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Estimation of Productivity Change of NBA Teams from 2006-07 to 2012-13 Seasons

Plácido Moreno[1] and Sebastián Lozano[2]

[1]Polytechnic School of Chimborazo – ESPOCH, Ecuador
[2]Dept. of Industrial Management, University of Seville, Spain

Plácido Moreno, PhD, is a lecturer of operational research. His research interests include the development of optimization models for decision making and the study of performance in sports using quantitative methods.
Sebastián Lozano, PhD, is a professor of quantitative methods in management. His research interests include performance and efficiency assessment in different sectors, especially in sports.

Abstract

The aim of this work is to evaluate the productivity change of the NBA teams during the last seven seasons (from 2006-07 to 2012-13). Within that period of time, a new collective bargaining agreement (CBA) of the National Basketball Association (NBA) was ratified before season 2011-12, ending a 161-day lockout. The Malmquist Productivity Index (MPI) has been used to measure the total factor productivity, while an input-oriented Network DEA approach is used to compute the distance of each observation to the corresponding frontier. The results reveal that there has been technological progress for the last few seasons, excluding that of the 2011 lockout, and an increasing efficiency change. This means that best practices are improving and that most teams have been reducing their payrolls to catch up with these practices, thus backing up the owners' proposal to reduce players' income. Also regression results show that changes in the number of wins are more dependent upon scale efficiency change than upon budget or efficiency changes.

Keywords: NBA, productivity change, Malmquist Productivity Index, Network DEA

Introduction

The National Basketball Association (NBA) is one of the most important sport franchises in the world and every NBA team is able to generate substantial revenues through merchandising, tickets sales, TV rights, etc. The NBA actually handles billions of dollars every year. But, at the same time, costs are increasing, mainly because players' contracts are becoming more and more expensive every year.

During the first five seasons covered in this study (2006-07 to 2010-11) the NBA lived under the 2005 collective bargaining agreement (CBA). The CBA is the contract between the NBA (the commissioner and the 30 team owners) and the NBA Players'

Association that states the business rules about players' contracts, trades, revenue distribution, salary caps, etc. The 2005 CBA expired on June 30, 2011, leading the NBA to a lockout, where the owners proposed to reduce players' income. Later that year, on December 8, 2011, the NBA Board of Governors ratified a new 10-year CBA after the played had accepted less money (Berri, 2012).

Some researchers have been concerned about the economic losses due to sports' lockouts (e.g., Coates & Humphreys, 2001). On the one hand, even before the lockout and according to the NBA commissioner, the owners claimed that NBA teams had lost more than $1 billion dollars during the validity of the 2005 CBA, mainly due to increasing players' salaries and guaranteed contracts, which are the most relevant points having been discussed in the negotiations to set up the 2011 CBA.

On the other hand, the need and incentives of the new agreement and its impact on competitive balance (Berri, 2012) have been questioned. Therefore, the negative criticism against the 2011 CBA justifies the need for an assessment of the teams' efficiency in economic resources management, since an analysis of the productivity change before and after the 2011 CBA will prove if owners had reasonable grounds for requesting a salary cut.

With that objective in mind, this paper estimates productivity change evolution of NBA teams during the five seasons prior to and the two seasons after the 2011 CBA. It makes sense to evaluate the changes in performance along a number of seasons, since players' contracts last for several years, and managers make the financial planning and coaches build the roster with a view to future seasons.

The productivity change between two periods can be estimated through the Malmquist Productivity Index (MPI), which is broken down into two components: efficiency change and technology change (Färe et al., 1992). Färe et al. (1994) further include a third component (related to scale change) in what is known as FGNZ decomposition.

To project the observations onto the corresponding efficient frontier, Data Envelopment Analysis (DEA) has been used (e.g., Cooper et al., 2007). DEA has been applied to many different sectors, sports among them, e.g., Spanish soccer teams' efficiency assessment (González-Gómez et al., 2010; Barros & Garcia-del-Barrio, 2011), estimation of efficiency scores for Germany's premier league football players depending on their playing positions (Tiedemann et al., 2011), ranking of professional tennis players by deriving a common set of weights (Ramón et al., 2012), efficiency assessment of local entities in the provision of public sports facilities (Benito et al., 2012), or performance evaluation of each country in the 2008 Beijing Summer Olympic Games (Wu et al., 2010).

Moreover, DEA has been recently used to reveal that most Portuguese football clubs are spending more money in players' wages than they need to (Ribeiro & Lima, 2012). In relation to basketball, Aizemberg et al. (2011) use DEA to analyze the efficiency of NBA teams. Also the effectiveness of basketball players (Cooper et al., 2009) and their ranking (Cooper et al., 2011) have been studied using DEA.

In order to gain a better understanding of the sources of inefficiency, Network DEA (e.g., Färe & Grosskopf, 2000) has been applied so that the internal processes can be identified and the internal links (i.e., intermediate products) included in the model. Network DEA has been applied to the study of efficiency in sports. Thus, Sexton and

Lewis (2003), Lewis and Sexton (2004a, 2004b), and Lewis et al. (2009) study the performance of baseball teams. Moreno and Lozano (in press) study the performance of NBA teams in the 2009-10 regular season, distinguishing between first and bench teams. The Network DEA approach proposed in Moreno and Lozano (in press) is the starting point for this research work, where the model itself has been revised and refined to consider several NBA seasons so that productivity changes (computed through MPI) could be estimated. NBA teams usually elaborate plans for several years, mainly due to the length of players' contracts, thus analyzing the productivity changes in the different periods becomes relevant.

Methodology

This section first reviews the Malmquist Productivity Index (MPI) and how it can be broken down into the usual two components, namely technical and efficiency change, plus a scale change component. This decomposition can be used when there exists Variable Returns to Scale (VRS). Also, the main concepts of Network DEA are introduced.

MPI and FGNZ Decomposition

MPI has been used to measure the variation of productive efficiency between two periods of time (Färe et al., 1992). The input-oriented MPI of a certain Decision Making Unit (DMU) labeled 0 is defined as the geometric mean

$$M^I_{t,t+1}(x^t_0, y^t_0; x^{t+1}_0, y^{t+1}_0) = \left[\frac{DF^I_t(x^{t+1}_0, y^{t+1}_0)}{DF^I_t(x^t_0, y^t_0)} \cdot \frac{DF^I_{t+1}(x^{t+1}_0, y^{t+1}_0)}{DF^I_{t+1}(x^t_0, y^t_0)} \right]^{\frac{1}{2}} \tag{1}$$

where x^{t1}_0 and y^{t1}_0 represent, respectively, the inputs and outputs of DMU 0 observed in period t1, while $DF^I_{t1}\left(x^{t2}_0, y^{t2}_0\right)$ stands for the proportional reduction of the inputs of DMU 0 observed in period t2, assuming that the production technology is constructed from the observations (of the different DMUs) in period t1. Note that t1 can correspond to period t or to period t+1 and the same applies for t2. Normally $DF^I_{t1}\left(x^{t2}_0, y^{t2}_0\right)$ is computed using a radial, input-oriented DEA model (Charnes et al., 1978). However, in this paper, instead of a conventional, single-process DEA, a Network DEA model, as formulated below, will be used.

MPI is commonly decomposed into efficiency change (EFFCH) and technical change (TECCH) as

$$M^I_{t,t+1}(x^t_0, y^t_0; x^{t+1}_0, y^{t+1}_0) = EFFCH^I_{t,t+1} \cdot TECCH^I_{t,t+1} \tag{2}$$

where

$$EFFCH^I_{t,t+1} = \frac{DF^I_{t+1}(x^{t+1}_0, y^{t+1}_0)}{DF^I_t(x^t_0, y^t_0)} \tag{3}$$

$$TECCH^I_{t,t+1} = \left[\frac{DF^I_t(x^t_0, y^t_0)}{DF^I_{t+1}(x^t_0, y^t_0)} \cdot \frac{DF^I_t(x^{t+1}_0, y^{t+1}_0)}{DF^I_{t+1}(x^{t+1}_0, y^{t+1}_0)} \right]^{\frac{1}{2}} \tag{4}$$

The first term, efficiency change (3), measures the magnitude of the change in technical efficiency between periods t and t+1. An improvement in $EFFCH^{I}_{t,t+1}$ can be interpreted as evidence of catching-up with the frontier for that DMU. In other cases, production is moving farther from the frontier. Concerning the second term, technical change (4) measures the shift in the frontier over time. In that way, an improvement in $TECCH^{I}_{t,t+1}$ implies progress in the technology under study and a worsening in $TECCH^{I}_{t,t+1}$ implies technological regress.

An improvement in productivity corresponds to a Malmquist index greater than unity. In case MPI is less than unity, productivity has declined over time. Analogously, improvements and worsening in its two components are also associated with values greater and less than unity, respectively.

