signed a diverse mix of over 100 designated players over the last 10 years. The names range from the Cuban defector, Osvaldo Alonso, to globally recognized idols like Beckham, Kaka and Gerrard and American "breakout striker" and MLS-returner Jozy Altidore. Despite this diversity, frequent talk refers to MLS as a league for old, formerly star players that have their best times behind them and now look for a comfortable and well-paying pre-retirement stop (see Bailey, 2014; Futterman, 2016). Much alike the former American professional soccer league NASL who "was seen as something of a 'football graveyard' for ageing professionals after one last big payday before they retired from the game" (Elliott & Harris, 2011, p. 566). This eminent comparison

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[1] Hockey manager Frank Patrick used it to describe Frederick Wellington "Cyclone" Taylor. Cyclone was one of Patrick's hockey players on the 1910 – 1920s Vancouver Millionaires team.

with the failed NASL, and, in absence of further prove, prejudice of a ‘retirement league’ hurts the image of MLS. And in turn, it might hinder professional development because talented players leave MLS and top players refrain from coming to a league with such a poor image. According to its mission, MLS not only strives to maximize profits but also wants to increase its quality and targets a better position in the worldwide competition of leagues. In 2017 the MLS commissioner Don Garber even went as far and said to Reuters (Keating, 2017):

> *"Teams are looking to sign players who can first and foremost help them on the field, and if they can bring them some celebrity that's great but that is no longer the objective."*

Consequently, MLS’s current goal is to hire players that contribute to on-field performance. This can be accomplished either by hiring talented players or those, whose experience can help other players in the team to perform better, e.g., thru off- and on-field coaching and mentoring. Under the assumption of superior talent, the designated players are remunerated far above their regular player colleagues. The top earner in 2015 and 2016, Kaka, received over 6 million per year while the average salary for regular players in MLS is around 100k. This indicates that MLS exhibits a superstar phenomenon in line with the definition of Rosen (1981): “relatively small numbers of people earn enormous amounts of money and dominate the activities in which they engage” (p. 845). So, if we have a group of superstars in MLS, who are they? What distinguishes them from the rest? Is the eminent prejudice of a star-retirement league true? This paper wants to answer these questions by analyzing who the MLS superstars actually are, what features characterize them and what features are most valued by MLS teams. The answers will help to decipher the code behind MLS superstars. With this, MLS’s position and strategy regarding superstars is illustrated and can help MLS officials to understand the value of their superstars better. Furthermore, any practitioner who is in charge to form teams that consist, among others, of superstars can profit from knowing what characterizes a superstar in the first place. As mentioned before, there are multiple studies on superstars in and out of the sport domain which could have covered this topic but they struggle with one aspect: the definition of who is a superstar and who is not. Krueger (2005, p. 17f) notes, while investigating the rock music market, that “the superstar model has proved difficult to test empirically because an objective measure of star quality […] is hard to define and even harder to quantify”. MLS’s setting facilitates this differentiation as the Designated Player Rule produces a discrete assignment of star status. The rule stipulates teams to name the players publicly and therefore delivers a quasi-objective status of stardom. This allows to identify the characteristics that explain why this person was chosen as a designated player, hence a star, without using the same criteria to determine their status. After identifying star characteristics, it can be determined what the stars are paid for by the league, and the question whether MLS values stars in accordance with Adler's definition or in line with Rosen's theory can be answered. In the event, however, that there is clear evidence for one of them. Furthermore, the commissioner's quote suggests that preferences changed over the last 10 years, for example, due to different club strategies in different seasons. After all, the league expanded during the observation period from 13 teams up to 20 team[2]. Therefore, the changes over time will also be analyzed with the available data.

To my knowledge, this is the first study that makes use of a quasi-objective measure of superstardom to analyze star characteristics and related employment strategies, i.e. payment schemes. For MLS, this is the first study that considers the individual designated players over a ten-year period, discusses individual characteristics, their value to teams and with that analyzes the MLS star code from different perspectives.

2 Background and Literature Review

2.1 Superstars

Superstars in sports are significant because of the quality they bring "which exists over and above productivity as indicated in official game statistics" (Mullin & Dunn, 2002, p. 620). Star quality "brings fans to the stadiums and impact team revenues in a significant way" (Mullin & Dunn, 2002, p. 620). Likewise, Hausman and Leonard (1997, p. 591) describe that a superstar can impact team revenues "beyond simply improving team quality" and point towards "personal appeal" that can also have positive externalities for other team's revenues. Superstar effects have therefore been investigated in various settings. Jewell (2017) presents an overview of the two distinct research streams for superstars that are present in sports economics. First, the relationship between superstars and salary and secondly, the influence of superstars on attendance. In both streams, researchers link back frequently to the essential explanations of superstardom emergence's by Rosen and Adler. Rosen (1981) believes stardom to be based on

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[2] MLS teams in alphabetical order, first MLS season listed in brackets: Chicago Fire (2008), Chivas USA (2005 – 2014), Colorado Rapids (1996), Columbus Crew (1996), D.C.United (1996), FC Dallas (1996), Houston Dynamo (2006), LA Galaxy (1996), Montreal Impact, New England Revolution (1996), New York City FC (2015), New York Red Bulls (1996), Orlando City SC (2015), Philadelphia Union (2010), Portland Timbers (2011), Real Salt Lake (2005), San Jose Earthquakes (1996 – 2005, 2008), Seattle Sounders (2009), Sporting Kansa City (1996), Toronto FC (2007), Vancouver Whitecaps (2011).

superior talent. A small difference in talent therefore results in large differences in earnings, hence produces stars that stand out from the crowd. Adler (1985) in turn also believes talent is a prerequisite but proposes that from a group of equally talented artists stars can emerge. According to him, consumption capital[3], based on discussing the star and his performance with other knowledgeable consumers, plays an important role as consumers try to minimize their search cost by favoring the same star. But who of the equally talented artists actually become(s) the star(s)? Adler links it back to "luck" – in his meaning, a collection of all other factors apart from talent. If it is truly luck, that sets some players apart from others, we should be able to find a common level of talent in superstars as well as consumption capital, but otherwise, a wide variety in other factors that characterize the star.

Next to popularity and talent, the ability to reach a large market with a "few sellers" is a pre-requisite for the generation of superstar rents. In modern world soccer, large stadiums and global media outlets that reach huge audiences account for that as highlighted by Lucifora and Simmons (2003). Empirically, Lucifora and Simmons (2003) test the superstar effect in Italian soccer and find a highly skewed salary distribution and salary premia for top scorers (they use the goal scoring rate as measure of superstardom) in line with Rosen's definition. Later, Bryson, Rossi, and Simmons (2014) investigated the Italian Serie A again with a richer set of productivity measures and found evidence for talented migrant footballers, in line with Rosen's theory, and greater popularity, in line with Adler's. Their research also demonstrates how modern papers make use of "talent" in a way that talented players help their teams perform better. Talent by itself is hard to grasp as it is intangible. Franck and Nüesch (2008) elaborate that "the exact talent of a soccer player is fuzzy and requires much player specific knowledge to be properly discovered and assessed." (p. 149). To avoid this complexity, many papers use a pragmatic solution. For example, Bryson et al. (2014) use straightforward productivity measures instead. Franck and Nüesch (2012) revisit the issue of determining talent in order to compare it objectively. They propose that "one possibility for dealing with heterogeneous tastes is to use specific talent indicators only within a genre" (p. 205) which reduces the complexity of finding universal indicators. But, the second issue they highlight is to find an appropriated measurement. After all, how should an inherent and often subjectively-perceived talent like charisma be measured in a quantitative way? They continue by arguing that in sports this is less of an issue as winning provides a valid measure of the underlying talent that an individual

[3] In his paper, Adler refers to the consumption capital theory developed by Stigler and Becker (1977).

athlete has. In turn, for team sports the ability to increase the team's chances of winning is a player's talent. This excludes everything but the on-field contribution. So, one part of stardom research is to determine which contribution the star makes to a team's success while the other lies in determining the parts of stardom that cannot be explained by his contribution on-pitch and are therefore possibly related to his popularity in addition to being a talented soccer player.

Many papers have therefore also turned their focus on the popularity aspect of superstardom. A selection of relevant papers is referred to in the following section. Especially, as the fans' possibilities in today's sports world to connect with their stars and talk about them are larger than ever and with that increase superstar effects. Stars share more and more of their "off-the-pitch" life with fans via media like Twitter, Facebook and lately particularly Instagram and Snapshot in real time. Increasing "Adler's consumption capital" is therefore an easier and quicker process for stars today, but the simplicity of it also makes the field more crowded. As a consequence, distinguishing between different star types in form of detailed analysis is more important today. To measure star quality, Krueger (2005, p. 18) uses the "number of millimeters of print columns (incl. photos) devoted to each artist in The Rolling Stone Encyclopedia of Rock & Roll", while in the soccer literature, Garcia-del-Barrio and Pujol (2007) use internet exposure as a measure to determine superstars. They outline that a popularity variable "can eventually play a significant role in helping to explain the economic behavior in the sport and entertainment industry" (p. 68). They use a filtered measure of Google hits to avoid multicollinearity with the performance variables as part of popularity is always linked to performance. A similar process is used by Franck and Nuesch (2012), but they employ popularity as an input factor in a wage determination model and not as a determinant of stardom as Garcia-del-Barrio and Pujol (2007) do. Franck and Nüesch (2012) refer back to the original definition of Rosen and define "superstars as the players at the top end of the market value distribution" (p. 208). They further employ the residuals from an auxiliary regression on press citations from the LexisNexis database to have a pure popularity measure without performance-related aspects. In their findings, players' market values are driven by performance (which they equate with talent) and popularity. Part of popularity is itself driven by performance on the pitch and part is driven by "nonperformance-related star attraction" (Franck & Nüesch, 2012). This latter could be related to the star's private life, or his fashion taste, or anything else that fans are interested in that happens off the pitch. The mentioned papers show how entangled the different aspects of stardom are and the importance to keep them separate in the analysis to receive distinct effects also for the forthcoming analysis in this paper.

Krueger (2005) has already acknowledged that his popularity measure is a "subjective measure" but at least reflects "the importance that the editors of the Encyclopedia implicitly attached to each artist" which should usually be "correlated with the band's prominence" (p. 18). Brandes et al. (2008) continue this discussion by claiming that "robustness checks reveal that a star attraction analysis requires a precise definition of superstardom." Hence, stardom research that is based on a subjective measure is questionable. For MLS research this is easier as the league has a quasi-objectively assigned status that sets the stars apart from other players – the designated player status. In this form, MLS delivers a specified group of stars that can be investigated to describe star characteristics and with that identify different types of stars. This combination has not been covered by any paper before and therefore this paper will address the different features of MLS stars in detail. Finally, with respect to characteristics we should remember that according to Adler (1985, p. 211) the characteristics of stardom are independent of the process by which a star evolves because "all artist could be stars" and "efficiency calls for very few artists with public recognition".

2.2 Major League Soccer and the Designated Player Rule

A designated player is, according to the MLS roster rules, a player "whose total compensation and acquisition costs exceed the maximum budget charge, with the club bearing financial responsibility for the amount of compensation above each player's budget charge" (Major League Soccer, 2016). Hence, DP salaries count towards the salary cap but only with the maximum budget charge, $457,500 in 2016, which is paid by the league. What the club pays in addition, financed by other club's resources, is not limited. In 2013, the MLS introduced an extension to the DP rule to foster the employment of younger but very talented players. They specified that a 'young' designated player (YDP) is a DP who is "23-years-old or younger during the league year". YDP also count against the salary cap but with a limited amount. The budget charge for YDP was $150,000 in 2016. This analysis uses a third group to distinguish DPs, the 'transfer' designated players (TDP). TDPs are officially considered by the league as DP but solely because their transfer fee exceeds the maximum budget charge while the salary is well below the maximum. Typically, those players receive the status for only one year until the acquisition costs are amortized. In this sense it is expected that the characteristics between DP and TDP differ in various ways and is also reflected in a lower salary. Every MLS club is entitled to fill two DP spots per se and has the right to buy a third spot by paying $150,000 to the league. This extra money is split among all clubs that do not fill a third spot. In this sense, the fee works as a luxury tax to improve parity in the league. If an YDP occupies the third spot the fee does not apply. Furthermore, clubs can use General Allocation money to “buy down” DP salaries under the maximum budget charge. Those players are not considered in the following analysis as they are not officially listed as DPs in the official league statistics.

The amount of recent publications with a focus on MLS unrelated to the introduction of DPs proves that MLS is a worthy subject for broader research. Nevertheless, most MLS studies incorporated the superstar topic somehow. For example, Lawson, Sheehan, and Stephenson (2008) found a positive effect on merchandising revenues traceable to the introduction of the DP rule and in this study particularly David Beckham. However, a reasonable question that has been asked multiply times is if MLS signed Beckham to really improve the game quality and performance in MLS? After all, he was a key player on the England national squad and achieved multiple club titles with Manchester and Real Madrid. Or was Beckham’s hiring more of a “publicity thing” to bring media attention to the hitherto neglected MLS? Wahl (2009) summarizes the first year of Beckham’s era as disappointing, for sure in terms of performance due to his many injuries, but also television ratings were just not great compared to other US sport events. Paul and Weinbach (2013) studied impact of different factors on MLS ratings but did not include a specific superstar measure which leaves the impact of them on TV ratings and viewership still open up to date. Almost 10 years after Beckham, the topic “DP effect”, at least, on attendance was examined by researchers again. DeSchriver, Rascher, and Shapiro (2016) confirm the unique contribution that the first DP, David Beckham, had but also highlight other star players’ impact on MLS attendance. Attendance figures increased according to DeSchriver et al., (2016) on average “by 2500 spectators for each additional designated player that the home team had on their roster” representing an increase of 15 percent. With an average ticket price of $25 this comes down to one additional million[4] from tickets sales per DP on the roster. Additionally, the number of visiting designated players increased attendance as well but to a smaller extent (~600 additional spectators). Nevertheless, it is still unclear if the “Beckham-effect” was unique or if this phenomenon could be repeated by hiring other stars. To answer this question, Jewell (2017) recently showed that not just Beckham but also designated players like Blanco and Marquez positively increased game-day attendance and even were “financially beneficial for MLS” (p. 249). He contributed much of the effects to novelty as the returns were diminishing over time. This finding limits hiring stars usefulness to the league in the long-term.

