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Determining the Players' Efficiency in NBA:

Some Economic and Managerial Results

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Abstract

Player efficiency is estimated by using Data Envelopment Analysis (DEA) and data of 401 players in NBA at 2006 in this study. Three approaches are generally used when measuring the efficiency of basketball players. In the first, which is frequently used in the literature, a variety of payments and fees are used as inputs. The second is used by basketball associations that correspond closely to the theoretical definition of efficiency because it tries to measure players' contribution to their team by using games statistics. The third which includes different type of approaches is used in the literature and takes into account games statistics like previous one. In this study, however, an alternative approach is used. It is different from the first method in that it measures the success of the players within the game, and it is also different of the second and third method because of the approach. According to results, there are differences between the ranking of the players obtained using the NBA system and the approach recommended in this study.

Keywords: NBA; sportive efficiency; managerial results

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Introduction

Sporting events play a significant role in the entertainment sector, and their effect is strengthening daily. Basketball games are among the most popular sporting events. In view of the increased importance and popularity of basketball, it comes as no surprise that basketball players now sign huge contracts. Hence, sporting events have a considerable direct and indirect effect on the economy.

In parallel with the increased importance and popularity of sports, there has been a rapid increase in the number of studies investigating the effects of this development on economic and social life. Studies of sports economics can be divided into two groups according to the objective of each study. The first group of studies focuses on the sports market. Scully (1974), for example, analyzes the relationship between players' fees and performance, whereas Zech (1981), Atkinson, Stanley and Tschirhart (1988) and Carmichael and Thomas (1995) analyze sports structures using production functions. Schmit and Berri (2001) focus on the competitive structure of basketball leagues, whereas Scully (1998) and Krautman and Berri (2007) examine inelastic pricing structures. Barget and Gouget (2007) analyze the determinability of the economic value of sports, and Schmit and Berri (2005) analyze the determinants of the players' talent. Surden (2006) uses chaos theory, developed in the 1960s, to analyze the American basketball league, and Leadley and Zygnot (2005) examine the honeymoon effect for different sportsmen. Finally, Osborne (2001), Rodney and Weinbach (2002) and Sapra (2008) discuss the market structure of the American football league.

The second group of studies is concerned with the efficiencies of teams, managers and players. These studies have usually been carried out via stochastic frontier analysis (SFA), data envelopment analysis (DEA) and the other statistical methods which are mentioned below. These studies have emphasized team, manager and players success. Some of the studies that have used SFA and DEA are as follows. Carmichael et al. (2001) analyzed the efficiency of football teams, and Berri and Jewell (2004) investigate whether there is a relationship between price imbalance and team productivity. Lee and Berri (2008) determined the variables influencing player talent in team production using multi-stage modeling and SFA with different estimators to determine the effect of player talent on team productivity. McGoldrick and Voeks (2005) used SFA to calculate the relationship between efficiency and a team's probability of winning. Escuer and Cebrian (2004) calculated the efficiency of Spanish football teams using SFA, and Haas (2003) did the same for the

English football teams. Leibenstein and Maital (1992) analyzed the efficiency of hockey players using DEA, as did Fizel and D'itri (1996) for college basketball coaches and Sueyoshi (1999) for basketball players. Lewis H. F., Sexton T. R. and Lock K. A. (2007) examined the relationship between payments to basketball players and efficiency. Besides SFA and DEA the other methods are also used for calculating the performances of players. These advanced and widespread methods are subjected to some researches. Hollinger (2005) used John Hollinger's Player Efficiency Rating method and give detailed information and formulation in his book. Other methods include Win Score and Win, by Berri, Schmidt and Brook (2006), and Win Shares, by James and Henzler (2002). Winston (2009) analyzed several rating systems, in addition to the NFL system, for many types of sports. All of these systems are very important and are used on websites such as basketball-reference.com, espn.go.com, and waynewinston.com. Additionally, Butenko Gil-Laufente and Pardalos (2004 and 2010) studied management and development strategies other than performances.

The current study aimed to focus on player efficiency. According to all parties interested in sports efficiency there are three different uses of the term of "player efficiency" that do not fully coincide, both of which capture "performance". The first is "technical efficiency"1, which is usually used in academic literature and calculated using DEA or SFA. The second is used to measure performance or the value of players in basketball federations such as NBA. The third is used the other statistical methods and game's statistics. The term "efficiency" in this study is used to express the efficiency of the players like the second and third group because this efficiency term is based on the statistical figures of players and the team as a whole during the game. Additionally, although the term is based on player statistics, it does not have the weaknesses of the efficiency term used by second and third methods based on the absolute values. Accordingly, the efficiency values have been obtained in this study based on economic terminology and referring to statistics for scoring, rebounds, etc., as used in calculating the efficiency value used by the NBA. As is mentioned in some of the literature above, the definition of efficiency used by the NBA that indicates players' contribution to their teams in terms of scores, rebounds, steals, etc., seems to be inadequate. Some questions are appropriate at this point. *Why is that definition inadequate? Will two players with the same efficiency level be seen as having the same level of success?* In other words, suppose that two players have the same efficiency levels but play for different teams, and one team has better performance statistics than the other team. In that case, will the two players with the same efficiency be accepted as equally successful? This perspective does not depend on relative evaluations and ignores the contribution of the entire team, whereas economics is analyzed using relative values rather

[1]Any decision-making unit output/full efficient decision-making unit output.

than absolute ones[2]. In other words, the efficiency scores calculated by the NBA to measure player performance are based on absolute values and are obtained by summing, subtracting, multiplying and dividing player statistics. However, a player's success is closely associated with the performance of his opponents and of his own team. Therefore, making calculations using absolute values exclusively may yield misleading results. Thus, there is a need for approaches that consider the effect of team success on the player while also calculating player efficiency. This will allow relative measurements to be consistent with standard economic analysis. Of course, the more successful the team is, the more successful the player is (ceteris paribus).

Based on all of these issues, this study makes pertinent recommendations and presents new ways to calculate player efficiency based on inputs and outputs that emerge during the game. As a result, this study presents information that can be used as an indicator in a more understandable, acceptable and clearer way. Additionally this study provides information that will enable the player (worker) to assess and learn his real value as a producer of a particular outcome, the boss/manager (employer) to learn the employee's real value, and the audience (the customer) to learn the real values of the players, who are the most important actors during the event (entertainment). Also, all inputs and outputs used in the analysis are acquired based on the interactive contributions of the players during the game, As far as we know, this study is unique in evaluating performance using these variables.

To that end, this study uses DEA. Even though SFA, a parametric method, is used in efficiency calculations, DEA is preferable in this study because it is based on a multiple-output analysis. In this study, data sets will be introduced, the methodology will be explained and the results and inferences will be discussed. Then, we will analyze whether the efficiency levels calculated in this study or those provided by the NBA system better predict team success.

Methodology

Data Sets

Because this study is a bit different in terms of its data sets, it may be useful to explain why and how the inputs and outputs in this study are used. This will help us to explain the motivation and purpose of the study more clearly. Whereas the fees paid to players have been used as the input in previous studies, game statistics are used as the input in this study.

[2] These definitions were the basis of the analyses by A. Smith and some pioneering economists. Moreover, relative values are taken more seriously in the analysis of economic variables. For example, any economic unit's variables, like wealth, wage and GDP, may be able to remain abstract and insubstantial unless compared with the other economic units.

There are a few concerns to take into consideration in this context. First is ambiguous of players' revenue. The revenues received by players have become more uncertain because they do not declare their income from advertisements and non-sports activities even if their contract fees are known. For example, a team with a high potential for attracting advertising contracts may assure a player that he will receive high advertising revenue and correspondingly offer a lower contract figure. Therefore, the fees paid to players on a particular team may not be homogeneous. Another problem is that sometimes two different contracts are issued, one legal and the other illegal, so that the player will be able to pay less in taxes. Legal contracts may declare lower fees in the countries where tax control is weak and where people often avoid paying or dodge their taxes. Therefore, contracts in some countries do not reflect actual compensation. Moreover, contracts are usually signed for just two years or so. This is largely because players in the middle of their careers in terms of age may not have sufficient motivation to maintain their level of performance if each contract covers a long period. In its current form, the contract guarantees the player's actual income but may not provide enough motivation for sustained high performance to enable the player's potential future income, as negotiated in the subsequent contract, to be high.