When the problem under study exhibits VRS, the following FGNZ decomposition (Färe et al., 1994) can be used

$$M^{I}_{t,t+1}(x_0^t, y_0^t; x_0^{t+1}, y_0^{t+1}) = EFFCH^{I,VRS}_{t,t+1} \cdot TECCH^{I}_{t,t+1} \cdot PURESCACH^{I}_{t,t+1} \tag{5}$$

where

$$EFFCH^{I,VRS}_{t,t+1} = \frac{DF^{I,VRS}_{t+1}(x_0^{t+1}, y_0^{t+1})}{DF^{I,VRS}_{t}(x_0^{t}, y_0^{t})} \tag{6}$$

$$TECCH^{I}_{t,t+1} = \left[\frac{DF^{I}_{t}(x_0^{t}, y_0^{t})}{DF^{I}_{t+1}(x_0^{t}, y_0^{t})} \cdot \frac{DF^{I}_{t}(x_0^{t+1}, y_0^{t+1})}{DF^{I}_{t+1}(x_0^{t+1}, y_0^{t+1})}\right]^{\frac{1}{2}} \tag{7}$$

$$PURESCACH^{I}_{t,t+1} = \frac{\dfrac{DF^{I}_{t+1}(x_0^{t+1}, y_0^{t+1})}{DF^{I,VRS}_{t+1}(x_0^{t+1}, y_0^{t+1})}}{\dfrac{DF^{I}_{t}(x_0^{t}, y_0^{t})}{DF^{I,VRS}_{t}(x_0^{t}, y_0^{t})}} \tag{8}$$

In the above expressions, $DF^{I,VRS}_{t1}\left(x_0^{t2}, y_0^{t2}\right)$ corresponds to the radial efficiency of DMU 0 in period t2 evaluated by using the VRS production technology of the period t1. Note that the basic difference between (1) and (5) is that the efficiency change is divided into a VRS efficiency change term and a pure scale efficiency change component (PURESCACH). The former measures the change in technical efficiency assuming VRS technology, while the latter detects differences over time in the distance between the efficient frontiers of the VRS and CRS technologies.

Network DEA

In this section, an input-oriented Network DEA model to compute the radial efficiency scores $DF^{I}_{t1}\left(x_0^{t2}, y_0^{t2}\right)$ and $DF^{I,VRS}_{t1}\left(x_0^{t2}, y_0^{t2}\right)$ is presented. This formulation is an extension of the relational Network DEA model proposed by Kao (2009) to general networks of processes. The notation used is the one proposed in Lozano (2011).

The main difference between Network DEA and conventional DEA is that while the latter considers a single process that consumes all the inputs and produces all the outputs, the former considers the existence of several processes each of which consumes its own set of inputs and produces its own set of outputs, in addition to consuming and producing intermediate products that are internal to the system under study.

For each process p of DMU j, denote x_{ij}^{p} as the observed amount of input i consumed and let y_{kj}^{p} be the observed amount of output j produced. Let $z_{rj}^{in,p}$ be the observed amount of intermediate product r consumed by process p of DMU j and $z_{rj}^{out,p}$ denote the observed amount of intermediate product r generated by process p of DMU j.

Let $P_1(i)$ be the set of processes that consume the input i and $P_O(k)$ the set of processes that generate the output o. In order to model the composition of intermediate flows inside the network, let $p^{out}(r)$ be the set of stages that produce the intermediate product r and $p^{in}(r)$ the set of processes that consume the intermediate product r.

In addition, λ_j^p stands for the set of multipliers that define the production possibility set of the process p, while θ symbolizes the proportional reduction of inputs of the DMU under assessment. Hence the input-oriented, Network DEA model to compute the maximal feasible radial reduction of inputs can be formulated (see Lozano, 2011) as

$$DF_0^I = \text{Min} \tag{9}$$

s.t.

$$\sum_{p \in P_I(i)} \sum_j \lambda_j^p x_{ij}^p \leq \theta \cdot x_{i0} \quad \forall i \tag{10}$$

$$\sum_{p \in P_O(k)} \sum_j \lambda_j^p y_{kj}^p \geq y_{k0} \quad \forall k \tag{11}$$

$$\sum_{p \in P^{out}(r)} \sum_j \lambda_j^p z_{rj}^{out,p} - \sum_{p \in P^{in}(r)} \sum_j \lambda_j^p z_{rj}^{in,p} \geq 0 \quad \forall r \tag{12}$$

$$\lambda_j^p \geq 0 \ \ \forall j \ \forall p \quad \theta \ \text{free} \tag{13}$$

The above model corresponds to assuming Constant Returns to Scale (CRS). In the VRS case the following constraints should be added.

$$\sum_j \lambda_j^p = 1 \quad \forall p \tag{14}$$

Note that a characteristic feature of Network DEA models is that each process has its set of variables λ_j^p and the reason is that each process has its own technology. This leads to a larger overall production possibility set, which increases the discriminatory power of the DEA model, so much so that it is very common in Network DEA to find that none of the DMUs is found to be efficient. That is so because in order for a DMU to be efficient, all its processes must be efficient—something that does not occur easily.

Another feature of Network DEA models is the intermediate products balance constraints (12). They guarantee that the amount of intermediate products internally generated by the system are enough to satisfy the consumption of these intermediate products by those processes that require them.

Network DEA model for NBA Teams

As stated previously, Network DEA has been developed to deal with the existence of multiple, linked processes inside a DMU. The network of processes used in this work is shown in Figure 1 and consists of four processes or stages. Process PERF (team-work performance) can be interpreted as an acquisition process, where the teams use the budget spent to sign players. In an intuitive way, the more salary a player is paid, the better he should perform during games. Therefore, the input of this first stage will be the total payroll of the team, while the number of attacking and defensive (against the opposing team) moves of the team are the corresponding outputs. The outputs of process PERF are actually intermediate products that are inputs for the two following stages, representing the offensive (OFF) and defensive (DEF) subsystems. Each of these processes generates one additional intermediate product that represents the number of points scored by the team and the inverse of the number of points scored by the opposing team, respectively.

The final stage (Wins Generation, WG) transforms the points scored by the team and by the opponent into victories, which is the final output of the DMU. The choice of team payroll and points in the league as an input and output, respectively, can be regarded as a constant feature in works related to sports efficiency (e.g., Barros et al., 2010, in their estimation of efficiency scores for Brazilian soccer teams). Table 1 shows the definition and label assigned to each of the variables. These labels are used in Figure 1 and in the mathematical model below.

There are several points to be clarified. First of all, the number of moves is measured in absolute figures (i.e., the sum of the moves by all players in all games of the regular season). Furthermore, the turnovers made by a team are an intermediate product that involves worse performance when it takes higher numerical values. Although traditionally these kinds of variables have coped with dummy variables or been treated as

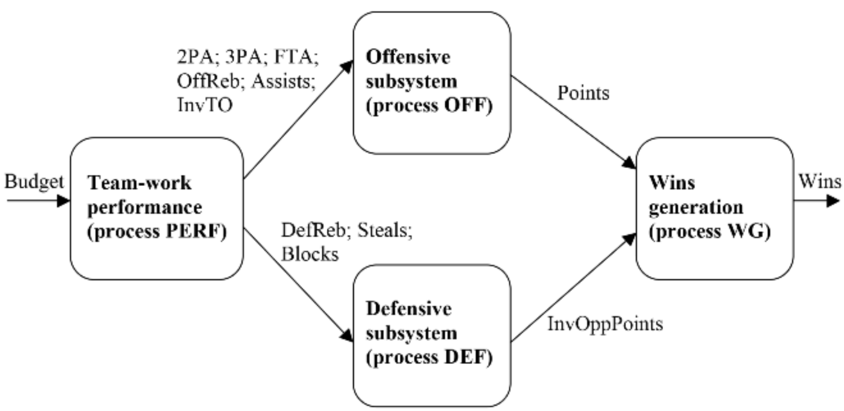


Figure 1. DMU as a network of processes

Figure 1. DMU as a network of processes

Table 1. Model variables

Name	Label	Type of variable
Total salaries of all players in the team	Budget	Input
Number of team victories	Wins	Output
2-Point shots attempted	2PA	Intermediate product
3-Point shots attempted	3PA	Intermediate product
Free throws attempted	FTA	Intermediate product
Offensive Rebounds	OffReb	Intermediate product
Number of Assists	Assists	Intermediate product
Inverse of Turnovers	InvTO	Intermediate product
Defensive rebounds	DefReb	Intermediate product
Number of Steals	Steals	Intermediate product
Blocked Shots	Blocks	Intermediate product
Points by the team	Points	Intermediate product
Inverse of Points by opponents	InvOppPoints	Intermediate product

reverse products (Lewis & Sexton, 2004a), the easiest way to handle them is to work with the inverse of the quantity, in the same way as other authors have done previously (e.g., Cooper et al., 2009).

The offensive subsystem (OFF) evaluates the efficiency of the team in transforming the available offensive resources on the field into points, while the defensive subsystem (DEF) evaluates how the team manages its defensive resources to minimize the points received. Robst et al. (2011) found no evidence that sports teams benefit from focusing on offense or defense, so both subsystems have being considered to be equally important in this paper.

Offensive and defensive subsystems are associated with the decisions of the coach, who has to plan proper strategies and tactics in order to maximize the number of points scored and minimize the number of points allowed, taking advantage of the skills and production abilities of his own players. The role of head coaches in team performance has been discussed in previous studies (e.g., Berri et al., 2009). As in the case of turnovers, and for the points made by the opponent, the inverse is taken as output, since a greater number of points received means worse performance.