[4] 2500*17 home games = 42.500*25 = 1 million

Finally, Sung and Mills (2017) provide supporting evidence with their significant positive home- and away-star effects over a longer period on MLS attendance as they include all DPs and not just marquee players like Jewell uses Beckham, Blanco and Marquez. Sung and Mills (2017) conclude with reference to the other studies, that superior teams and superstars are "particularly important for the growth and popularity of MLS, at least in terms of attendance" (p. 12). The relevance of the presented MLS superstar study is justified by statements like this. Furthermore, DeSchriver et al. (2016, p. 220) promote the idea that "future research on individual star athletes would be valuable in this context".

Apart from superstar salaries, wages are effectively suppressed through the salary cap in MLS (compare Twomey & Monks, 2011) and range at around 25 percent of revenues. Nonetheless, some teams jumped ahead recently. Toronto FC is spending almost 60 percent now, and New York City FC close to 50, driven in both cases by three expensive DPs on the roster. Therefore, it comes as no surprise that the amount used for DPs salaries, compared to regular player salaries, increased from roughly one fourth in 2007 to almost half in 2015[5]. Still, paying players less than is warranted by their marginal product and less than the "competition" is clearly hindering the top talent acquisition and retention process of MLS in the long run and in order to compete with the international soccer world. Also, the tight MLS governing system was challenged by the introduction of the DP rule. The question is if superstar externalities (see Jewell, 2017) can balance the DP rule advantages for big market teams who were able to afford paying millions to marquee players with the disadvantages for smaller teams with less financial resources. On a first look, MLS still manages to keep competitiveness high as the spread of MLS champions and the mixed playoff picture show almost every season since 2007.[6] High levels of competitiveness was shown by previous literature to increase fan interest and with that improve television ratings and attendance numbers. Paul and Weinbach (2013) show that this relationship is also true for MLS and therefore a vital element in fulfilling the profit goal of

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[5] Own calculation based on revenues reported by Forbes for 2015 on https://www.forbes.com/sites/chrissmith/2016/09/07/major-league-soccers-most-valuable-teams-2016-new-york-orlando-thrive-in-first-seasons/2/#185a2da14d6e and team salaries as reported on the Players Union Website.

[6] From 2007 until 2016 8 different teams claimed the 10 champion's trophies. Only LA Galaxy managed three victories (2011, 2012, and 2014) in this time, two of them with David Beckham and all three with Robbie Keane on the roster. Seattle is the only team that made all playoffs since they entered in 2009 and New York Red Bulls missed once. Otherwise there is no team that never made the playoff at least once in the observation period which indicates that the playoff round is mixed throughout by teams.

MLS. Although, Sung and Mills (2017) also show the positive impact of designated players, they negate the impact of competitive balance and the uncertainty of outcome hypothesis. Consequently, an unambiguous confirmation for this relation is still open for further research. Another part that is influenced by this relationship is team productivity. Better teams attract more fans and more fans mean more revenues. Coates, Frick, and Jewell (2016) explains the dilemma with team productivity in MLS as follows: greater salary inequality hurts team productivity while spending more on team wages in general increases productivity. Therefore, any superstar addition to a team which most likely increases both, team wages in total but also team wage inequality, needs to be managed with great care. Being able to place superstars in different groups and anticipating the impact of individual players will support the decision-making in the hiring process.

To summarize, the presented research illustrates first, why stars that can generate higher revenues are important to a league in which profit is often even more important than win maximization. Secondly, it was explained why talent and popularity are as important in superstar research but also why and how to keep them separated for analysis-purposes. Thirdly, the necessity for a detailed analysis of superstar characteristics in general and in MLS was highlighted. Employing the right players and spend money wisely will be a result of this. However, prior studies have failed to reach the depth and capture the various individual player characteristics. Both is necessary to draw conclusions from superstar characteristics for other discussions around attendance, salary structures, revenue, development of the league, and team performance. Therefore, this study aims to look behind the broad categories of talent and popularity, and explores several characteristics of players and will try to identify different star types among MLS's designated players.

3 Data

This research is built on multiple data points for all MLS designated players from 2007 to 2016. Below, Table 1 shows the adoption of the DP slots by teams and DP numbers per season. While not all teams made use of the option immediately, in 2013 all teams employed at least one DP for the first time. The total number of DP observations in the ten-year period is 284, of whom

98 individual players started as DP, 13 as YDP, and 22 players as TDP. Therefore, the sample of all star entries includes 133 observations[7] and 98 if only the "true" DPs are considered.

Table 1 Club and DP Count Over Time

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	*Total*
Clubs with DPs / all clubs	5/13	5/14	9/15	8/16	12/18	16/19	19/19	19/19	20/20	20/20	
Sum of (T)(Y)DP	7	7	10	14	23	32	36	43	54	58	*284*
Entries: (T)(Y)DP	7	3	4	8	14	16	15	21	30	15	*133*
Sum of only DP	7	7	9	13	18	24	22	30	42	49	*221*
Entries: DP only	7	3	3	8	9	10	8	17	22	11	*98*

One goal of this paper is to find out who the MLS superstars are and characterize them based on several key criteria that the players possessed at their MLS arrival. This will illustrate what type of players were employed as stars by MLS. To determine the time the player started as DP the official MLS acquisition details were used. The criteria are grouped into three categories. First, everything inherent to the player himself – player characteristics. Secondly, everything that describes his career as a soccer player – soccer characteristics. Jointly, these two categories should describe the talent and performance aspects of a player adequately. And thirdly, a measure that describes the popularity of the player.

Player Characteristics: Age, origin, height, preferred foot.

Soccer Characteristics: Professional seasons, previous club level, career games/goals/assists, titles, national team games, captain, position.

Popularity measure: press citations

The sources used to retrieve this data are the official mlssoccer.com website for personal traits and contract information, newspaper articles to confirm some of the contract and start dates if they were not posted directly by MLS, players personal Social Media accounts, and the platform transfermarkt.com for further personal characteristics and performance statistics.

[7] Two players have started twice and are recorded with two separate observations. In one case a player (Octavio Rivero) started first as YDP and switched status after one year to DP. In the other case the player (Eddie Johnson) started in 2007 and then later in 2014 again as DP.

All information was collected at the point of entry as a DP. For example, the number of *national games* played was relates to the period up until the player started as DP in MLS. The *level* the star played before is categorized by the league in which they played before receiving the DP status and the quality of this league. All top-tier first division leagues, with reference to the UEFA and FIFA rankings, are classified as 1a. In this group we list the Bundesliga, EPL, Serie A, La Liga, and Ligue 1. Second group, 1b, are the first division leagues Eredivisie, Jupiler Pro League, Brasileirão, Liga MX, Raiffeisen Super League, Süper Lig and the Argentinean Primera Division (formerly called Torneo). In the third group, 1c, all other first division leagues are listed, e.g., from Sweden, Chile, or Australia. Groups 4 and 5 list second- or third-tier divisions. The base category, 0, for the *club level* is MLS. The *captain* variable is a dummy that captures if a player has led a team before. The *origin* variable is grouped into four regions to facilitate the analysis of 39 different nationalities. The base category is "Local" including Canada and the USA, "Americas" includes the Caribbean, South, Central and Latin America, "Europe" Western and Eastern Europe, and "Others" Asia, Oceania and Africa. *Footedness* groups players together who prefer the right foot, left foot or are equally talented with both feet. All other variables are continuous. The popularity measure was retrieved from the global news database Factiva. Factiva covers local sports and general interest newspapers and magazines like "La Gazetto dello Sport" or "The Toronto Sun", as well as newspapers and magazine with global reach like "The New York Times", "The Guardian" or "The Times (U.K.)". All citations in the worldwide press in relation to the term "Soccer" to avoid misspecifications with popular names are counted. Similar approaches have been used by Garcia-del-Barrio and Pujol (2016), Brandes, Franck, and Nüesch (2008), and Franck and Nüesch (2012). For each player the observation period from which relevant citations were drawn is 12 months before entry. Again, this allows us to infer the status the player had before entering the MLS. Finally, the corresponding salaries were collected from the official MLS Players Association page. Usually DP contracts span over a certain period under which the base salary is fixed. Beckham for example earned $5.5 million base salary over five years. Hence, the decision to hire the player and the salary that is paid for him is taken once before the player enters the league. Investigating salary determinants and criteria for why this player was chosen should therefore also refer to the same time, i.e. before entry. The analysis uses real market values and salaries that were corrected for inflation with the Consumer Price Index as reported by the United States Bureau of Labor Statistics. The first year, 2007, serves as base year. Table 2 shows the descriptives for all types of DPs, including YDPs and TDPs, at point of entry. A separate table (6) for the smaller group of just DPs can be found in the Appendix. For some players certain career statistics were not available which reduces the number of observations. Three anomalies with regards to the descriptives are also worth mentioning: First, many variables have a large standard deviation indicating the diversity of the group. Secondly, the young and transfer designated players reduce, as expected, particularly the age of the overall group and the career statistics. Thirdly, many variables are highly skewed to the right, e.g. salary and popularity why log values should be used instead.

Table 2 Descriptives for DP, YDP, and TDPs

	count	mean	median	sd	min	max
season	133				2007	2016
player	133				1	131[8]
DP	133	0.74			0	1
YDP	133	0.10			0	1
TDP	133	0.17			0	1
age	133	28.6	28.9	4.35	19.0	38.0
nationality	133				1	39
origin	133				1	4
homegrown	133	0.16			0	1
height	133	1.79	1.80	0.069	1.60	1.96
footedness	133				1	3
profseasons	133	9.76	9	4.43	1	20
level	133				1	6
Cgp	133	251.9	222	154.5	17	821
Cgp / Prof.s.	133	24.7	24.5	6.6	8.8	41.05
Cgo	133	60.2	41	57.5	0	289
Cgo / Prof.s.	133	5.9	5.4	4.1	0	18
Cassists	84[9]	32.2	27	29.0	0	176
titles	133	3.29	2	4.24	0	22
natgames	133	30.1	16	34.8	0	123
captain	133	0.30			0	1
position	133				1	4
popularity	133	1,761	491	3,761	3	25,857
logpub	133	6.11	6.20	1.79	1.10	10.2
Sbase	133	1,169,384	600,000	1,567,482	42,000	6,660,000
RealSal	133	1,050,014	542,994	1,403,691	38,486	5,808,319
LogRealSal	133	13.2	13.2	1.15	10.6	15.6
club	133				1	21[10]

4 Superstar Characteristics

4.1 Descriptive Analysis

A straightforward classification of MLS stars is based on their **age**. Mean age for all MLS stars is 28.6 and 30.0 for the smaller group of only DPs. To put this in perspective, the turning point, where salary starts to decrease again, is around 28 years in the Bundesliga (Frick, 2011), and the turning point for productivity is 27 years (Rossi, 2012, for Serie A). This seems to support

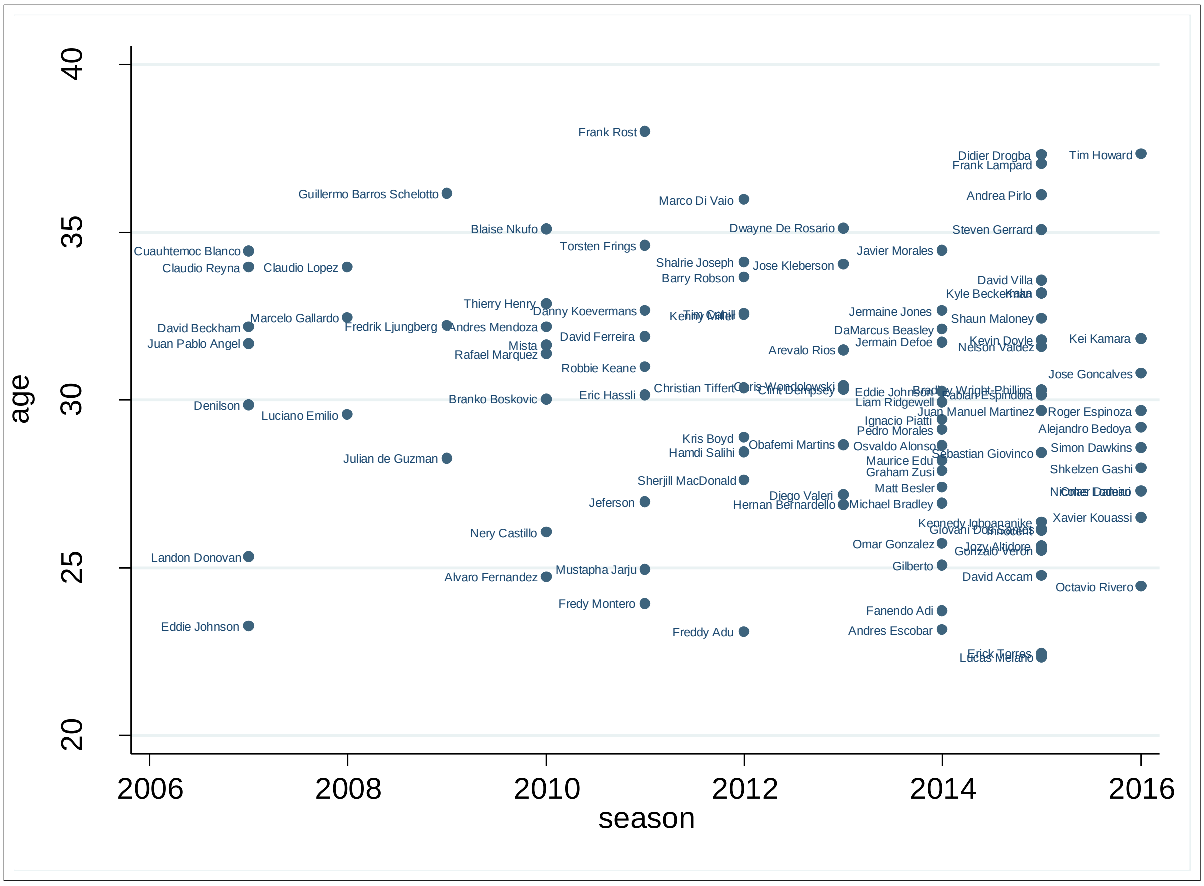
[8] See footnote 47.