In addition, a large contract may cause a trade-off similar to the labor-spare time relationship in the literature. Thus, the performance analyses that are carried out using the statistics for all players on a team are also important because they indicate the success of each player in the game and the level of his interaction with the rest of the team.

Considering all of these issues, this study suggests an alternative way of calculating player efficiency. Each player's scoring, rebounds, blocks, steals and assists were taken as the outputs. The score is the basic indicator of player and team performance. Blocking and stealing are the beginnings of the attempt to score. Assists are the last movements that occur before a team scores. Accordingly, each of these moves contributes to performance. What is different about this study is the input: the sum of the assists, blocks, steals and rebounds of all of the team's players except for the player being analyzed. No player can score unless he is supported and assisted by his team through blocks, steals, assists and rebounds. The operative assumption is that the other players' attempts should also be taken into account in evaluating a particular player's performance.

As a result, four different alternatives were tested in this study. In the first one, the outputs were taken separately from the assists, rebounds, steals, blocks and scores for each player. The inputs, however, were the assists, rebounds, steals and blocks for all players on the team except for the player under analysis (DEA1). In the second alternative, because the values of all outputs except for scoring were lower, their sum was accepted as an output, while the outputs were defined. In this way, the outputs were taken separately as the sum of player scoring and other statistics (DEA2). In these two alternatives, each match was analyzed separately. In other words, all the matches in which each player played were taken as separate decision units (15548 units). In the third alternative, each player's seasonal average assists, rebounds, steals, blocks and scores were taken as output, while the seasonal average assists, rebounds, steals and blocks of the other players in the team were taken as inputs (DEA3). In the fourth alternative, the outputs and inputs are same with second alternative but they depend on seasonal average like DEA 3 (DEA 4). In the last two alternatives each player were taken as separate decision units (401 units). The average statistics are given in Table 1[3].

Table 1. Descriptive statistics.

Stats	**Means**	**Standart deviations**
Player		
1. Total rebound	4.05	3.49
2- Assist	2.03	2.51
3- Personel foul	2.25	1.56
4- Steal	0.71	0.99
5- Turnover	1.36	1.41
6- Bloces	0.47	0.91
7- Points	9.62	8.46
8- (1+2+3+4+6)	87.31	13.65
Teams		
1. Total rebound	36.79	6.74
2- Assist	18.49	5.30
3- Personel foul	20.55	4.62
4- Steal	6.42	2.70
5- Turnover	12.37	3.71
6- Bloces	4.23	2.47
7- Points	87.31	13.65

There are two reasons why we used player-based statistics in c analysis. Firstly we seek to determine what kind of distinctions we can arrive at using game statistics, and secondly, we wish to inspire debate about the different alternatives suggested in this study.

A total of 401 players are included in this study. The total number of games that these individuals have played is 15,548. Accordingly, 15,548 decision units exist for analysis using the first and second alternative methods. We thereby calculated the average efficiency scores for the players in each game.

Data Envelopment Analysis

In this study, players' efficiency levels were analyzed via the DEA method, which is commonly used in scientific research and performance measurement. DEA has also proven to be an ideal method for use in cases with several outputs. In this study, because there is more than one output, the DEA method is considered a suitable method of analysis. The foundational studies using the constant returns to scale (CRS) DEA method were performed by Charnes et al. (CCR) (1978 and 1981). Banker et al. (1984) also used the variable returns

[3] The data set used in this study was downloaded item by item from the team information pages at http://www.nba.com.

to scale (VRS) DEA method for efficiency analysis. CCR used piece-wise linear hull production technology as proposed by Farrell in 1957.

In this study, the analysis is conducted under the assumption of variable returns to scale because this technique yields more efficient and successful results. For instance, imperfect competition and financial difficulties prevent firms from working at an optimal scale, and CRS solutions can reflect technical and scale efficiency jointly. However, the use of VRS enables us to distinguish values for technical efficiency from those for scale efficiency values and measure pure efficiency. VRS includes the convexity constraint $I1'\gamma=1$, whereas CRS does not, and can be written as:

$$\begin{aligned} &\min_{\phi,\gamma} \phi \\ &st \quad q_i + Q\gamma \geq 0 \\ &\qquad \phi x_i - X\gamma \geq 0 \\ &\qquad I1'\gamma = 1 \\ &\qquad \gamma \geq 0 \end{aligned}$$

Where $I1$ is an Ix1 vector of ones, ϕ is a scalar and γ an Ix1 vector of the constants. x_i and q_i are the input and output column vectors of the *i*-th firm, assuming that there are *K* inputs and *T* outputs, respectively. Therefore, for *I* firms, *X* denotes the *K*x*I* input matrix and *Q* denotes the *T*x*I* output matrix. The technical efficiency scores of this approach are greater than or equal to those obtained using the CRS model because the VRS model provides a convex hull of intersecting planes that envelop the data points more tightly than the CRS conical hull does [Coelli (1996), Coelli et al. (1998), Yesilyurt (2008)].

Results

Each player's performance in the games was taken as the output, whereas the team's performance was taken as the input. In this way, the efficiency analysis conducted under significant limitation and according to absolute values presented by the NBA and other organizations was rendered more functional. With the effect of the other players' performance on the player in question determined in this context, the players' performance was analyzed using relative values. In the 1st column of the Table 3, there is the rank of the players where the efficiency score is based on NBA system and in the 2nd there is the efficiency scores is based on NBA system. In the 3rd and 4th column rank of the players and the players' efficiency scores are based on DEA1 respectively, in the 5th and 6th column, rank of the players and the players' efficiency scores are based on DEA2 respectively, in the 7th and 8th column rank of the players and the players' efficiency scores are based on DEA3 respectively, in the 9th and 10th column rank of the players and the players' efficiency scores are based on DEA4 respectively.

Table 2. Efficiency scores of players.

