Accounting for Complementary Skill Sets When Evaluating NBA Players' Values to a Specific Team

Joseph Kuehn
CSU East Bay
Email: joseph.kuehn@csueastbay.edu

Abstract

This paper develops a player evaluation framework that stresses the importance of accounting for complementarities between teammates when evaluating players. This is done by developing a probabilistic model of a basketball possession as a progression of events, where the probability of each event's occurrence is determined by the offensive players' skills, the defensive players' skills, and the complementarities between the skills of teammates. Evaluating players using this framework allows me to assess the substitutability between different game actions, the lineup-specific value a player brings to a team, and the players that are the best and worst teammates. It also allows me to separately identify the individual effect from the effect teammates have on a player's statistical production, and to evaluate whether player complementarities are valued in the market for NBA players in terms of higher salaries. I find that complementarities are under-valued, and that players are instead paid mainly for their individual statistical production.

1 Introduction

A key element to constructing any NBA team lineup is understanding how well the skills of the players in that lineup complement each other. Like in any team setting, an NBA lineup can be better, or it can be worse, than the sum of its parts. Teams that have a good understanding of what player types complement each other, can use complementarities between teammates to overcome deficiencies in talent, and win games against more skilled opponents. The effect of teammates is also important when evaluating player talent at the individual level. It is not uncommon to see below average players produce at an above average level when put in a lineup that accentuates their strengths, or conversely see a highly skilled player with below average numbers when playing with teammates with higher usage rates. This can make it difficult to distinguish between the ability of the individual player and the extent to which his performance has been influenced by his teammates.

In this paper I develop a player evaluation framework that stresses the importance of accounting for complementarities between teammates when evaluating players. What separates this player evaluation scheme from previous ones[1] is the focus here on identifying the substitutability between different game actions, and then using that to quantify the complementary effect teammates have on one another. This framework allows me to compute the value a player brings to a *particular* lineup taking teammate spillovers into account, and allows me to assess which players help and hurt their teammates' production the most. It also allows me to separate out how much of a player's statistical

[1]These include papers by Maymin, Maymin, and Shen[4], and Oh, Keshri, and Iyengar[5], whose modeling approaches are conceptually similar to mine, but differ in their focus and implementation, and by using game simulations to get expected outcomes.

production can be attributed to the player individually (and thus will translate to a new team) and how much is due to the team he is currently playing on (in which case you wouldn't see the same statistical output if the player moved teams). Finally this framework allows me to assess how much value current GMs place on the spillover benefits a player has on his teammates, by looking at whether NBA salaries reflect these potential spillovers or are based solely on individual production.[2]

2 Data

The data I use is play-by-play data from SI.com[3] for the 2014-2015 NBA season. With this data I record the 10 players on the court for each possession and the detailed result of the possession. To avoid trying to calculate ratings for players with few possessions, I only look at the 250 players with the most possessions during the 2014-2015 season. All the rest of the players are considered "replacement" players. I also use data on player salaries for the 2015-2016 NBA season from ESPN.com[2].

3 Model

I model a basketball game as a series of possessions where each possession is a sequence of events that have the potential to generate value (i.e. points) for the offensive team. The probabilities with which each of these events occur determine the number of points a team receives in expectation per possession according to the model outlined in Section 3.1. The probabilities that certain events occur during a possession are then determined by the skills of the players on the court, and importantly the *interaction* between those players and their teammates. The model determining these probabilities is outlined in Section 3.2.

3.1 Event Tree Model

Each possession is modeled as a sequence of actions represented graphically by the tree structure in Figure 2 of the Appendix. On a given possession each of the five offensive players can either shoot from a number of locations on the court, turn the ball over in a number of ways (i.e. bad pass, offensive foul, etc.), or be fouled without shooting. If the player receives a non-shooting foul then the offensive possession starts over, while if they turn the ball over then the possession ends. If they shoot, then at each location there are 4 possibilities: they make the shot, they miss the shot, they make the shot and are fouled, or they miss the shot and are fouled. If the shot is made the team gets 2 or 3 points depending on the shot location, and if the player is fouled then the expected number of points depends on their free throw percentage. If the player misses the shot then there are 2 possibilities: an offensive rebound by one of the offensive players, which results in the possession starting over, or a defensive rebound which ends the possession.