[9] Career assists were not reported for all players in the analysis. This will be considered in the following analysis.

[10] A maximum of 20 clubs per season but as Chivas exited after the 2014 season the total club count is 21.

the prejudice that many players who had their best days behind them are hired by MLS. Adding the seasonal component, Figure 1 shows how old DPs were in the respective year they were hired. Here we see that before 2014 the typical DP was indeed rather old. Johnson and Donavan for example appear as outliers in the early years of the DP rule. Also in the years to follow only a handful of players were under 30. For the first time in 2014, a majority of newly hired DPs was actually under 30. Twelve, compared to four players, are younger than 30. Currently, it is too early to say if this constitutes a long-term trend, because for 2015 old and young players are in balance, but at least for 2016 the younger generation took over again.

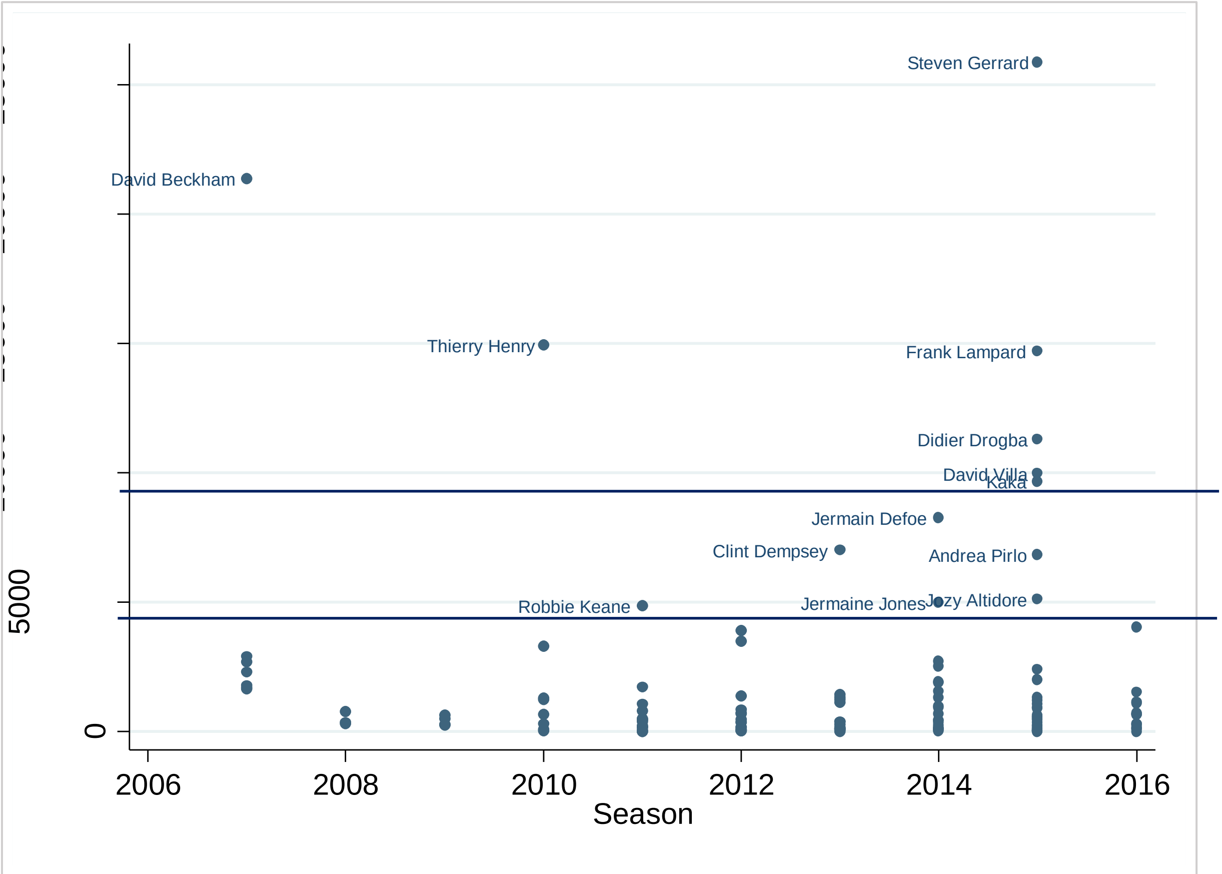
Figure 1 Scatterplot of Designated Player Age at Entry



Among all MLS stars, the age groups are more balanced. In the ten-year observation period, equally many players are under the age of 25 (n=31), between 25 and 28 (n=37), between 29 and 31 (n=33), and over 32 (n=32).

Next to age, **popularity** is said to be a key determinant for MLS clubs to hire players. As mentioned in the literature review, this is due to the positive effects these stars have, e.g., on attendance and merchandizing revenues. Steven Gerrard and David Beckham were by far the most popular players hired by MLS in the last 10 years (see Figure 2). Gerrard, maybe surprisingly, tops Beckham in this popularity count which has a couple of reasons. For one, the year before Gerrard joined was a World Cup year and he captained England for the first two games and before being eliminated in the group stage. Gerrard announced his retirement from international football shortly after the tournament. This generated obviously a lot of press, positive as well as negative in kind. Also, Gerrard's contract at Liverpool expired at the end of the 2014/15 season, in which he played his 500th league match for the club, and received a late offer to renew which he turned down in favor to sign with LA Galaxy after the EPL season ended. He also was the longest-serving Liverpool captain (appointment back in 2003). This situation most likely increased the press coverage. Overall, Figure 2 shows a group of 7 stand-out players, if the line is drawn at ~10,000 citations in the year before joining MLS, or 13 players, > ~5000 citations.

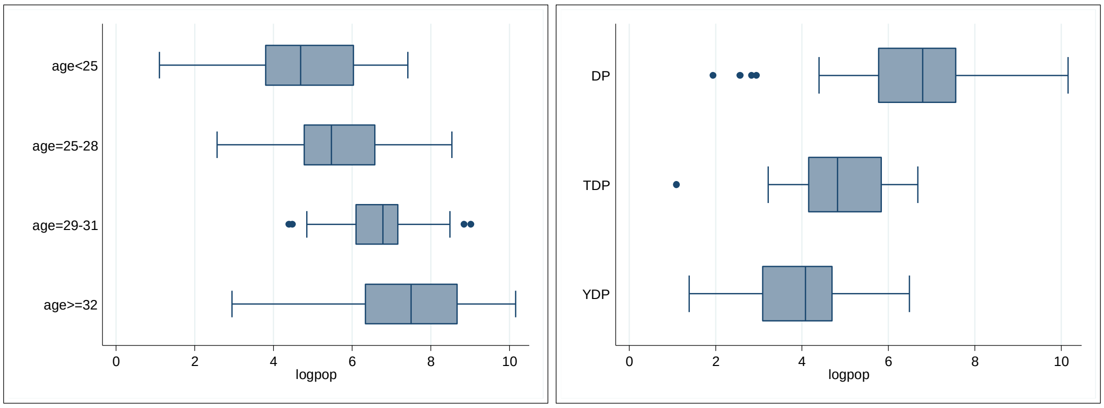
Figure 2 Popularity of Designated Players by Entry Season



From Figure 2 and the descriptives (large deviation from median and mean) it appears that the popularity score is extremely skewed (to the left, score of 3.24) and suffers from high kurtosis

(13.78). The logarithm of popularity, by contrast, is close to normality[11]. Therefore, the following analysis use the transformed variable *logpop*. The boxplot, Figure 3, below displays a general tendency that the older the player the more popular he is[12]. Apart from some outliers[13], players with DP status are as expected more popular than TDPs and YDPs.

Figure 3 Popularity by Age Group and Type



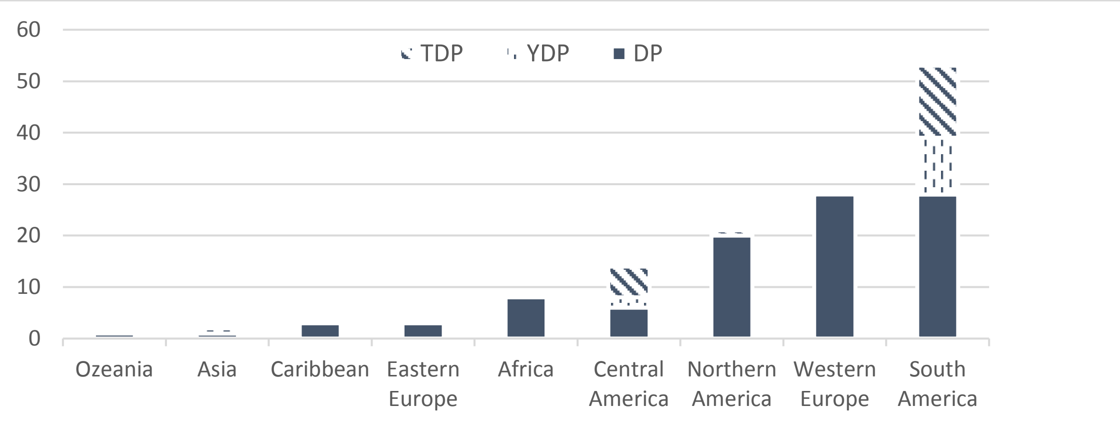
Turning to the **origin** of players, we find that most stars are from South America and Western Europe (see Figure 4). With regards to Europe, this is no surprise as European players are internationally acknowledged for being well trained and play on a qualitatively high level. From the South American stars, 80% come from Argentina which soccer league also has a good reputation and historical close ties to MLS (e.g. from hiring players).

[11] For reference, the kernel density estimation for *logpop* is shown in the Appendix (Figure 9).

[12] Outliers in the age group 29-31 are on the right-hand side Clint Dempsey (USA) and Jermain Defoe (England) and on the left-hand side Claudio Bieler (Argentina) and Branko Boskovic (Montenegro).

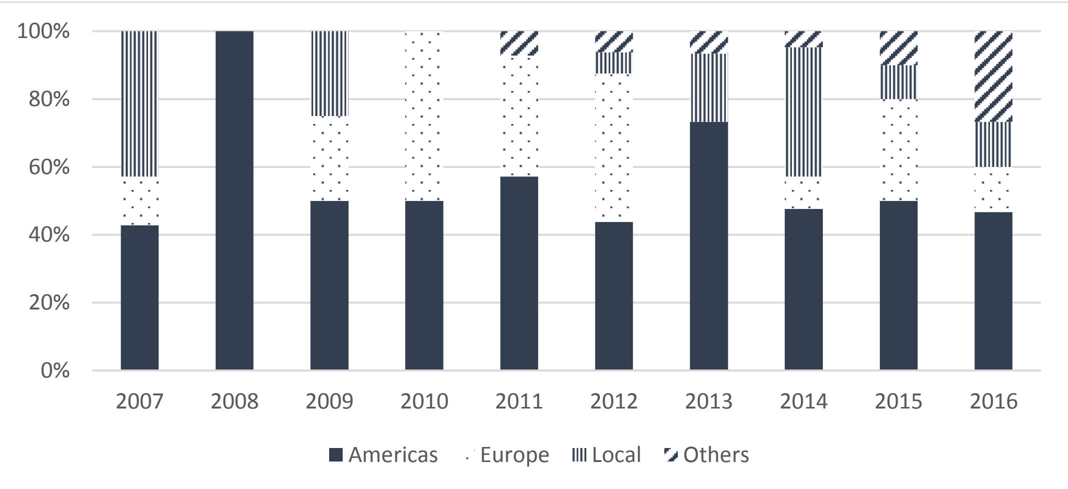
[13] DP outliers are Mustapha Jarju (from Gambia), Kennedy Igboananike (Nigeria), Sherjill MacDonald (Netherlands), and Andres Mendoza (Peru). TDP outlier is Milton Caraglio (Argentina).

Figure 4 Region of Origin of DP, TDP and YDPs



The dominance of players from the Americas has changed little over time (see Figure 5), but from time to time European or Local players claim at least half the spots for new incoming stars. In 2015 and 2016 regional diversity was increased with new stars from Azerbaijan, Israel, Ghana, Ivory Coast, Nigeria and Sierra Leone.

