A New Look on Athletes' MRP

A Study of NBA Players' Salary and Performance

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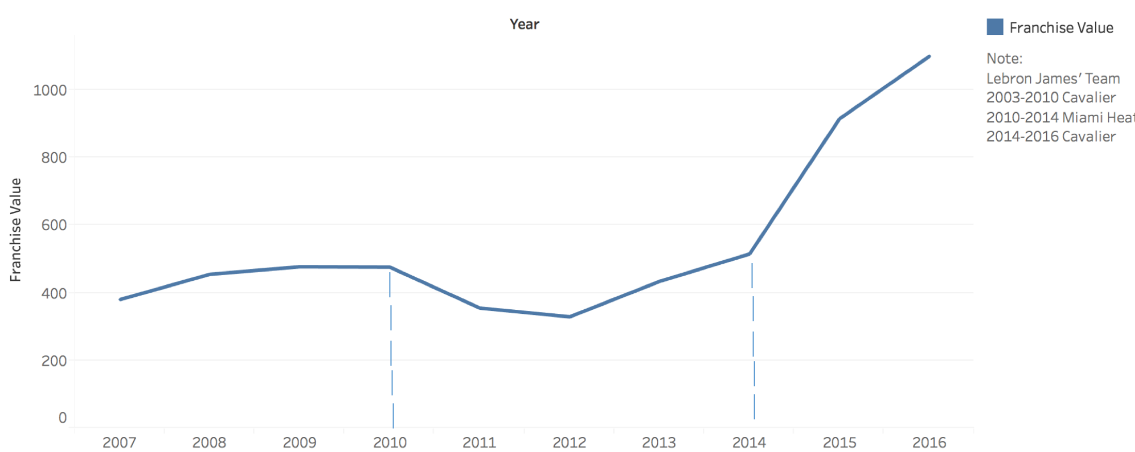
I. Introduction

In the world of sports, top tier players are the treasure of their teams. These small number of players are paid top dollars for their performance. However, their value does not solely lay in their role on the court. They also carry the duty of attracting new fans for teams and generate revenue for team owners. Their presence is the guarantee of box-office. As such, each trade a team made or each decision stars imposed will bring shock to the original teams.

Figure 1 shows the value of NBA team Cleveland Cavaliers' franchise. Its value dropped after Lebron James left in 2010, stayed low during 2010 and 2014 and spiked in recent years after James' return from the Heat. Other statistics such as home court attendance, ticket price and team revenue all follow similar pattern in a different scale. Although some players also left in 2010 or joined the Cavaliers in the summer of 2014, Lebron James's presence is no doubt one of the most important factors that explain the abnormal fluctuation in Figure 1. However, it is hard to derive his value solely from this graph.

Figure 1. Cleveland Cavaliers' Franchise Value from 2007 to 2016



There was another player who brought a similar shock. In Hausman and Leonard's paper (Hausman and Leonard,1997), they estimated Michael Jordan increased Bulls' revenue by about 8.6 million dollars per season in 1997 dollars, which is about 12.7 million dollar in 2016 value[1]. In the case of Lebron James and the Cleveland Cavaliers, team revenue increased from \$145 million in 2014 to \$191 million in 2016, an average of \$23 million increase per season. In contrast, between 2010 and 2013, teams' revenue decreased 9.33 million per season despite continuously drafting of the number one pick for three seasons.

In recent years, Lebron James is not the only player that had impact on his team's attractiveness. Figure 2 shows the impacts of trades of other well-known players. I used average home attendance as an indicator. Intuitively, home attendance is the most

[1] Calculated using CPI index.

sensitive index among all three measurements (attendance, ticket price, team revenue), and is likely to be the cause of other changes. The x-axis shows the time slots relative to the trade and the y-axis shows average attendance in a season. I used attendance data two years prior to trades and two years after the trades to show potential effects resulting from the departure of players. Due to the limitation of the data source, attendance statistic prior to 2007 is unavailable.

Figure 2. The Effect of Trade on Attendance of Original Teams.

