Salary cap and National Basketball Association teams' productive performance. A two stage Data Envelopment Analysis approach under a metatechnology framework

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Abstract

This paper evaluates NBA team's productive performance using a two-stage approach under a metafrontier framework. The proposed approach decomposes overall efficiency into salary-cap and on-court efficiency while a structure type of heterogeneity arises in the context of East and West conferences. The inclusion of salary cap, an important contributing element, as an input allow us to examine its effect on different types of efficiency.The empirical results show that NBA teams present a diachronically performance in terms of overal, on court and salary cap efficiency. Moreover, technology gaps reduce over time while a *beta* and *sigma* convergence examination reveal a path of convergence. Finally, a catch-up index denotes a speed of convergence especially after the salary cap implementation.

Keywords::Salary cap, National basketball association, two-stage production process, Metatechnology production function
JEL Classifications: C44, D24, Z2

1 Introduction and motivation

It is likely that no other subject binds together more people in animated interest than professional teams sports. Basketball is one of the favorite among sports fans. Beyond the highly publicized heroics of favorite players and teams there is a world of sports based mainly on economics and business that attract the interest of fans confirming the interaction between team, public, management and policy makers aiming at individual player and team's performance. Researchers on this field, stemming from the seminal work of Scully (1974), have estimated production functions to measure the relationship between inputs and outputs for teams in several sports mainly focused on football, basketball and baseball. For the basketball case and especially for the National Basketball Association (NBA) Zak et al. (1979) provides the basis of our inquiry. During the last three decades a group of various research papers has been focused on teams and players specific productive performance while

The National Basketball Association is one of the top major professional sports leagues in the United States and Canada and it is widely considered to be the best professional basketball league in the world due to popularity, advertising, merchandising and broadcasting rights. According to Forbes, total revenue for NBA teams as well as those involved reached \$80 billion last season while each team, on average, worths approximately around \$1.9 billion for the last year, about three times their valuation from just five years ago. The dramatic increase of worldwide spectators, national and local TV contracts, ticket sales and sponsors has fueled serious concerns about intra team wage disparity across the two conferences that may cause a breakdown of teams' cohesiveness and performance.

The last lockout in 2011 and the new 10-year collective bargaining agreement (CBA) in the end of the same year [1] questioned the profitability of NBA teams (Coates and Humphreys, 2001) and put into discussion the role of salary cap (Dietl et al. 2012) instead of individual contracts. Salary cap can enhance the competitive equilibrium as they avoid big market clubs from offering for additional talent the entire marginal price (Quirk and Fort,1992) while an alteration of salary cap increases the balance of competition and reduces overall pay in the league (Dietl et al. 2012). This impact enables small-scale clubs to maintain their star players while facilitate a collusion of teams to increase their league profits by regulating employment expenses at the cost of the league's less competitive equilibrium (Vrooman, 1995;2000). In addition, teams with different size will have a gain in their revenues (Késenne, 2000) while an impact on social welfare in a league with profit-maximizing clubs will arise (Rathke, 2009).

This study adopts a two-stage DEA approach under a metafrontier framework to perform an efficiency analysis of the NBA teams operating in their own technology/frontier as also in the metatechnology/metafrontier. Particularly, our purpose is evaluate NBA teams' productive performance due to the increase of thier salary cap while using their separation based on the Conference (West-East) to which they belong, we estimate metafrontier and finding technology gaps. For both the frontier and the metafrontier we decompose the overall team efficiency into two additive efficiencies: the first-stage salary cap efficiency that measures the effectiveness of transforming salaries to on-court performance and the second-stage on-court efficiency that measures the efficacy of transforming players' on-court performance to a better winning rate and higher revenue.

[1] The contract signed between the NBA commissioner, the teams' owners and the NBA players.

In this paper we built on the argument that salary cap adoption alters, significantly, NBA teams' performance leading to a process of convergence.Thus, the contribution differs in three, so far, important dimensions. Firstly, we include in our analysis salary cap as an input, aiming at a more integrated picture regarding NBA teams/ overall performance. Secondly, our methodologically approach allows the interaction between the two conference and U.S. production function and provides with overall, salary cap and on-court efficiency scores at both levels. Thirdly, the catch-up index provides an indication of the differences in the speed of convergence towards the two conferences and the U.S production function especially after salary cap's adoption.

The structure of the paper is the following. Section 2 presents a review of the literature of the DEA applications to sports and especially to basketball teams.Section 3 presents the methodology while in section 4 we present our dataset used. Section 5 presents our main results. Finally, Section 6 concludes.