With respect to the win generation stage (process WG), this assesses the competence of the team to administer the differences in points (points scored minus points received), so that the team would win the most possible number of games. The number of victories has many additional benefits, like a significant increase in attendance (Morse et al., 2008).

The proposed Network DEA model is the particularization of the model formulated shown in Figure 1. Note that this formulation corresponds to the CRS case, while in the VRS case the corresponding constraints (14) are considered.

$$DF_{t_1}^{I}\left(x_0^{t_2}, y_0^{t_2}\right) = \text{Min} \quad \theta \tag{15}$$

s.t.

$$\sum_j \lambda_j^{PERF} \cdot \text{Budget}_j^{t_1} \leq \theta \cdot \text{Budget}_0^{t_2} \tag{16}$$

$$\sum_j \lambda_j^{PERF} \cdot 2PA_j^{t_1} - \sum_j \lambda_j^{OFF} \cdot 2PA_j^{t_1} \geq 0 \tag{17}$$

$$\sum_j \lambda_j^{PERF} \cdot 3PA_j^{t_1} - \sum_j \lambda_j^{OFF} \cdot 3PA_j^{t_1} \geq 0 \tag{18}$$

$$\sum_j \lambda_j^{PERF} \cdot FTA_j^{t_1} - \sum_j \lambda_j^{OFF} \cdot FTA_j^{t_1} \geq 0 \tag{19}$$

$$\sum_j \lambda_j^{PERF} \cdot OffReb_j^{t_1} - \sum_j \lambda_j^{OFF} \cdot OffReb_j^{t_1} \geq 0 \tag{20}$$

$$\sum_j \lambda_j^{PERF} \cdot Assists_j^{t_1} - \sum_j \lambda_j^{OFF} \cdot Assists_j^{t_1} \geq 0 \tag{21}$$

$$\sum_j \lambda_j^{PERF} \cdot InvTO_j^{t_1} - \sum_j \lambda_j^{OFF} \cdot InvTO_j^{t_1} \geq 0 \tag{22}$$

$$\sum_j \lambda_j^{PERF} \cdot DefReb_j^{t_1} - \sum_j \lambda_j^{DEF} \cdot DefReb_j^{t_1} \geq 0 \tag{23}$$

$$\sum_j \lambda_j^{PERF} \cdot Steals_j^{t_1} - \sum_j \lambda_j^{DEF} \cdot Steals_j^{t_1} \geq 0 \tag{24}$$

$$\sum_j \lambda_j^{PERF} \cdot Blocks_j^{t_1} - \sum_j \lambda_j^{DEF} \cdot Blocks_j^{t_1} \geq 0 \tag{25}$$

$$\sum_j \lambda_j^{OFF} \cdot Points_j^{t_1} - \sum_j \lambda_j^{WG} \cdot Points_j^{t_1} \geq 0 \tag{26}$$

$$\sum_j \lambda_j^{DEF} \cdot InvOppPoints_j^{t_1} - \sum_j \lambda_j^{WG} \cdot InvOppPoints_j^{t} \tag{27}$$

$$\sum_j \lambda_j^{WG} \cdot Wins_j^{t_1} \geq Wins_0^{t_2} \tag{28}$$

$$\lambda_j^{PERF}, \lambda_j^{OFF}, \lambda_j^{DEF}, \lambda_j^{WG} \geq 0 \tag{29}$$

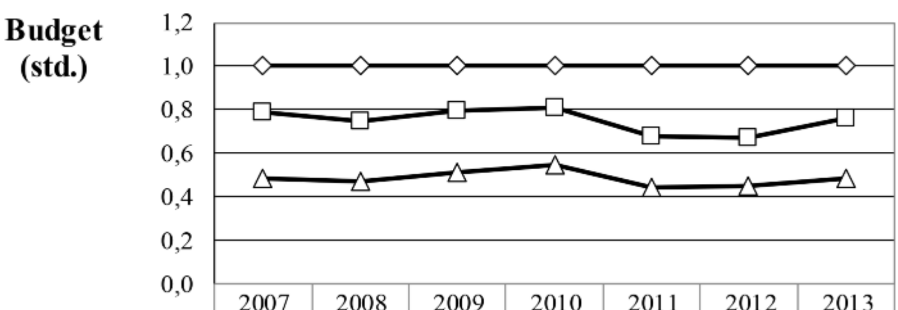
Results and Discussion

The approach described in the previous sections has been applied to all 30 NBA teams using data corresponding to the regular seasons 2006-07 to 2012-13. Each regular season consists of 82 matches, except for season 2011-12, when only 66 matches were played due to the lockout. Teams are grouped in two conferences, each conference consisting of three divisions. If the team performs well during the regular season, not only can it gain access to playoffs for the title, but it can also achieve a good ranking in the team's conference and thus have home court advantage and play against less competitive teams in the first rounds of the playoffs.

The data about the intermediate products and the output for all teams were taken from official statistics of the NBA, available from its official website www.nba.com. Data corresponding to teams' budgets were extracted from http://www.storytellerscontracts.com, which is considered to be the most reliable website about NBA players' contracts. For the seven seasons included in this work, the input (budget) and output (wins) data are shown in Table 2. The budget data have been deflated, so budget data shown in Table 2 are in millions of constant 2009 dollars. Moreover, budget data have been normalized by computing the relative measure to the average budget from the corresponding season. Note that each season is identified by the year when the season finished. Thus, for example, the 2008-09 season is referred to as season 2009 in the tables and figures. In addition, although the team OKC (Oklahoma City Thunder) was previously located in Seattle (and was known as the Seattle Supersonics) before 2008-09 and the team NJ (New Jersey Nets) moved to New York (and is now known as the Brooklyn Nets) in 2012-13, we refer to them as OKC and NJ, respectively, during all seven seasons, to keep homogeneity within the tables and figures.

Regarding the results, first of all, let us take a look at the efficiency scores of the 30 NBA teams in each season, computed using the Network DEA approach proposed previously. These efficiency values are included in Table 3. When CRS scores differ from VRS ones, there is scale inefficiency and this means that the team is operating away from the Most Productive Scale Size (MPSS) (Banker, 1984). Thus, for instance, Memphis Grizzlies (MEM) is VRS efficient in 2008 but has a CRS efficiency score of just 0.335.

Figure 2 shows, for each season, the average of the relative target budgets of all 30 teams computed using the proposed Network DEA approach. The relative target



	2007	2008	2009	2010	2011	2012	2013
Observed	1,00	1,00	1,00	1,00	1,00	1,00	1,00
Target VRS	0,79	0,75	0,79	0,81	0,68	0,67	0,76
Target CRS	0,48	0,47	0,51	0,54	0,44	0,45	0,48

Figure 2. Average normalized budgets (observed and target)

Table 2. Input-output data for the NBA regular seasons from 2006-2007 to 2012-2013.