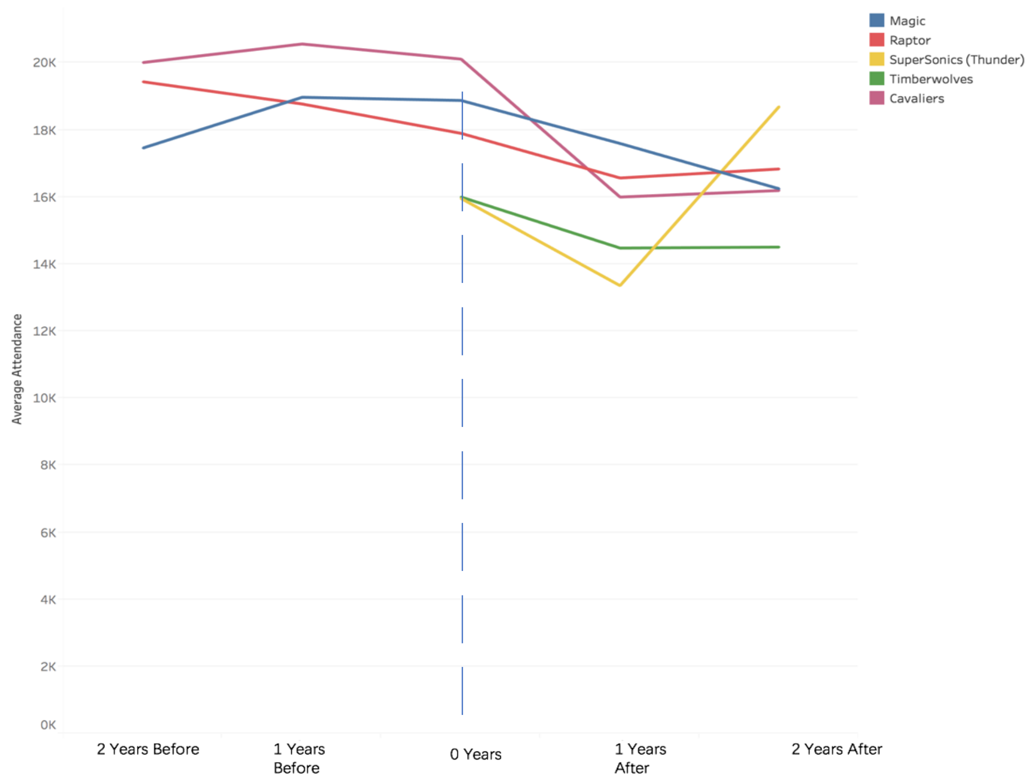


Figure 2 only included 5 players that are representative[2]. I concluded that the trade of Kevin Garnett (from Timberwolves to Celtics), Ray Allen (from Supersonics to Celtics), Lebron James (from Cavaliers to Heat), Chris Bosh (from Raptors to Heat), Dwight Howard (from Magic to Lakers) all brought significant negative effects to the attendance of their original teams in the following season. Other trades did not seem to take away audiences' enthusiasm. The reason could be that the managers foresaw the potential impact and reacted in a timely manner, or that those stars are not as attractive to see at the first place.

The influences of those stars result from personal characteristics. Lucifora and Simmons claimed that stars are preferred by audiences because of their "scarcity", "uniqueness" and lack of substitutes (Lucifora and Simmons, 2003). For example, Michael Jordan's fans would never characterize anyone as a suitable replacement for him, not Kobe Bryant nor Lebron James. Thoughts are the same for James' and Bryants' fans. Thus, if a fan would like to see his/her idol playing, he/she must watch that particular

[2] Exclude trades of players that brought little or no effect on attendance.

team’s game, which eventually turns into more TV ratings, attendance and thus revenue for that team.

The scarcity can mainly be characterized by two channels: charisma and professional skills. Charisma also lies into two categories: personal charisma and his interaction with teammates, which can act as either catalyst or cancer. Team performance is a good indicator for the later one. Do superstars attract more audience hence increase teams’ commercial values because of their existing popularity, outstanding on-court performances, or both? Alder’s research (Alder, 1985) stated the former assertion, while Berri and Schmidt’s study (Berri and Schmidt, 2006) as well as Berri, Schmidt and Brook’s study (Berri, Schmidt and Brook, 2004) stated that performance played an important role while the effect of charisma is insignificant. Later Brandes, Franck and Nüesch studied German Soccer (Brandes, Franck and Nüesch, 2007) and concluded stars’ popularity along does not facilitate attendance for teams’ popularity.

However, those studies did not take into consideration of the rapid development of the Internet and the boom of new ways to convert popularity into revenue. Social media is one example. Team and players’ social medias’ posts are equivalent to advertisements. Consumers, who are interested in either players or the team as a whole, even voluntarily follow accounts to acquire updated information timely. Consequently, teams’ increase exposure and facilitate ticket selling with this low cost method. Thus, the effect of popularity, especially online popularity should be reconsidered.

Clearly, there is a bilateral relationship between players and teams. Players contribute to teams through their influence as well as performances and generate more revenue for teams. In return, teams compensate players through salary. The key question I would like to answer in this paper is how well are players compensated. What is the wage premium for being a star in the league. In the following sections, I will first illustrate facts, details and conclusions from previous studies. Then I will define who the superstars are, introduce the data I used, describe their importance and several preliminary evidences directly acquired from the data. At last, empirical models and their implications will also be introduced.

II. <u>Literature Review:</u>

Michael Wallace has studied the salary determinants for NBA players. One of the important findings of his research is the significance of labor market segment. He divided all players into three tiers: starters, off the bench players and benchwarmers. The three tiers indicate different importance to their teams. Without any surprise, being a starter (upper tier) instead of a benchwarmer (lower tier) lead to more salary holding performance statistics the same. Also, he found that points per forty-eight minutes and rebounds per forty-eight minutes are all positive significant determinants of salary. Offensive proficiency ratio, calculated by dividing assists by turnovers, is positive and significant when not controlling labor market segment variables but becomes insignificant when controlling those variables. Wallace’s study provided me evidences supporting the inclusion of rebound and assist into the model. The effect of interaction between these three variables is also interesting to see.