I	II	III	IV	V	VI	VII	VIII	IX	X	I	II	III	IV	V	VI	VII	VIII	IX	X
1	K. Garnett , MIN	3	0.736	3	0.757	1	1	1	1	102	C. Frye , NYK	45	0.584	34	0.660	19	0.925	22	0.925
2	L. James , CLE	1	0.775	1	0.769	1	1	1	1	103	J. Magloire , MIL	78	0.520	61	0.632	36	0.906	41	0.906
3	S. Marion , PHX	12	0.703	11	0.711	1	1	1	1	104	S. Parker , LAL	134	0.471	204	0.565	141	0.835	170	0.828
4	E. Brand , LAC	13	0.696	19	0.685	1	1	4	0.978	105	P. Brezec , CHA	192	0.438	201	0.565	219	0.803	233	0.803
5	K. Bryant , LAL	15	0.686	22	0.681	1	1	1	1	106	E. Curry , NYK	50	0.564	41	0.652	16	0.93	20	0.927
6	D. Nowitzki , DAL	33	0.610	54	0.637	42	0.903	46	0.903	107	E. Jones , MEM	99	0.500	104	0.608	45	0.9	54	0.896
7	D. Wade , MIA	14	0.688	17	0.685	1	1	8	0.961	108	R. Felton , CHA	83	0.517	138	0.589	95	0.864	139	0.843
8	A. Iverson , PHI	7	0.713	13	0.705	1	1	1	1	109	M. Dunleavy , GSW	131	0.474	150	0.584	186	0.815	197	0.815
9	M. Yao , HOU	30	0.617	37	0.657	1	1	1	1	110	B. Gordon , CHI	165	0.449	243	0.553	142	0.834	153	0.834
10	C. Bosh , TOR	16	0.683	5	0.753	1	1	1	1	111	M. Harpring , UTA	264	0.406	254	0.551	176	0.82	186	0.82
11	P. Pierce , BOS	24	0.634	18	0.685	12	0.945	15	0.945	112	S. Claxton , NOK	58	0.551	53	0.638	58	0.889	62	0.889
12	G. Arenas , WAS	8	0.712	12	0.707	1	1	3	0.984	113	L. Barbosa , PHX	351	0.372	331	0.529	267	0.78	279	0.78
13	S. Nash , PHX	20	0.656	91	0.614	1	1	97	0.863	114	J. Przybilla , POR	26	0.624	25	0.676	1	1	21	0.927
14	P. Gasol , MEM	10	0.706	6	0.736	1	1	1	1	115	D. Stoudamire , MEM	174	0.445	164	0.580	79	0.874	95	0.864
15	T. Duncan , SAS	21	0.652	14	0.696	1	1	5	0.975	116	A. Mourning , MIA	130	0.474	281	0.544	106	0.857	250	0.794
16	M. Camby , DEN	29	0.617	29	0.666	1	1	2	0.999	117	A. Walker , MIA	251	0.412	239	0.554	172	0.822	180	0.822
17	A. Kirilenko , UTA	18	0.670	27	0.671	1	1	17	0.939	118	C. Duhon , CHI	139	0.468	213	0.563	135	0.839	146	0.839
18	J. O'Neal , IND	19	0.668	20	0.684	1	1	35	0.908	119	M. Daniels , DAL	160	0.450	235	0.555	198	0.812	207	0.812
19	C. Webber , PHI	34	0.607	28	0.670	6	0.958	25	0.923	120	E. Dampier , DAL	132	0.472	180	0.574	169	0.823	181	0.822
20	L. Odom , LAL	5	0.717	8	0.719	1	1	1	1	121	K.Korver , PHI	195	0.437	211	0.564	242	0.792	255	0.792
21	J. Kidd , NJN	37	0.596	38	0.655	15	0.932	36	0.908	122	D. Miles , POR	119	0.485	26	0.674	4	0.973	6	0.973
22	D. Howard , ORL	6	0.716	2	0.769	1	1	1	1	123	C. Wilcox , SEA-LAC	196	0.436	212	0.563	215	0.806	227	0.806
23	C. Paul , NOK	2	0.754	4	0.754	1	1	1	1	124	A. Croshere , IND	272	0.403	206	0.564	178	0.819	189	0.819
24	R. Allen , SEA	62	0.547	74	0.624	72	0.88	98	0.863	125	V. Radmanovic, LAC-SEA	181	0.442	224	0.560	256	0.784	270	0.784
25	C. Anthony , DEN	80	0.518	131	0.594	25	0.92	27	0.92	126	M. Blount , MIN-BOS	224	0.423	172	0.578	137	0.836	150	0.836
26	C. Billups , DET	41	0.588	122	0.600	14	0.933	113	0.856	127	D. Marshall , CLE	150	0.459	133	0.593	92	0.866	94	0.866
27	V. Carter , NJN	31	0.612	30	0.664	2	0.995	30	0.918	128	M. Ely , CHA	163	0.450	195	0.569	202	0.81	214	0.81
28	R. Jefferson , NJN	100	0.500	108	0.607	81	0.872	117	0.855	129	K.Brown , LAL	217	0.426	214	0.563	260	0.782	273	0.782
29	S. O'Neal , MIA	53	0.561	82	0.619	67	0.884	92	0.866	130	T. Battie , ORL	94	0.504	68	0.626	55	0.891	60	0.891
30	T. McGrady , HOU	22	0.641	21	0.684	3	0.994	7	0.964	131	D. Williams , UTA	200	0.433	251	0.552	212	0.807	225	0.807
31	B. Miller , SAC	44	0.585	33	0.660	32	0.908	59	0.891	132	N. Collison , SEA	191	0.439	130	0.594	158	0.828	171	0.828
32	M. Redd , MIL	66	0.528	85	0.617	88	0.868	123	0.853	133	R. LaFrentz , BOS	180	0.442	157	0.582	162	0.826	173	0.826
33	A. Jamison , WAS	52	0.561	44	0.650	39	0.906	44	0.904	134	B. Haywood , WAS	82	0.518	371	0.513	313	0.76	325	0.76
34	M. Okur , UTA	59	0.550	78	0.622	101	0.86	103	0.86	135	A. McDyess , DET	364	0.363	319	0.533	223	0.8	237	0.8
35	G. Wallace , CHA	27	0.623	48	0.640	1	1	108	0.858	136	E.Boykins , DEN	332	0.381	337	0.528	302	0.763	334	0.757
36	B. Diaw , PHX	32	0.611	31	0.662	1	1	1	1	137	D. Granger , IND	186	0.440	205	0.564	166	0.824	176	0.824
37	C. Boozer , UTA	67	0.525	84	0.617	54	0.893	65	0.887	138	M. Banks , MIN-BOS	190	0.439	183	0.572	145	0.833	155	0.833
38	J. Richardson , GSW	61	0.547	96	0.612	120	0.85	141	0.842	139	R. Patterson , DEN-POR	142	0.463	233	0.556	165	0.824	190	0.819
39	J. Johnson , ATL	35	0.607	42	0.652	38	0.906	47	0.903	140	J. Stackhouse , DAL	171	0.447	269	0.547	234	0.796	247	0.796
40	M. James , TOR	28	0.618	15	0.695	10	0.946	13	0.946	141	J. Rose , NYK-TOR	103	0.496	52	0.638	61	0.887	66	0.887
41	R. Lewis , SEA	57	0.553	51	0.638	70	0.881	85	0.872	142	A. Daniels , WAS	117	0.487	123	0.598	116	0.854	120	0.854
42	B. Davis , GSW	4	0.732	10	0.712	1	1	9	0.961	143	S. Blake , POR	91	0.511	66	0.629	35	0.906	42	0.906
43	B. Wallace , DET	9	0.710	9	0.715	1	1	1	1	144	D. Harris , DAL	178	0.444	285	0.542	228	0.799	239	0.799
44	Z. Ilgauskas , CLE	49	0.569	359	0.521	349	0.737	365	0.737	145	J. Tinsley , IND	90	0.513	114	0.604	31	0.908	38	0.907
45	T. Parker , SAS	65	0.530	94	0.613	37	0.906	40	0.906	146	T. Lue , ATL	170	0.448	200	0.566	190	0.814	201	0.814
46	M. Bibby , SAC	47	0.572	69	0.626	87	0.868	99	0.863	147	J. Posey , MIA	239	0.416	248	0.552	134	0.839	147	0.839
47	R. Wallace , DET	124	0.479	366	0.516	353	0.731	369	0.731	148	K. Perkins , BOS	95	0.503	100	0.610	85	0.869	135	0.847
48	T. Murphy , GSW	79	0.520	73	0.624	111	0.856	114	0.856	149	E. Watson , SEA-DEN	246	0.413	301	0.539	282	0.774	320	0.761
49	A. Miller , DEN	40	0.589	87	0.616	11	0.945	126	0.852	150	M. Jaric , MIN	81	0.518	93	0.613	20	0.924	26	0.923
50	W.Szczerbiak BOS-MIN	98	0.500	372	0.512	321	0.757	333	0.757	151	B. Jackson , MEM	143	0.462	116	0.601	99	0.86	106	0.86
51	S. Cassell , LAC	75	0.522	154	0.583	133	0.84	143	0.84	152	A. Jefferson , BOS	187	0.440	161	0.581	123	0.848	131	0.848
52	R. Davis , MIN-BOS	96	0.503	109	0.607	66	0.884	69	0.884	153	R. Evans , DEN-SEA	169	0.449	110	0.607	151	0.831	162	0.831
53	C. Butler , WAS	55	0.558	55	0.637	30	0.911	82	0.873	154	T. Thomas , PHX-CHI	356	0.370	272	0.547	127	0.844	195	0.816
54	C. Kaman , LAC	76	0.522	112	0.606	107	0.857	118	0.855	155	T. Ratliff , POR	84	0.516	63	0.630	56	0.89	87	0.87
55	A. Harrington , ATL	77	0.520	62	0.631	75	0.878	76	0.878	156	R. Gomes , BOS	221	0.424	141	0.588	156	0.829	165	0.829
56	B. Knight , CHA	17	0.677	32	0.662	1	1	23	0.924	157	D. Songaila , CHI	319	0.386	286	0.542	197	0.812	208	0.812
57	P. Stojakovic, IND-SAC	189	0.439	190	0.570	146	0.833	154	0.833	158	J. Jeffries , WAS	105	0.493	103	0.609	96	0.862	101	0.862
58	B. Wells , SAC	39	0.595	24	0.678	1	1	19	0.932	159	L. Head , HOU	144	0.461	151	0.584	161	0.826	174	0.826
59	R. Hamilton , DET	199	0.433	279	0.544	192	0.814	199	0.814	160	B. Bowen , SAS	223	0.423	216	0.563	97	0.861	102	0.861
60	E. Okafor , CHA	46	0.576	140	0.589	1	1	213	0.81	161	D. Stevenson , ORL	127	0.476	105	0.607	84	0.87	88	0.87
61	K. Hinrich , CHI	51	0.562	92	0.613	18	0.929	50	0.899	162	R. Swift , SEA	152	0.458	162	0.580	164	0.824	184	0.821
62	A. Iguodala , PHI	93	0.507	90	0.614	91	0.867	100	0.863	163	J. Dixon , POR	125	0.477	215	0.563	193	0.813	205	0.813
63	Z. Randolph , POR	60	0.547	327	0.531	314	0.76	324	0.76	164	A. Foyle , GSW	111	0.488	188	0.571	115	0.854	217	0.809
64	R. Artest , SAC-IND	43	0.586	143	0.587	129	0.843	138	0.843	165	G. Payton , MIA	184	0.441	255	0.551	136	0.837	148	0.837
65	S. Marbury , NYK	11	0.703	7	0.724	1	1	1	1	166	D. Wesley , HOU	149	0.459	179	0.575	185	0.815	198	0.815
66	C. Maggette , LAC	226	0.422	343	0.525	68	0.882	133	0.847	167	M. Sweetney , CHI	212	0.428	218	0.563	209	0.808	219	0.808
67	M. Ginobili , SAS	114	0.487	393	0.487	48	0.896	61	0.889	168	T. Hassell , MIN	211	0.429	181	0.574	144	0.833	156	0.833
68	L. Deng , CHI	146	0.460	177	0.576	102	0.859	111	0.857	169	M. Finley , SAS	275	0.402	253	0.551	155	0.829	166	0.829
69	M. Peterson , TOR	64	0.532	39	0.654	5	0.965	10	0.957	170	S. Livingston , LAC	135	0.471	196	0.569	189	0.814	202	0.814
70	J. Terry , DAL	112	0.488	209	0.564	181	0.818	192	0.818	171	B. Cook , LAL	327	0.382	335	0.528	338	0.752	352	0.752
71	L. Ridnour , SEA	36	0.605	40	0.653	17	0.93	24	0.924	172	S. Swift , HOU	133	0.472	148	0.585	180	0.818	193	0.818
72	M. Miller , MEM	116	0.487	97	0.611	93	0.866	93	0.866	173	M. Bonner , TOR	159	0.451	106	0.607	80	0.873	83	0.873
73	H. Turkoglu , ORL	70	0.525	56	0.637	47	0.898	53	0.898	174	N. Mohammed , SAS	258	0.409	252	0.552	175	0.82	187	0.82
74	D. Gooden , CLE	121	0.484	89	0.616	59	0.888	64	0.888	175	A. Griffin , DAL	205	0.430	265	0.549	208	0.808	220	0.808
75	J. Nelson , ORL	48	0.572	45	0.644	24	0.92	28	0.92	176	Ed. Najera , DEN	280	0.399	222	0.561	183	0.817	211	0.811
76	Z. Pachulia , ATL	115	0.487	77	0.623	26	0.916	73	0.879	177	J. Hayes , WAS	126	0.476	144	0.587	149	0.832	159	0.832
77	T.J. Ford , MIL	42	0.588	43	0.651	21	0.921	37	0.907	178	S. May , CHA	350	0.373	354	0.522	359	0.725	376	0.725