		Budget														Wins						
		2007		2008		2009		2010		2011		2012		2013		2007	2008	2009	2010	2011	2012	2013
Division	**Teams**	Abs	Norm	Abs	Norm	Abs	Norm	Abs	Norm	Abs	Norm	Abs	Norm	Abs	Norm	Abs	Abs	Abs	Abs	Abs	Abs	Abs
Atlantic	BOS	70.4	0.99	77.3	1.10	80.1	1.11	85.1	1.21	75.2	1.12	107.8	1.59	88.1	1.33	24	66	62	50	56	39	41
	NJ	71.7	1.01	64.1	0.91	59.3	0.82	61.1	0.87	58.2	0.87	59.2	0.87	79.2	1.19	41	34	34	12	24	22	49
	NYK	127.1	1.79	98.9	1.41	94.2	1.31	75.1	1.07	65.6	0.98	61.4	0.91	77.5	1.17	33	23	32	29	42	36	54
	PHI	77.5	1.09	72.8	1.04	68.9	0.95	62.3	0.89	67.6	1.01	76.6	1.13	62.1	0.93	35	40	41	27	41	35	34
	TOR	57.5	0.81	68.1	0.97	70.7	0.98	67.6	0.96	68.3	1.02	60.6	0.89	64.0	0.96	47	41	33	40	22	23	34
Central	CHI	58.8	0.83	64.1	0.91	69.8	0.97	67.8	0.97	54.9	0.82	67.1	0.99	71.5	1.08	49	33	41	41	62	50	45
	CLE	68.9	0.97	83.7	1.19	94.6	1.31	85.9	1.22	69.0	1.03	53.1	0.78	52.7	0.79	50	45	66	61	19	21	24
	DET	61.7	0.87	68.2	0.97	71.8	0.99	58.6	0.83	64.2	0.96	63.2	0.93	70.6	1.06	53	59	39	27	30	25	29
	IND	67.7	0.95	69.0	0.98	69.6	0.96	66.9	0.95	65.1	0.97	50.6	0.75	63.6	0.96	35	36	36	32	37	42	49
	MIL	68.1	0.96	65.7	0.94	69.9	0.97	68.5	0.98	70.2	1.05	60.1	0.89	58.7	0.88	28	26	34	46	35	31	38
South-east	ATL	55.6	0.78	57.6	0.82	69.5	0.96	65.1	0.93	69.4	1.04	71.7	1.06	67.7	1.02	30	37	47	53	44	40	44
	CHA	58.2	0.82	55.7	0.79	64.1	0.89	68.6	0.98	63.3	0.94	61.7	0.91	55.4	0.83	33	32	35	44	34	7	21
	MIA	70.1	0.99	76.3	1.09	71.0	0.98	71.5	1.02	65.6	0.98	75.0	1.11	79.5	1.20	44	15	43	47	58	46	66
	ORL	65.1	0.92	76.3	1.09	74.5	1.03	82.1	1.17	88.8	1.33	82.0	1.21	63.9	0.96	40	52	59	59	52	37	20
	WAS	66.9	0.94	70.4	1.00	70.5	0.98	74.5	1.06	57.7	0.86	56.5	0.83	58.0	0.87	41	43	19	26	23	20	29
South-west	DAL	102.2	1.44	108.4	1.54	95.5	1.32	87.8	1.25	87.9	1.31	68.8	1.01	57.8	0.87	67	51	50	55	57	36	41
	HOU	69.7	0.98	70.6	1.01	71.9	1.00	69.3	0.99	68.8	1.03	58.7	0.87	53.8	0.81	52	55	53	42	43	34	45
	MEM	68.8	0.97	52.5	0.75	55.8	0.77	57.1	0.81	68.9	1.03	76.3	1.13	70.2	1.06	22	22	24	40	46	41	56
	NO	58.1	0.82	64.4	0.92	67.4	0.93	69.6	0.99	67.4	1.01	76.0	1.12	60.8	0.91	39	56	49	37	46	21	27
	SAS	72.6	1.02	62.6	0.89	71.5	0.99	79.4	1.13	67.9	1.01	81.6	1.20	76.1	1.14	58	56	54	50	61	50	58
North-west	DEN	72.3	1.02	85.4	1.22	70.9	0.98	75.3	1.07	66.6	0.99	57.1	0.84	66.9	1.01	45	50	54	53	50	38	57
	MIN	72.5	1.02	68.1	0.97	70.6	0.98	63.2	0.90	54.8	0.82	56.3	0.83	58.9	0.89	32	22	24	15	17	26	31
	OKC	62.2	0.88	59.7	0.85	67.7	0.94	56.7	0.81	57.4	0.86	59.4	0.88	65.0	0.98	31	20	23	50	55	47	60
	POR	80.7	1.14	64.6	0.92	77.1	1.07	57.8	0.82	73.3	1.09	66.5	0.98	55.6	0.84	32	41	54	50	48	28	33
	UT	68.1	0.96	60.5	0.86	66.3	0.92	72.0	1.03	74.4	1.11	90.9	1.34	72.5	1.09	51	54	48	53	39	36	43

Table 2. Input-output data for the NBA regular seasons from 2006-2007 to 2012-2013, continued

Division	Teams	Budget 2007 Abs	2007 Norm	2008 Abs	2008 Norm	2009 Abs	2009 Norm	2010 Abs	2010 Norm	2011 Abs	2011 Norm	2012 Abs	2012 Norm	2013 Abs	2013 Norm	Wins 2007 Abs	2008 Abs	2009 Abs	2010 Abs	2011 Abs	2012 Abs	2013 Abs
Pacific	GSW	59.0	0.83	64.6	0.92	66.8	0.93	68.6	0.98	67.5	1.01	56.8	0.84	67.1	1.01	42	48	29	26	36	23	47
	LAC	69.3	0.98	66.0	0.94	62.4	0.86	59.2	0.84	52.6	0.78	67.5	1.00	67.1	1.01	40	23	19	29	32	40	56
	LAL	84.6	1.19	74.8	1.07	78.8	1.09	91.3	1.30	89.3	1.33	96.2	1.42	108.1	1.63	42	57	65	57	57	41	45
	PHO	70.0	0.99	65.4	0.93	74.8	1.04	75.0	1.07	65.3	0.97	69.5	1.02	50.7	0.76	61	55	46	54	40	33	25
	SAC	70.5	0.99	69.4	0.99	69.0	0.96	62.6	0.89	45.3	0.68	45.5	0.67	51.0	0.77	33	38	17	25	24	22	28
Average	70.9	1.00	70.2	1.00	72.2	1.00	70.2	1.00	67.0	1.00	67.8	1.00	66.5	1.00	41	41	41	41	41	33	41	

Note: Abs. budget data in millions of US$

budget for every team is the relative budget of the corresponding projected point on the efficient frontier. In other words, it represents the normalized budget that the team would have consumed, had it been efficient. Note that the average normalized observed budget is constant and equal to unity. Moreover, it is larger than the average normalized VRS target budget which is, in its turn, larger than the average normalized CRS target budget. Note also that both relative target values decreased in the season prior to the lockout.

Note further that because this application considers just one exogenous input and one final output, the overall efficient frontier is a straight line (passing through the origin) in the case of CRS technology. Figure 3 shows the efficient projections of every team, for both Network DEA and conventional (i.e., single-process) DEA, thus revealing the corresponding efficient frontiers for every season under CRS. Since the frontier is a straight line, it means that the ratio of the target budget to target wins is the same for every team and represents the optimal (i.e., minimum) “effective cost” of a victory in each regular season. That means the optimal effective cost of a victory is defined as the proportional amount of non-normalized target budget consumed for achieving a single victory. Such a ratio corresponds to the inverse of the slope of the frontiers shown in Figure 3 times the average observed budget of that season. These optimal effective costs are shown in Figure 4. Note that the optimal effective costs estimated with Network DEA are lower than by conventional DEA. This results from the fact that the network DEA efficient frontier has a larger slope than the conventional DEA. Analogous to the evolution of the average normalized target budget, the “effective cost” increased in the 2009 and 2010 seasons, but decreased in the 2011 and 2013 seasons (i.e., the slope of the efficient frontiers in Figure 2 decreased for the 2009 and 2010 seasons, whereas it increased in 2011 and 2013).

Table 3. Efficiency scores for CRS and VRS Network DEA approaches

		2007		2008		2009		2010		2011		2012		2013	
Division	**Teams**	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
Atlantic	BOS	0.29	0.79	0.68	0.71	0.70	0.75	0.55	0.67	0.54	0.60	0.33	0.42	0.37	0.58
	NJ	0.48	0.77	0.42	0.82	0.52	0.95	0.18	0.93	0.30	0.78	0.34	0.77	0.49	0.64
	NYK	0.22	0.44	0.19	0.53	0.31	0.60	0.36	0.75	0.46	0.69	0.54	0.74	0.55	0.65
	PHI	0.38	0.72	0.42	0.69	0.54	0.82	0.40	0.91	0.44	0.67	0.42	0.59	0.43	0.82
	TOR	0.68	0.97	0.48	0.77	0.42	0.80	0.55	0.84	0.23	0.66	0.35	0.75	0.42	0.79
Central	CHI	0.70	0.95	0.41	0.82	0.53	0.81	0.56	0.84	0.82	0.98	0.68	0.69	0.50	0.71
	CLE	0.61	0.81	0.43	0.63	0.63	0.70	0.66	0.66	0.20	0.66	0.36	0.86	0.36	0.96
	DET	0.72	0.91	0.69	0.77	0.49	0.79	0.43	0.97	0.34	0.71	0.36	0.72	0.33	0.72
	IND	0.43	0.82	0.42	0.76	0.47	0.81	0.44	0.85	0.41	0.70	0.76	0.90	0.61	0.80
	MIL	0.34	0.82	0.32	0.80	0.44	0.81	0.62	0.83	0.36	0.65	0.47	0.76	0.51	0.86
South-east	ATL	0.45	1.00	0.51	0.91	0.61	0.82	0.76	0.87	0.46	0.65	0.51	0.63	0.51	0.75
	CHA	0.47	0.95	0.46	0.94	0.49	0.88	0.60	0.83	0.39	0.72	0.10	0.74	0.30	0.91
	MIA	0.52	0.79	0.16	0.69	0.55	0.80	0.61	0.79	0.64	0.69	0.56	0.61	0.66	0.66
	ORL	0.51	0.85	0.70	0.88	0.71	0.80	0.67	0.69	0.42	0.51	0.41	0.55	0.25	0.79
	WAS	0.51	0.83	0.49	0.75	0.24	0.79	0.32	0.76	0.29	0.79	0.32	0.80	0.40	0.87
South-west	DAL	0.55	0.56	0.38	0.48	0.47	0.60	0.58	0.65	0.47	0.52	0.48	0.66	0.56	0.88
	HOU	0.62	0.80	0.62	0.74	0.67	0.81	0.56	0.82	0.45	0.66	0.53	0.77	0.66	0.94
	MEM	0.27	0.81	0.33	1.00	0.39	1.00	0.65	0.99	0.48	0.66	0.49	0.60	0.63	0.72
	NO	0.56	0.96	0.70	0.82	0.66	0.85	0.49	0.81	0.50	0.67	0.25	0.60	0.35	0.83
	SAS	0.67	0.77	0.65	0.76	0.68	0.81	0.59	0.71	0.65	0.67	0.56	0.57	0.60	0.67
North-west	DEN	0.52	0.77	0.47	0.61	0.69	0.82	0.65	0.75	0.54	0.68	0.61	0.80	0.67	0.76
	MIN	0.37	0.77	0.26	0.77	0.31	0.79	0.22	0.90	0.22	0.83	0.42	0.81	0.42	0.86
	OKC	0.42	0.89	0.26	0.84	0.31	0.82	0.82	1.00	0.70	0.79	0.72	0.77	0.73	0.79
	POR	0.33	0.69	0.50	0.80	0.63	0.75	0.80	0.98	0.47	0.62	0.39	0.68	0.47	0.91
	UT	0.63	0.82	0.71	0.87	0.65	0.86	0.68	0.79	0.38	0.61	0.36	0.50	0.47	0.70
Pacific	GSW	0.60	0.94	0.59	0.81	0.39	0.84	0.35	0.83	0.39	0.67	0.37	0.80	0.55	0.76
	LAC	0.48	0.80	0.28	0.80	0.28	0.90	0.46	0.96	0.44	0.86	0.54	0.67	0.66	0.76
	LAL	0.42	0.66	0.61	0.70	0.74	0.77	0.58	0.62	0.46	0.51	0.39	0.47	0.33	0.47
	PHO	0.73	0.81	0.60	0.72	0.56	0.76	0.67	0.76	0.44	0.69	0.44	0.65	0.39	1.00
	SAC	0.39	0.79	0.47	0.81	0.22	0.81	0.37	0.91	0.38	1.00	0.44	1.00	0.43	0.99