As one of the author who lay a foundation for the discussion of superstars, Adler argues the fact that “appreciation increases with knowledge” (Alder, 1985). In other words, more discussion and increasing depth of learning are the basic effects of superstars. He further emphasizes the attraction of superstars lies in the low cost of learning instead of true talent. As a generalization, the more frequent a name is mentioned, the more exposure (both voluntarily and involuntarily) on the side of information consumers. Once the searching cost is lowered, less knowledge is required to consume such information and encourages more consumption. Stardom will also lead more exposure and formed a cycle. Stars generate heat and popularity despite their talent according to Alder. However, in the case of professional basketball league, the assertion is not necessarily true. Studies conducted by Berri and Schmidt, David, Schmidt and Brook all show that superstars' own appeal does not necessarily defines their contribution. Their facilitation on teams' performance is the key.

Despite the dissonance, Alder's study provides me evidence to support a discussion of the influence of players' social media and online influences. Those factors help both themselves and their teams by increasing exposure and lowering searching cost for potential fans.

Alder's study provides us a general image of stars in all fields. Hausman and Leonard then focused on the impact of superstars in professional basketball (Hausman and Leonard,1997). Their paper is one of the pioneer studies that focus on superstars' effect on team revenue, in particular, how their presence leads to more revenue for teams. The source of revenue is telecasters' rights fee. The authors first discussed the phenomena of declining "The Final's" Nielson television ratings in 1994, which the absence of superstars like Michael Jordan or Shaquille O'Neal played an important role. A more convincing evidence is the return of Michael Jordan in 1995. The rating of his first returning match is 10.9%, "the highest NBA regular- season game rating since 1975" stated by the authors. According to the definition of Nielson rating about 10.9% of all United States' TV households have watched the game. A player with such impact on television ratings is characterized as superstar by the authors. Similar evidence appeared in the home attendance statistics of the Cleveland Cavaliers after summer 2014, when Lebron James returned. In addition to the benefit received by stars' home team, the other teams in the same league all enjoyed benefits when superstars are playing road games. Such phenomenon is called superstar externality. However, the rent generated by the player will not be fully compensated in the form of salary. They argued that the presence of salary cap is the main cause which "overcorrect "the externality and shift rent from superstars towards team owners, especially owners of small market teams. In some sense, such externality can also be seen as free-riding since the other teams did not compensate the superstars for their productivity. As a result, to study the effect of current superstars, merely study their effects on home teams is not enough. The revenue generated for their home team is just a part of the whole pie.

For home revenue, Berri, Schmidt and Brook explored the impact of superstars on gate revenues, a part which Hausman and Leonard "less formal[ly]" studied (Berri, Schmidt and Brook, 2004). In their study, they used All-Star Game votes as an indicator for superstars rather than TV ratings. After carefully selected the form of variables, the authors focused on the impacts of wins and star attraction on team revenue. The regression outputs show that team revenue is most sensitive to changes in stadium capacity as well as wins and is the least responsive to star attractions. In other words, players' ability to win determines whether they are superstar or not, not the low learning cost according to Alder.

Berri and Schmidt further developed on the superstar externality and studied their influence on road game attendance (Berri and Schmidt, 2006). Similar to their previous study in 2004, the authors used All-Star votes as a measurement for star power. They further discussed the effect of market size in team exposure, which possibly turn into attendance. In particular, large cities like New York City and Los Angeles tend to have better media coverage which "may lead to an increase in demand from fans". Their model shows that the attendance is influenced by star power and racial composition. In particular, "an additional All-Star vote increases aggregate road attendance by 0.005 fans". They also decomposed the effect of "showmanship" and "player's wins' production". The partial effect of star appeal is 4353 (numbers of attendance), which is about just one half of players' ability to generate wins (9846). Their findings prove that the true ability of a player is the main determination of his attractiveness.

In other professional sports, the effect of superstar is also studied. Brandes, Franck and Nüesch studied the difference of "local heroes" and "superstars" in German soccer league (Brandes, Franck and Nüesch, 2007). Local heroes are defined as "the most expensive player in a team, given that his market value does not belong to the highest 2% of the league". However, the skill of superstars is no doubt superior than local heroes. Due to geographical proximity, fans do not necessarily view well-known teams match as a substitute for "local" team's game. As a result, local heroes can be viewed as superstars in the sense of popularity or star attraction, according to Berri and Schmidt, at local level. The study of the difference of the two different kinds of top players provided us evidences to compare if popularity played an important role in facilitating home and road game attendance. From the regression results, superstars are more attractive in both home and road games. In contrast, local heroes' impact is not significantly different than 0. As a results, superstars can attract fans by both being more skillful and popular, where charisma, if there is any, at local level is the only attraction that local heroes can provide to their teams. This study provides us similar evidences in a different professional sport that the skills of players are more important than mere popularity in both home and road games.

III. Data

Labors' productivity is measured by their ability to generate revenue for employers. Some common indicators are years of education, professional experiences etc. Basketball players' productivity should also be defined as their ability to generate revenue for their teams. As discussed above, the two mean channels for players to generate revenue is performance and popularity. Thus, statistics about performance and popularity should be used as indicators of players' productivity. I collected data from different sources[3] to build up a panel regression dataset. The dependent variables are team revenues and player salaries.