78	A. Bogut , MIL	74	0.523	75	0.624	53	0.893	58	0.893	**179**	G. Buckner , DEN	299	0.392	329	0.531	248	0.79	342	0.755
79	R. Alston , HOU	23	0.636	36	0.657	1	1	18	0.938	**180**	C. Bell , MIL	244	0.414	264	0.550	281	0.774	301	0.772
80	A. Nocioni , CHI	182	0.441	210	0.564	159	0.828	169	0.828	**181**	E. Griffin , MIN	88	0.514	99	0.611	44	0.901	127	0.852
81	N. Krstic , NJN	238	0.418	170	0.579	124	0.847	134	0.847	**182**	F. Elson , DEN	315	0.387	273	0.547	211	0.807	231	0.804
82	S. Rahim , SAC	137	0.469	147	0.585	194	0.813	204	0.813	**183**	L. Wright , MEM	209	0.430	171	0.578	154	0.829	167	0.829
83	U. Haslem , MIA	215	0.427	191	0.570	118	0.851	128	0.851	**184**	F. Jones , IND	218	0.425	241	0.553	227	0.799	240	0.799
84	C. Mobley , LAC	148	0.459	223	0.561	110	0.856	124	0.853	**185**	K. Bogans , HOU-CHA	287	0.397	294	0.540	306	0.762	335	0.757
85	S. Dalembert , PHI	38	0.596	46	0.642	1	1	51	0.899	**186**	S. Telfair , POR	92	0.507	64	0.629	23	0.92	29	0.92
86	C. Villanueva , TOR	89	0.513	47	0.641	29	0.911	34	0.911	**187**	V. Khryapa , POR	145	0.461	80	0.621	43	0.902	49	0.902
87	G. Hill , ORL	71	0.524	50	0.639	52	0.894	56	0.894	**188**	J. Calderon , TOR	85	0.515	57	0.637	33	0.907	39	0.907
88	L. Hughes , CLE	110	0.489	119	0.600	77	0.876	78	0.876	**189**	R. Murray , CLE-SEA	164	0.450	167	0.580	148	0.832	160	0.832
89	S. Battier , MEM	87	0.514	88	0.616	63	0.886	80	0.875	**190**	D.Anderson , MIA-HOU	220	0.424	189	0.570	207	0.808	221	0.808
90	R. Bell , PHX	276	0.402	67	0.628	1	1	89	0.868	**191**	J. Salmons , PHI	197	0.435	194	0.569	231	0.798	243	0.798
91	J. Childress , ATL	151	0.458	124	0.598	100	0.86	104	0.86	**192**	D. Lee , NYK	72	0.524	58	0.635	73	0.879	75	0.879
92	B. Simmons , MIL	157	0.453	153	0.583	153	0.83	163	0.83	**193**	Q. Woods , NYK	63	0.532	49	0.639	51	0.894	57	0.894
93	T. Prince , DET	316	0.387	302	0.538	191	0.814	200	0.814	**194**	K. Van Horn , DAL	304	0.391	320	0.533	266	0.78	280	0.78
94	S. Jackson , IND	122	0.481	160	0.581	138	0.836	149	0.836	**195**	C. Atkins , MEM-WAS	140	0.467	132	0.593	152	0.83	164	0.83
95	J. Foster , IND	179	0.443	149	0.584	150	0.832	158	0.832	**196**	S. Hunter , PHI	213	0.428	237	0.555	273	0.777	288	0.777
96	P.J. Brown , NOK	107	0.492	72	0.625	74	0.879	74	0.879	**197**	E. Snow , CLE	129	0.475	156	0.582	104	0.858	109	0.858
97	J. Crawford , NYK	25	0.630	16	0.687	7	0.957	11	0.957	**198**	D. Mason , NOK	158	0.452	126	0.597	128	0.843	140	0.843
98	J. Williams , MIA	136	0.471	203	0.565	117	0.853	125	0.853	**199**	Q. Richardson , NYK	56	0.556	35	0.659	28	0.913	33	0.913
99	D. Fisher , GSW	109	0.491	176	0.576	170	0.823	183	0.821	**200**	R. Horry , SAS	253	0.411	208	0.564	98	0.86	107	0.86
100	T. Chandler , CHI	97	0.501	121	0.600	86	0.868	105	0.86	**201**	D. George , LAL	274	0.402	284	0.542	263	0.781	276	0.781
101	C. Mihm , LAL	193	0.438	207	0.564	224	0.8	249	0.795	**202**	S. Jasikevicius , IND	206	0.430	238	0.554	241	0.792	256	0.792
203	C. Andersen , NOK	113	0.487	115	0.602	60	0.887	84	0.873	**303**	S. Marks , SAS	377	0.352	373	0.512	331	0.754	348	0.754
204	D. Diop , DAL	147	0.460	261	0.550	179	0.818	259	0.791	**304**	R. Ivey , ATL	328	0.382	298	0.539	285	0.773	298	0.773
205	S. Pollard , IND	259	0.409	290	0.542	271	0.779	283	0.779	**305**	L. Murray , NJN	372	0.358	314	0.535	265	0.78	281	0.78
206	J Tsakalidis , MEM	237	0.418	198	0.568	182	0.817	194	0.817	**306**	W. Simien , MIA	367	0.361	360	0.521	308	0.761	322	0.761
207	C. Hayes , HOU	245	0.414	219	0.562	218	0.805	232	0.804	**307**	H. Eisley , DEN-LAC	279	0.400	340	0.526	330	0.754	349	0.754
208	A. Varejao , CLE	201	0.433	185	0.572	119	0.85	129	0.85	**308**	L. Kleiza , DEN	390	0.334	369	0.513	358	0.726	373	0.726
209	K. Dooling , ORL	102	0.497	79	0.621	27	0.914	32	0.914	**309**	B. Cardinal , MEM	302	0.392	236	0.555	230	0.798	244	0.798
210	C. Robinson , NJN	268	0.404	226	0.558	237	0.794	251	0.794	**310**	S. Randolph , PHI	311	0.389	282	0.543	315	0.759	330	0.759
211	N. Robinson , NYK	73	0.523	70	0.626	57	0.889	63	0.889	**311**	J. Reed , MIN-BOS	255	0.410	199	0.568	177	0.819	191	0.819
212	I. Diogu , GSW	273	0.402	309	0.537	332	0.754	347	0.754	**312**	J. Powell , DAL	289	0.396	342	0.525	318	0.758	331	0.758
213	B. Robinson , CHA	250	0.412	242	0.553	247	0.79	291	0.775	**313**	K. Humphries , UTA	349	0.373	363	0.519	297	0.765	314	0.765
214	E. House , PHX	387	0.338	384	0.501	325	0.756	338	0.756	**314**	J. Pargo , CHI	312	0.389	159	0.582	210	0.807	226	0.807
215	K. Snyder , NOK	161	0.450	168	0.580	168	0.823	178	0.823	**315**	D. Ewing , LAC	360	0.367	378	0.507	303	0.762	319	0.762
216	L. Walton , LAL	306	0.390	311	0.536	295	0.767	307	0.767	**316**	C. Delfino , DET	393	0.323	388	0.499	320	0.757	336	0.757
217	J. Petro , SEA	210	0.429	341	0.526	226	0.799	241	0.799	**317**	T. Diener , ORL	138	0.469	137	0.589	126	0.844	137	0.844
218	R. Nesterovic , SAS	216	0.427	118	0.601	69	0.881	71	0.881	**318**	A. Pavlovic , CLE	278	0.401	293	0.541	187	0.814	203	0.814
219	J. Jack , POR	128	0.475	76	0.624	34	0.906	43	0.906	**319**	A. Hardaway , NYK	68	0.525	127	0.597	9	0.946	14	0.946
220	T. Allen , BOS	208	0.430	232	0.556	203	0.809	218	0.809	**320**	B. Nachbar , NJN-NOK	339	0.379	316	0.534	336	0.752	354	0.752
221	T.Hudson , MIN	256	0.409	247	0.552	109	0.856	115	0.856	**321**	C. Miles , UTA	309	0.390	308	0.537	245	0.79	262	0.79