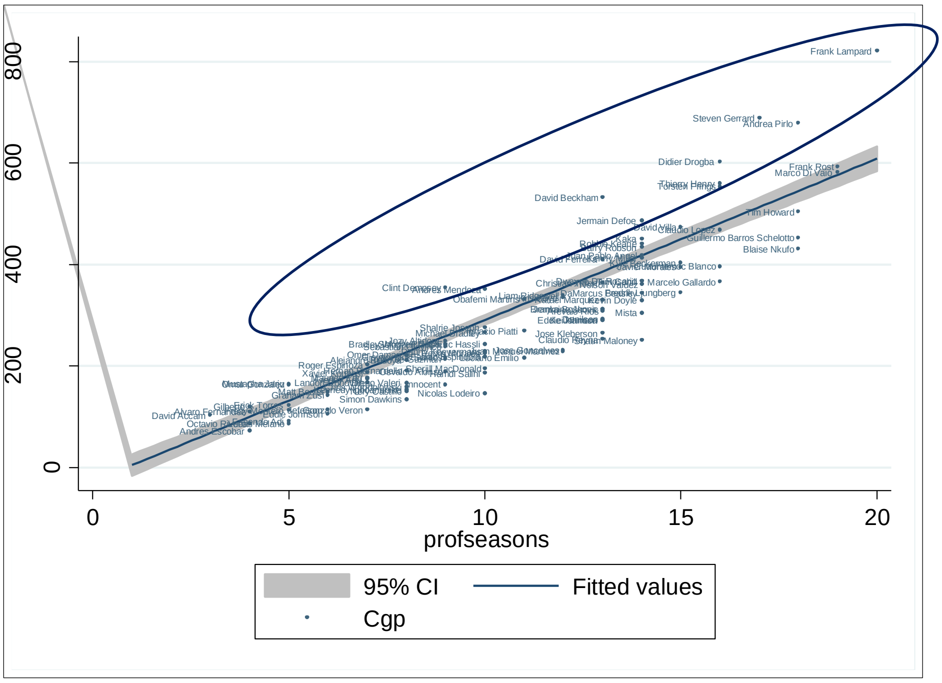
Figure 5 Origin of Players by Season

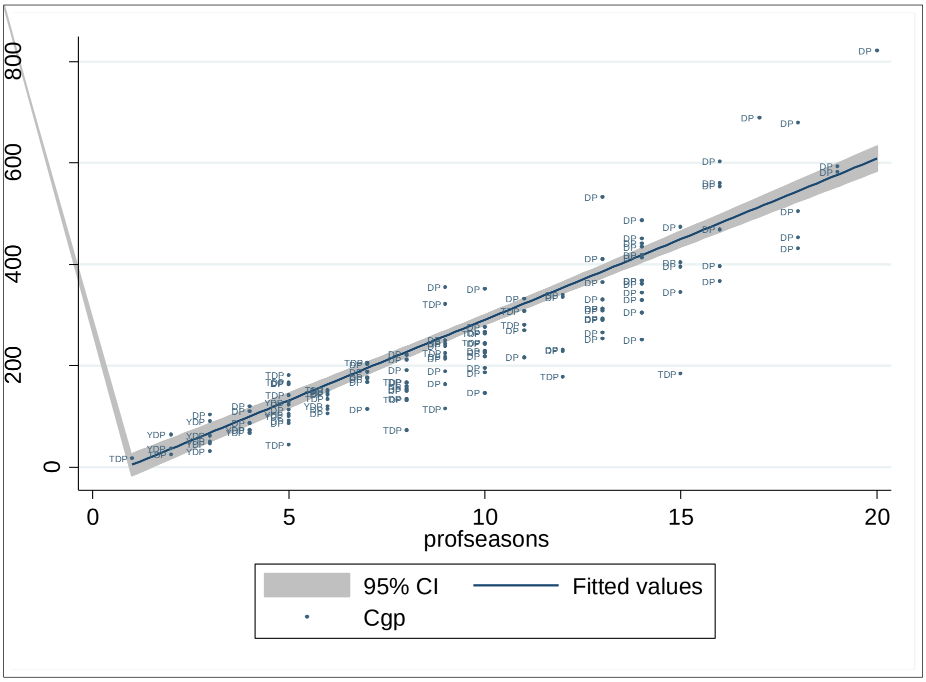


Birth region is one factor, but for soccer players the national league **level** they play in at senior level is probably most important. Club-level competitions have a particularly high significance in the world of soccer due to their regularity, while international competitions, like the World Cup, only take place every four years. Of the MLS stars, about a third played in top first division teams right before joining MLS as DP. Most notably, they played in England (e.g. Manchester City, Tottenham Hotspurs, FC Chelsea, Hull City, FC Everton or FC Liverpool), Spain (e.g. Real Madrid, FC Villareal, Deportivo La Coruna, FC Malaga or FC Barcelona), and Argentina (e.g. Argentinos Juniores, Club Atlético Boca Juniors, or Club Atlético Lanús). Only one fifth played in MLS already before becoming DP. In more recent years[14] the number of players from lower divisions (e.g. 8 players from the English Championship) increased, but one might argue that the second English league is qualitatively as good as some of the second-tier, and for sure some of the third-tier, first division leagues that MLS stars come from. Obviously, a good league is associated with good training, great coaches, and valuable experiences as the player competes at a high level with other teams in the national and international competitions. Nevertheless, while having been part of a top team is one thing, having played on a regular basis at top level is another. To depict 'net' experience, Figure 6 shows a fitted graph of DP's **career league games** set in relation to his **professional soccer seasons**.

[14] A detailed overview of league level by season and by age can be found in the Appendix (Table 6).

Figure 6 Fitted Graph of Professional Seasons and Career Games Played





Note: first graph shows only DP, second graph shows all stars by type

With regards to net experience, a few players stand out, namely Lampard (with 227 games more, ~11 more per season than predicted by the DP model[15]), Gerrard, Beckham, Pirlo, Drogba, Dempsey, Frings and Henry. This group stands out with a disproportionally high share

[15] The estimations for prediction model and associated player scores are available upon request from the author.

of career games per professional seasons played. This illustrates how regularly they must have played and consequently how important they have been for their teams. The second graph, including all stars, shows how successful the YDPs started their career (considering that they played only a few senior seasons so far) and that many TDPs fall far below the fitted line. This tells us that not all TDPs can match the high standards set by the DP group. Another differentiating factor, between the DP group on the one hand and the YDP/TDP group on the other, is the **captain** quota. Almost 40 percent of DPs captained their senior club team or/and the national squad before joining MLS. Only 14 percent of TDP's have been named captain and, not unexpected, none of the YDPs captained at senior level so far. Over the years, 27 to 63 percent of the incoming DPs have been captains before. Based on this, we assume that leadership qualities were at all times a relevant aspect for teams' hiring decisions. Also, all the players with disproportionately high levels of experience were captains. An additional aspect that they all share is **experience with the national team.** In the referenced top group, everyone played over 80 games for their national team (Henry tops the list with more than 120 games). In fact, of the 98 DPs only 18 have not played for the national team before joining MLS. In contrast, half of the TDPs and YDPs have no senior national team experience. The nationalities of the non-capped players: 5 from Argentina, 3 from Brazil, 2 from England, 2 from Nigeria, and 1 each from the Netherlands, Portugal, France, Germany, Colombia and Uruguay. At least for seven players the chance to be capped might still be out there as they are under the age of 26. Another factor that the stand-out players share is their success, i.e., they won **titles**. With the exception of Clint Dempsey who won only two titles (and is the only homegrown player in the group), the others in the top group have won over 10 titles before joining the US league. Again, Henry leads the list with 22 titles at the national and international level. Then again, not all MLS stars have had this kind of success. Twenty-nine players have never won a title and the overall mean is low with three titles. Yet, this makes the success of Henry, Pirlo (20 titles), Drogba (17) and the other top group players (>10) even more distinctive.

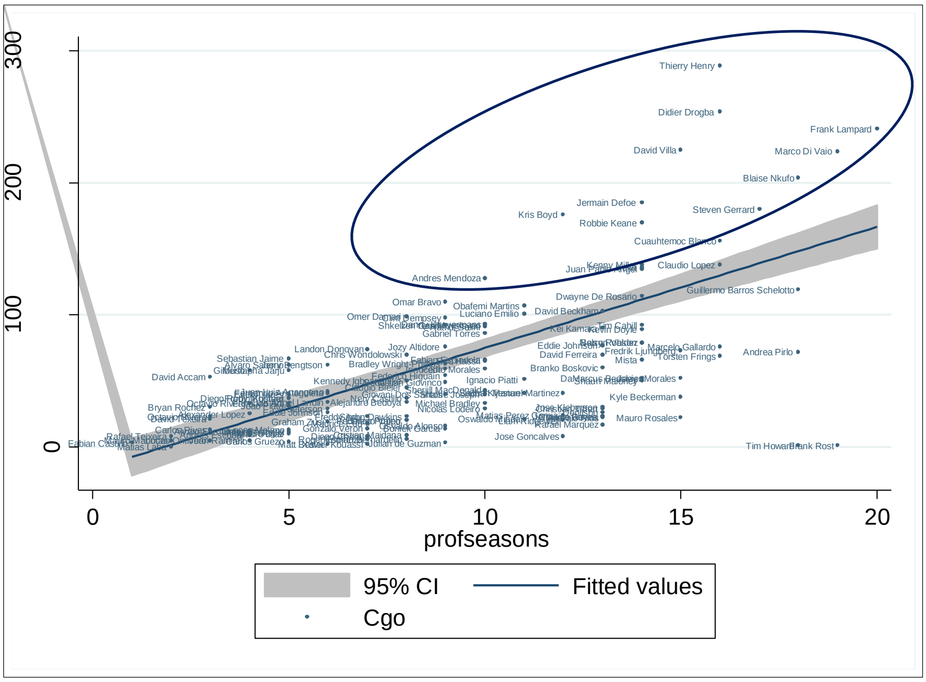
Having said that, Dempsey and Henry have something as distinctive in common. They are the two forwards in this stand-out group. In general, many DPs are forwards which can be seen in Table 3. The table shows that, apart from two goalkeepers (Frank Rost and Tim Howard, =1.5%) and six defenders (=4.5%), 94 percent of stars play offensive **positions**.

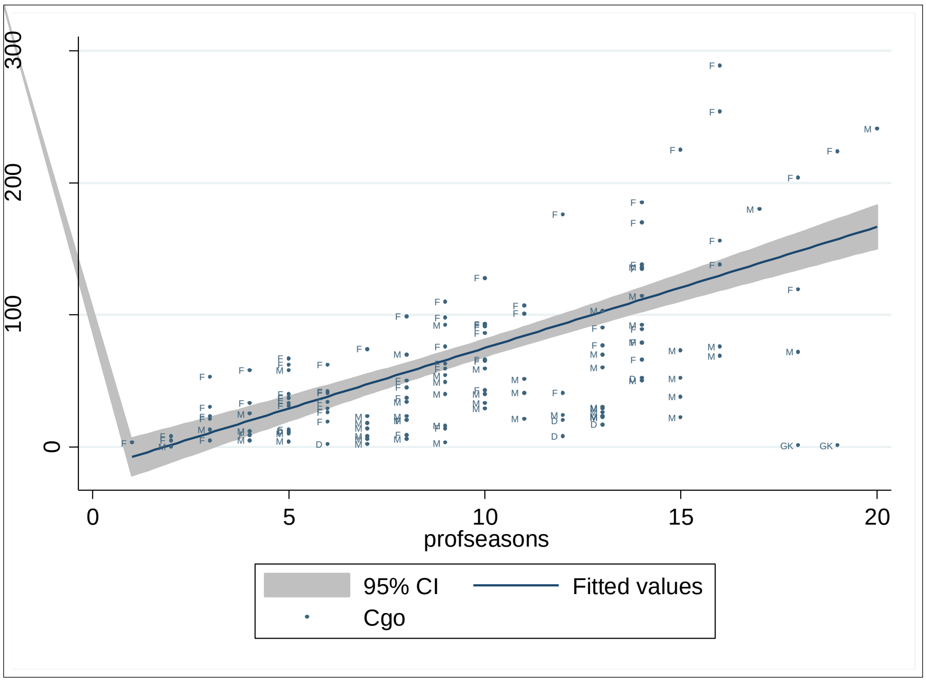
Table 3 Spread of Positions

In %	Forward	Midfielder	Defender	Goalkeeper	
DP	35	33	4.5	1.5	*74*
YDP	5	4.5			*9.5*
TDP	12	4.5			*16.5*
	52	*42*	*4.5*	*1.5*	*100*

In this line, Franck and Nüesch (2008, p. 152) suggest that “[e]ven though there are many constructive elements in a game which enable the teams to score goals, the public’s attention is largely concentrated on the players who finally score.” They explain that consumers do not need to be an expert or have specific knowledge to “ascertain the goal scorer” or the final passer. Furthermore, in a low-scoring game like soccer, good offensive players can decide a whole game with one individual action where they score which in turn might lead to a one-goal ahead win or at least a tie. Also, it is probably no coincidence that the Ballon’dOr winners since 2008 were all forwards, namely Cristiano Ronaldo and Lionel Messi who competed for the award since then every year. Ultimately, the publicity gain and the performance aspects mentioned before are both rational arguments for hiring offensive star players to complete a MLS team. This is also reflected in a fitted graph of **career goals** relative to professional seasons played. First, it is important to note that the range and the standard deviation of career goals scored (see descriptives) is quite large. In Figure 7 the ratio between goals and professional seasons played is shown with interesting findings. Forwards and midfielders average at 6.3 goals per professional season played. Only DP forwards even average at 8.9 goals per professional season. Henry (18 goals per season), Drogba (16), Lampard (12), Gerrard (11) are, once more, among the outstanding players while Beckham and Dempsey are average in this category. Pirlo is found even below average which is justified by his positions as defensive midfielder. Over proportional “goal-productivity” is also shown by forwards David Villa, Marco Di Vaio, Blaise Nkufo, Jermain Defoe, Kris Boyd, Robbie Keane and Andres Mendoza. Of this group, only the former Spanish captain Villa, Irish national team captain Keane, and English-national squad player Defoe were above-average also in the aforementioned categories.

Figure 7 Fitted Graph of Career Goals per Professional Season Played





Note: first graph with all stars, second graph listed by position

For **career assists** (see Appendix Figure 14 for graphs) results must be interpreted with caution as no statistics were available for one fourth of the players. Nevertheless, the results are similar to goals scored in terms of spread and few outstanding performers. The top group of stars identified so far performs above average again and three additional players perform exceptionally: Kaka (also with high popularity scores), and local players Dwayne DeRosario (age 35, Canadian, captain, national squad, decorated MLS player, e.g. MVP) and Landon

Donovan (age 25, American, national squad, short stints in the Bundesliga, two-times U.S. Soccer Player of the Year and among the first DPs[16]).