Player performance statistics include players on-court performance data from 2011-2016 and consist both fundamental measurements such as points per game, rebounds per game etc. and advanced metrics such as versatility index, which is calculated by the following formula:

[3] Player Performance Statistics are acquired from http://www.nbastuffer.com/player_stats. Players' salary is acquired from http://www.draftexpress.com/nba-player-salaries/. Fans numbers are acquired from http://fanpagelist.com/category/athletes/nba/ . Google Trends manually downloaded from https://www.google.com/trends/ . Historical mentioning is acquired from http://global.nba.com/nbapulse/ .

Versatility Index = [(Points Per Game(ppg))*(Rebounds Per Game(rpg))*Assists Per Game(apg)]]^(0.333)[4]

In Michael Wallace's study, he mentioned the significance impact of points, rebounds and assists on players' salary. The effect of their interaction, the versatility index, is interesting to see. In addition, Versatility Index is added because a more well-rounded player is more enjoyable to watch and can help his team to win in more than one ways. Players who can achieve excellence in one or more categories are more likely to achieve double-double (two basic statistics among five basic statistics: points, rebounds, assists, steals, blockings greater or equal to ten) or triple-double (three basic statistics greater or equal to ten) even quadruple-double (four basic statistics greater or equal to ten) and make headlines thus lead to exposure and lowering learning costs.

Based on player performance statistics, I divided all NBA players into two groups: superstars and other players. I did not follow the grouping method introduced by Berri, Schmid and Brook. All-star Votes is a good indicator of players' popularity prior to All-star games but does not constantly describe players' performance during the whole season. All-star Votes can be influenced by numerous factors other than performance. Being an international player will normally receive all the support from his home country. An recent example is the votes for Zaza Pachulia in 2017 All-star voting round one. He received 439,675 votes as the second place. Behind him are Kawhi Leonard and Anthony Davis who are no doubts better players than Pachulia. Performance wise, Zaza Pachulia averaged 6 points, 6 rebounds and 2 assists per game while Leonard averaged 25.5 points 5.8 rebounds and 3.3 assists. Anthony Davis even has a stunning 27.9 points 12.3 rebounds and 2.2 assists per game. By any standard, 2014 Final MVP Kwahi Leonard and MVP Anthony Davis are more qualified as superstars. In addition, voting rules and standards changed year by year thus lead to unreliable results. The total number of votes can fluctuate between over 40 million in 2011 and 20 million in 2013 due to rule changes. Thus, to solely rely on All-star votes as an indicator is unwise.

To propose a better way, my criteria are as follow. I selected players with Point Per Game (ppg) and Versatility Index (vi) in a season both exceed two standard deviations from the pooled mean. To be specific, players in any season with both vi above 9.878 and ppg above 19.839 are labeled as superstars in this study. While previous studies all showed performance is the key in determining players' salary and teams' earning. Thirty-nine total observations are filtered out. Note that a player can be categorized as superstar in multiple seasons. The total number of distinct players is 15. Preliminary regression also does not support Distribution of superstars is shown in Figure 4. Each colored circles represents each player and their relative location is determined by average statistics in the six seasons (2011-2016). The figure clearly represents superstars' relatively dominant positions in the league.

4 "NBAstuffer.com - V - Player Evaluation Metrics - Glossary." NBAstuffer.com - V - Player Evaluation Metrics - Glossary. NBAstuffer.com, n.d. Web. 07 Nov. 2016.

Figure 3. Distribution of Superstars Vs. Other Players.