222	A. Biedrins , GSW	261	0.408	270	0.547	316	0.759	329	0.759	**322**	P. Burke , PHX	398	0.306	398	0.468	362	0.715	379	0.715
223	R. Butler , NOK	156	0.453	173	0.578	196	0.812	209	0.812	**323**	E. Williams , TOR	284	0.398	202	0.565	160	0.826	175	0.826
224	E. Thomas , WAS	173	0.446	197	0.568	206	0.808	222	0.808	**324**	S. Anderson , MIA	344	0.376	353	0.523	279	0.774	296	0.774
225	D. Mutombo , HOU	118	0.486	128	0.595	130	0.842	142	0.842	**325**	S. Monia , SAC-POR	177	0.445	155	0.582	64	0.885	68	0.885
226	S. Stoudamire , ATL	292	0.395	297	0.540	174	0.82	188	0.82	**326**	B.Scalabrine , BOS	281	0.399	244	0.553	249	0.789	264	0.789
227	B. Barry , SAS	314	0.387	256	0.551	238	0.793	254	0.793	**327**	I. Udoka , NYK	267	0.404	163	0.580	143	0.833	157	0.833
228	J. Graham , TOR	233	0.419	139	0.589	125	0.846	136	0.846	**328**	M. Kasun , ORL	168	0.449	136	0.590	139	0.835	152	0.835
229	T. Delk , DET-ATL	383	0.343	347	0.524	286	0.773	297	0.773	**329**	R. Whaley , UTA	384	0.342	392	0.490	360	0.724	377	0.724
230	D. Wilkins , SEA	185	0.441	158	0.582	201	0.81	215	0.81	**330**	C. Williamson , SAC	307	0.390	304	0.538	278	0.775	292	0.775
231	C. Arroyo , ORL-DET	295	0.393	259	0.551	163	0.824	177	0.824	**331**	D. Wright , MIA	375	0.353	382	0.504	343	0.746	359	0.746
232	G. Giricek , UTA	359	0.367	356	0.521	329	0.755	343	0.755	**332**	R. Araujo , TOR	262	0.408	339	0.526	216	0.805	238	0.8
233	M. Olowokandi ,BOS-MIN	167	0.449	129	0.594	132	0.84	144	0.84	**333**	F. Oberto , SAS	353	0.370	345	0.524	222	0.801	236	0.801
234	F. Garcia , SAC	162	0.450	193	0.570	188	0.814	206	0.813	**334**	B. Bass , NOK	242	0.415	303	0.538	339	0.751	356	0.751
235	J. Butler , NYK	69	0.525	65	0.629	40	0.904	45	0.904	**335**	M. Norris , NOK-HOU	207	0.430	249	0.552	221	0.802	234	0.802
236	J. Voskuhl , CHA	270	0.404	234	0.555	232	0.797	246	0.797	**336**	E. Batista , ATL	347	0.374	283	0.543	288	0.771	303	0.771
237	M. Pietrus , GSW	334	0.380	361	0.520	299	0.765	312	0.765	**337**	Z. Cabarkapa , GSW	340	0.378	107	0.607	105	0.857	112	0.857
238	A. Davis , TOR-NYK	123	0.480	98	0.611	114	0.854	121	0.854	**338**	R. Turiaf , LAL	330	0.381	317	0.534	277	0.775	293	0.775
239	B. Wright , MIN	153	0.458	59	0.634	46	0.899	52	0.899	**339**	R. Marshall , DAL	104	0.493	113	0.604	82	0.871	86	0.871
240	D.Gadzuric , MIL	227	0.422	230	0.557	236	0.794	252	0.794	**340**	J. James , NYK	204	0.431	246	0.552	354	0.73	371	0.73
241	D. Milicic , ORL-DET	240	0.416	275	0.546	272	0.778	287	0.778	**341**	J. Hart , SAC	391	0.328	146	0.585	113	0.855	122	0.854
242	K. Rush , CHA	277	0.401	326	0.531	352	0.731	370	0.731	**342**	M. Bradley , PHI	243	0.415	228	0.557	292	0.767	310	0.767
243	T. Ariza , ORL-NYK	86	0.515	60	0.633	76	0.877	77	0.877	**343**	R. Frahm , HOU-MIN	368	0.361	338	0.526	291	0.768	305	0.768
244	D. Harrison , IND	285	0.398	325	0.532	287	0.772	302	0.772	**344**	Z. Planinic , NJN	374	0.355	81	0.620	65	0.884	70	0.883
245	D. Brown , UTA	358	0.368	362	0.520	280	0.774	295	0.774	**345**	D. Armstrong , DAL	357	0.368	375	0.509	341	0.748	358	0.748
246	T. Outlaw , POR	155	0.454	111	0.606	90	0.867	90	0.867	**346**	M. Madsen , MIN	346	0.375	277	0.545	214	0.806	228	0.806
247	R. McCants , MIN	335	0.380	280	0.544	217	0.805	230	0.805	**347**	D. Thompson , PHX	400	0.270	401	0.455	346	0.742	363	0.742
248	M. Carroll , CHA	345	0.375	332	0.529	345	0.743	361	0.743	**348**	E. Basden , CHI	324	0.384	271	0.547	289	0.77	304	0.77
249	G. Ostertag , UTA	320	0.385	351	0.523	334	0.753	350	0.753	**349**	D. Taylor , WAS	265	0.405	267	0.549	253	0.785	269	0.785
250	M. Ellis , GSW	260	0.409	322	0.533	328	0.755	344	0.755	**350**	M. Sanders , SAS	363	0.363	374	0.511	311	0.76	327	0.76
251	M. Palacio , UTA	248	0.413	306	0.537	243	0.791	260	0.791	**351**	J. Sampson , SAC	385	0.341	396	0.479	364	0.712	381	0.712
252	J. Singleton , LAC	326	0.383	333	0.529	257	0.783	272	0.783	**352**	W. Bynum , GSW	231	0.421	186	0.571	213	0.806	229	0.806
253	T. Kukoc , MIL	172	0.446	175	0.577	171	0.822	182	0.822	**353**	W. McCarty , LAC	342	0.378	227	0.557	199	0.811	212	0.811
254	M. Taylor , NYK	101	0.497	101	0.610	103	0.858	110	0.858	**354**	C. Booth , WAS	247	0.413	240	0.553	284	0.773	299	0.773
255	Q. Ross , LAC	337	0.379	364	0.519	173	0.821	185	0.821	**355**	S. Augmon , ORL	202	0.432	182	0.574	147	0.832	161	0.832
256	M. Rose , NYK	120	0.485	117	0.601	121	0.849	130	0.849	**356**	J. Vroman , NOK	293	0.395	268	0.549	274	0.776	290	0.776
257	M. Fizer , NOK	106	0.492	83	0.618	22	0.92	31	0.916	**357**	L. Schenscher , CHI	198	0.433	352	0.523	276	0.775	294	0.775
258	L. Woods , TOR	230	0.421	288	0.542	1	1	1	1	**358**	M. Cleaves , SEA	241	0.416	125	0.597	122	0.848	132	0.848
259	D. Johnson , DEN	389	0.334	383	0.502	363	0.714	380	0.714	**359**	H. Seung-Jin , POR	232	0.421	258	0.551	269	0.779	285	0.779
260	M. Webster , POR	236	0.419	120	0.600	94	0.864	96	0.864	**360**	D. Mbenga , DAL	203	0.432	310	0.536	301	0.763	316	0.763
261	M. Evans , DET	392	0.323	387	0.500	305	0.762	317	0.762	**361**	C. Cheaney , GSW	297	0.393	287	0.542	310	0.76	328	0.76
262	V. Lenard , POR-DEN	194	0.438	134	0.592	50	0.895	55	0.895	**362**	D. Davis , DET	396	0.316	391	0.493	348	0.737	366	0.737
263	P. Sow , TOR	188	0.440	135	0.591	78	0.875	81	0.875	**363**	A.Blatche , WAS	308	0.390	318	0.533	296	0.766	311	0.766