Concerning the MPI results, Figure 5 includes the evolution of the (geometric) mean of the MPI of the 30 teams for the different periods computed using Network and single-process DEA. Furthermore, the evolution of the mean MPI components (as per the FGNZ decomposition) is also shown. Note that the mean MPI takes the same value for both Network and single-process DEA approaches. This is no coincidence. Actually, the MPI computed by both Network DEA and conventional DEA coincide for all teams. The reason must be that this application considers a single input and an input-orientation. Looking at the mean MPI, a slightly increasing pattern is evident prior to the lockout, with values less than unity in periods 2007-08 and 2008-09, and greater than unity in 2009-10 and 2010-11. Right after the lockout there was a dramatic decrease in productivity, due to the fewer number of games played in the 2011-12 season. Productivity recovered during the last season.

Although the MPI computed by Network and single-process DEA are the same, the MPI components differ. Thus, for instance, according to Network DEA results, the

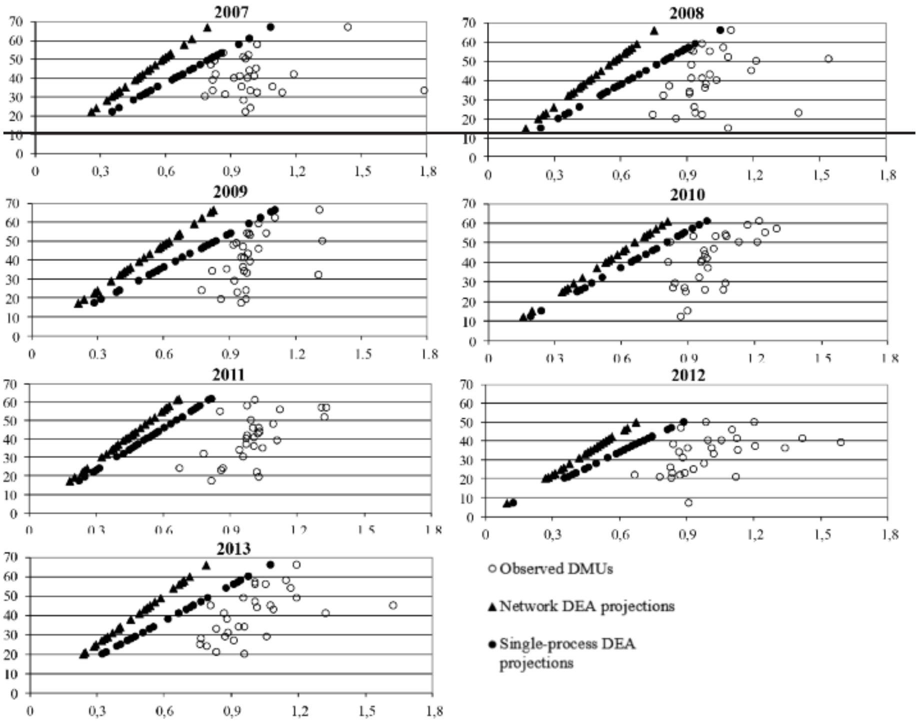
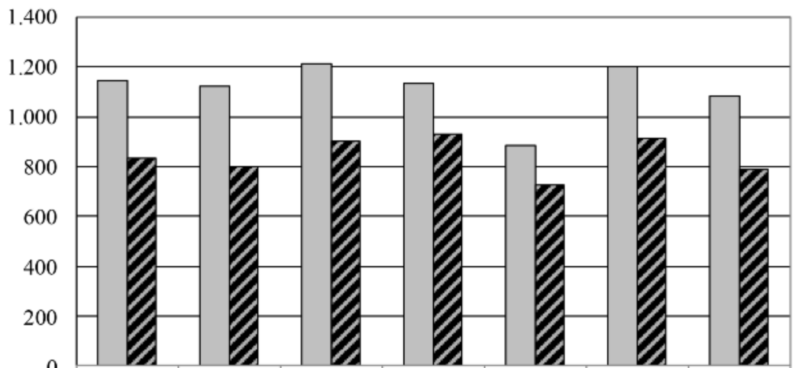


Figure 3. Observed DMUs and efficient VRS projections (y-axis = wins, x-axis = target standardized budget).



	2007	2008	2009	2010	2011	2012	2013
Single Process	1147,84	1120,30	1212,65	1133,67	886,27	1204,80	1083,43
Network DEA	836,65	799,76	902,92	929,41	725,49	915,96	791,63

Figure 4. CRS effective cost per victory in each regular season (in thousands of dollars).

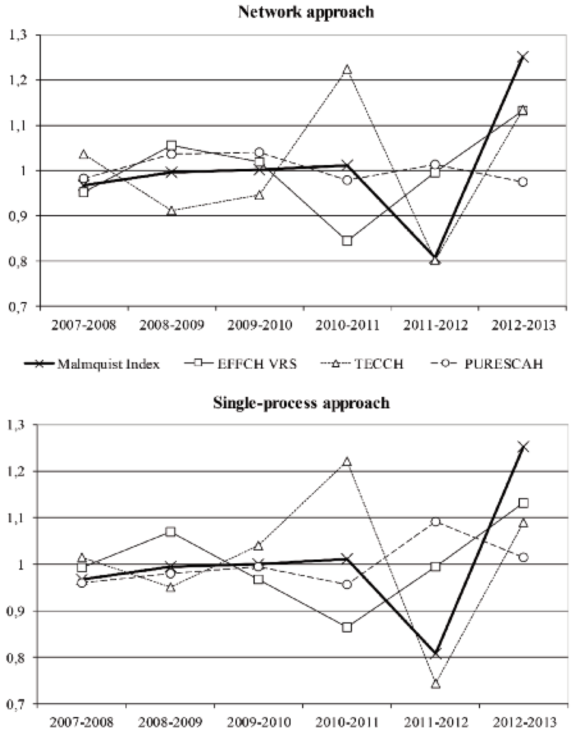


Figure 5. Evolution of mean MPI and its FGNZ components

slight productivity growth (on average) in the period 2009-10 is explained by a positive scale efficiency change (i.e., PURESCACH>1) and a positive VRS efficiency change, hindered by small a technological regress. The conventional DEA approach, on the other hand, does not indicate any scale efficiency change (on average) in that period and attributes the productivity growth to a technological progress hindered by a worsening VRS efficiency change. This clearly shows that the results from the two approaches are dissimilar. Our claim is that those obtained by the Network DEA approach are more reliable than those of conventional DEA because Network DEA is a more fine-grained analysis that uses more information and therefore its results should be more informative and valid.

Looking again at the mean values of the MPI components (in Figure 5), the two periods in which there have been a large technological progress (positive frontier shift) have been the last one and the one previous to the lockout (explained by a significant drop in target budgets, as commented above). In other words, the best performing teams are increasing their efficiency by achieving better results while spending less money. Hence the fall in the season where the lockout occurred can be explained by the fewer number of games played.

Not only has the technical change improved, but there has also been a steady increase in the VRS efficiency change during the last few seasons (Figure 5). Hence most teams are trying to catch up with the best practices (i.e., managing their economic resources in a more efficient way).