The probabilities with which each of these events occurs is determined by the individual player model in section 3.2. Given probabilities for each action for each of the five offensive players on the court, I can solve the event tree model for the expected number of points associated with each action and the expected number of points per possession. Thus the model is used to determine how the probabilities of particular actions being executed by a team of five players against five opposing players, affects the expected number of points per possession for the offensive team.

[2]Arcidiacono, Kinsler, and Price[1] do a similar analysis in a setting with a more general model of player complementarities.

To evaluate the model I classify shots into 7 shooting locations and classify turnovers as either forced or unforced. I calculated the average probability of each event occurring during the 2014-2015 season, and then using those probabilities solved for the expected value of each event and the overall expected points per possession for the "average" lineup of players. The results are in Table 1 below.

Table 1: Probabilities of each event and the associated expected points, for a lineup of "average" players during the 2014-2015 NBA season

Event	Average Probability	Expected Points
Possession		1.0765
2FGA: 0ft-3ft	24.1%	1.4626
2FGA: 4ft-8ft	11.0%	1.1569
2FGA: 9ft-15ft	9.1%	1.0539
2FGA: 16ft+	12.8%	0.9661
3FGA: 22ft-23ft	4.4%	1.3478
3FGA: 24ft-25ft	10.3%	1.2605
3FGA: 26ft+	6.7%	1.2032
TO Unforced	4.9%	0
TO Forced	7.0%	0
Non-Shooting Foul	9.7%	1.1055

The results in the table indicate that for a lineup with 5 average players, the possession outcome with the highest expected point total is shooting from inside 3 feet. For this lineup, a possession that results in a shot from inside 3 feet will increase the team's expected points per possession by 0.386 points over the average expected points per possession of 1.077 points. The worst outcome is a turnover as this drops the expected points on the possession to zero. These expected values take into account the probability that a player is fouled on a given shot, and the probability that an offensive rebound off a missed shot (or missed free throw) gives the offensive team another possession.

3.2 Individual Player Model

I next model how individual player skills coalesce with the skills of teammates (and are counteracted by the defensive skills of opponents) to affect the probabilities that the events outlined above occur. Players create value for their team either directly through the probabilities that they themselves commit certain actions during a possession, or indirectly by affecting their teammates' probabilities of committing certain actions. By affecting these probabilities, a player brings value to the team through the effect these changing probabilities have on the team's expected points per possession.

For each potential game event outlined above (e.g. taking a 2pt shot from inside 3 feet), I model the conditional probability of a particular offensive player, j_1, with teammates j_2, j_3, j_4, j_5, and opposing players k_1, k_2, k_3, k_4, k_5, executing the particular event E^i as:

$$Pr\left(E^i_{j_1} | L^{k_1,k_2,k_3,k_4,k_5}_{j_1,j_2,j_3,j_4,j_5}\right) = exp\left(U^{E^i}_{j_1}\right) / \left(\sum_{j=j_1:j_5} \sum_{x \in \mathbf{X}(\mathbf{E^i})} exp\left(U^x_j\right)\right) \tag{1}$$

$$U^{E^i}_{j_1} = \gamma^{E^i}_{j_1} + \beta_{E^i} \sum_{j=j_2:j_5} \gamma^{E^i}_j + \sum_{x \in \mathbf{X}(\mathbf{E^i})_{-\mathbf{E^i}}} \delta_{E^i,x} \left(\sum_{j=j_1:j_5} \gamma^x_j\right) + \left(\sum_{k=k_1:k_5} \gamma^{E^i,def}_k\right) \tag{2}$$

where γ^x_j is the propensity of player j_1 to commit action x (and $\gamma^{x,def}_k$ is a defensive player's ability to affect his opponent's propensity to commit action x), and $\mathbf{X}(\mathbf{E^i})$ is the set of actions with the same parent node as action E^i, in the tree in Figure 2. The parameter β_x measures the own-substitutability of action x (e.g. how much the propensity of j_1's teammates to shoot a 2pt shot from inside 3 feet affects j_1's probability of doing so) and the parameter $\delta_{x,y}$ measures the cross-substitutability of action y on action x (e.g. how much the propensity of j_1's teammate to shoot a 3pt shot from 24-25 feet out affects j_1's probability of shooting from inside 3 feet). Equation (2) shows that a player's probability of executing a particular action during a possession (such as shooting a 3pt shot from 24-25 feet out), depends on their own propensity to commit the action, their teammate's propensity to commit the action, the player and his teammates propensity to commit other actions during the possession (such as turning the ball over or shooting from another location), and the defensive players' abilities to affect the probability of the event occurring.

