An Analysis of New Performance Metrics in the NBA and Their Effects on Win Production and Salary

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This thesis is dedicated to my mother, Rebecca Rust, who has always inspired me to pursue perfection, and has given me more support than I've deserved throughout my life. It is also dedicated to my father, Kevin Rust, who taught me to be more inquisitive and curious about the world in which we live. It is dedicated to my brother, William Rust, and sister, Kathryn Rust, both of whom have helped mold me into the person I am today.

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ABSTRACT

An Analysis of New Performance Metrics in the NBA and Their Effects on Win Production and Salary

In this study I perform statistical analysis on new metrics in the NBA designed to expose information about the inputs of basketball production. These input data were collected manually for every NBA player in the 2012-13 season, along with common advanced statistics. With these new metrics regression analysis is used to separately determine their effects on existing win production metrics and salary. In this analysis I control for team and position effects. Once these effects were determined, I was able to compare them and look for specific skills or strategies that may be undervalued or overvalued by NBA teams relative to their impact on producing wins. Offensive rebounding (ORB%) and usage rate (USG%) are found to be undervalued and overvalued, respectively. Teams generally allocated salary consistent with the effects identified by the input data from Synergy. Nonetheless further study, chiefly expanding the sample and controlling for individual heterogeneity among players, needs to be conducted.

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LIST OF ABBREVIATIONS

WS	Win Shares
WP	Wins Produced
TS%	True Shooting Percentage
eFG%	Effective Field Goal Percentage
ORB%	Offensive Rebound Percentage
DRB%	Defensive Rebound Percentage
AST%	Assist Percentage
STL%	Steal Percentage
BLK%	Block Percentage
TOV%	Turnover Percentage
USG%	Usage Percentage
ORtg	Offensive Rating per 100 possessions
DRtg	Defensive Rating per 100 possessions

Introduction

This purpose of this study is to use new statistics produced by Synergy Sports Technology, commonly used by NBA front offices, to determine if some metrics created to discover how many wins an NBA player is worth to his team fall short of accurately portraying what goes on during a game. More importantly, I want to see how these new statistics correlate with salary, and see if there are any specific skill sets or strategies NBA front offices may be under or overvaluing.

Two common metrics that measure a player's value in terms of how many wins he contributes to his team are used in this study. The first, Wins Produced (WP), created by economists David J. Berri and Martin B. Schmidt, was one of the first metrics that claimed to pinpoint exactly how many wins a player was worth to his team. A measure of this type should have become a cornerstone of advanced metrics in basketball, many discussions of player value in baseball now begin and end with the well-established Wins Above Replacement metric. But while Berri and Schmidt created a model that accurately determined the relationship between traditional box score stats (such as Points, Rebounds, Assists and Turnovers) and winning percentage, they were limited by the lack of information inherent in box scores. NBA teams now understand that these traditional stats fail to capture all of a player's contributions on the court. Daryl Morey, general manager of the Houston Rockets, famously once said, "Someone created the box score, and he should be shot."[1]

[1] Michael Lewis, "The No-Stats All-Star." *New York Times Magazine*. February 13, 2009.

Another metric that tries to determine how many wins a player contributes to his team is Win Shares (WS) developed by Jason Kubatko for the website Basketball-Reference.com. Kubatko's metric is founded on the same principles as a similar metric that Bill James created for use in baseball. Win Shares is split into two categories, offensive and defensive, and attempts to define a player's value by how many points the player produces or gives up relative to league average. This metric has a distinct advantage over Wins Produced in that it accounts for possessions, or how many times within a game a team has the opportunity to score, now established as a foundation of analysis in the sport.

NBA teams have dramatically increased their focus on analytics over the past decade. Encouraged by the success of the Oakland Athletics in Major League Baseball and their "Moneyball" approach, teams in professional sports leagues throughout the world started investing in analytics and trying to discover a similar edge. Increasing the amount of information available is crucial, and in this regard the NBA has been one of the most proactive leagues. NBA analytics personnel use vast amounts of data that isn't available to the public, and have been able to adopt much better metrics as a result. However, teams were still frustrated by the amount of the game they were unable to quantify. To address the growing need for new information the NBA outfitted every one of its stadiums with a data collection system called SportVU. This system uses optical tracking, through six small cameras placed in the rafters of the arena, to record data about player and ball location throughout the course of a game. Everything from how fast a player runs to how many times he dribbles or passes is recorded. The sample size for this data needs time to grow, but experts have already begun making interesting discoveries from these massive datasets.[2]