264	Z. Rebraca , LAC	361	0.366	23	0.680	8	0.954	12	0.954	**364**	R. Dupree , MIN	365	0.362	278	0.545	204	0.808	224	0.808
265	J.McInnis , NJN	381	0.348	334	0.528	337	0.752	353	0.752	**365**	J. Edwards , ATL	341	0.378	328	0.531	300	0.764	315	0.764
266	M. Allen , CHI	321	0.385	370	0.513	312	0.76	326	0.76	**366**	B. Thomas , WAS	235	0.419	355	0.521	244	0.79	263	0.79
267	S. Vujacic , LAL	313	0.388	225	0.560	83	0.871	168	0.829	**367**	A. Bynum , LAL	382	0.346	389	0.494	368	0.696	385	0.696
268	D. Zimmerman , NJN	348	0.374	346	0.524	309	0.761	321	0.761	**368**	L. Roberts , MEM	386	0.340	386	0.501	357	0.726	374	0.726
269	K. McLeod , UTA	336	0.379	365	0.517	298	0.765	313	0.765	**369**	R. Brunson , HOU-SEA	291	0.395	313	0.535	251	0.787	266	0.787
270	A. Anderson , CHA	318	0.386	276	0.546	259	0.782	274	0.782	**370**	L. Jackson , CLE	269	0.404	229	0.557	229	0.798	245	0.798
271	D. Fortson , SEA	290	0.396	217	0.563	167	0.823	179	0.823	**371**	A. McKie , LAL	366	0.362	323	0.532	283	0.773	300	0.773
272	S. Padgett , NJN	338	0.379	263	0.550	246	0.79	261	0.79	**372**	K. Burleson , CHA	305	0.391	315	0.535	326	0.755	346	0.755
273	N. Van Exel , SAS	322	0.384	321	0.533	225	0.799	242	0.799	**373**	D. Smith , ATL	378	0.352	379	0.506	335	0.752	355	0.752
274	A. Barrett , TOR-PHX	141	0.465	174	0.577	131	0.84	145	0.84	**374**	B. Russell , DEN	401	0.263	400	0.457	333	0.753	351	0.753
275	P. Garrity , ORL	166	0.449	145	0.585	157	0.828	172	0.828	**375**	. Newble , CLE	301	0.392	348	0.523	307	0.761	323	0.761
276	A. Carter , MIN	263	0.407	289	0.542	195	0.812	210	0.812	**376**	A. Miles , GSW	325	0.384	324	0.532	342	0.746	360	0.746
277	M. Ruffin , WAS	183	0.441	178	0.575	184	0.816	196	0.816	**377**	A. Burks , MEM	317	0.386	296	0.540	264	0.78	282	0.78
278	B. Outlaw , ORL	108	0.492	71	0.626	71	0.88	72	0.88	**378**	R. Bowen , HOU	286	0.397	291	0.542	290	0.768	306	0.768
279	V. Baker , LAC	300	0.392	330	0.530	344	0.743	362	0.743	**379**	J. Lucas , HOU	252	0.412	220	0.561	240	0.792	257	0.792
280	J. Barry , HOU	54	0.559	165	0.580	62	0.886	79	0.876	**380**	E. Piatkowski , CHI	343	0.376	357	0.521	319	0.757	337	0.757
281	J. Welsch , MIL	288	0.396	266	0.549	254	0.785	268	0.785	**381**	N. Tskitishvili , PHX-MIN	397	0.310	397	0.470	369	0.683	386	0.683
282	B. Udrih , SAS	352	0.370	260	0.550	205	0.808	223	0.808	**382**	A. Roberson , MEM	380	0.349	377	0.507	355	0.729	372	0.729
283	M. Doleac , MIA	283	0.398	307	0.537	275	0.776	289	0.776	**383**	S. Ford , PHX	303	0.392	395	0.481	361	0.722	378	0.722
284	M. Moore , SEA	219	0.424	184	0.572	252	0.786	267	0.786	**384**	E. Johnson , MIL	266	0.404	250	0.552	220	0.802	235	0.802
285	D. Harrington , CHI	355	0.370	367	0.516	294	0.767	308	0.767	**385**	R. Price , SAC	369	0.360	350	0.523	317	0.758	332	0.758
286	D. Dickau , BOS	228	0.421	142	0.588	108	0.856	116	0.856	**386**	A. Macijauskas , NOK	176	0.445	187	0.571	200	0.81	216	0.81
287	A. Grundy , ATL	379	0.350	376	0.508	327	0.755	345	0.755	**387**	M. Wilks , SEA-CLE	310	0.390	299	0.539	255	0.784	271	0.784
288	L. Profit , LAL	370	0.359	349	0.523	262	0.781	277	0.781	**388**	J. Thomas , NJN-ATL-MEM	271	0.403	245	0.552	258	0.782	275	0.782
289	K. Cato , DET-ORL	354	0.370	336	0.528	324	0.756	339	0.756	**389**	L. Williams , PHI	282	0.399	262	0.550	347	0.74	364	0.74
290	M. Barnes , PHI-NYK	331	0.381	300	0.539	304	0.762	318	0.762	**390**	J. Maxiell , DET	399	0.298	399	0.462	366	0.707	383	0.707
291	L. Baxter , CHA-HOU	234	0.419	231	0.557	250	0.788	265	0.788	**391**	J. Davis , PHX-HOU-MIL	214	0.428	86	0.616	41	0.903	48	0.903
292	C. Taft , GSW	294	0.394	295	0.540	270	0.779	284	0.779	**392**	A. Wright , NJN	371	0.358	344	0.525	340	0.75	357	0.75
293	A. Henderson , CLE	175	0.445	152	0.583	89	0.867	91	0.867	**393**	E. Gill , IND	376	0.352	381	0.504	350	0.735	367	0.735
294	K. Ollie , PHI	296	0.393	312	0.536	323	0.756	340	0.756	**394**	M. Andriuskevicius , CLE	229	0.421	192	0.570	13	0.942	16	0.942
295	B. Grant , PHX	395	0.321	95	0.612	49	0.895	67	0.886	**395**	E. Barron , MIA	333	0.380	274	0.547	233	0.796	248	0.796
296	L. Hunter , DET	394	0.321	390	0.493	367	0.705	384	0.705	**396**	R. Livingston , CHI	225	0.423	368	0.516	268	0.779	286	0.779
297	D. Greene , BOS	249	0.412	221	0.561	140	0.835	151	0.835	**397**	R. Gaines , MIL	154	0.458	169	0.579	239	0.792	258	0.792
298	W. Green , PHI	323	0.384	305	0.538	293	0.767	309	0.767	**398**	J. Hodge , DEN	388	0.335	380	0.505	365	0.709	382	0.709
299	P. Podkolzin , DAL	254	0.411	102	0.610	1	1	1	1	**399**	M.Lampe , HOU-NOK	222	0.423	166	0.580	112	0.855	119	0.855
300	J. Vaughn , NJN	298	0.392	292	0.541	261	0.781	278	0.781	**400**	V. Wafer , LAL	362	0.365	358	0.521	356	0.726	375	0.726
301	J. Kapono , MIA	373	0.356	385	0.501	322	0.756	341	0.756	**401**	V. Potapenko , SAC	329	0.382	394	0.485	351	0.734	368	0.734
302	H. Warrick , MEM	257	0.409	257	0.551	235	0.794	253	0.794										