The individual player model is estimated using a 2-step approach where in the first step maximum likelihood is used to map observed probabilities into 3 player scores which measure, respectively, the player's propensity to execute an event, the player's effect on teammates' propensities to execute an event, and the player's defensive effect on opponents' probabilities of executing an event. In the second stage I then use a least-squares approach to match these scores with the parameters (β and δ) and player ratings (γ_j^x and $\gamma_k^{x,def}$) of the above model.

3.2.1 Substitution Parameters

Estimation of the model parameters tells us how substitutable certain player actions are. For example we can see how substituting in a player who is 10% more likely to shoot a 3pt field goal from 24-25 feet out, affects his teammates' probabilities of shooting the same shot, and their probabilities of executing other events such as shooting from within 3 feet or committing a turnover. The estimated parameters are displayed in the table in Figure 1, and are interpreted as the effect a 1% increase in a player's propensity to commit the column event during a possession, affects their teammates' propensities to commit the row event. For example the entry in column 1, row 1 of -0.086, means that if you substitute in a player that is 10% more likely to shoot from within 3 feet, then all else equal this will decrease the probability that each teammate shoots from within 3 feet by 0.86%.

Figure 1: Substitution Parameters: The estimated effect of a 1% increase in the probability a player executes the column action on the probabilities that his teammates execute the row action for a team of average players

	2FGA: 0ft-3ft	2FGA: 4ft-8ft	2FGA: 9ft-15ft	2FGA: 16ft+	3FGA: 22ft-23ft	3FGA: 24ft-25ft	3FGA: 26ft+	TO Unforced	TO Forced	Non-Shooting Foul
2FGA: 0ft-3ft	-0.08575	-0.02014	-0.07731	0.00696	0.03133	-0.02421	-0.01671	0.00547	0.02333	-0.06957
2FGA: 4ft-8ft	-0.02979	-0.09915	0.00857	-0.00226	0.02151	0.01117	-0.01911	-0.04382	0.01722	-0.02027
2FGA: 9ft-15ft	0.02589	-0.01043	-0.06482	0.03572	-0.06091	-0.01012	-0.01694	-0.01760	0.00331	-0.05658
2FGA: 16ft+	-0.09587	0.04233	-0.02997	-0.10692	-0.08022	-0.06114	0.03038	0.00511	-0.02927	-0.08281
3FGA: 22ft-23ft	-0.00646	-0.01485	-0.06495	-0.02028	-0.17842	-0.01348	-0.00136	0.02654	0.00855	0.01333
3FGA: 24ft-25ft	-0.04388	-0.04148	0.01244	-0.01496	-0.00328	-0.11104	-0.04846	0.02827	0.00761	-0.01015
3FGA: 26ft+	-0.01051	-0.00891	-0.00947	-0.04178	0.00458	-0.05316	-0.14089	-0.05438	-0.05666	0.12967
TO Unforced	-0.00972	-0.01017	0.00435	-0.01246	0.01596	0.01117	0.01637	-0.08693	0.01311	-0.00296
TO Forced	-0.00156	-0.05478	-0.00276	-0.01025	0.01805	0.01297	-0.00858	-0.03656	-0.22084	0.01175
Non-Shooting Foul	0.04050	-0.00224	0.01097	-0.05517	-0.00427	0.01565	-0.02288	-0.04346	-0.01054	-0.14053

	Off Reb	Def Reb
Off Reb	-0.1499	-0.0801
Def Reb	-0.0580	-0.1775

The tables indicate that getting rebounds are the most substitutable action for teammates, in that a player who gets 10% more offensive rebounds really only helps his team get 4% more offensive rebounds in total because he is taking some rebounds away from his teammates. Defensive rebounds are even more substitutable in that a player who gets 10% more defensive rebounds only helps his team get a little less than 3% more defensive rebounds in total, again because he is taking some rebounds away from teammates. Taking 3pt shots is also highly substitutable in that substituting in a player who takes 10% more 3pt shots from 22-23 feet out, will only increase the overall team's probability of taking that shot during a possession by 2.9%, again since he is taking this shot away from teammates. This is contrasted with taking 2pt shots from within 3 feet, where substituting in a player who takes 10% more of these shots increases the overall team's probability of taking that shot during a possession by 6.6%. This is because putting in a player with a propensity to take close-range shots doesn't take as many close-range shots away from teammates, and instead leads to a lower probability of other events, such as the team taking 2pt field goals from outside 16 feet.