The new performance statistics used in this study are provided by Synergy Sports Technology. These statistics are only partially available to the public, but teams have access to more data and are able to retrieve it much more effectively. However, Synergy's fan database provides some information about the inputs of basketball production, in that they describe types of plays, or actions, NBA and NCAA teams use to score. The objective goal of any team in a basketball game is to score on offense and prevent the other team from scoring on defense. Knowing the input values for scoring, and the probability that a player will score on a specific type of play, could potentially allow teams to find the marginal products of individual players. This makes Synergy's data unique, and yields a distinct advantage over measuring simple outputs of production such as traditional box score stats. Output data recorded in the traditional box score and advanced box score data can still be useful, if applied in the right way, but teams need to augment this limited information. Teams can potentially use these inputs to better allocate their salary cap however, if they understand how these inputs impact expected wins.

Synergy analyzes NBA and NCAA game film to determine which specific plays, or actions, on the court yield points. They do this for offense and defense at both the team and player levels. Synergy breaks offensive plays into eleven categories (such as Isolation, Transition, or Post-Up) and defensive plays into seven categories (the same as offensive, excluding four of those categories). For example, if you

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[2] Dan Cervone, Alexander D'Amour, Luke Bornn, and Kirk Goldsberry. "Pointwise: Predicting Points and Valuing Decisions in Real Time with NBA Optical Tracking Data." 2014. Presented at Sloan Sports Analytics Conference.

wanted to know a player’s field goal percentage or points per play on post ups, Synergy’s database could give us that exact number. This data could also be crucial in potentially quantifying coaching and schemes.

Analyzing win production for players is critical in the sports world because these teams and clubs may be unique in that they seek to optimize wins rather than profits[3]. The findings are not concrete, and some economists believe these two may be related. There are certainly examples of teams that take cost-cutting measures to ensure larger profits, but generally accumulating wins leads to more long-term viability for teams rather than accumulating profits. A reason for this could be that these individual firms operate within and are dependent upon the leagues or associations to which they belong. Teams are allowed to make their own hires and are responsible for filling their stadiums, but the leagues regulate many of the business practices. Most professional sports leagues can be described as cartels that seek to maximize joint profits, and this is precisely why leagues disperse revenue from TV deals according to market share and engage in other common practices to promote equity among their teams. The structure and stability a league provides allow teams to covet winning over profits. Ultimately, wins help fill the seats, attract better players, and make for a better overall product that these teams sell to the consumer.

[3] Stefan Szymanski and Pedro Garcia del Barro, “Goal! Profit Maximization and Win Maximization in Football Leagues.” 2006. Paper presented by International Association of Sports Economists.

Insight into Advanced Metrics in Basketball

Advanced metrics or analytics, as in-depth statistical analysis in sports has come to be known, have taken huge strides in the last twenty years. Bill James is often cited as one of the pioneers of analytics in baseball, and his Baseball Abstracts inspired experts to apply this type of thinking to other sports. James spent years creating new statistics and constructing models in order to better understand a game that was being misrepresented by traditional statistics; and this was well before any of his methods became accepted practices in MLB front offices. This was a decided advantage for baseball over other sports, in that analysts like Bill James had ample time to correct mistakes and improve methods before demand for this type of work soared. In other sports the need for advanced metrics came on much more rapidly.

Basketball can be a difficult sport to analyze. A sport such as baseball can essentially be broken down into a series of one on one interactions and teammates do very little to affect the outcomes of those situations. The effects they do have are small and easily quantifiable (i.e. runners on base). In basketball, teammates contribute a great deal to what happens throughout the course of a game, and their impact can be hard to discern quantitatively. Consider a player such as J.J. Redick who was traded to the Los Angeles Clippers over the summer. Redick saw his output improve because he plays with a premier point guard, Chris Paul, and a top power forward, Blake Griffin. Redick benefits by having a great point guard throw accurate passes to him, which allows him to take a shot faster and with less difficulty, and also because opposing defenses concentrate so much of their efforts defending the duo of

Chris Paul and Blake Griffin. As a result, his effective field goal percentage (eFG%) and true shooting percentage (TS%), both advanced stats that weight field goal percentage for three point attempts and free throws, have risen this season by 1.8% and 2.7% respectively. So this represents our dilemma, how much of this is due to playing with great teammates and how much is due to increased individual performance?