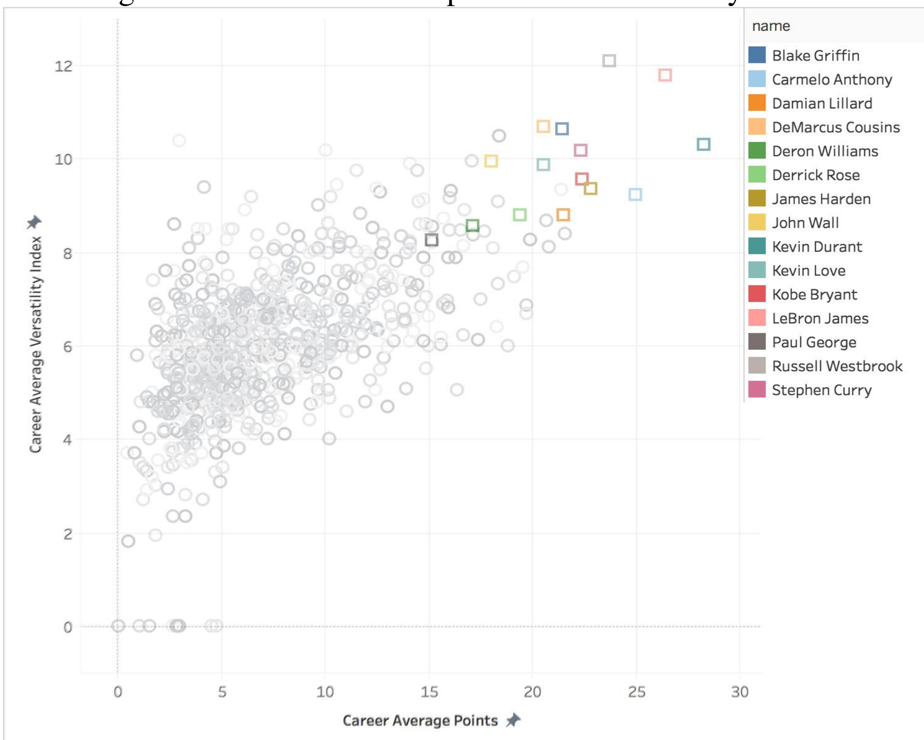


Figure 3 shows us the distribution of all players. Colored squares indicate individual superstars while grey circles are other players by using ppg and vi as star selection criteria. Interestingly, there are some overlaps between superstars and other players. Some superstars' performances are even lower than a few of the other players'. The reason is that since I defined superstars as players who have their vi and ppg are outstanding in a season, it is possible that their career averages are still relatively moderate. For example, Paul George is one of the rising superstars that has just proved himself in recent years. He then suffered unfortunate injury and is recovering. His statistics were no doubt being influenced. However, we cannot deny his previous phenomenal performances as a superstar in previous years. Thus, it is not surprising or abnormal for us to observe such overlap. Furthermore, the distribution also presents us the consistent of some superstars, whose statistics are no doubt better than other players. No "other players" has reached career above 20 ppg and 10 vi during his career. The six players are the absolute outliers from the rest of the league. Among the six, Lebron James, Russel Westbrook and Kevin Durant are the three leaders of the league in performance statistics sense thus their effects should be studied further.

In Berri, Schmidt and Brook's study, they used midseason All-Star vote to differentiate superstars and other players. Although intuitively All-Stars are likely to be skillful players, selection based on performance statistics is a more direct and secure way to filter players.

Furthermore, online popularity indexes will also be included in the model. The most important indicator is Google Trend. According to the Official Google Trends Blog, it is defined as "[an index] that shows how often a particular search-term is entered relative to the total search-volume"[5]. GoogleTrend indexes span over a five-year period and can show players' timely effect on online popularity such as the impact on search heat of Lebron James because of his first championship. The value of this index lies in its time span. Other indexes I used such as Social Media Followers/Fans, NBA historical mentioning are all accumulated numbers that do not show changes through time. However, they are still valuable indicators since they will illustrate the relative popularity between players. More popular players will have more followers and fans as well as mentioning. In fact, a simple correlation matrix (Table 3) confirms my claim.

Table 1. Summary Statics of Points Per Game and Versatility Index Average Players and Superstars

	Other Players		Superstars		All players	
Variable	Points Per Game	Versatility Index	Points Per Game	Versatility Index	Points Per Game	Versatility Index
Mean	8.61808	6.32549	24.78205	11.22051	8.866365	6.400709
Std. Dev.	5.141231	1.63887	2.882604	1.069722	5.486682	1.739089
Min	0	0	19.9	9.9	0	0
Max	28.7	11.5	32	14.5	32	14.5

From Table 1 we can see that superstars excel in Points Per Game and Versatility Index. The results are not surprising since we define superstars by their performance. However, superstars are better in other aspects as well.

Table 2. Summary Statics of Performance for Other Players and Superstars

	Other Players				Superstars			
Variable	Player Usage	Rebound Per Game	Assist Per Game	Google Trends	Player Usage	Rebound Per Game	Assist Per Game	Google Trends
Mean	18.73992	3.788	1.89528	0.623028	31.1641	7.448718	6.048718	2.859905
Std. Dev	4.883143	2.373795	1.745441	1.053652	2.923722	2.763852	2.045904	2.301013
Min	0	0	0	0	23	3.9	2.5	0.6938776
Max	35.9	15	11.7	7.326531	38.9	15.2	10.4	10.20408

Table 2 shows the summary statistics for Player Usage, Rebound Per Game Assist Per Game and GoogleTrends Index. Player Usage is defined as the percent of attempts a player takes, that includes free throw attempts, shooting attempts etc. This metrics gives us a rough image about the trustworthiness of a player. Since players with better ability to score tend have more "fire rights" thus more portion of attempts. I also included points

[5] Insights into what the world is searching for the new Google Trends, Yossi Matias, Insights Search, The official Google Search blog, September 28, 2012.

and assists because they are two significant factors that determine players' salary. GoogleTrends index is included to see if the online popularity is different between superstars and other players. The results show that in all 4 aspects, superstars are better than other players. This summary statistics shows us that superstars should be studied separately since they are better in each category. Other online popularity's statistics are not included due to the incompleteness of the dataset. However, some trend can be seen through GoogleTrends Index.

Table 3. Correlation Matrix of Historical Mentioning, Number of Facebook Fans and Number of Twitter Followers

	Historical Mentioning	Facebook Fans	Twitter Followers
Historical Mentioning	1		
Facebook Fans	0.9375	1	
Twitter Followers	0.7666	0.8195	1

As Table 3 shows, online popularity numbers are highly correlated. This matrix provide me evidence to say that superstars in general also have more Facebook Fans, Twitter Followers and Historical Mentioning.

IV. Empirical Analysis

To answer the question of how superstars influence revenue (through popularity or actual performance), and how their abilities determine their salary, multiple models will be introduced. After finding the answer for my first question, that is, through which channel do players affect teams' statistics, I will then mainly focus on the impact of on court performances (points, field goal percentage etc.) on players' salary due to the size and completeness of the information. More than one model will be used to explore non-linear effect of variables. A panel dataset will be used to reduce the effect of omitted variables (up to 550 players per season for 6 seasons). Intuitively, the model is likely to be causative.