In relation to offensive positions, Bryson, Frick, and Simmons (2013) found in their study an impact of **footedness** on wages for different European Soccer leagues. According to them, the ability to play equally strong with both feet is disproportionally high among forwards and midfielders. The results for the unbalanced MLS star group differ a bit. Among the forwards, 22% are equally strong with both feet (compared to 26% in Bryson et al.'s sample) and among midfielders 18% (22% in the European sample). Across all positions, 65% of MLS star players are right-footed, 17% left-footed, and 19% play equally strong with both feet which is comparable to the findings presented by Bryson et al.. These findings suggest that MLS teams are less focused of hiring stars based on their footedness.

All categories considered, the MLS star group is diverse on multiple levels. Large standard deviations are driven by outliers in almost all categories particularly for the continuous characteristics, i.e. professional seasons, career games/goals/assists, titles won, and national games played. Also the inherent player characteristics like age (range of 19 years, 16 for DP-only group) and nationality (players come from 39 different nationalities) increase the variety. But, besides the variety, the descriptive analysis presented above also indicated that there are indeed different player types among all star players. Therefore, I present a cluster analysis in the next section.

4.2 Cluster Analysis

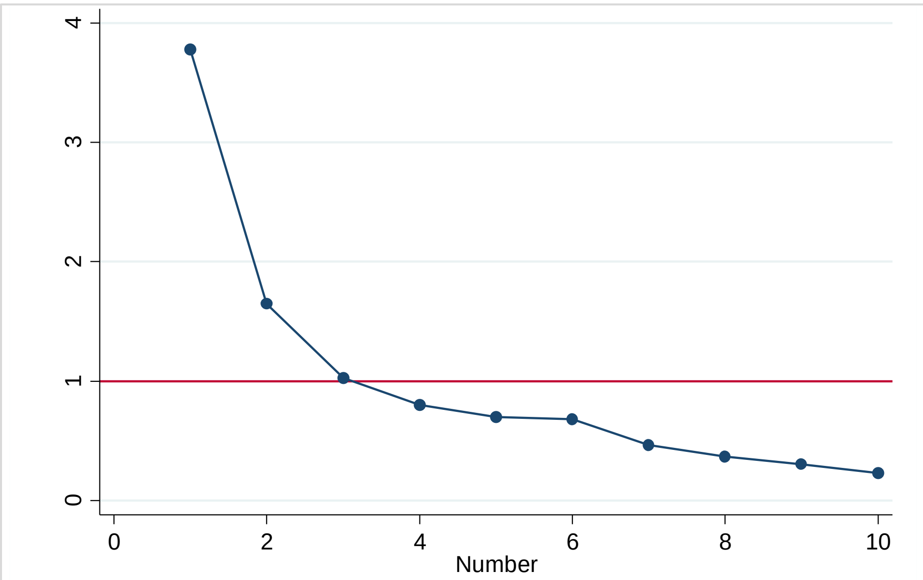
As outlined in the introduction, one goal of this paper was to determine different groups or classes of stars along the various categories. Such a grouping would be useful for future research to distinguish star's impact. The previous paragraph already indicated the existence of different groups among the stars and the highlighted variable variety is a necessary and suitable pre-condition to apply clustering methods. Considering the data structure, I perform a partitioning cluster analysis based on a Principal Component Analysis (PCA). Both methods are data reduction methods that can be combined to facilitate data interpretation of diverse, high variation, data. Cluster analysis places observations, in our case the players, in groups that have

[16] Officially, Donovan was grandfathered into the rule in 2007, together with Eddie Johnson, and did not count officially as DP until 2010. As he fulfilled all the requirements 2007 is noted down as first DP year for Donovan for the purpose of this analysis.

high intra-group and low inter-group homogeneity. PCA expresses multivariate data with fewer components that are linear combinations of the original variables. Taken together, the cluster analysis shows the different groups of players, while the PCA and the key components help to interpret why they are different.

Before PCA, I standardize the variables to set the variable scales to the same level. This is necessary because the cluster algorithm is not scale invariant. Furthermore, the categorical variables are simplified as only continuous and binary variables work well with PCA. Hence, origin is transformed into *homegrown* (1=player is from the USA or Canada, 0=foreigner), Level into *toplevel* (1=played in a top first division team before MLS,0= all other levels), position into *offense* (1=midfielder and forwards, 0=goalkeeper and defenders). Conducting the PCA for the 98 DPs in the sample reveals that three components can be used to express already over 65% of variation. As a standard rule, only components should be kept where the eigenvalue, the variance of the components, exceeds 1 as those explain at least as much of the variation as the original variables. This can also be seen in the screeplot in Figure 8 that presents with a kink at component 3.

Figure 8 Screeplot of Eigenvalues after PCA

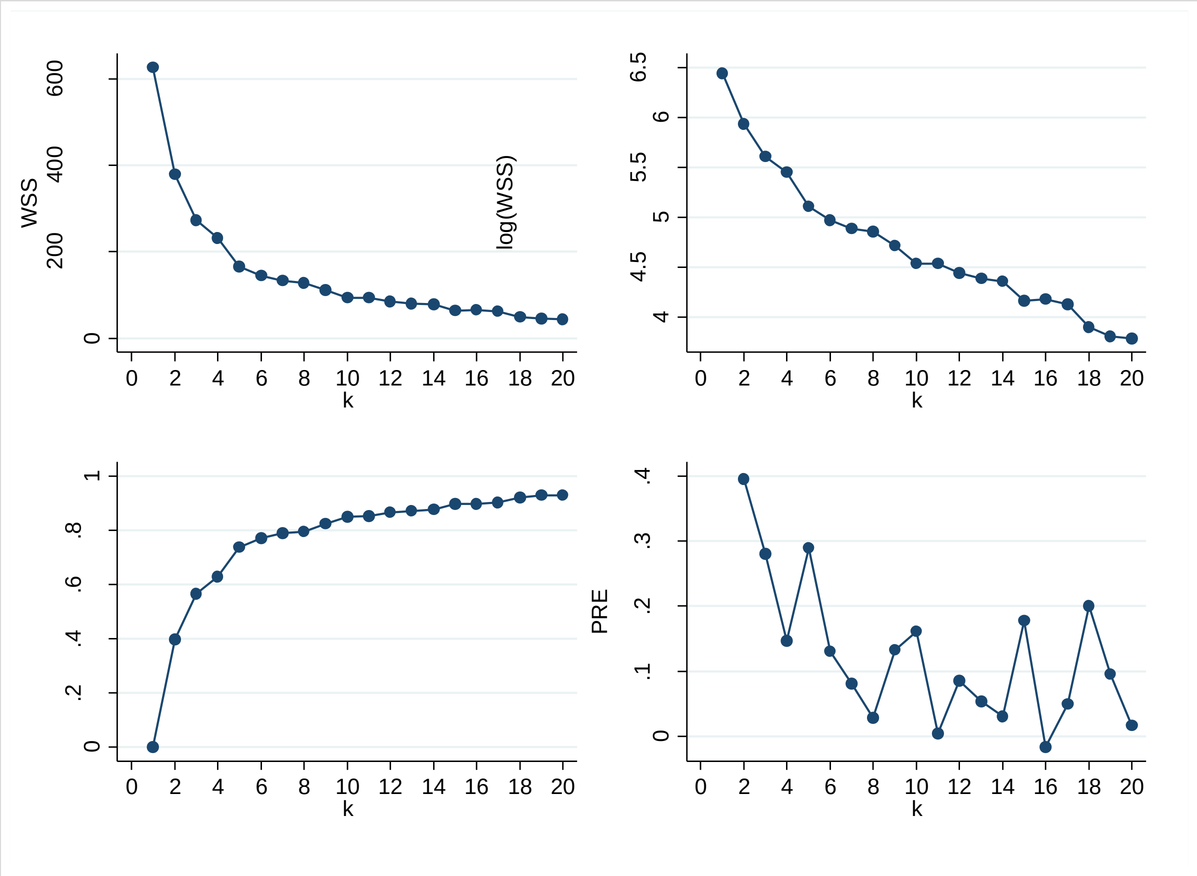


All the eigenvalues for the components and the different component loadings for the original variables can be seen in the Appendix (Table 8 and 9). The three kept components can be shortly explained as follows:

- Component 1 loading is particularly high for *natgames* and *logpop*. But with an eigenvalue of >0.3 also high for *Cgp_PS*, *titles*, *age, captain, and toplevel*. Summarized, this component captures high-flyers on a range of characteristics.
- Component 2 loading is high for *Cgo_PS* and *offense* and particularly negative for *homegrown*. Summarized, internationals that score frequently are captured.
- Component 3 loading is high for *homegrown*, *offense*, *Cgo_PS* and particularly negative for *age*. Summarized, younger and local offense players are captured.

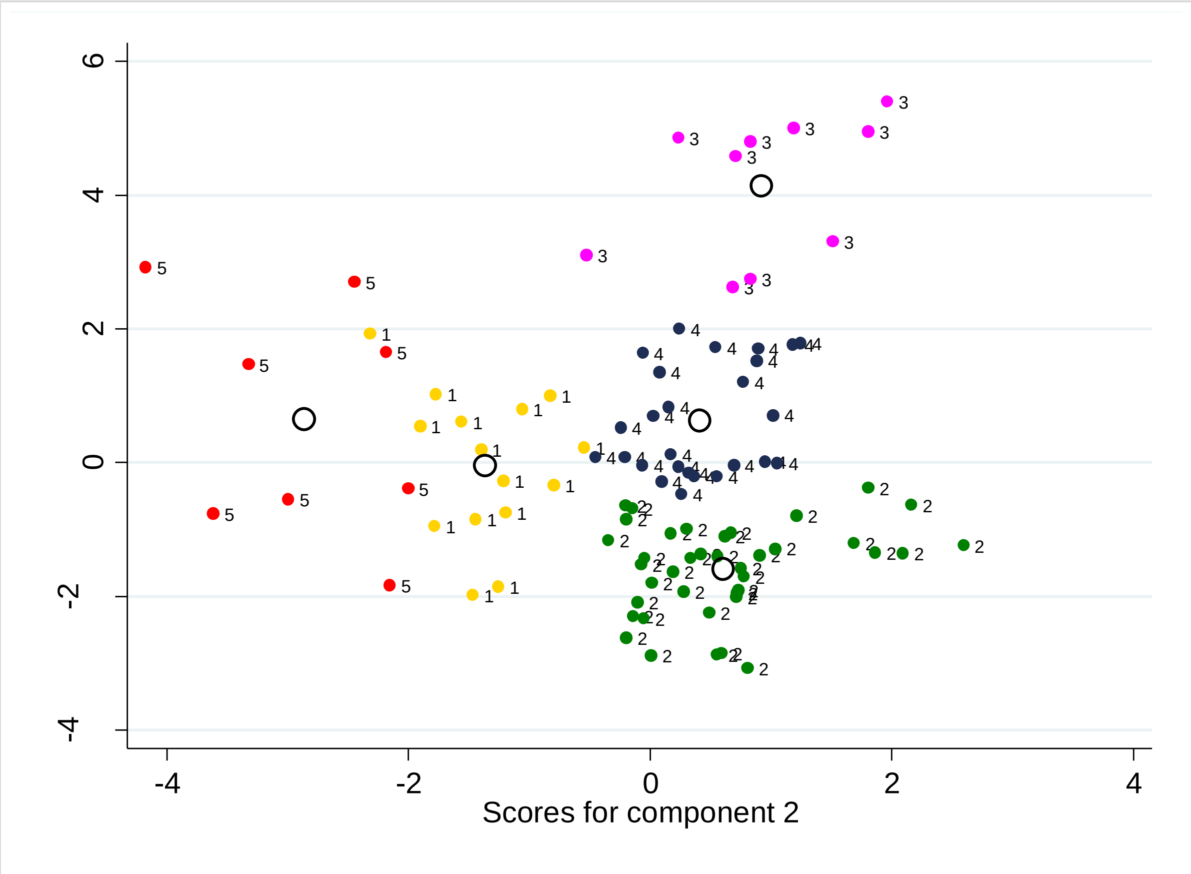
Next, I turn to the clustering of the player observations. For clustering, the k-means partitioning method forms groups that exhibit optimal intra-cluster homogeneity based on a defined number of cluster groups, *k*. The observations have a smaller variance to the group center of the chosen cluster than to other cluster centers. As recommended by theory, a sensitivity analysis was run with different cluster solutions, *k*, and sets of clustering variables, *m*. These tests the robustness of the clustering algorithm applied. Two set of variables are tested. The first set includes only the continuous variables to enable an Euclidian measure. The second set includes, next to the continuous variables, also the categorical variables (transformed to binary dummies) for the clustering. For the second set, the Gower measure for mixed variables was selected. Overall, the second, and more comprehensive, set of variables results in better cluster groups (tested with variance statistics) that can be also linked back to the descriptive findings above. The screeplot shown in Figure 9 is used to plot the within-cluster sum of squared errors (WSS) against each cluster solution. The kink in the WSS and log(WSS) indicate the optimal solution for clustering to be with k = 5. Eta-Squared points to a reduction of WSS by 74% and PRE to a reduction of about 28% compared to the k =4 solution. The reduction in WSS is negligible for k>5.

Figure 9 WSS, log(WSS), eta-squared, and PRE for all K Cluster Solutions



The five identified clusters, including cluster centers, are visualized in the exemplary scoreplot for component 1 and component 2 in Figure 10. The scoreplots for the two additional component combinations can be found in the Appendix (Figure 15 and 16).