The parameter results also indicate the substitutability between *different* events. For example, the entry in column 1, row 2 of -0.0298, means that if you substitute in a player that is 10% more likely to shoot from within 3 feet, then this will decrease the probability that each teammate shoots at a location between 4-8 feet by 0.298%. Thus if you look at the first column you can see that a player who takes more close range shots from within 3 feet, decreases the probability that teammates take 2pt shots from outside 16 feet and 3pt shots between 24-25 feet, but also that there is a positive correlation between shooting close-range shots and getting non-shooting fouls. This positive correlation is most likely a result of players getting fouled as they drive to the basket for the close-range shot.

3.2.2 Player Ratings

Estimation of the player model also leads to player ratings that tell us the propensity for players to commit certain actions during a possession (e.g. shoot from particular locations, turn the ball over, or be fouled), the probability they make or miss a shot (and the probability they are fouled during a shot) from a particular location, and the probability they get an offensive rebound off a missed shot from a particular location. I also get defensive player ratings which tell us how defensive players affect the probability that their opponent commits a particular action during a possession, makes a shot from a particular location, and gets a rebound off a missed shot. These ratings are estimated simultaneously with the substitution parameters above, and thus take into account the substitutability and complementarity between different actions. For example, a player who gets a lot of rebounds in a lineup where no one else gets rebounds will get a lower rebounding rating compared to a player who has similar rebounding statistics, but is in a lineup with other strong rebounders. The top 5 players for each rating are displayed in Tables 11 and 12 in the Appendix.

4 Player Evaluations

With the estimated model I can then evaluate the value a player has to a lineup through their own offensive output, the effect they have on teammates' offensive outputs, and their defensive effect. These player evaluations do not require simulation, but are instead based on how a player's skills affect their own, *and their teammates*, propensities to commit certain actions during a basketball possession, and the associated values of those actions based on the expected points they will produce, derived from the event model of section 3.1. These player valuations are lineup-specific in that certain players' skills coalesce better with particular teammates rather than others. For example the additional value Andre Drummond brings to a lineup that already contains Greg Monroe is less than the value he would provide to a lineup without another solid rebounder, particularly because Drummond's biggest skill is his rebounding ($\gamma_{AD}^{OR} = 0.167$) and rebounding is highly substitutable ($\delta_{OR,OR} = -0.1499$).

4.1 Lineup-Specific Player Valuations

To illustrate how this model can generate lineup-specific player valuations, I first look at the value players brought to the lineups they were a part of during the 2014-2015 NBA season. I do this by comparing the lineup's expected points per possession with the player in the lineup versus the same lineup's expected points per possession if the player were instead replaced by a ”replacement” player.[3] This takes into account both the player's direct contribution and his spillover contribution to teammates.

Table 2: Players who caused the largest increase in their lineup's expected points per possession

Player	Lineup	Increase in EVP
Anthony Davis	Tyreke Evans, Eric Gordon, Dante Cunningham, Omer Asik, Anthony Davis	0.0614
Al Horford	Kent Bazemore, Dennis Schroeder, Kyle Korver, Mike Scott, Al Horford	0.0610
Stephen Curry	Stephen Curry, Klay Thompson, Andre Iguodala, Draymond Green, Andrew Bogut	0.0609
Pau Gasol	Kirk Hinrich, Jimmy Butler, Mike Dunleavy, Pau Gasol, Joakim Noah	0.0575
LaMarcus Aldridge	Steve Blake, Damian Lillard, Nicolas Batum, LaMarcus Aldridge, Chris Kaman	0.0553

Table 3: Players who caused the largest decrease in their opponent's expected points per possession

Player	Lineup	Opp Change in EVP
Zaza Pachulia	Brandon Knight, Khris Middleton, Giannis Antetokounmpo, Jared Dudley, Zaza Pachulia	-0.0648
Marc Gasol	Mike Conley, Courtney Lee, Tony Allen, Zach Randolph, Marc Gasol	-0.0506
John Wall	John Wall, Bradley Beal, Paul Pierce, Nene Hilario, Marcin Gortat	-0.0477
Andrew Bogut	Stephen Curry, Klay Thompson, Andre Iguodala, Draymond Green, Andrew Bogut	-0.0464
Kyle Lowry	Kyle Lowry, Lou Williams, DeMar DeRozan, Pattrick Patterson, Jonas Valanciunas	-0.0455