The players' efficiency scores as calculated in this study vary from 0.000 to 1.000, whereas the efficiency scores calculated by the NBA are above or below zero.

Some interesting results are given separately below for four alternatives as compared to the NBA scores:

The results are based on DEA1: It is more meaningful to make these comparisons by considering the rank of each player. The rankings used in this study are very different from the NBA efficiency score rankings for some players. Some players moved forward[4] or backward in the rankings according to their efficiency level measured via DEA. For example, L. Barbosa of the Phoenix Suns moved backward by 238 positions (from 113 to 351); on the other hand, A. Hardaway of the New York Knicks moved forward by 251 positions (from 319 to 68). In addition, K. Garnett of the Minnesota Timberwolves, who was ranked first, based on the NBA's calculations, moved backward to the third rank based on the new method, however, L. James of the Cleveland Cavaliers, who was ranked third according to the NBA, moved forward to the first position.

The results are based on DEA2: According to the results, M. Ginobili of the San Antonio Spurs moved backward by 326 positions (from 67 to 393), and W. Szczerbiak of

[4] Moves backward and forward are calculated based on the NBA's rankings.

the Boston Celtics and Minnesota Timberwolves moved backward by 322 positions (from 50 to 372); whereas J. Davis of the Phoenix Suns, Houston Rockets and Milwaukee Bucks moved forward by 305 positions (from 391 to 86) and Z. Planinic of the New Jersey Nets moved forward by 263 positions (from 344 to 81). K. Garnett of Minnesota Timberwolves, who was ranked first based on the NBA's calculation method, moved downward to the third position based on the new method; S. Marion of Phoenix Suns, who was ranked third based on the NBA's method, moved backward to the eleventh position. However, L. James of the Cleveland Cavaliers, who was ranked third, moved forward to the first rank.

The results are based on DEA3: As DEA is used with the average values of variables such as ribaunt in these alternative, full efficient players can be determined. According to the new method, while M. Andriuskevicius of the Cleveland Cavaliers moved forward by 381 positions, J. Dixon of the Portland Trail Blazers for 350 positions. However, R. Turiaf of the Los Angeles Lakers moved backward by 306 lines, Z. Cabarkapa of the Golden State Warriors by 305 positions, W. Simien (MIA) of the Miami Heat by 271 positions. All of the players who were in the first five in terms of their efficiency levels calculated by the NBA are full efficient.

The results are based on DEA4: In this method, J.Dixon of the Portland Trail Blazers moved forward by 378 positions, A. Hardaway of the New York Knicks by 343 positions and P. Podkolzin of the Dallas Mavericks by 305 positions, while R. Turiaf of the Los Angeles Lakers backward by 322 positions, Z. Cabarkapa of the Golden State Warriors by 321 positions and W. Simien of the Miami Heat by 283 positions. All the players in the first five in the NBA except for E.Brand (0.978) are full efficient according to this alternative.

Discussion and Conclusion

It is considered the correlations between the results to determine whether they are consistent. The Spearman rank correlation coefficients for the efficiency statistics obtained by the NBA and the efficiency scores obtained via DEA using the different alternatives are statistically significant ($p<0.05$). This significant coefficient indicates that all of the methods produce basically consistent results, although some individual differences may arise.

Table 3. Spearman rank correlation coefficients.