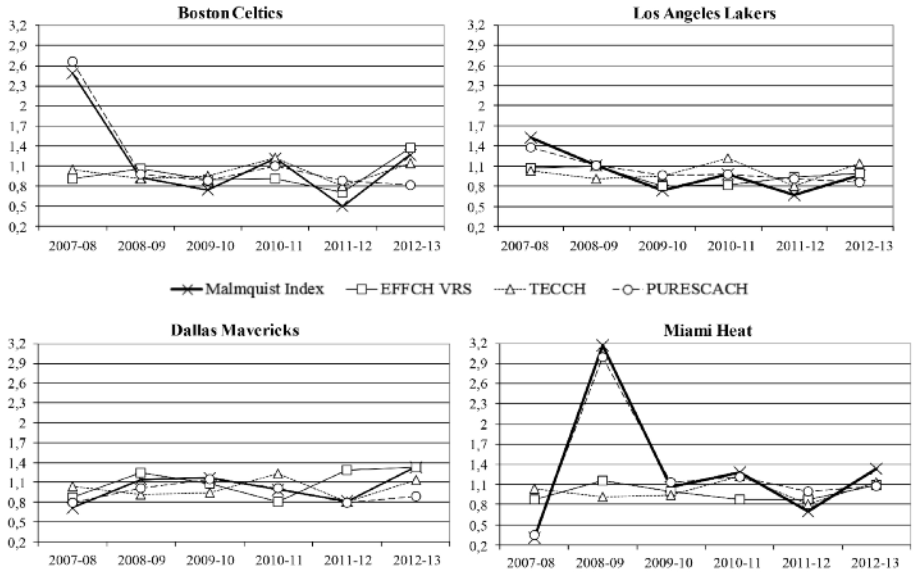


Figure 6. Evolution of MPI and its FGNZ components for the last four NBA champions.

With respect to the variation for individual teams, Figure 6 shows the evolution of the MPI and its components for the NBA champions for the last six seasons (Boston Celtics in 2008, Los Angeles Lakers in 2009 and 2010, Dallas Mavericks in 2011, and Miami Heats in 2012 and 2013). Note the high MPI value for the Boston Celtics (BOS) in 2007-08 due to the significant positive scale change that took place because the team achieved a greater number of wins (66) in 2008 without increasing its budget proportionally. Regarding the high MPI for the Miami Heat (MIA) in 2008-09, the team went through a significant development from the 2008 to 2009 season, becoming a top team and shaping one of the best rosters in the NBA without increasing its investment.

The specific MPI for each team in each period are shown in Table 4 while the MPI components estimated for each team are shown in Table 5. The (geometric) mean of the different divisions and of the whole league are also shown. Note that the technical change component takes the same value for each team in a given period. This is due to the fact that there is only one input and one output, and the CRS efficient frontiers in both periods (t and t+1) are a straight line.

Concerning the period 2010-11 (right before the 2011 CBA), let us emphasize the fact that most teams underwent a worsening in their technical efficiency (VRS EFFCH less than unity) due in part to a significant technological progress (TECHCH=1.22). First, this finding shows that the production possibility set allowed the teams to reduce their payrolls, thus being able to cope with the economics losses—results that were in line with the negotiation of the 2011 CBA. Second, it can be deduced from the decrease in efficiency change that most teams were far away from the best practice frontier. However, according to the results from the following two periods (i.e., 2011-12 and 2012-13), after the lockout teams' managers must have worked hard to make up a ros-

Table 4. MPI computed using the proposed Network DEA approach

Division	Network Malmquist Index Teams	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013
Atlantic	BOS	2.483	0.932	0.739	1.209	0.492	1.262
	NJ	0.919	1.111	0.333	2.005	0.912	1.632
	NYK	0.887	1.502	1.105	1.585	0.925	1.166
	PHI	1.151	1.167	0.708	1.336	0.762	1.176
	TOR	0.729	0.797	1.233	0.520	1.192	1.373
	Mean	1.112	1.077	0.750	1.217	0.823	1.311
Central	CHI	0.612	1.174	1.002	1.781	0.668	0.827
	CLE	0.733	1.334	0.991	0.370	1.452	1.129
	DET	0.996	0.646	0.824	0.968	0.857	1.019
	IND	1.000	1.020	0.898	1.135	1.478	0.911
	MIL	0.953	1.265	1.341	0.709	1.047	1.230
	Mean	0.843	1.055	0.997	0.875	1.052	1.013
Southeast	ATL	1.177	1.083	1.172	0.743	0.891	1.142
	CHA	1.004	0.978	1.142	0.800	0.213	3.274
	MIA	0.310	3.166	1.056	1.283	0.702	1.327
	ORL	1.402	0.935	0.883	0.778	0.780	0.680
	WAS	0.987	0.454	1.260	1.092	0.898	1.384
	Mean	0.873	1.073	1.095	0.917	0.622	1.361
Southwest	DAL	0.711	1.145	1.164	0.988	0.816	1.328
	HOU	1.034	0.974	0.799	0.984	0.937	1.417
	MEM	1.298	1.055	1.584	0.911	0.814	1.457
	NO	1.283	0.861	0.711	1.226	0.409	1.577
	SAS	1.000	0.962	0.811	1.362	0.690	1.220
	Mean	1.041	0.995	0.968	1.081	0.706	1.394
Northwest	DEN	0.931	1.339	0.898	1.019	0.896	1.255
	MIN	0.724	1.082	0.679	1.248	1.506	1.118
	OKC	0.636	1.092	2.526	1.038	0.834	1.144
	POR	1.567	1.148	1.202	0.722	0.650	1.383
	UT	1.180	0.834	0.989	0.680	0.764	1.469
	Mean	0.955	1.087	1.129	0.917	0.890	1.267
Pacific	GSW	1.034	0.601	0.849	1.345	0.768	1.694
	LAC	0.598	0.899	1.564	1.186	0.984	1.381
	LAL	1.520	1.113	0.736	0.977	0.675	0.958
	PHO	0.859	0.837	1.138	0.812	0.785	1.018
	SAC	1.244	0.431	1.577	1.265	0.924	1.112
	Mean	1.001	0.736	1.119	1.099	0.820	1.205
Mean		0.9663	0.995	1.0002	1.0104	0.8077	1.2517

Table 5. Components from MPI decomposition obtained by Network DEA

Division	Teams	2007-08			2008-09			2009-10			2010-11			2011-12			2012-13		
		EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH
Atlantic	BOS	0.90	1.04	2.66	1.05	0.91	0.97	0.89	0.94	0.88	0.90	1.22	1.09	0.70	0.80	0.88	1.36	1.13	0.81
	NJ	1.06	1.04	0.84	1.16	0.91	1.05	0.98	0.94	0.36	0.84	1.22	1.95	0.99	0.80	1.15	0.83	1.13	1.73
	NYK	1.21	1.04	0.70	1.12	0.91	1.47	1.26	0.94	0.93	0.92	1.22	1.41	1.07	0.80	1.08	0.88	1.13	1.16
	PHI	0.96	1.04	1.16	1.19	0.91	1.07	1.11	0.94	0.68	0.74	1.22	1.48	0.89	0.80	1.07	1.38	1.13	0.75
	TOR	0.80	1.04	0.88	1.03	0.91	0.85	1.05	0.94	1.24	0.79	1.22	0.54	1.13	0.80	1.32	1.06	1.13	1.15
Central	CHI	0.86	1.04	0.68	0.99	0.91	1.30	1.03	0.94	1.03	1.17	1.22	1.25	0.71	0.80	1.18	1.03	1.13	0.71
	CLE	0.77	1.04	0.91	1.12	0.91	1.31	0.94	0.94	1.11	0.99	1.22	0.31	1.30	0.80	1.39	1.12	1.13	0.89
	DET	0.85	1.04	1.13	1.02	0.91	0.69	1.23	0.94	0.71	0.73	1.22	1.08	1.02	0.80	1.05	1.00	1.13	0.90
	IND	0.93	1.04	1.04	1.07	0.91	1.05	1.04	0.94	0.91	0.82	1.22	1.13	1.29	0.80	1.43	0.89	1.13	0.90
	MIL	0.98	1.04	0.94	1.01	0.91	1.38	1.03	0.94	1.38	0.78	1.22	0.74	1.17	0.80	1.11	1.14	1.13	0.95
South-east	ATL	0.91	1.04	1.25	0.90	0.91	1.32	1.06	0.94	1.17	0.75	1.22	0.81	0.97	0.80	1.14	1.18	1.13	0.85
	CHA	0.99	1.04	0.98	0.93	0.91	1.15	0.94	0.94	1.29	0.87	1.22	0.75	1.03	0.80	0.26	1.24	1.13	2.33
	MIA	0.87	1.04	0.35	1.16	0.91	2.99	0.99	0.94	1.13	0.87	1.22	1.20	0.88	0.80	1.00	1.09	1.13	1.08
	ORL	1.03	1.04	1.31	0.90	0.91	1.13	0.87	0.94	1.08	0.74	1.22	0.86	1.09	0.80	0.90	1.43	1.13	0.42
	WAS	0.90	1.04	1.06	1.06	0.91	0.47	0.96	0.94	1.39	1.03	1.22	0.86	1.02	0.80	1.09	1.09	1.13	1.12
South-west	DAL	0.87	1.04	0.79	1.24	0.91	1.01	1.07	0.94	1.15	0.80	1.22	1.01	1.28	0.80	0.80	1.33	1.13	0.88
	HOU	0.93	1.04	1.08	1.08	0.91	0.99	1.01	0.94	0.83	0.81	1.22	1.00	1.18	0.80	1.00	1.22	1.13	1.03
	MEM	1.24	1.04	1.01	1.00	0.91	1.16	0.99	0.94	1.69	0.66	1.22	1.12	0.91	0.80	1.12	1.21	1.13	1.06
	NO	0.85	1.04	1.45	1.04	0.91	0.91	0.96	0.94	0.78	0.83	1.22	1.21	0.89	0.80	0.57	1.39	1.13	1.00
	SAS	0.98	1.04	0.99	1.07	0.91	0.98	0.88	0.94	0.98	0.93	1.22	1.19	0.85	0.80	1.01	1.18	1.13	0.91