Table 4: Players who caused the largest increase to the difference between their lineup's offensive expected points per possession and expected points per possession given up on defense

Player	Lineup	Increase in EVP
Marc Gasol	Mike Conley, Courtney Lee, Tony Allen, Zach Randolph, Marc Gasol	0.0818
LaMarcus Aldridge	Damian Lillard, Wesley Matthews, Nicolas Batum, LaMarcus Aldridge, Robin Lopez	0.0721
Tyson Chandler	Devin Harris, Monta Ellis, Chandler Parsons, Al-Farouq Aminu, Tyson Chandler	0.0721
DeMarcus Cousins	Darren Collison, Ben McLemore, Rudy Gay, Jason Thompson, DeMarcus Cousins	0.0718
Anthony Davis	Tyreke Evans, Eric Gordon, Dante Cunningham, Omer Asik, Anthony Davis	0.0701

Table 2 lists the 5 players that increased their respective lineup's offensive expected points per possession by the largest amount. Table 3 lists the 5 players that decreased their respective lineup's opponent's expected points per possession by the largest amount. Table 4 then lists the 5 players that increased their respective lineup's difference between expected points per possession on offense and expected points given up on defense, by the largest amount. As an example, the way to interpret the first number in Table 2 is that on offense Anthony Davis provides 0.065 more expected points per possession (or 6.5 more expected points per 100 possessions) than a replacement player to that lineup.

4.2 Best Teammates

I can also evaluate which players were good or bad teammates by looking at which players increased or decreased *their teammates'* expected points per possession by the largest amount, after subtracting

[3] A replacement player has skills equal to the average skills of a player during the 2014-2015 NBA season that fell *outside* of the top 250 players in terms of possessions.

out the player's individual production. Table 5 lists the 3 players that increased (and decreased) their teammates production by the most upon entering the respective lineup. These are then the players that had the largest positive (and negative) spillover effect on the offensive production of their teammates.

Table 5: List of 3 players whom increased their teammates' expected points per possession by the most and 3 players who decreased their teammates' expected points per possession by the most

Best Teammates		
Player	Lineup	Increase in Teammate EVP
Wesley Johnson	Jeremy Lin, Wesley Johnson, Wayne Ellington, Jordan Hill, Ed Davis	0.0668
Joe Ingles	Dante Exum, Gordan Hayward, Joe Ingles, Derrick Favors, Rudy Gobert	0.0579
Kirk Hinrich	Kirk Hinrich, Jimmy Butler, Mike Dunleavy, Pau Gasol, Joakim Noah	0.0571
Worst Teammates		
Player	Lineup	Increase in Teammate EVP
Russell Westbrok	Russell Westbrook, Dion Waiters, Andre Roberson, Enes Kanter, Steven Adams	-0.1414
DeMarcus Cousins	Darren Collison, Ben McLemore, Rudy Gay, Jason Thompson, DeMarcus Cousins	-0.1356
Derrick Rose	Derrick Rose, Kirk Hinrich, Jimmy Butler, Pau Gasol, Joakim Noah	-0.1342

4.3 Players Whose Teammates Helped Improve Their Stats by the Most (Least)

This player evaluation framework also allows me to look at which players saw the biggest increase in their individual production due to the lineups they were in. This is important because if a player is putting up good numbers because they are on a bad team, you would not expect these numbers to translate if the player goes to a better team, and if the player is putting up not as good numbers because they are on a good team, then they might have a higher production on a lesser team. I thus compared the individual expected points per possession that a player received in the lineup they appeared in the most during the 2014-2015 season, with the individual points per possession they would expect to receive on a team full of replacement players. The 5 players with the largest positive (and negative) change in expected points per possession due to the lineup they played in, are displayed in Table 6.