Relations	Spearman correlations
NBA efficiency score - DEA 1 efficiency score	0.765
NBA efficiency score - DEA 2 efficiency score	0.586
DEA 1 efficiency score - DEA 2 efficiency score	0.999
DEA 1 efficiency score - DEA 4 efficiency score	0.632
NBA efficiency score - DEA 3 efficiency score	0.983
NBA efficiency score - DEA 4 efficiency score	0.632
DEA 1 efficiency score - DEA 3 efficiency score	0.765
DEA 2 efficiency score - DEA 3 efficiency score	0.635
DEA 1 efficiency score - DEA 4 efficiency score	0.529
DEA 2 efficiency score - DEA 4 efficiency score	0.919

It will be useful to determine which approach represents the success of players and the team better and to discover which methods better predict success. Accordingly, our aim is to compare the effects of team success on the efficiency scores calculated using each of the four alternatives to the NBA system. To this end, the number of baskets scored by the team in each game is used as the criterion for success. Our hypothesis is that if the players' performances (efficiency levels) are enhanced, the performance of the team will improve, as evidenced by a higher team score[5]. Our primary objective is to determine how the efficiency levels calculated using each method and NBA method will impact team success. To achieve this goal, the players who are played in each game were identified. First, sum of the individual player' efficiency score was computed to obtain the total efficiency score of the team. Then, the points by the team in a game are attributed to each player, and the sum of these individual player points was computed to obtain the total game scores of the team. Finally, the total

[5] Two important points should be clarified. The main challenge here is to determine how the efficiency levels calculated to measure a player's performance will affect team performance. On one side there are a few teams and some success craterous which can be explained in different ways on the other side there are many players. Therefore, the units in each series are not equal. To compare them, it is necessary to make equal the number of units in each series. For this purpose (for the NBA system and each of the methods in this study), the performance indicators of all of the players on a team have been reduced to equal the number of teams, considering the teams in which they take place. In other words, a value had been obtained for each team by adding the players' performances. A value has been obtained from the player's performance for the team in this manner, and the scores of the team have been taken as the team success that will be used in comparison. One may question why the total score has been used as the criterion or why only the scores have been used. It is accepted that the best indicator of success is the score. For a team to achieve a higher score, the team must defend well, steal often, gain more rebounds and attack well. Additionally, when using more than one statistic, one may question why those statistics were used or why they were weighted differently. Therefore, the score is the most useful indicator in this pilot study. Other indicators may be utilized in the studies to follow.

efficiency score values and the sums of the game scores obtained from each team were put into two different series to observe the correlation. The alternative with the highest correlation will be considered better measurement – ceteris paribus.

The hypothesis is that if the aggregate NBA efficiency score of a team is high, that team will be more successful. So the relationship between NBA efficiency scores and the team game scores (accepted as one of the performance indicators) will be analyzed by taking into account this hypothesis. The same practice has been applied to the other four efficiency indicators calculated in this study. The results are in the Table 4.

Table 4. Efficiency scores and success relations.

The correlations of	
NBA efficiency scores total-match score total	0.55
Efficiency scores basis on DEA1 and game scores	0.57
Efficiency scores basis on DEA2 and game scores	0.56
Efficiency scores basis on DEA3 and game scores	0.59
Efficiency scores basis on DEA4 and game scores	0.60

The results indicate that all of the alternatives presented in this manuscript represent team success better than the NBA system does. We observe that the two-input and five-input alternatives (DEA3 and DEA4), in which the season average was used, have higher correlations with team performance and also a higher representative force. The reason for this result may be that the efficiency scores obtained from the statistics based on each player's season average include the full-efficient decision units. For each player, only one efficiency score is calculated for the entire season.[6] Accordingly, the ranking obtained from the method is completely represented. Even though each game is taken as a different decision unit in the alternative systems, this study yield very useful information, the efficiency scores based on the average statistics under data limitation represent the success better than those of the NBA system and the other alternatives which are computed in this study. Because of these results, discussing

[6] In the case in which each game is a separate decision unit, a player may have a lower efficiency score in one game than in other games, even though he is fully efficient in those other games. To measure a single efficiency score for a player, the average of the efficiency scores of the player for each game is calculated. As long as the efficiency score is not 1 in all of the matches, the average efficiency score will be lower than 1 as well

the offered method in the scientific community may yield useful results, and decision-makers may use these results in making decisions.

The scores obtained using DEA appear to be significant for the some economic and managerial reasons.

- The first reason is economics. The definitions in the science of economics are basically based on relative rather than absolute values. However, the efficiency scores calculated by the NBA that indicate player performance are based on absolute values. In other words, they are calculated by adding, subtracting, multiplying and dividing the statistics for the player in question. Clearly, a player's success is also closely associated with the performance of his own team and with that of his opponents. Therefore, any calculation based on absolute values may yield misleading results. All of the variables were excluded from the scores calculated by the NBA except for the statistics that referred to the player himself. However, an activity that has as much of an effect on society and the economy as NBA basketball does should be analyzed in ways that will express the economic truth more meaningfully. The scores calculated in this study serve this purpose.
- The second reason is the scores calculated here better help to determine the real value of each player. Essentially, this study contributes valid and clear information about this product. The players themselves, who are the employees in this context, can also learn from this information. For example, they might be able to use this data to assess and learn their real value as producers. This data also allow team managers (the employers) and the fans (the customers) to learn the players' real value.
- There are differences between the ranking of the players obtained using the NBA system and the ranking obtained using the methods recommended here. As discussed earlier, there is a more significant relationship between team success and the efficiency scores obtained from the methods recommended here than there are between team success and the NBA efficiency scores. Such changes would serve to distribute resources more efficiently, reflecting an improvement in the accuracy of economic decision mechanisms in this context. It is also important to note that players in the top ranks according to their NBA efficiency scores may not be able to achieve the same success when they change teams because those scores do not adequately reflect the economic reality.

All in all, the new method presented in this paper offers a more useful means of evaluating the performance of NBA players as well as that of individuals in other basketball federations and different sports. This method may also make it possible to determine the real values of these players and to allocate financial resources more successfully. To that end, this approach can be used in transfer decisions or player contract negotiations. However, the existing statistics do not provide exact measurements of efficiency. To solve this problem, more specific player statistics should be obtained.

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Appendix 1. Stats of teams.

Rank	Teams	Assists	Steals	Blocs	Turnovers	Personal fouls
1	New York Knicks	29	20	28	1	1
2	Dallas Mavericks	28	13	2	24	19
3	Portland Trail Blazers	27	28	9	8	20
4	Orlando Magic	26	24	17	6	10
5	New Orleans/Oklahoma City Hornets	25	8	23	26	22
6	Washington Wizards	24	2	21	21	18
7	Cleveland Cavaliers	23	17	15	19	24
8	Houston Rockets	22	12	22	10	17
9	Memphis Grizzlies	21	11	7	22	23
10	Toronto Raptors	20	27	29	28	6
11	Atlanta Hawks	19	14	14	4	2
12	Indiana Pacers	18	9	11	5	21
13	Philadelphia 76ers	17	3	13	17	25
14	Miami Heat	16	25	8	14	15
15	Golden State Warriors	15	6	16	18	8
16	Seattle SuperSonics	14	5	24	9	9
17	Los Angeles Clippers	13	23	1	15	16
18	Minnesota Timberwolves	12	19	5	13	14
19	San Antonio Spurs	11	22	6	23	26
20	Charlotte Bobcats	10	1	18	16	7
21	Boston Celtics	9	16	10	2	4
22	Los Angeles Lakers	8	4	19	20	13
23	Utah Jazz	7	26	4	3	5
24	Milwaukee Bucks	6	10	27	12	11
25	Chicago Bulls	5	29	20	7	3
26	Sacramento Kings	4	7	25	11	28
27	New Jersey Nets	3	18	26	25	12
28	Detroit Pistons	2	15	3	29	29
29	Phoenix Suns	1	21	12	27	27