Table 5. Components from MPI decomposition obtained by Network DEA, continued

Division	Teams	2007-08			2008-09			2009-10			2010-11			2011-12			2012-13		
		EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH	EFFCH VRS	TECCH	PURE SCACH
North-west	DEN	0.80	1.04	1.13	1.34	0.91	1.10	0.92	0.94	1.04	0.91	1.22	0.92	1.17	0.80	0.96	0.95	1.13	1.16
	MIN	1.01	1.04	0.70	1.03	0.91	1.16	1.13	0.94	0.63	0.92	1.22	1.11	0.98	0.80	1.93	1.07	1.13	0.92
	OKC	0.94	1.04	0.65	0.98	0.91	1.22	1.21	0.94	2.20	0.79	1.22	1.07	0.97	0.80	1.08	1.03	1.13	0.98
	POR	1.17	1.04	1.30	0.94	0.91	1.34	1.30	0.94	0.98	0.63	1.22	0.94	1.10	0.80	0.73	1.33	1.13	0.91
	UT	1.06	1.04	1.08	0.99	0.91	0.92	0.91	0.94	1.15	0.77	1.22	0.72	0.82	0.80	1.16	1.40	1.13	0.93
Pacific	GSW	0.86	1.04	1.16	1.03	0.91	0.64	0.98	0.94	0.91	0.81	1.22	1.35	1.19	0.80	0.80	0.94	1.13	1.58
	LAC	0.99	1.04	0.58	1.12	0.91	0.88	1.07	0.94	1.55	0.90	1.22	1.08	0.78	0.80	1.57	1.12	1.13	1.09
	LAL	1.07	1.04	1.37	1.10	0.91	1.11	0.81	0.94	0.97	0.82	1.22	0.98	0.93	0.80	0.91	0.99	1.13	0.85
	PHO	0.90	1.04	0.92	1.05	0.91	0.87	0.99	0.94	1.21	0.92	1.22	0.72	0.94	0.80	1.04	1.53	1.13	0.59
	SAC	1.03	1.04	1.16	1.00	0.91	0.48	1.12	0.94	1.49	1.10	1.22	0.94	1.00	0.80	1.15	0.99	1.13	0.99

ter with payroll and results able to catch up with the new frontier, since there is an increasing efficiency change pattern. To sum up, the 2011 CBA has set up a proper environment that has lead teams to control their budgets in a much more efficient way.

A least squares linear regression analysis has been performed in order to establish the effects of the different MPI components and of the normalized budget change on the wins change between two seasons. The standardized regression coefficients presented in Table 6 correspond to setting the change in wins as the independent variable while taking the normalized budget change, the VRS efficiency change, and the scale change as the dependent variables. Since technology change does not vary across teams, its effect on win change is included in the estimated intercept of the regression.

Note that the influence of all three variables is significant and that the estimated coefficients are rather similar for both Network and single-process DEA. Moreover, it can be concluded from Table 6 that a budget change has little importance in the number of wins (i.e., a team would hardly get more wins by just spending more money on more expensive contracts). In the same way, improving efficiency to catch up with the frontier also has a relative effect on wins. However, the scale change is very relevant to achieve a greater number of wins (i.e., teams should aim to operate in the Most Productive Scale Size [MPSS] by managing their current resources to increase the number of victories in the regular season).

Finally, for comparison, as suggested by one of the reviewers, the network DEA approach proposed in Lewis et al. (2009) has been also applied to this

Table 6. Standardized regression coefficients for the change in the variable Wins between seasons.

	2007-08		2008-09		2009-10	
Component	Network	Single	Network	Single	Network	Single
Budget Change	0.079	0.444*	0.236*	0.212*	0.275*	0.300*
EFFCH VRS	0.077	0.575*	0.229*	0.293*	0.302*	0.393*
PURESCACH	0.995*	0.715*	0.979*	0.883*	0.983*	0.915*
	2010-11		**2011-12**		**2012-13**	
Component	Network	Single	Network	Single	Network	Single
Budget Change	0.297*	0.289*	0.238	0.427*	0.029	0.460*
EFFCH VRS	0.348*	0.425*	0.265	0.403*	0.028	0.428*
PURESCACH	0.986*	0.861*	0.994*	0.927*	0.999*	0.915*

* p-value ≤ 0.001

dataset. The main advantage of their approach is that it allows computing explicitly the efficiency of every process (sub-DMU in their terminology). The adaptation of their approach to the present application is described in the Appendix. Table 7 shows the differences between the full efficiency computed by the Lewis-Lock-Sexton approach and the approach proposed in this paper.

Note that the efficiencies of both approaches differ, with the proposed approach computing stricter efficiency scores. However, the Pearson s correlation coefficient between the results of both approaches ranges from 0.878 to 0.965, which implies a rather high positive correlation between both Network DEA results. Due to lack of space, the efficiencies of the sub-DMUs computed by the Lewis-Lock-Sexton approach are displayed only for the Pacific Division in Figure 7. The results from other divisions are similar and are available from the authors upon request.

OFF and DEF efficiencies are very close to 1 for all teams and seasons, which implies that transforming offensive resources into points and defensive resource in minimizing points allowed is relatively straightforward, revealing the lesser extent of the influence of the coach decisions. Although PERF sub-system also exhibits an efficiency close to one, the Los Angeles Lakers (LAL) have undergone a fall in PERF efficiency during the last few years, because of the relative poor performance of highly paid players. In contrast, WG sub-system seems to be decisive to the overall efficiency, which makes a lot of sense, since the best teams master how to administer the differences in points in order to win the largest possible number of games.

Summary and Conclusions

In this paper an analysis of productivity change of NBA teams during the last seven years has been carried out. The results have shed light on the path taken by each team (and the NBA in general) in terms of the efficient use of its economic resources, specifically with regard to the players' payroll. The research uses an innovative Network DEA approach to assess the efficiency of teams and measure the distance to the corresponding efficient frontier. In general, although Network DEA models require much more

Table 7. Differences between Lewis-Lock-Sexton approach and the proposed approach from 2007 to 2013 seasons.

Division	Teams	2007	2008	2009	2010	2011	2012	2013
Atlantic	BOS	0.12	0.23	0.29	0.24	0.29	0.30	0.23
	NJ	0.36	0.18	0.19	0.05	0.13	0.21	0.26
	NYK	0.20	0.20	0.41	0.31	0.51	0.41	0.45
	PHI	0.37	0.30	0.38	0.14	0.23	0.31	0.42
	TOR	0.32	0.26	0.20	0.21	0.16	0.16	0.20
Central	CHI	0.30	0.22	0.27	0.21	0.18	0.31	0.32
	CLE	0.34	0.24	0.24	0.15	0.08	0.16	0.18
	DET	0.28	0.31	0.35	0.20	0.18	0.15	0.17
	IND	0.20	0.23	0.24	0.22	0.27	0.24	0.39
	MIL	0.38	0.18	0.24	0.34	0.17	0.25	0.28
Southeast	ATL	0.28	0.31	0.24	0.22	0.19	0.23	0.27
	CHA	0.23	0.18	0.21	0.21	0.14	0.05	0.17
	MIA	0.18	0.06	0.29	0.20	0.26	0.27	0.25
	ORL	0.35	0.30	0.29	0.33	0.42	0.41	0.21
	WAS	0.30	0.26	0.12	0.08	0.19	0.15	0.24
Southwest	DAL	0.16	0.21	0.20	0.19	0.29	0.28	0.35
	HOU	0.37	0.28	0.29	0.29	0.34	0.27	0.34
	MEM	0.18	0.22	0.20	0.35	0.42	0.35	0.37
	NO	0.29	0.30	0.34	0.29	0.24	0.18	0.22
	SAS	0.22	0.30	0.32	0.16	0.34	0.28	0.28
Northwest	DEN	0.37	0.35	0.31	0.25	0.39	0.39	0.33
	MIN	0.23	0.15	0.15	0.11	0.20	0.22	0.20
	OKC	0.30	0.22	0.27	0.18	0.30	0.28	0.27
	POR	0.13	0.27	0.28	0.20	0.30	0.21	0.26
	UT	0.37	0.29	0.35	0.32	0.17	0.28	0.21
Pacific	GSW	0.40	0.41	0.27	0.26	0.36	0.24	0.36
	LAC	0.37	0.13	0.15	0.12	0.27	0.31	0.34
	LAL	0.22	0.28	0.26	0.16	0.17	0.22	0.19
	PHO	0.27	0.40	0.28	0.33	0.40	0.20	0.21
	SAC	0.41	0.28	0.11	0.11	0.26	0.24	0.24
Mean		0.28	0.25	0.26	0.21	0.26	0.25	0.27
Min		0.12	0.06	0.11	0.05	0.08	0.05	0.17
Max		0.41	0.41	0.41	0.35	0.51	0.41	0.45
Spearman coef.		0.878*	0.965*	0.946*	0.933*	0.889*	0.941*	0.958*