Table 6: Players with the largest positive and largest negative change in expected points per possession due to the lineup they played the most time in during the 2014-2015 season

Largest positive teammate effect		Largest negative teammate effect	
Player	Lineup Effect on EVP	Player	Lineup Effect on EVP
Jeremy Lin	0.0562	Rudy Gay	-0.0955
Jordan Clarkson	0.0556	Kyrie Irving	-0.0879
Gordon Hayward	0.0492	Lou Williams	-0.0843
Jordan Hill	0.0463	Anthony Davis	-0.0841
Michael Carter-Williams	0.0413	Kevin Love	-0.0839

5 Does the NBA Player Market Take Into Account Complementarities?

To assess whether player salaries take into account the spillover benefit a player provides to a team, I regress the log annual salary for each player for the 2015-2016 season, on the player's own contribution to the expected points per possession for a lineup of average players, the player's spillover contribution to the expected points per possession for that lineup, and his defensive contribution to the lineup. I also include fixed effects for the player's position. The results are in Table 7.

Table 7: Salary Regression

Dep Variable: ln(yearly salary)		
Variable	Coefficient	SE
Own	16.373*	3.535
Team	-4.615	21.806
Def	2.037	11.621
SG	-0.109	0.170
SF	-0.232	0.185
PF	0.302	0.222
C	0.395	0.272
Const	15.169*	0.148
Obs	250	
R^2	0.129	

The results indicate that players are largely paid for their individual statistical output on offense. The coefficient on teammate contribution is negative (but not statistically significant at the 5% level) indicating that the market does not place a great enough value on a player's potential spillover benefit to teammates. The coefficient on defense (which also is not significant at the 5% level,) shows that defensive contributions are also undervalued compared to offensive output. These results indicate that NBA teams are not doing a good job of identifying the value a player brings to a team through his complementarities with existing players, and are largely paying players based on their individual offensive contributions.

5.1 Free Agent Acquisitions

To illustrate how this paper's player evaluation model could be used to take team complementarities into account when evaluating free agents, I look at the case of LaMarcus Aldridge during the 2015 NBA offseason. For the five teams he was most interested in joining (San Antonio, Portland, New York, Los Angeles, and Dallas), I look at the additional expected points per possession he would of brought to the lineup with the most possessions on each team, above the player he most likely would have replaced in the lineup. The results are in Table 8, and they indicate that the New York Knicks would have had the highest value for Aldridge. This is not surprising since they were one of the worst teams in 2014-2015. What is a little surprising is that the Spurs had a higher value for him than both the Lakers and Mavericks, two teams with much weaker lineups. If complementarities were not taken into account, Aldridge would have provided much more value to the Lakers than the Spurs because the Lakers had a weaker existing lineup. Once complementarities are taken into account, Aldridge is shown to be of greater value to the Spurs. This quantifies the conventional wisdom during the offseason that Aldridge was a good "fit" with the Spurs.

Table 8: Lineups that have the most value for LaMarcus Aldridge

Player In	Rest of Lineup	Player Replaced	Increase in Off Team EVP	Increase in Def Team EVP	Increase in Tot Team EVP
LaMarcus Aldridge	Jose Calderon, Langston Galloway, Carmelo Anthony, Cole Aldrich	Jason Smith	+0.0439	+0.0398	+0.0837
LaMarcus Aldridge	Steve Blake, Damian Lillard, Nicolas Batum, Chris Kaman	"Replacement"	+0.0553	+0.0242	+0.0795
LaMarcus Aldridge	Tony Parker, Danny Green, Kawhi Leonard, Tim Duncan	Boris Diaw	+0.0351	+0.0302	+0.0653
LaMarcus Aldridge	Jeremy Lin, Wesley Johnson, Kobe Bryant, Jordan Hill	Carlos Boozer	+0.0127	+0.0377	+0.0504
LaMarcus Aldridge	Devin Harris, Monta Ellis, Chandler Parsons, Dirk Nowitzki	Tyson Chandler	+0.0236	+0.0099	+0.0335

I also look at which team would provide Aldridge the best opportunity to showcase his skills. Table 9 lists the increase in Aldridge's individual expected points per possession from joining each of the five teams. If Aldridge was solely interested in increasing his own points per possession than the best team for him to join would have been the Lakers since the lack of talent on their current roster would have meant Aldridge would not have had to "compete" as much with teammates for statistical output.