The Redick example of why applying statistical analysis to basketball is difficult. One area where basketball is especially difficult to quantify is on defense. Traditional stats like steals and blocks give us some information about how a player performs defensively, but these are a relatively rare occurrences in a game and defense is as much about forcing teams to take bad shots as it is taking shots away from them. The NBA understands that this lack of quantitative information to evaluate defense poses a problem. As I stated earlier, this one they're trying to address with the implementation of systems like SportVU. Plus-minus statistics are some of the only tools available to the general public for analysts to use to determine defensive value. However, those are simple tallies of a team's point differential while a specific player is on the court. These statistics make it difficult to know just how much the specific player contributes to this differential. Statistical methods have been applied to these stats to help tease out individual offensive and defensive value. Advanced Statistical Plus Minus[4] developed by Daniel Myers does this effectively, and ESPN also just released data on a new metric they've created that performs similarly called Real Plus Minus.[5]

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[4] Daniel Myers, "ASPM and VORP." *GodismyJudgeOK.com.*
[5] Steve Ilardi, "The Next Big Thing: Real Plus Minus." *ESPN.com*. April 7, 2014

Despite the hindrances I've discussed, our understanding of the game of basketball has increased greatly thanks to the advancement of analytics. The corner three was discovered to be one of the more valuable shots in the NBA because of its reduced distance from the goal, and because it offers teams optimal spacing on the floor to run sets. Midrange shots have been found to be less valuable because they typically fall at lower rates than closer shots, but without the benefit of the extra point that a shot from an extra few feet away provides. Teams have recognized these facts and have managed their rosters accordingly.[6]

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[6] Kirk Goldsberry, "CourtVision: How the Spurs and Heat Use the Most Important Shot in Basketball." *Grantland.com.* June 5, 2013.

Methods and Regression Model

In order to perform this study I collected data from Synergy's online database for the 2012-13 NBA season. For each player in the NBA during this season I compiled points per play in every offensive and defensive category, along with total number and percentage of plays used[7]. The sample size for this study is 524 players, and I collected rosters from Basketball-Reference.com, which includes all players activated for a team throughout the season, and this means that players on 10-day contracts or called up from the NBA Development League are included as well. In addition, to simplify things I treat players traded during the season as separate players, which was crucial in order to control for team effects. I also collected advanced statistics, including the Win Shares metric, for the 2012-13 season from Basketball-Reference.com[8]. The Wins Produced data comes from BoxScoreGeeks.com and the model from Berri's and Schmidt's website WagesofWins.com as well as their two books, *The Wages of Wins* and *Stumbling on Wins*. Figures for player salary for the 2012-13 season comes from the website ShamSports.com.

The next step is using multiple linear regression analysis to determine if there's a relationship between these win production metrics and the Synergy data. I expect there should be, since as I stated previously the win production metrics use

[7] The term "used" has a specific application in basketball analysis, as a used possession is one that ends in a FGA, FT, TO, or ORB. Synergy catalogues plays instead of possessions, and they define a used play as one that ends in a FGA, FT, or TO; they exclude ORB because it is listed as one of these plays.

[8] Basketball Reference calculates the advanced stats I used for the study and they consist of eFG%, TS%, ORB%, DRB%, AST%, STL%, BLK%, TOV%, USG%, ORtg, and DRtg.

output data which still serves as a useful proxy for the input skills Synergy records. I also apply the multiple linear regression method to determine if there's a correlation between the Synergy statistics and salary. Given these estimates, I can then compare whether the skills with the largest marginal product are also the most important determinant of salaries.

I used the standard ordinary least squares regression function to define this relationship and performed the analysis using R statistical software.

$$Y = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p + \varepsilon$$

The regression is estimated using WP, WS, and salary as separate dependent variables. The independent variables (x_1, x_p) are the Synergy statistics, advanced statistics, height, and dummy variables for teams, β_0 is an intercept term, and ε is an error term. Thus, in this model we can determine the effects each of these independent variables has on WP, WS, and salary. Salary is measured per $100,000, and the inputs are measured in terms of total points per 100 plays.

Crucially, in the final step I compared the effects of these statistics on win production and salary to determine if there may be specific input skills that are undervalued or overvalued in the NBA. I compared only the significant independent variables, minimum 10% significance level, from each test.

Results

In the first regression, full results in Table 1, I examine the effects of the input data on WS. Thirteen of the input categories have significant effects on WS. Points scored on All Other Plays has the largest positive effect, with a marginal effect of 4.226. This is more than four times the effect of any other input category. All of the offensive input categories Synergy defines have positive effects of WS, and all of the defensive categories have negative effects on WS. This gives us more evidence that these inputs explain WS with some accuracy. Points allowed on Handoffs has the largest negative effect, with a marginal effect of -1.263. The adjusted R^2 value for this model is 0.89.