* p-value ≤ 0.01

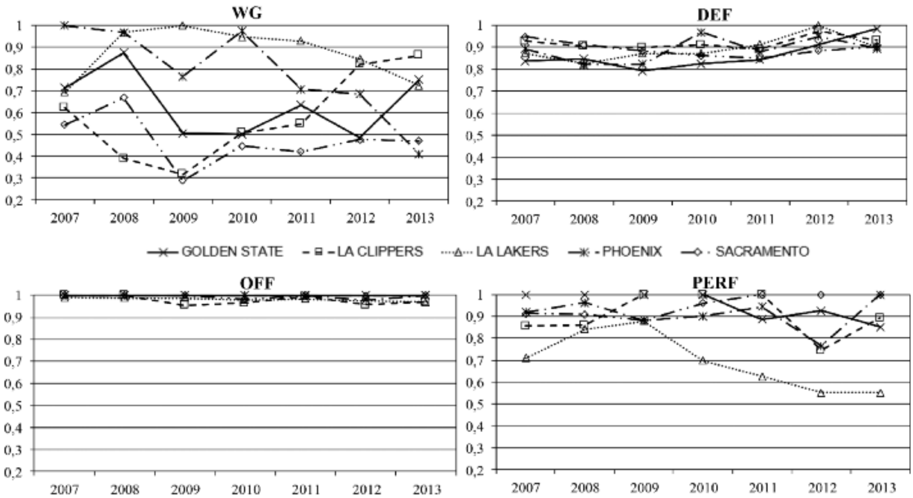


Figure 7. Efficiency of the four sub-DMUs for the Pacific Division according to the Lewis-Lock-Sexton methodology.

data (e.g., about internal links and intermediate products) than the conventional DEA approach, the results obtained are more accurate and valid. In particular, the network of process considered consists of four stages: team performance (that uses the budget and produces offensive and defensive actions), offensive and defensive subsystems (that transform the offensive and defensive actions into points scored and points allowed, respectively), and a final wins generation stage (that produces the victories from the points scored and received). In total, 11 intermediate products are considered, thus increasing the complexity, but also the power, of the analysis with respect to the conventional DEA approach that, in this case, would involve a simple single-input, single-output problem.

It can be concluded from the study that during the last seasons there has been a technological progress consisting of a reduction in the budgets of the efficient teams. Although before the lockout there were teams that did not act accordingly and experienced an efficiency worsening, after the 2011 CBA was signed most teams have caught up with the best practices the most efficient teams have established, slashing their budgets without a significant drop in performance. Hence, the course of action towards efficiency is clear: budget reductions while maintaining (or improving) performance.

These conclusions also match up with regression results; that is, change in wins between seasons is mainly affected by the shift in scale efficiency, and thus managers should adjust their resources properly in order to operate in their MPSS. Concerning the 2011 CBA, this information supports the team owners' claims when negotiations took place and encouraged players to adapt to the new realities of a changing world.

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Authors' Note

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Appendix

In this appendix, the approach in Lewis et al. (2009) is adapted to the network DEA model shown in Figure 1. For a certain sub-DMU, an input-oriented CCR model is applied taking into account only the inputs and outputs of the sub-DMU under assessment. Note that the inputs and outputs of a sub-DMU may be intermediate products in the network DEA approach, e.g., the variables "Points" and "InvOppPoints" are intermediate products within the DMU but inputs for the process "Wins generation" (WG).

The input-oriented CCR model to compute the maximal feasible radial reduction of inputs for process WG in time period t1 can be formulated as:

$$WG\_Eff^{t_1} = \text{Min} \quad \theta \tag{30}$$

s.t.

$$\sum_j \lambda_j^{WG} \cdot \text{Points}_j^{t_1} \le \theta \cdot \text{Points}_0^{t_1} \tag{31}$$

$$\sum_j \lambda_j^{WG} \cdot \text{InvOppPoints}_j^{t_1} \le \theta \cdot \text{InvOppPoints}_0^{t_1} \tag{32}$$

$$\sum_j \lambda_j^{WG} \cdot \text{Wins}_j^{t_1} \ge \text{Wins}_0^{t_1} \tag{33}$$

$$\lambda_j^{WG} \ge 0 \tag{34}$$

The input-oriented CCR model to compute the maximal feasible radial reduction of inputs for process OFF in time period t1 can be formulated as:

$$\text{OFF\_Eff}^{t_1} = \text{Min} \quad \theta \tag{35}$$

s.t.

$$\sum_j \lambda_j^{WG} \cdot 2PA_j^{t_1} \leq \theta \cdot 2PA_0^{t_1} \tag{36}$$

$$\sum_j \lambda_j^{WG} \cdot 3PA_j^{t_1} \leq \theta \cdot 3PA_0^{t_1} \tag{37}$$

$$\sum_j \lambda_j^{WG} \cdot FTA_j^{t_1} \leq \theta \cdot FTA_0^{t_1} \tag{38}$$

$$\sum_j \lambda_j^{WG} \cdot OffReb_j^{t_1} \leq \theta \cdot OffReb_0^{t_1} \tag{39}$$

$$\sum_j \lambda_j^{WG} \cdot Assists_j^{t_1} \leq \theta \cdot Assists_0^{t_1} \tag{40}$$

$$\sum_j \lambda_j^{WG} \cdot InvTO_j^{t_1} \leq \theta \cdot InvTO_0^{t_1} \tag{41}$$

$$\sum_j \lambda_j^{WG} \cdot Points_j^{t_1} \geq Points_0^{t_1} \tag{42}$$

$$\lambda_j^{OFF} \geq 0 \tag{43}$$

The input-oriented CCR model to compute the maximal feasible radial reduction of inputs for process DEF in time period t1 can be formulated as:

$$\text{DEF\_Eff}^{t_1} = \text{Min} \quad \theta \tag{44}$$

s.t.

$$\sum_j \lambda_j^{WG} \cdot DefReb_j^{t_1} \leq \theta \cdot DefReb_0^{t_1} \tag{45}$$

$$\sum_j \lambda_j^{WG} \cdot Steals_j^{t_1} \leq \theta \cdot Steals_0^{t_1} \tag{46}$$

$$\sum_j \lambda_j^{WG} \cdot Blocks_j^{t_1} \leq \theta \cdot Blocks_0^{t_1} \tag{47}$$

$$\sum_j \lambda_j^{WG} \cdot InvOppPoints_j^{t_1} \geq InvOppPoints_0^{t_1} \tag{48}$$

$$\lambda_j^{DEF} \geq 0 \tag{49}$$

The input-oriented CCR model to compute the maximal feasible radial reduction of input for process PERF in time period t1 can be formulated as:

$$PERF\_Eff^{t_1} = Min \quad \theta \tag{50}$$

s.t.

$$\sum_j \lambda_j^{WG} \cdot Budget_j^{t_1} \leq \theta \cdot Budget_0^{t_1} \tag{51}$$

$$\sum_j \lambda_j^{WG} \cdot 2PA_j^{t_1} \geq 2PA_0^{t_1} \tag{52}$$

$$\sum_j \lambda_j^{WG} \cdot 3PA_j^{t_1} \geq 3PA_0^{t_1} \tag{53}$$

$$\sum_j \lambda_j^{WG} \cdot FTA_j^{t_1} \geq FTA_0^{t_1} \tag{54}$$

$$\sum_j \lambda_j^{WG} \cdot OffReb_j^{t_1} \geq OffReb_0^{t_1} \tag{55}$$

$$\sum_j \lambda_j^{WG} \cdot Assists_j^{t_1} \geq Assists_0^{t_1} \tag{56}$$

$$\sum_j \lambda_j^{WG} \cdot InvTO_j^{t_1} \geq InvTO_0^{t_1} \tag{57}$$

$$\sum_j \lambda_j^{WG} \cdot DefReb_j^{t_1} \geq DefReb_0^{t_1} \tag{58}$$

$$\lambda_j^{PERF} \geq 0 \tag{59}$$

The efficiency for the entire DMU is computed in three steps according to the methodology proposed by Lewis et al. (2009). First, the optimal values for the inputs consumed by the WG process are computed using model (30)-(34). Second, using those optimal values in the models (35)-(43) and (44)-(49), instead of the corresponding observed values, the OFF and DEF efficiencies, respectively, are computed. Finally, the optimal values for the inputs consumed by the OFF and DEF processes are used in the model (50)-(59), instead of the observed values, and the efficiency score of process PERF, which will be the efficiency for the entire DMU, is computed. Note that the described method is just the opposite of the one described in Lewis et al. (2009), since the model used in that paper was output-oriented.