Table 9: Lineups that provide the most value to LaMarcus Aldridge

Player In	Rest of Lineup	Individual EVP
LaMarcus Aldridge	Jeremy Lin, Wesley Johnson, Kobe Bryant, Jordan Hill	0.3699
LaMarcus Aldridge	Jose Calderon, Langston Galloway, Carmelo Anthony, Cole Aldrich	0..2850
LaMarcus Aldridge	Devin Harris, Monta Ellis, Chandler Parsons, Dirk Nowitzki	0.2833
LaMarcus Aldridge	Tony Parker, Danny Green, Kawhi Leonard, Tim Duncan	0.2680
LaMarcus Aldridge	Steve Blake, Damian Lillard, Nicolas Batum, Chris Kaman	0.2578

5.2 Lineups That Took the Most Advantage of Complementarities

To conclude I look at what lineups during the 2014-2015 NBA season were the most successful at taking advantage of complementarities between teammates. I do this by comparing the expected points per possession for each lineup if complementarities are taken into account, with their expected points per possession if complementarities are ignored. The five teams that most took advantage of teammate complementarities are listed in Table 10. The lineups that were the most successful at taking advantage of complementarities were the lineups where low percentage shooters did not take shots away from high percentage shooters, and there was less shooting from locations with low expected point values that reduced the probability of shots coming from locations with high expected point values.

Table 10: 2014-2015 lineups that took the most advantage of player complementarities

Lineup	Diff in EVP from Comps
Andre Miller, Bradley Beal, Rasual Butler, Kevin Seraphin, Nene Hilario	0.1089
Kyle Lowry, DeMar DeRozan, Terrence Ross, Patrick Patterson, Jonas Valanciunas	0.1195
Kemba Walker, Gerald Henderson, Lance Stephenson, Cody Zeller, Al Jefferson	0.1259
Kirk Hinrich, Jimmy Butler, Mike Dunleavy, Pau Gasol, Joakim Noah	0.1308
Tony Parker, Manu Ginobili, Kawhi Leonard, Tim Duncan, Boris Diaw	0.1323

6 Conclusion

This paper introduces a framework for identifying the substitutability between player actions during a NBA game, and using that to derive player evaluations that take into account the complementarities between teammates in manufacturing production. I showed how this can be used to identify which players are good and bad teammates, and also to separate out how much of a player's statistical output is due to their individual skills and how much is due to the team they play on. I also showed that current NBA salaries indicate that player complementarities are undervalued in the market for NBA talent, and that many teams could improve their rosters by better identifying spillovers between players, possibly with a framework similar to the one developed in this paper. One limitation of the current paper is that player actions are broadly defined, and so future work should adapt the current model to take advantage of more detailed player action data such as exact shot locations and defensive player positions.