In the second regression, full results in Table 2, I examine the effects of input data on WP. Of the eighteen input categories, nine have significant effects. Points scored on All Other Plays has the largest positive effect on WP, with a marginal effect of 5.353. This effect is not as large relative to the other offensive input categories as it is for WS. Points scored on Post-Ups is the only offensive input category with a negative impact on WP, one of -0.229. Other than points on Post-Ups, all other offensive input categories have positive effects on WP. All of the defensive categories have a negative effect on WP. Points allowed on Post Ups has the largest negative effect, with a marginal effect of -1.427. The adjusted R^2 value for this model is 0.74.

With the third regression, full results in Table 3, I determine the effects of input data on player salary. Nine of the input categories have significant effects on salary, with points scored on All Other Plays having the largest, with a marginal effect of 58.296. The offensive input categories all have positive marginal effects on salary, and all of the defensive input categories have negative marginal effects on salary. Points allowed on post ups has the largest negative effect, with a value of -17.09. The adjusted R^2 value for this model is 0.47.

To evaluate how effectively NBA teams are spending relative to these inputs I compare the effects of these measures between WS, WP, and salary; the full results can be found in Table 4. I also include the advanced stats in this comparison to determine if any of these are misrepresented in salary relative to their impact on win production. There are 13 variables with significant effects on salary and 9 of those also have significant effects on WS and WP. Points allowed on post ups and points allowed on pick and rolls where the ball handler shoots both have negative effects on all dependent variables. USG% has a positive correlation with salary, while negatively affecting both WS and WP. ORB% has a negative effect on salary, but correlates positively with WS and WP.

Conclusion

First, in interpreting these results I need to reiterate that this study is only performed for one season, so the sample size is relatively small and single season anomalies such as injuries can have an impact. Now, the high adjusted R^2 values for regressions with WP and WS demonstrate that these input variables are correlated with these win productions metrics, as I suspected they would be. Generally, the points allowed categories also had negative effects on WP and WS. This makes sense intuitively, as giving up more points tends to reduce wins a player produces.

To my surprise, points from All Other Plays consistently has relatively large effects on WS and WP. Originally, I was very dubious of this result, because "All Other Plays" is the most loosely defined category in Synergy's database, and I'm not even sure of all the play types they consider to be in this category. These values are also consistently low relative to other Synergy data. The mean points per play for All Other Plays is only 0.35, much smaller than means in other categories, and on average these plays only occurs 7% of the time. However, there are certainly other possibilities. This All Other Plays category could capture shots that come after a play has broken down and a player is forced to improvise. If this is the case, then All Other Plays should definitely correlate well to WS, WP, and salary because this measure could capture a player's ability to create his own shot and score in unlikely circumstances, decidedly valuable attributes. Further study needs to be completed in order to discern what types of plays fall in this category, and how it affects win production overall.

Another intriguing discovery in this study is that ORB% is undervalued by the NBA relative to its impact on win production. Generating offensive rebounds can lead to shots close to the rim or open looks on the perimeter as a result of the defense scrambling to get back into position, and this is why players convert on these plays at a relatively high rate compared to other input categories Synergy defines. I've often suspected that this would be an undervalued attribute, and this study provides some evidence of that. Typically, offensive rebounds are grabbed by larger post players, and players who hustle and venture into areas they may not naturally be within the offense. Some coaches also place less value on offensive rebounds because they would rather have players in better position to defend in transition. Synergy's data could shed much more light on this subject because it allows us to compare how effective these two plays are and the impact they have on producing wins, and this could help coaches choose the optimal strategy.

Two of the three significant defensive categories Synergy records have negative effects on WS, WP, and salary; and this tells us that teams recognize the effects of bad defense in these areas and allocate their salary accordingly. It is interesting to note that points given up on pick and roll plays where the screener takes the shot has a relatively large positive effect on salary. Unfortunately, this category does not have a significant relationship with WS and WP, so we can't be sure how it affects these dependent variables. This could be that players who give up more of these types of points are simply on the court longer and provide for their teams in other areas and are compensated thusly.

Generally teams are spending efficiently when it comes to offense. They recognize the impacts of scoring in areas like spot-up plays, post-ups, and points from cuts within the offense. It is surprising however that points from post-ups have positive effects on salary and WS, but negatively correlate with WP. I cannot speak as to why this is the case, but simply recommend that further study should be conducted for this category.