Figure 10 Scoreplot of Component 1 and Component 2



The detected clusters are:

- Cluster 1, characterized by high levels for component 3, mixed outcome for component 1 and negative scores for component 2. The 15 players grouped in this cluster all play offense positions and are homegrown. They logged average career games played and low to average goals scored in relation to their professional seasons. Most players in cluster 1 have played more-than average national games, but they have won few titles, only some have been captain before, and show average (within one standard deviation) popularity levels while their age range is wide from 25-34 years. This cluster is defined as "*Local Stars*".
- Cluster 2, characterized by positive and partially high levels for component 2, negative scores for component 1 and mixed scores for component 3. The 39 players in cluster 2 are all internationals, more forwards than midfielders, only one has played on top-level before joining MLS, and only four have been captain of their team. Also for the other criteria this group falls below average except for career goals scored per professional

season. The cluster mean and standard deviation for *Cgo_PS* is the same as for the overall DP group mean. This cluster is labelled "*International Goal-Getters*".

- Cluster 3, characterized by very high scores for component 1, medium scores for component 2, and almost neutral scores for component 3 apart from two outliers[17], one on the negative and one on the positive side. The 10 players in this cluster show over proportional high levels of popularity, played substantially more national games and career games (per professional season) than average, scored more goals in relation to professional season, and won 13 titles on average. They all have been captain and apart from two (Villa and Kaka) have played on the top-level before joining MLS. Five players are midfielders and five are forwards. Only one player is non-international (Dempsey). This cluster is defined as "*Superstars*".
- Cluster 4, characterized by weak scores for all components. The graph shows this group "in-between" with component 1 showing the highest levels. And indeed, the 26 players in cluster 4 show average scores for all original variables but high standard deviations are behind the mean scores of most of those variables. I.e., national games range from 0 to 97, titles from 0 to 17, age from 26 to 36, and Cgo_PS from 1.7 to 13.2. The common factors for all are being international, average popularity and holding offensive positions. This cluster is labeled "*International Allrounders*".
- Cluster 5, characterized by negative scores particularly for component 2 but also component 3, and mixed scores for component 1. All 8 players in this group are defensive players (6 defenders and 2 goalkeepers) which explains the negative scores for component 2. The average popularity scores and average career games played drive the positive scores for component 1. Half of the players are homegrown, half of them have been captain, and half have played on the top-level directly before joining MLS. Age range is wide from 25 to 38. This cluster is labeled "*Defense*".

As a measure of goodness, Table 4 shows the within and between cluster inertia. High inter-cluster homogeneity increases the confidence in the appropriateness of the groupings. The presented clusters have higher between than within variation which supports the chosen clustering approach.

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[17] Clint Dempsey scores high on component 3 as homegrown player and for being youger than the rest of his cluster, and Andrea Pirlo scores negatively on component three due to his higher age (only Lampard is older), and below average Cgo_PS.

Table 4 Cluster Goodness

Cluster	1 - "*Local Stars*"	2 - "*International Goal-Getters*"	3 - "*Superstars*"	4 - "*International Allrounders*"	5 – "Defense"
N	15	39	10	26	8
Inertia within cluster	2.2357	1.9498	2.6489	1.8404	3.8992
Inertia between clusters			4.7848		

Overall, the groupings reflect the findings from the descriptive analysis well. As expected, one group stands out with exceptional performance variables and high popularity levels, the superstar group, cluster 3. These superstars according to the descriptive analysis and the cluster approach are Steven Gerrard, David Beckham, Thierry Henry, Frank Lampard, Didier Drogba, Andre Pirlo, Clint Dempsey, David Villa, Kaka, and Robbie Keane.

5 Superstar Value

5.1 Star Salaries as Value Measure

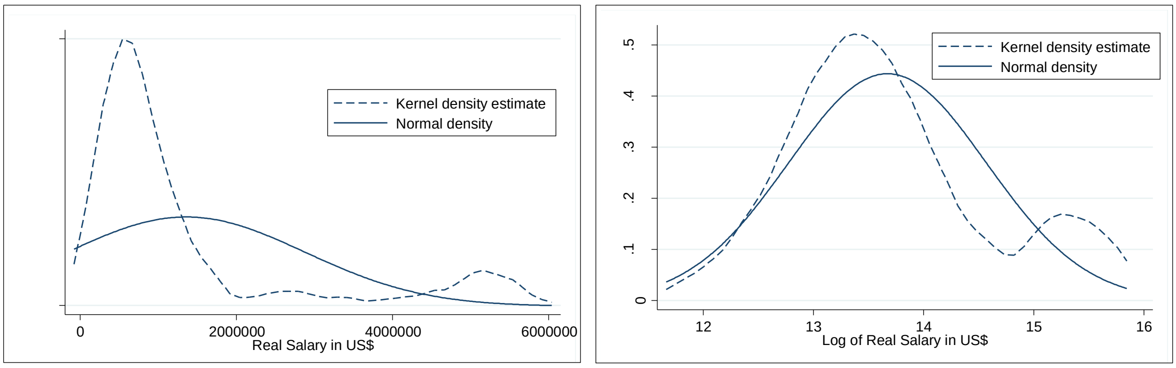
MLS teams that chose to hire a designated player, first, need to disclose this player officially as DP according to the rules stipulated by MLS because, secondly, they pay him substantial amounts of salary above the maximum salary. Hence, salary is not restricted in any form by the league but, if applicable, only by the financial resources of the teams. Considering the dual motivation of teams, to win and to earn profits, the salary they pay to athletes should reflect the value they expect to be brought to the team in one or the other form. Consequently, salaries are used as a proxy for the expected value of star players for a team.

Researchers devoted much attention to athletes' salaries and found in various team sports systematic influence of age, experience and productivity and more selectively, contract duration, position played, special talent like footedness, and origin[18]. Obviously, each sport has its own specialties, the US Sport Leagues face, for example, salary restrictions and closed league dynamics. Nonetheless, most salary studies use the basic Mincer earnings function as their framework. The main difference between sports and standard labor markets is "the

[18] Selection of the relevant studies that found those effects: Contract duration [Stiroh (2007), Rossi (2012) or Frick (2011)], position played [Frick (2006), Leeds and Kowalewski (2001)], special talent like footedness [Bryson et al. (2013)], origin [Pedace (2007), Frick (2011), Allmen, Leeds, and Malakorn (2015)].

distribution of salaries which is even more highly skewed” (Bryson et al., 2013, p. 608). The extreme skewedness in sports can be explained with superstar effects (Lucifora & Simmons, 2003). These findings are based on entire team or sport leagues while the focus of this paper is narrower as it only analyses the sub group of (transfer/ young) designated players. This sub group is already at the long tail of the league’s salary distribution. However, even in the small group of 98 DPs the distribution is still skewed to the left and suffers from kurtosis (see Figure 11).

Figure 11 Nonparametric (Kernel) Estimates of the DP Salary Distribution compared to the Normal Distribution



To that end, the salary distribution points towards a group within the group of stars that is remunerated substantially higher than the rest – superstars? The long tail starts around $2 million which captures 17 players[19]. With the exception of Pirlo ($1.7 mio) and Drogba ($1.5 mio), all superstars identified before in the characteristics and cluster analysis fall within this group. Notably, we encounter players from the first DP season of 2007, and then consequently from 2010 up to 2015. This points to some consistency of hiring decisions over the ten-year period. Nevertheless, over time the average DP salary fluctuated substantially between $1.9 million (calculated based on 7 DPs in 2007) to $790,000 in 2013 (based on 36 players) and up to $1.3 million again in 2016 (based on 58 players). So, even if top players were hired at almost all times, the increase of total DPs increased the salary range within the group.

[19] The following players earn more than $2 million base salary: Kaka, David Beckham, Steven Gerrard, Rafael Marquez, Frank Lampard, Jermain Defoe, Michael Bradley, David Villa, Sebastian Giovinco, Thierry Henry, Clint Dempsey, Jozy Altidore, Giovani Dos Santos, Tim Cahill, Robbie Keane, Jermaine Jones, Cuauhtemoc Blanco.

5.2 *The Value Regression*

As outlined in the literature review, adding popularity to the value equation most likely causes multicollinearity with the productivity measures as, at least, part of a player's popularity is due to his previous sporting achievements. This is confirmed by the high correlation between various individual players as well as career measures and popularity. As outlined in the literature review[20], the popularity score is filtered from performance-relevant influences to reduce the risk for multicollinearity in the value regression. Therefore, in a first step, career performance and other control variables are regressed on the log of the popularity score. Secondly, the residuals ε_{it} of this equation are used in the main value regression. In this way, it is possible to determine how much impact the intangible, i.e. non-performance-related, aspects of popularity have on a star's salary. The popularity model[21] presents a fit of 0.69 adjusted R-squared. This is higher than the 0.58 found in Garcia-del-Barrio and Pujol's (2007) baseline model. In consequence, this means that for MLS stars, less of the popularity is due to intangible factors. Nevertheless, an important share still cannot be explained by sporting performance (i.e. league games played, league level, national games played), this "share" is considered as filtered popularity.

To answer the second research question of this paper, what teams value, the salary model takes the following form:

$$\text{lnRealSalary} = \alpha0 + \alpha1 \text{ pophat} + \alpha2 \text{ Cgp\_PS} + \alpha3 \text{ Cgo\_PS} + \alpha4 \text{ natgames} + \alpha5 \text{ captain} + \alpha6 \text{ titles} + \alpha7 \text{ level} + \alpha8 \text{ age} + \alpha9 \text{ age2} + \alpha10 \text{ pos} + \alpha11 \text{ YDP} + \alpha12 \text{ TDP} + \alpha13 \text{ club} + \varepsilon$$

where pophat: Log popularity residuals from auxiliary regression

Cgp_PS: Number of career games played per professional season

Cgo_PS: Number of career goals scored per professional season

natgames: Number of senior national games played

captain: Player hold captain role in his senior career (0=no; 1=yes)

titles: Number of titles won with a senior team (national and int. level)

[20] See, e.g., Franck and Nüesch (2012) and Garcia-del-Barrio and Pujol (2007).

[21] The regression results for the best model for DP only and for all stars can be found in the Appendix (Table 10 and 11).

level: Vector of dummies for the league level of the previous team

age: Player age

pos: Vector of position dummies (ref.: midfielder)

YDP: Young designated player (0=no; 1=yes)

TDP: Transfer designated player (0=no; 1=yes)

club: Vector of region of club dummies (ref.: Chicago)

Due to the low number of observation and the consequences for the degrees of freedom, two models are presented. The first main model excludes the 20 club variables while the second includes them. The inclusion of team-fixed effects might be relevant as this controls for differences in financial resources between teams. Also, robust standard errors were omitted in the main regressions as the cluster-number is too high for the small number of observations. Anyhow, a model with robust standard errors was also tested separately and produced no different results in term of significance for the main explanatory variables. The results for the two main models can be found in Table 5[22].

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[22] Various specifications, with multiple variables that are commonly used for salary determinations, have been tested and using diagnostics tested for heteroskedasticity, multi-collinearity and omitted variable bias the presented models were chosen based on the test results.

Table 5 Estimation Results for OLS with Real Salary as Dependent Variable, with and without Club Fixed Effects

	(1) Log Real Salary		(2) Log Real Salary	
pophat (log)	0.185^{***}	(0.053)	0.185^{**}	(0.055)
Cgp_PS	0.001	(0.011)	-0.013	(0.012)
Cgo_PS	0.027	(0.020)	0.032	(0.021)
natgames	0.009^{***}	(0.002)	0.009^{***}	(0.002)
captain	0.477^{***}	(0.133)	0.622^{***}	(0.153)
titles	0.018	(0.016)	0.023	(0.017)
level - MLS	-0.674^{***}	(0.171)	-0.531^{**}	(0.190)
level - 1a		*Base Category*		
level - 1b	-0.419^{**}	(0.157)	-0.332^{*}	(0.165)
level - 1c	-0.682^{***}	(0.183)	-0.537^{**}	(0.199)
level - 2	-0.514^{*}	(0.198)	-0.476^{*}	(0.218)
level - 3	-0.442	(0.580)	0.063	(0.601)
age	0.439^{*}	(0.174)	0.509^{**}	(0.187)
age2	-0.008^{*}	(0.003)	-0.009^{**}	(0.003)
Midfielder		*Base Category*		
Forward	0.122	(0.141)	0.127	(0.147)
Defender	0.241	(0.255)	0.356	(0.260)
Goalkeeper	0.138	(0.482)	0.562	(0.513)
YDP	-0.440	(0.234)	-0.345	(0.241)
TDP	-1.452^{***}	(0.150)	-1.367^{***}	(0.161)
			Includes club fixed effects	
Constant	7.196^{**}	(2.520)	6.430^{*}	(2.708)
Observations	133		133	
R2*100	79.7		84.7	
R2 adj.*100	76.5		78.5	
F-Value	24.9^{***}		13.7^{***}	
aic	238.3		241.0	
bic	293.2		353.7	

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, it appears that the model has a good fit. The key findings can be summarized as follows:

- First, the key variable *pophat* is significant and indicates that a 10% increase in non-performance-related popularity is followed by a 1.9% increase in salary. In contrast, the basic performance indicators of career games played and career goals (in relation to professional seasons) are not significant at all. Also, the success of players, measured in titles won, and the position of the players are not relevant.
- Secondly, one more national game is followed by a 0.9% increase in salary and being a captain is associated with a huge salary increase of 47.7% (when controlling for club fixed effects even 62.2%). A substantial premium, between 41.9 and 67.4%, is further paid to stars who played at top-level before coming to MLS, e.g. in the EPL or La Liga.

In turn, MLS players (and players from other leagues) who turn DP are paid significantly less compared to top-tier players.

- Thirdly, age shows the typical inverted u-shape with a turning point at 27.9 years (28.1 when controlling for clubs).
- Finally, transfer designated players confirm their separation in status as they are paid substantially less even after controlling for performance, popularity, and age. TDP face a minus of 145% of salaries, or respectively 137% after controlling for club fixed effects, in comparison to normal designated players.