1. Team Statistics

First, multiple models are constructed to find the influence of superstars on numerous team statistics. The dependent variables that I looked at are Team Revenue, Franchise Value (in percentage change form, four dependent variables in total), and Team Winning Percentage. The independent variables are all the same except for the last model. For the last model, I used Superstar Dummy, Team Winning Percentage, and Playoff Dummy as independent variables and Team Winning Percentage as the response variable. My focus for the last model will be the effect of superstar on winning. I included Winning Percentage and Playoff Dummy as control variables.

$$Y_{it}{}^{*} = B_0 + B_1 Superstar\ Dummy + B_2 Winning\ Percentage + B_3\ Playoff\ Dummy + E$$

*: the list of dependent variables are: Team Revenue (percent change); Franchise Value (percent change) ;

$$Winning\ Percentage_{it} = B_0 + B_1 Superstar\ Dummy + E$$

Table 4. The Influences of Super Stars' Presence on Teams' Value/ Revenue

	Team Revenue (percent) (1)	Franchise Value (percent) (2)	Winning Percentage (3)
Superstar (Dummy)	-.0001083 (.030273)	-.0394589 (.036354)	.1206172** (.0363625)
Winning Percentage	.1198855 (.1350789)	.4044843*** (.1165429)	
Playoff (Dummy)	-.0025995 (.0453781)	-.0139682 (.0387037)	
Number of Observation	84	84	84

Notes: Standard Error clustered at team level. Standard Error in parentheses.
*** indicates significance at 0.01 level
** indicates significance at 0.05 level
* indicates significance at 0.1 level
same for the following models

The response variables are the percentage change of Team Revenue and the percentage change of Franchise Value for (1) and (2). The results show us that neither model Superstar Dummy has a significant effect on the two response variables. However, Winning Percentage does have significant and strong influences on Franchise Value. For example, in 2013-14 season, Cavaliers' winning percentage was 0.293 while in the following season, when Lebron James joined, rose to 0.646. The predicted rise in Franchise Value resulting from increase in winning is (0.646-0.293) *0.4045= 14.28%, which is equivalent to about 75 million more franchise value solely from winning.

For model (3), superstars do seem to have significant impact on teams' winning percentage. The presence of superstar on average increases winning percentage by 12.1%, which is equivalent to about 10 more wins per regular season. More wins are also associated with higher franchise value as model (2) suggested. The presence of superstar in general leads to 4.8% increase in franchise value.

In conclusion, my empirical findings resonate with the studies done by Berri, Schmid and Brook: superstars do benefit their teams by generating more wins and then lead to higher revenue and greater franchise value.

2. Player Performance

Then, four models are constructed to find impact of on court performance and popularity on players' salary.

Performance Statistics include: Points, Assists, Steals, Rebounds Per Game and Versatility Index.

Popularity Measurements include: Google Trends, Historical Mentioning, Number of Facebook Fans and Number of Twitter Followers.

Control Variables include: Super Star Dummy, Team Dummy, Position Dummy, Year Dummy and the interaction of Year Dummy and Team Dummy.

For all four models, wage is used as the response variable. Wage is a reasonable indicator of how much managers value a player.

Model 1A:

$$\text{Log}(Wage_{it}) = \beta_i(Performance\ Statistics) + \delta_i(Control\ Variables) + E_{it}$$

Because of the potential non-linearity impact of on court performance, I decided to divide performance statistics into 4 different tiers based.

Table 5. Performance Statistics Segmentation Criteria

Tier/Variables	Points	Rebounds	Assists	Steals	Versatility Index
1st Quartile	0-4.6	0-2.1	0-0.7	0-0.4	0-5.3
2nd Quartile	4.6-7.7	2.1-3.3	0.7-1.4	0.4-0.62	5.3-6.3
3rd Quartile	7.7-12.1	3.3-4.9	1.4-2.6	0.62-0.92	6.3-7.4
4th Quartile	>12.1	>4.9	>2.6	>0.92	>7.4

Model 2A:

$$\text{Log}(Wage_{it}) = \beta_i(Performance\ Segements\ Statistics) + \delta_i(Control\ Variables) + E_{it}$$

Based on Model 1A, I further added popularity measurements to discover the significance of online influence on salary change.

Model 1B:

$$\text{Log}(Wage_{it}) = \beta_i(Performance\ Statistics) + \gamma_i(Popularity\ Measurements) + \delta_i(Control\ Variables) + E_{it}$$

Similarly, Model 2B becomes:

Model 2B:

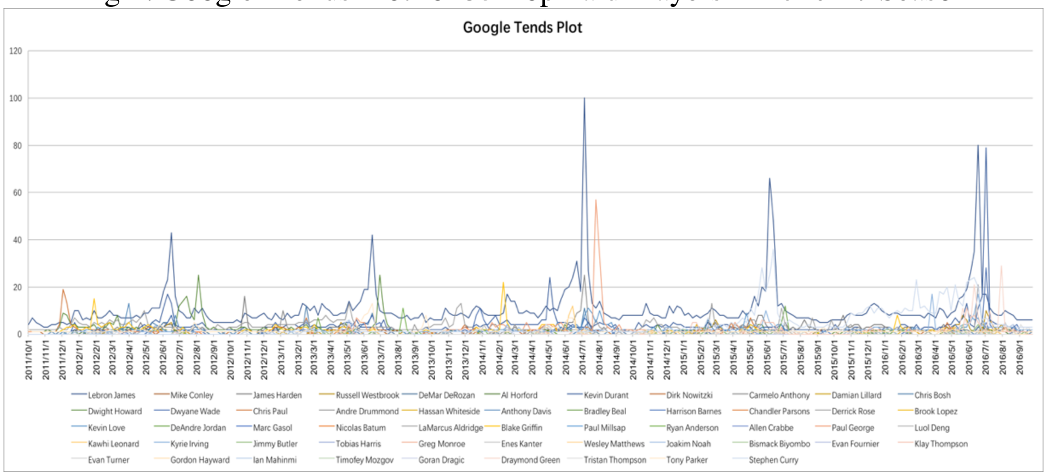
$$\text{Log}(Wage_{it}) = \beta_i(Performance\ Segements\ Statistics) + \gamma_i(Popularity\ Measurements) + \delta_i(Control\ Variables) + E_{it}$$

Before regressions are run and the results are discussed, there are two topics I would like to discuss.

I. Google Trends.

As an important measurement of online popularity, I included Google Trends as a control variable. Google Trends value act like benchmark where Lebron James' popularity in the week of July 5th ,2014 is marked as 100. Other players' popularity is a percentage of that marked popularity. To better coordinate with players' seasonal performance statistics, I took a yearly average of the Google Trends index. Although the appropriate time span of five years can be a benefit, the small sample size can be a problem. Only the data for 53 top paid players are collected manually. However, after reviewing the original data (Fig 4), the small sample size should not be a concern. Besides Lebron James' constant internet influence during the time span, only a few players have significant impact on the internet. The majority (40 out of 53) of the top paid players' indexes have never reached 10. For the most time, the heat of those top paid players is less than 5. Not to mention players other than them. Consequently, replacing the index to be 0 for them is safe.

Fig 4. Google Trends Plot for 53 Top Paid Players in 2016-17 Season



In addition, other popularity statistics such as number of Facebook fans, twitter followers and NBA historical mentioning are all cumulated variables. That is, they only have one value within the time span. However, Google Trends are highly correlated with each of the variables mentioned above. So that the direction and magnitude of those variables should also be similar to Google Trends, including those variables will not only lead to multicollinearity but also shrink the sample size significantly. As a result, in the regression models, I only included Google Trends as the popularity measurement.

II. Salary Cap.

According to NBA.com, the league imposed both the maximum team salary and the minimum. Violation in either situation will lead to penalty.

The presence of salary cap tends to affect the results, especially for superstars. As mentioned in the previous lectures, salary cap transfers economic rents generated by players towards team owners. That is, without the presence of salary cap, we should expect to see superstars with much higher salary due to their high productivities.

Not only for superstars, the salary of players who are in the same team with the superstar will be affected. With the finite amount of available salary space, to satisfy the needs of superstars are top priority of managers. Consequently, the salary for other players will be compressed, which will lead to inaccurate coefficients estimation. To capture and control the effect, the interaction term of team and year will be added.

III. Regression Results

Table 6. Regression results of Model 1

Independent Variable	Log Salary	
	Model 1A	Model 1B
Points Per Game	0.0532*** (0.0102)	0.0505* (0.00999)
Versatility Index	0.0365 (0.0329)	0.0356 (0.0329)
Assist Per Game	0.109*** (0.0303)	0.0885* (0.0350)
Rebound Per Game	-0.0150 (0.0211)	-0.0142 (0.0211)
Steal Per Game	-0.202* (0.0964)	-0.206* (0.0965)
Superstar Dummy	-0.193 (0.154)	-0.208 (0.149)
Google Trends	N/A	0.0475 (0.0358)
Number of Observations	2292	2292

Table 7. Regression Results of Model 2

Independent Variable		Log Salary	
		Model 2A	Model 2b
Points Per Game	1st Quartile	-0.499*** (0.104)	-0.493*** (0.104)
	2nd Quartile	-0.341*** (0.0850)	-0.339*** (0.0847)
	3rd Quartile	-0.279*** (0.0617)	-0.276*** (0.0616)
	4th Quartile	0	0
Versatility Index	1st Quartile	-0.0806 (0.0997)	-0.0814 (0.0995)
	2nd Quartile	-0.0779 (0.0755)	-0.0771 (0.0754)
	3rd Quartile	-0.774 (0.0610)	-0.0761 (0.0609)
	4th Quartile	0	0
Assist Per Game	1st Quartile	-0.259*** (0.126)	-0.255*** (0.126)
	2nd Quartile	-0.165 (0.0922)	-0.160 (0.0923)
	3rd Quartile	-0.0468 (0.0632)	-0.0428 (0.0629)
	4th Quartile	0	0
Steal Per Game	1st Quartile	-0.0142 (0.0963)	-0.0127 (0.0963)
	2nd Quartile	-0.0135 (0.0788)	-0.0133 (0.0786)
	3rd Quartile	-0.0307 (0.0571)	-0.0301 (0.0569)
	4th Quartile	0	0
Rebound Per Game	1st Quartile	-0.101 (0.113)	-0.0970 (0.113)
	2nd Quartile	-0/0226 (0.0803)	-0.0168 (0.0803)
	3rd Quartile	0.00406 (0.0658)	0.0107 (0.0659)
	4th Quartile	0	0
Superstar Dummy		0.173 (0.165)	0.144 (0.153)
Google Trends		NA	0.0813* (0.0381)
Number of Observations		2292	2292