Usage rate (USG%) also provided an intriguing result in this study. Usage rate is the amount of possessions a player "uses" in a game. Therefore, players at the focal point of offenses, i.e. point guards, Kevin Durant, LeBron James, typically have high usage rates. USG% corresponds positively with salary, and this result is not surprising because increasing usage rate means a player is taking more of his team's shots. Therefore teams feel they must compensate these players more heavily. USG% has a negative effect on WS and WP however, and this is because simply taking more shots usually means players become less efficient and take away better shots from teammates. On bad teams this may not be the case because the efficient scoring options are scarce. Also this result could be evidence of bad teams, ostensibly producing less wins, relying too heavily on a few players and eschewing healthy and efficient shot distributions.

Ultimately the results of this study are not entirely conclusive, and more tests need to be conducted to better determine the effects of these input categories. In further study I would need to better account for the effectiveness of each of each of these categories regardless of playing time. With more time I could also get the full details about how Synergy defines these play types and better understand how these inputs demonstrate team strategies and player skills. What excited me most about the project however was not what I'd be able to accomplish with my first exposure to this new data, but simply learning how to manipulate this data to discover what's relevant. I believe these datasets that Synergy is compiling have extremely useful applications in furthering our understanding of the game of basketball. The problem remains that this data is still proprietary and the general public may not get a chance to see its full analytical capabilities. NBA teams and college programs are already charging their analytics personnel with the same types of tasks I tried to tackle with this study. They have the benefit of full-time employment and full access to Synergy's database. I for one am very hopeful that this new knowledge does not stay confined to the front office, but eventually pervades the public sphere so anyone may attempt to learn more about the game of basketball.

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Table 1: **Regression Measuring Input Effects on WS**
(Significant Effects Listed in Bold)

Inputs and Adv.	**Estimate**	**Std. Error**	
(Intercept)	5.903	15.576	
Total.Isolation	0.001	0.007	
TotalP.R.Ballhandler	**0.557**	**0.094**	***
Total.Post.Up	**0.272**	**0.079**	***
Total.P.R.Roll.Man	**0.787**	**0.154**	***
Total.Spot.Up	**0.497**	**0.097**	***
Total.Off.Screen	**0.615**	**0.159**	***
Total.Handoff	-0.510	0.355	
Total.Cut	**0.774**	**0.162**	***
Total.Offensive.Rebound	**0.795**	**0.229**	***
Total.Transition	**0.936**	**0.122**	***
Total.All.Other.Plays	**4.226**	**0.520**	***
Total.Isolation.Allowed	0.177	0.319	
Total.P.R.Ballhandler.Allowed	**-0.288**	**0.139**	*
Total.Post.Up.Allowed	**-0.421**	**0.234**	.
Total.P.R.Roll.Man.Allowed	-0.625	0.501	
Total.Spot.Up.Allowed	0.009	0.147	
Total.Off.Screen.Allowed	**-0.910**	**0.379**	*
Total.Handoff.Allowed	**-1.263**	**0.724**	.
TS%	1.562	2.266	
eFG%	-1.173	1.286	
ORB%	0.033	0.012	**
DRB%	-0.009	0.041	
AST%	**0.032**	**0.010**	**
STL%	-0.094	0.296	
BLK%	-0.034	0.104	
TOV%	0.000	0.010	
USG%	**-0.076**	**0.015**	***
ORtg	0.011	0.012	
DRtg	-0.060	0.135	
Significance codes	'***' 0.001 '**' 0.01	'*' 0.05 '.' 0.1 ' '1	
Adjusted R^2	0.8856		