References

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Appendix

Figure 2: Event Tree

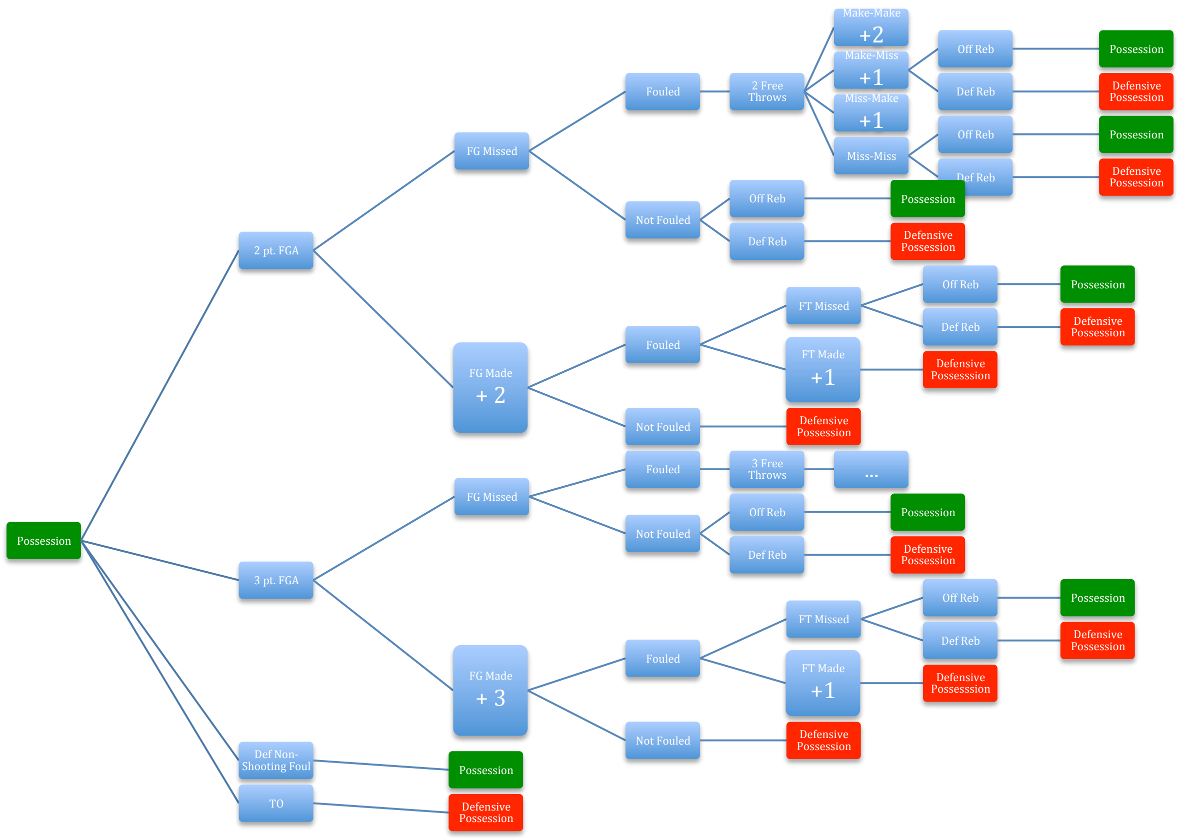

Table 11: Top 5 Players in Possession Ratings

Offense										
Rank	2FGA: 0ft-3ft	2FGA: 4ft-8ft	2FGA: 9ft-15ft	2FGA: 16ft+	3FGA: 22ft-23ft	3FGA: 24ft-25ft	3FGA: 26ft+	TO Unforced	TO Forced	Non-Shooting Foul
1	DeMarcus Cousins	DeMarcus Cousins	Dwayne Wade	Marreese Speights	Anthony Morrow	Lou Williams	Stephen Curry	DeMarcus Cousins	Russell Westbrook	DeMarcus Cousins
2	Tyreke Evans	Brook Lopez	Chris Bosh	DeMar DeRozan	Lou Williams	Gerald Green	Lou Williams	Kevin Seraphin	Derrick Rose	Dirk Nowitzki
3	Russell Westbrook	Al Jefferson	DeMar DeRozan	Dwayne Wade	O.J. Mayo	Greivis Vasquez	C.J. Miles	Nene Hilario	John Wall	Chris Paul
4	Enes Kanter	Greg Monroe	Al Jefferson	LaMarcus Aldridge	Terrence Ross	Terrence Ross	Jamal Crawford	Amir Johnson	LeBron James	DeAndre Jordan
5	Andre Drummond	Dwight Howard	Rudy Gay	Blake Griffin	Avery Bradley	Wesley Matthews	Klay Thompson	Dwight Howard	Aaron Brooks	Dwight Howard
Defense										
Rank	2FGA: 0ft-3ft	2FGA: 4ft-8ft	2FGA: 9ft-15ft	2FGA: 16ft+	3FGA: 22ft-23ft	3FGA: 24ft-25ft	3FGA: 26ft+	TO Unforced	TO Forced	Non-Shooting Foul
1	Kris Humphries	Anthony Tolliver	Kyle Korver	Andrew Bogut	Marc Gasol	Kent Basemore	Patrick Patterson	Marcus Smart	Kyle Lowry	Otto Porter
2	Carl Landry	Jonas Valanciunas	Robin Lopez	Marcin Gortat	Chris Bosh	Andre Roberson	C.J. Miles	Dennis Schroder	Tony Allen	Paul Pierce
3	Miles Plumlee	Robin Lopez	Roy Hibbert	Chris Kaman	Al Horford	Wesley Matthews	Amir Johnson	Mario Chalmers	Zaza Pachulia	O.J. Mayo
4	J.J. Hickson	J.J. Barea	LaMarcus Aldridge	Robin Lopez	Chase Budinger	Reggie Jackson	Andre Iguodala	Manu Ginobili	Ty Lawson	Marco Bellinelli
5	Serge Ibaka	Shaun Livingston	Tyler Zeller	Omer Asik	Kobe Bryant	Paul Millsap	Jamal Crawford	Zaza Pachulia	Draymond Green	Andre Drummond

Table 12: Top 5 Players in Rebound Ratings

Rank	Off Reb	Def Reb
1	Andre Drummond	DeAndre Jordan
2	DeAndre Jordan	Dwight Howard
3	Enes Kanter	Andre Drummond
4	Rudy Gobert	Pau Gasol
5	Ed Davis	Jordan Hill