1. Model 1A and Model 1B

Both models use linear approximation, that is, treating the effect of performance variables constant. A one point increase from 29 points per game to 30 points per game has the same impact on players' salary as point increase from 5 to 6 points. The regression outputs show us points, assists all have positive significant effect on salary. In particular, 1 point increase in points is associated with 5% increase salary while 1 more assists per game is associated with 10% increase (Model 1A) and 9% increase (Model 1B). However, rebounds do not seem to have significant effect on salary, neither does the interaction term Versatility Index. One other finding worth mentioning is the negative and significant effect of steal. Stealing usually leads to success defense and fast break, which are all positive facilitator of team performance. Intuitively, the coefficient should be positive. However, most steal attempts end up failing thus lead to defensive chaos and eventually a negative impact on both the teams' moral and performance.

The dummy variable superstar has a negative coefficient, which is also counter-intuitive. The key reason may lie in the presence of salary cap. As mentioned previously, salary cap limits the salary received by a player. Each player also has his own cap, that is, the maximum salary he can receive. Although superstars, in general, will receive the maximum salary, their true value should be higher than the cap. A player with 30 points per game, 10 assists should be paid around 37 million each season. The 37 million is higher than the players' salary cap (at most around 30 million).

If Google Trends is included, the coefficients of all performance statistics all drop in magnitude as well as significance. That is, performance statistics have picked up the effect of internet popularity on players' salary. Although the coefficient is not significant, the positive sign implies a player's online popularity is associated with his salary. To be specific, a one point increase in the yearly average of Google Trends lead to 5% increase in salary. The magnitude of impact is similar to points. However, to claim Google Trends is as important as Points Per Game in determining players' salary is inaccurate. With a mean of around 0.9 and max of around 10.0, the variation is limited in comparison to points (mean is 8.9 and the max is 32). Furthermore, due to the strong seasonality of NBA players' attractiveness, to increase his yearly average by one points is difficult.

2. Model 2A and 2B

Model 2A and 2B took non-linear transformation of performance indexes. For both models, every coefficient of Points Per Game is significant at 1% significance level, which implies that different scoring ability does lead to distinct dispersion of salary. To be specific, if a player's average points per game is among the lower 25% of the league, he will be paid about 50% less than players who are in the top 25% ceteris peribus. For players in the 25th to 50th and 50th to 75th percentile, the percentage will be 34.1% and 27.9% less. The coefficients are similar for both Model 2A and 2B. In addition, the difference between individual coefficients are also interesting to observe. The difference between the 1st and 2nd quartile is about 15%, while the difference is around 7% between 2nd and 3rd quartile. The largest difference occurred between the 3rd and 4th quartile, which is around 28%. The large dispersion provides us evidence to claim that the effect of scoring is not linear, especially for players in the upper level. The above data also suggested that being in the 25%-50% or the 50%-75% are not distinctively different in comparison (7% vs. 28% or 15%).

Another performance statistics that also shows significant influence is assist per game. However, among the four coefficients of quartiles, only the coefficient of the lower quartile shows significant impact on salary. Being in the lower quartile of assist will lead to around 26% less salary paid than the players above 75th percentile. The difference is not as large as the difference in the case of points (26% vs 50%). Although the other two coefficients are not significantly in 5% level, the coefficients' magnitude are increasing: the difference from the top players is shrinking as assists per game increases. The above finding is consistent with general intuition.

Like Model 1A and 1B, points and assist per game are the two major positive facilitators of salary, which is different than Wallace's claim that points, rebounds, assists are all significantly affect players' salary.

None of four coefficients of the other performance statistics are significant. However, as performance statistics increases, similar trend is also observed: the coefficients are less negative (except the 2nd quartile and 3rd quartile of steal), thus implies more salary in general.

Superstar dummy is positive in Model 2A and 2B. Although the coefficients are not significant, the positive sign provides us evidence to say that within each quartile, superstars are paid better on average.

The coefficient of Google Trend is both positive and significant, thus shows within each performance quartile, more internet influence will lead to higher salary. Numerically, one point increase in Google Trend will lead to 8% increase in salary. However, as previously mentioned, Google Trend index is harder to improve than points and assists. As a result, players' performance is still the key in determining their salary.

V. Conclusion

The above panel regression results are consistent with previous studies. Performance statistics, especially offensive performances heavily influence a players' salary. The non-linear regression results confirm that performance statistics, especially points per game, has an accelerated effect on players' salary. Internet popularity, in the form of Google Trends, do not necessarily affect a player's salary, even in the era of Internet. In conclusion, a player's value is still lay in his talent on the court. One's popularity alone is less likely to ensure him a desirable contract.

V. Reference:

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