Table 2: Regression Measuring Input Effects on WP

Inputs and Adv.	**Estimate**	**Std. Error**	
(Intercept)	-25.758	27.339	
Total.Isolation	-0.007	0.012	
TotalP.R.Ballhandler	0.245	0.164	
Total.Post.Up	**-0.229**	**0.138**	.
Total.P.R.Roll.Man	0.364	0.270	
Total.Spot.Up	0.005	0.170	
Total.Off.Screen	**0.595**	**0.280**	*
Total.Handoff	-0.810	0.623	
Total.Cut	**1.124**	**0.284**	***
Total.Offensive.Rebound	**1.917**	**0.401**	***
Total.Transition	**0.843**	**0.214**	***
Total.All.Other.Plays	**5.353**	**0.912**	***
Total.Isolation.Allowed	0.743	0.560	
Total.P.R.Ballhandler.Allowed	**-0.414**	**0.245**	.
Total.Post.Up.Allowed	**-1.427**	**0.410**	***
Total.P.R.Roll.Man.Allowed	-0.233	0.879	
Total.Spot.Up.Allowed	0.403	0.259	
Total.Off.Screen.Allowed	**1.143**	**0.665**	.
Total.Handoff.Allowed	-1.200	1.270	
TS%	4.847	3.978	
eFG%	0.039	2.258	
ORB%	**0.092**	**0.021**	***
DRB%	**0.141**	**0.072**	*
AST%	**0.073**	**0.017**	***
STL.	0.793	0.519	
BLK.	0.134	0.183	
TOV.	-0.010	0.018	
USG%	**-0.179**	**0.026**	***
ORtg	-0.019	0.020	
DRtg	0.258	0.236	
Significance codes	'***' 0.001 '**' 0.01	'*' 0.05 '.' 0.1 ' ' 1	
Adjusted R^2	0.7428		

Table 3: Regression Measuring Input Effects on Salary

Inputs and Adv.	Estimate	Std. Error	
(Intercept)	-812.6615	512.1244	
Total.Isolation	**-0.4807**	**0.2254**	*
TotalP.R.Ballhandler	4.1989	3.081	
Total.Post.Up	**10.4878**	**2.5823**	***
Total.P.R.Roll.Man	-1.8358	5.0595	
Total.Spot.Up	**5.5569**	**3.1828**	.
Total.Off.Screen	6.5725	5.2389	
Total.Handoff	**20.3934**	**11.6704**	.
Total.Cut	**18.8844**	**5.3265**	***
Total.Offensive.Rebound	-10.1139	7.5205	
Total.Transition	-5.4351	4.0055	
Total.All.Other.Plays	**58.2955**	**17.0883**	***
Total.Isolation.Allowed	3.5104	10.493	
Total.P.R.Ballhandler.Allowed	**-11.9249**	**4.5865**	**
Total.Post.Up.Allowed	**-17.0896**	**7.6782**	*
Total.P.R.Roll.Man.Allowed	**30.9865**	**16.4577**	.
Total.Spot.Up.Allowed	-6.2638	4.849	
Total.Off.Screen.Allowed	4.0692	12.4582	
Total.Handoff.Allowed	34.017	23.7894	
TS%	-110.0036	74.5109	
eFG%	11.9388	42.2936	
ORB%	**-0.8091**	**0.3999**	*
DRB%	1.2872	1.3485	
AST%	**1.0381**	**0.324**	**
STL%	9.8326	9.7182	
BLK%	4.12	3.419	
TOV%	0.3177	0.3439	
USG%	**1.217**	**0.4937**	*
ORtg	**0.746**	**0.3826**	.
DRtg	4.6011	4.4273	
Significance codes	‘***’ 0.001 ‘**’ 0.01	‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1	
Adjusted R^2	0.4653		

Table 4: Comparing Significant Effects on WS, WP, and Salary

Inputs	WS	WP	Salary
All Other Plays	4.226	5.353	58.296
Cut	0.774	1.124	18.884
Spot-Up	0.497	—	5.557
Post-Up	0.272	-0.229	10.488
ORB%	0.033	0.092	-0.809
AST%	0.032	0.073	1.038
USG%	-0.076	-0.179	1.217
P&R Ballhandler Allowed	-0.288	-0.414	-11.925
Post-Up Allowed	-0.421	-1.427	-17.09

Table 5: Mean Synergy Sports Data

Variable	Mean	Standard Deviation
Total Plays	528.3	497.5
PPP Overall	0.843	0.211
PPP Isolation	0.659	0.424
PPP P&R Ball Handler	0.498	0.484
PPP Post-UP	0.574	0.519
PPP P&R Roll Man	0.619	0.64
PPP Spot-Up	0.818	0.357
PPP Off Screen	0.621	0.55
PPP Handoff	0.614	0.604
PPP Cut	1.01	0.478
PPP Offensive Rebound	0.939	0.51
PPP Transition	0.999	0.403
PPP All Other Plays	0.351	0.258
Total Plays Against	335.5	281.3
PAPP Overall	0.864	0.228
PAPP Isolation	0.777	0.325
PAPP P&R Ball Handler	0.718	0.522
PAPP Post-Up	0.796	0.36
PAPP P&R Roll Man	0.773	0.539
PAPP Spot-Up	0.937	0.337
PAPP Off Screen	0.828	0.522
PAPP Handoff	0.745	0.591