As a robustness check, another set of models was tested. For example, one set included dummies for the identified superstars, e.g. with interaction terms, but no significant changes in the explanatory power of the variables was found. Another set included further variables that were shown to be significant in other soccer salary studies, e.g. origin or footedness, but with no impact for MLS. The insignificance of the origin dummies is rather surprising as the "Argentinean dominance", as described before, was expected to be also rewarded with higher salaries. Maybe the detailed variables of *level* and *captain* that were include in the presented model take up effects that are usually captured by origin. Yet, a final robustness check revealed additional insights. Along the lines of the descriptive analysis, I separated the early players (until season 2013) from the more recent group of DPs (2014 – 2016)[23]. The regression for the stars hired in the first seven years confirms most of the results from the overall regression, i.e., significant values for popularity, national games, age, and captain, as well as premiums for players from top-level clubs. For the group of stars hired in the last three observed seasons (where the same number of DPs was hired than in the 7 years before) being a captain, national games and playing for a top club are still rewarded more but interestingly, popularity and age are not significant anymore. This might show that the leagues move towards younger, but less popular players was effective as those factors are not rewarded more than is warranted anymore. Obviously, these results need to be interpreted with caution due to the very small observation numbers in the split sample.

[23] The results of the two separate regressions can be found in the Appendix (Table 11).

6 Discussion and Conclusion

Diverse MLS stars can be grouped in five distinct clusters. This starts to answer the first question posed by this paper: *Who are the stars* that MLS teams hired from 2007 thru the 2016 season? A detailed analysis of 13 main attributes showed the diversity of the 133 players that earned the status of designated player, young designated player of transfer designated player. The diversity in age, origin, popularity, previous club level and different performance indicators jointly rebuts the prejudice that only old and formerly famous guys are hired. The variety is also in line with Garcia-del-Barrio and Puyol (2007) findings in their analysis about monopsony rents in La Liga. They explain that "there seem to be different categories of league-superstars" (p. 67). For MLS, I find that the 98 DPs can be placed in five groups whereas one group stands out significantly. This group holds 10 players that stand out in multiple dimensions from the rest of the players. Due to their special achievements, high popularity, and other personality traits that separate them from other designated players we can probably call them "*Superstars*". The other groups have been labeled "*Local Stars*", "*International Goal-Getters*", "*International Allrounders*", and "*Defense*". Each group has their strength and a specific characteristic combination which makes them distinct. The presented results can be interpreted with Adler's (1985) theory for stars emergence. According to him, stars can separate themselves from an equally talented group out of "luck". The diversity shown in MLS might be due to this "process". Different types of DPs might also be an indication for different team preferences. The descriptives have shown that in the early years (first 5-7 years) of the DP rule predominantly older and "decorated" players from top-tier clubs who were born in Western Europe or Argentina were hired. This preference seem to have changed in the recent years as more younger players with less exclusive backgrounds joined as DP. As discussed in the introduction, MLS teams hire DPs and pay them over proportional wages because they believe that they are valuable to the team, either on the pitch (i.e., better team performance) or off the pitch (i.e., more revenue).

This brings us to the second research question, *What do MLS teams value*? To answer this question, a two-stage regression was conducted with star salary as the dependent variable. While market values (from transfermarkt.de) are also available for MLS's designated players, the author chose salaries for this specific analysis. In contrast to regular players' salaries that are restricted by the salary cap regulations, DP salaries are not subject to any financial restrictions apart from the team's financial resources in MLS. Therefore, DP salaries are a suitable way to proxy the value that the team believes a player brings. The regression results show, first of all, no significant differences in the remuneration patterns by teams. These are good news to all MLS clubs and the league that is after competitive balance. Why? Because it means that even if big-market teams like LA Galaxy or New York Red Bulls, in the early days, and New York FC and Toronto FC in later seasons have substantial more financial power than teams like Chivas USA or Sporting Kansas City the qualities they look for in players are a) similar and b) seem to exist in various price categories. The qualities they value are non-performance driven popularity, leadership experience, previous playing level, and national team experience. Career games played and goals scored, relevant factors in almost all soccer-related salary studies, tend to show no significance. Also, for MLS's DPs the position is no significant predictor. Lehmann and Schulze (2008) show similar findings for the top quantile of Bundesliga superstars. Hence, MLS superstars are rewarded more due to a combination of fame and some performance related aspects which are rather publicity-related soccer qualities like leading a team, being prominently on a national squad, and having played in a top league instead of "basic" performance indicators like games played. Obviously, a player would have not played that many matches for the national team or has been part of a top club if he has no superior soccer skills as well. Age is also relevant and increases a DP's salary until they are 28 years. After this, salary is reduced marginally each year which means that MLS teams prefer experienced players but not necessarily ones that are close to retirement. In addition, further insights were gained from splitting the dataset into two time periods. In the more recent years, popularity of players is no key determinant for salaries anymore. So, the prejudice of a retirement league that aims for a higher profile by hiring famous athletes that have their best performance days behind them, might have been true in the past, but a shift seems to have happened around 2014. Now, the key drivers, as partly also before, are leadership experience and games for the national team.

In summary, teams indeed favored popularity and in this sense Adler superstars, at least in the first seven years of the DP rule. However recently, the tide has changed towards a younger-Rosen star type. All in all, this paper advocates that the DP rule produced a lot of stars that have different strength, but only a handful of superstars that are truly exceptional were hired by MLS teams so far.

6.1 Limitations

Even if the time span is quite long with 10 years, the number of observations is considered quite small with n=133 players. That means that some players can influence the results disproportionately when outliers are not controlled for. This circumstance was accordingly limited in the analysis with robustness checks but certain methods that are usually helpful like a quantile regression could not be performed due to the small numbers. Another limitation is the generalizability of results to other settings. Due to the specific regulation in place that govern the centralized MLS, the results are not per se applicable to more open settings.

6.2 Future Research

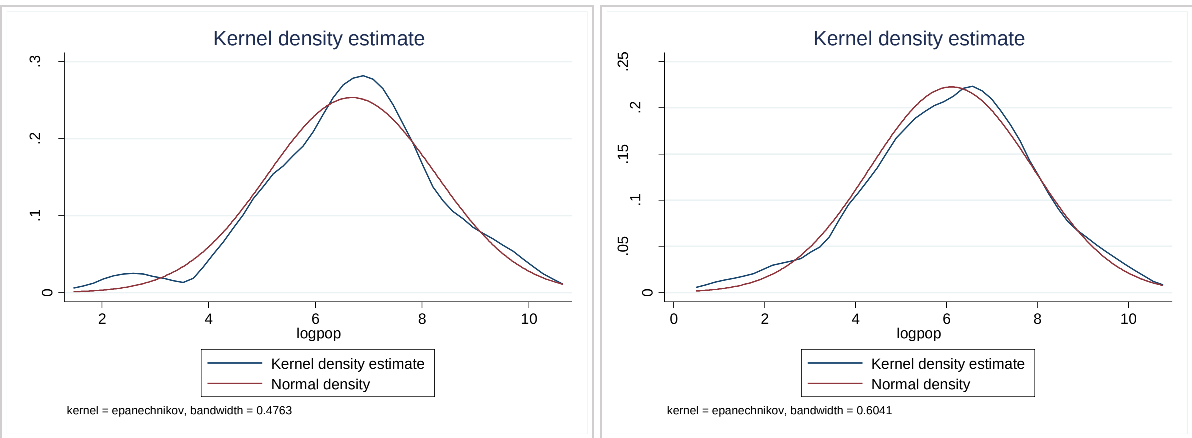
There are various pathways for future research. For one, dealing with the effect that certain superstar groups have on the dual strategy of the league, wins and profit, is promising. As Coates et al. (2016) outlined, the hiring of DPs has a twofold effect on team success. What has not been covered is the contribution of individual stars to team's success. Building on this study's findings might help to explore this relationship with various features of a star and help clubs to maximize their revenue streams by hiring specific stars. For example, understanding if highly popular stars and/or superior performers differ in their impact. Another promising research area, citing multiple MLS reporters and experts, is connected to the unarguable presence of DPs on and off the field. This impact and effect they have on their team members is interesting to follow as it is not directly reflected in merchandising success nor individual superstar moments on the pitch but rather in the collective team spirit and maybe even performance of team members. The off-pitch or "locker room" contribution is an extremely broad and unexplored path that should be followed by researchers of various discipline jointly in the future. Understanding those mechanisms can also improve team composition and in turn enhance team performance. And finally, with more DPs joining MLS at different stages in their career it might be worthwhile to investigate what happens after MLS. Does a player finish his career in MLS? Does he manage to play in a top division elsewhere? This kind of information can be used as a proxy to determine the quality of MLS in the international soccer market in the future.

Appendix

Table 6 Descriptives for DPs only

	count	mean	median	sd	min	max
season	98				2007	2016
player	98				1	130
age	98	30.0	30.2	3.78	22.3	38.0
nationality	98				1	38
origin	98				1	4
homegrown	98	0.20			0	1
height	98	1.80	1.80	0.069	1.64	1.96
footedness	98				1	3
profseasons	98	11.0	11	4.08	3	20
level	98				1	6
Cgp	98	294.1	259	152.4	73	821
Cgp / Prof.s.	98	25.9	24.9	5.9	14.7	41.05
Cgo	98	70.7	55.5	61.8	1	289
Cgo / Prof.s.	98	6.2	5.4	4.2	0.05	18.1
Cassists	68	35.9	29	30.1	6	176
titles	98	3.96	2	4.63	0	22
natgames	98	36.8	21.5	36.8	0	123
captain	98	0.38			0	1
position	98				1	4
popularity	98	2,327	895	4,243	7	25,857
logpop	98	6.68	6.80	1.57	1.95	10.2
Sbase	98	1,511,359	800,000	1,698,739	175,000	6,660,000
RealSal	98	1,358,318	712,828	1,519,779	152,621	5,808,319
LogRealSal	98	13.7	13.5	0.90	11.9	15.6
club[8]	98				1	21

Figure 12 Kernel Density Plot for logpop



Note: first graph with all stars, second graph only for DPs

Figure 13 *Level of Newly Hired DPs Over Time*

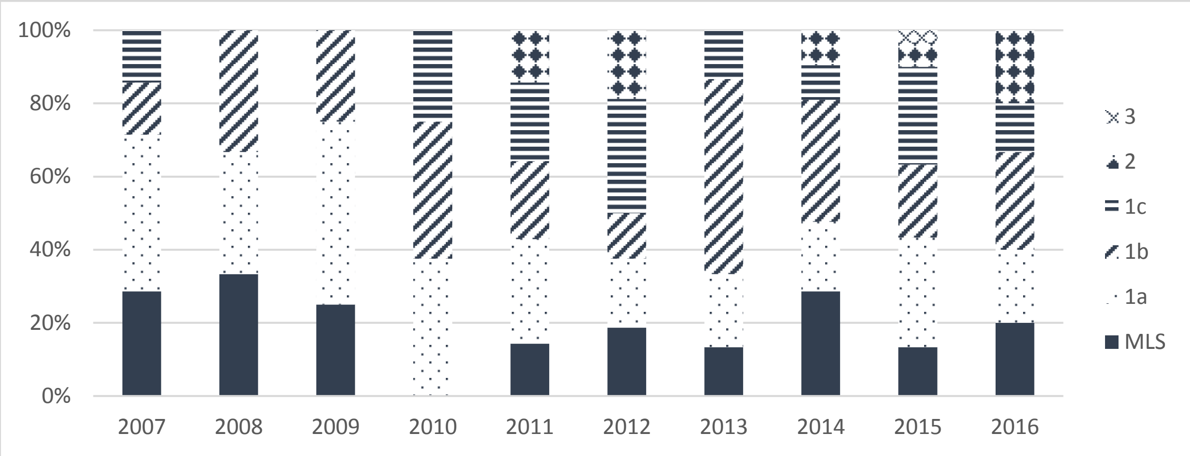
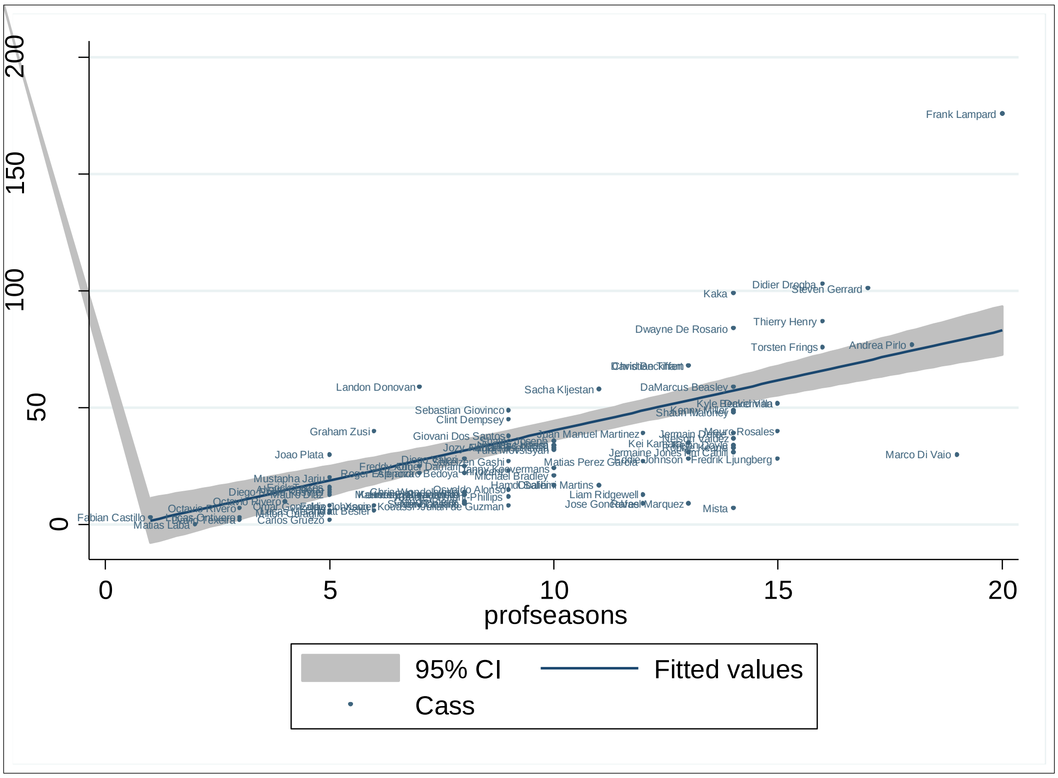


Table 7 Level of Newly Hired DP by Age Group

Level Before DP	ageGroup age<25	age=25-28	age=29-31	age>=32	*Total*
MLS	5	5	7	5	*22*
1a	1	6	11	14	*32*
1b	1	10	2	9	*22*
1c	3	4	3	1	*11*
2nd	1	3	3	3	*10*
3rd	0	0	1	0	*1*
Total	*11*	*28*	*27*	*32*	*98*

Figure 14 Fitted Graph of Career Assists per Professional Seasons Played



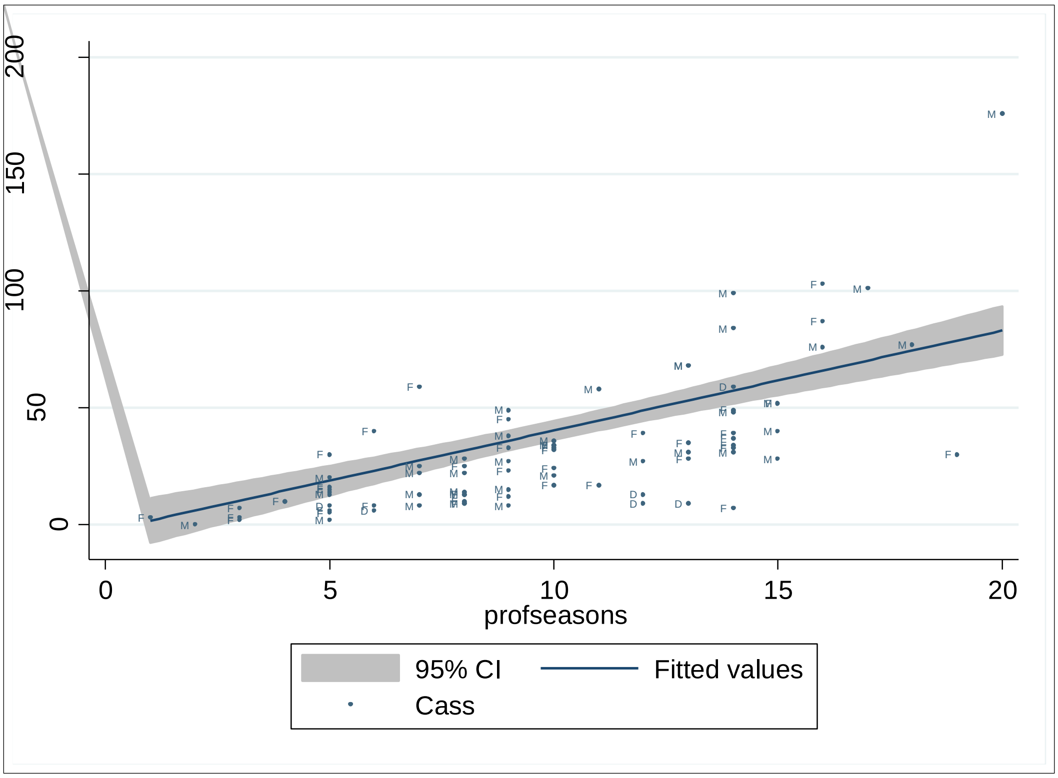


Table 8 Principal Components/Correlation

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.78094	2.13413	0.3781	0.3781
Comp2	1.64681	0.618214	0.1647	0.5428
Comp3	1.02860	0.228509	0.1029	0.6456
Comp4	0.800089	0.102115	0.0800	0.7256
Comp5	0.697973	0.0160771	0.0698	0.7954
Comp6	0.681896	0.215907	0.0682	0.8636
Comp7	0.465989	0.0986331	0.0466	0.9102
Comp8	0.367356	0.0660548	0.0367	0.9470
Comp9	0.301301	0.0722563	0.0301	0.9771
Comp10	0.229045	.	0.0229	1
Obs.	98			
Trace	10			

Table 9 Principal Components (Eigenvectors)

Variable	*Comp1*	*Comp2*	*Comp3*	*Unexplained*
z_logpop	0.4011	-0.1794	0.2238	0.2871
z_natgames	0.4297	-0.1308	0.2439	0.2126
z_titles	0.3691	0.1223	-0.1809	0.4267
z_age	0.3581	-0.0013	-0.4132	0.3396
z_Cgp_PS	0.3737	0.1951	0.064	0.405
z_Cgo_PS	0.1795	0.5664	0.3202	0.2443
homegrown	0.0369	-0.5438	0.6003	0.1371
captain	0.3325	-0.0566	-0.2162	0.5287
toplevel	0.3218	-0.0787	0.0306	0.5972
offense	-0.0515	0.5212	0.4152	0.3653

Figure 15 Scoreplot of Component 1 and Component 3

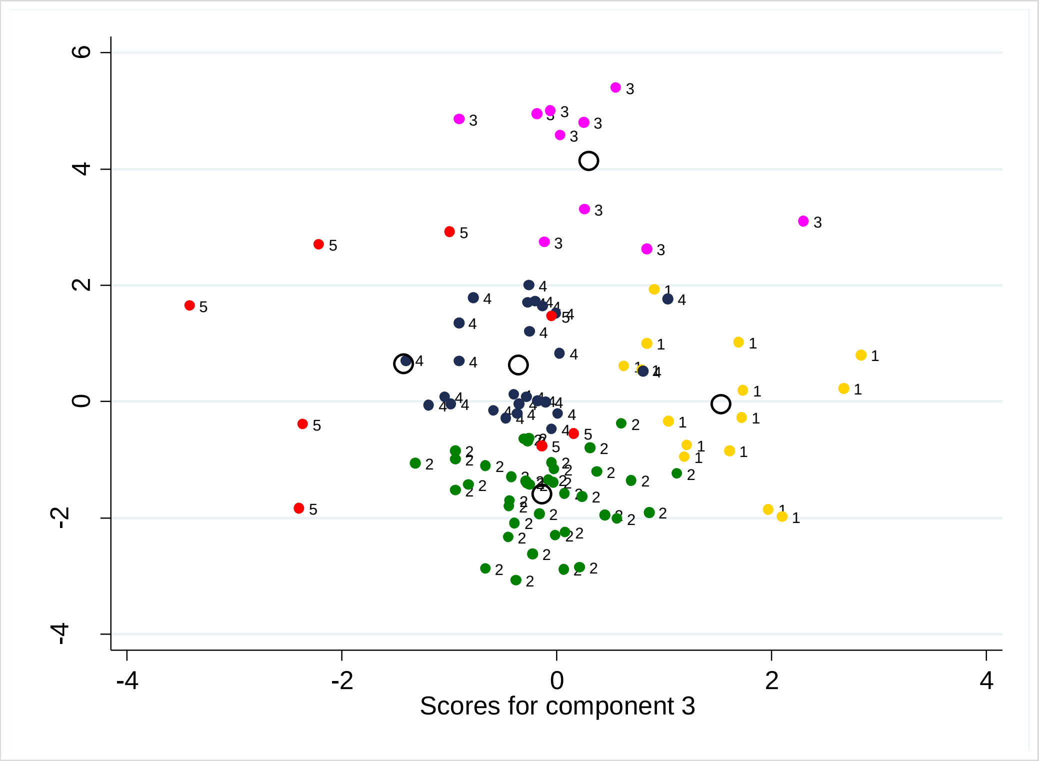


Figure 16 Scoreplot of Component 2 and Component 3

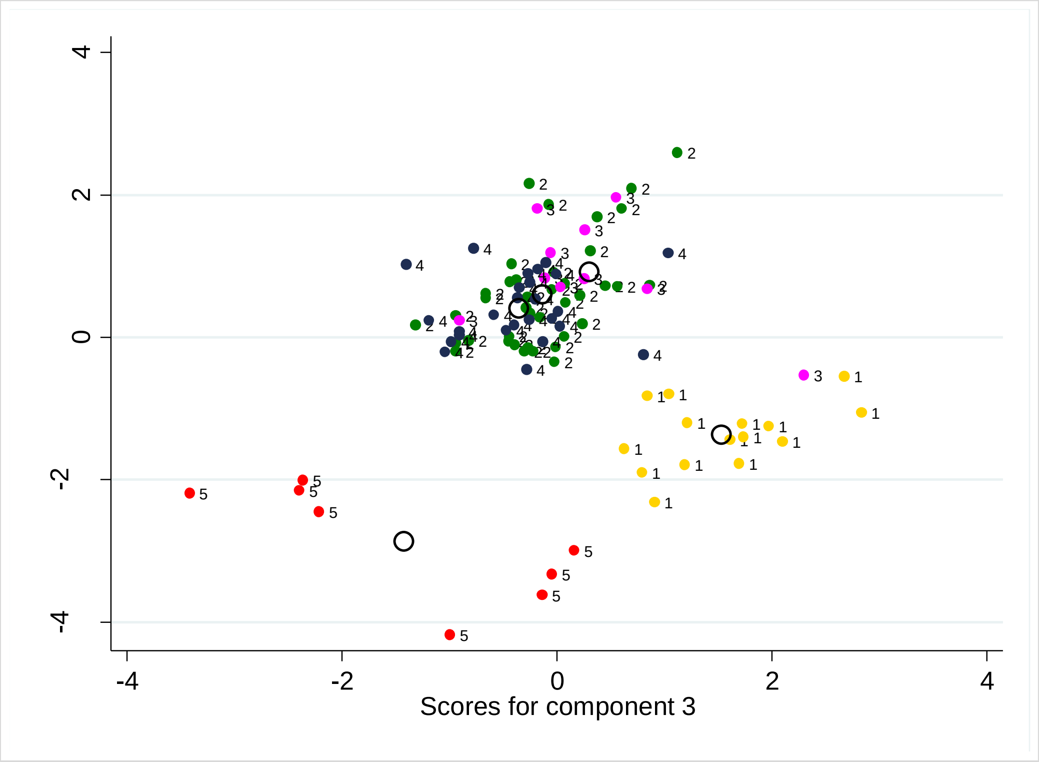


Table 10 Auxiliary Regression with logpop as Dependent Variable

	DP only		All stars	
Cgp	0.003**	(0.001)	0.003***	(0.000)
natgames	0.019***	(0.004)	0.018***	(0.004)
Level MLS	0.441	(0.318)	0.466	(0.303)
Level 1a		Base Category		
Level 1b	-0.561	(0.312)	-0.645*	(0.280)
Level 1c	-1.066**	(0.394)	-1.095***	(0.320)
Level 2	-0.431	(0.390)	-0.109	(0.356)
Level 3	0.670	(1.052)	0.662	(1.040)
TDP			-0.366	(0.275)
YDP			-0.974**	(0.350)
	Year fixed effects included			
Constant	5.884***	(0.534)	5.859***	(0.518)
Observations	98		133	
R2*100	66.9		73.7	
R2 adj.*100	60.4		69.5	
F-Value	10.25***		17.70***	

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11 Auxiliary Regression with logpop as Dependent Variable, Split by Seasons

	2007 - 2013		2014 - 2016	
Cgp	0.004**	(0.001)	0.004**	(0.001)
natgames	0.014*	(0.005)	0.022***	(0.005)
Level MLS	0.420	(0.485)	0.859*	(0.383)
Level 1a	0.000	(.)	0.000	(.)
Level 1b	-1.227*	(0.464)	-0.129	(0.352)
Level 1c	-1.118*	(0.508)	-1.264**	(0.408)
Level 2	-0.312	(0.604)	0.264	(0.436)
Level 3	n.a.		1.178	(0.981)
	Year fixed effects (2007-2013) included		*Year fixed effects (2014-2016) included*	
Constant	6.022***	(0.765)	4.847***	(0.404)
Observations	67		66	
R2*100	68.3		78.1	
R2 adj.*100	61.3		74.6	
F-Value	9.7***		22.2***	

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12 Estimation Results, Split by Seasons

	Log Real Salary 2007 - 2013		Log Real Salary 2014 - 2016	
Popularity (log) 0713	0.202***	(0.053)		
Popularity (log) 1416			0.212	(0.107)
Cgp / prof.seasons	-0.001	(0.012)	0.010	(0.023)
Cgo / prof.seasons	0.014	(0.026)	0.028	(0.040)
Midfielder		*Base Category*		
Defender	0.959	(0.503)	0.190	(0.367)
Forward	0.224	(0.173)	0.103	(0.244)
Goal Keeper	0.036	(0.544)	-0.138	(0.895)
natgames	0.006*	(0.002)	0.010*	(0.004)
captain	0.434**	(0.157)	0.763**	(0.265)
titles	0.031	(0.017)	-0.013	(0.039)
Level MLS	-0.389	(0.201)	-1.154***	(0.309)
Level 1a		*Base Category*		
Level 1b	-0.431*	(0.192)	-0.654*	(0.279)
Level 1c	-0.637**	(0.214)	-0.770*	(0.332)
Level 2	-0.298	(0.253)	-0.809*	(0.341)
Level 3	*n.a.*		-0.780	(0.735)
age	0.488*	(0.194)	0.561	(0.341)
age2	-0.008*	(0.003)	-0.010	(0.006)
YDP	0.058	(0.344)	-0.601	(0.349)
TDP	-1.367***	(0.161)	-1.183***	(0.303)
	Year fixed effects (2007-2013) included		*Year fixed effects (2014-2016) included*	
Constant	6.443*	(2.861)	5.718	(4.828)
Observations	67		66	
R2 *100	91.4		78.0	
R2 adj. *100	86.8		68.2	
F	19.862		7.968	

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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