2 Review of the literature

Measuring performance in the sports industry is not newfound. Performance evaluation approaches such as Stochastic Frontiers and Data Envelopment Analysis (DEA) have been employed in various settings (i.e. Hofler & Payne, 2006; Lee& Berri, 2008; Yang et al., 2014) while several scholars have emphasized on their advantages and disadvantages. Given the flexibility of the non-parametric branch (i.e. DEA) two strands of studies have been surfaced in the empirical literature. The first one concerns the measurement of player's efficiency using a variety of measures such as composite indices and player's productivity (Anderson & Sharp, 1997; Hakes & Turner, 2011) whereas the second focuses on team's performance constructing an overall player performance index for using as an intermediate factor in two-stage DEA in NBA teams (Yang, 2014) or multipliers to evaluate various outputs and then apply DEA to specify component profiles and overall indices of basketball players' performances (Cooper et al., 2009). However, the benefits of a two-stage approach have been advocated in many contexts (Sexton & Lewis 2003; Yang et al., 2014).

In a non-parametric context both DEA orientations (input-output) have been adopted in the empirical literature. Indicatively, at a team level framework, Haas (2003a) presents an input-oriented DEA model, taking total wages and salaries as inputs, plus population of the clubs' home-town as a non-discretionary input variable. The outputs include points awarded during the season and the total revenue figures which serve as an indicator for a team's success in international competitions. In addition, Haas (2003b) studies the technical efficiency of the Major Soccer League in the United States considering players' wages and head coach's wage as inputs and awarded points, number of viewers and revenues as outputs. Moreover, Espitia-Escuer and García-Cebrián (2006) study on an annual basis the potential of the teams in the Spanish soccer league between 1998 and 2005. The concept of the output-oriented approach is to use efficiently the available resources to acquire maximum results on the domain of play.In the same line, Barros et al. (2010) and Barros and Garcia-del-Barrio (2011) implement bootstrap DEA technique to investigate the technical efficiency of Brazilian first soccer league and Spanish first division soccer league, respectively while Kounetas (2014) uses the same approach to examine the impact of winning the European

Championship on Greek teams' efficiency. In the first stage, a bootstrapped DEA is used to figure out the relative efficiency scores.Note that the majority of the recent efforts require the use of a two stage approach.

Nevertheless, applications do not exhaust in the above-mentioned sports only expanding DEA methodologies and applications to other sports.For instance, Sexton and Lewis (2003) apply the Network DEA Model under a two-stage structure to analyze Major League Baseball (MLB) team efficiency, which allows to look deeper into both the front office and the on-field operations while Lewis et al., (2009) use a two-stage DEA model as a part of a broader analysis to determine the minimum total player salary required to be competitive in each non-strike year of MLB.

To the best of our knowledge, only a few attempts have been made to study basketball using a non-parametric approach. Moreno and Lozano (2012) applied a Network DEA approach to evaluate the efficiency of NBA teams which is compared to the DEA approach. Results indicate that network DEA is more informative compared to the traditional DEA. Yang et al. (2014) estimate the efficiency of National Basketball Association (NBA) teams based on a two-stage additive DEA where the overall team efficiency is decomposed into the first-stage wage efficiency and the second-stage on-court efficiency respectively. The empirical results illustrate that NBA teams exhibit better performance on wage than on-court efficiency, since on-court efficiency is affected by many factors.

Regrettably, the above-mentioned researches uses the two-stage DEA method to assess the efficiency separately, ignoring the possibility of the effect of salary cap as an input.Depken (1999) addresses how wage differences impact teamwork on professional baseball teams bringing to the forefront the potential effect of the salary cap as an input. The spectacular increase in baseball salaries detonates interest that wage disparity among team players may cause a breakdown of team performance. As team productivity is objectively defined and accurate measures of player salaries are available, it is relatively easy to test two competing hypotheses of wage disparities on team performance. In addition, Adcroft et al. (2009) examine the effects of salary distribution and incentive pay on team performance for the National Football League (NFL). The empirical results reveal a relationship among improved on-field performance and increased payroll, lower levels of salary distribution, and increased incentive payments. As far as the National Basketball Association (NBA) is concerned, Katayama and Nuch (2006) evaluate the causal effect of team salary dispersion on team performance using three measures of salary distribution and examining the effect at multiple levels. In particular whether the outcome of the game is influenced by salary dispersion among (1) players participating in the current game (active players), (2) players who played more than half of their team's games in a season (regular and occasional players) and (3) the entire player population.

3 Methodology and conceptual underpinnings

3.1 Technology heterogeneity in NBA teams

We relax the technological isolation assumption (Tsekouras et al. 2016; 2017), to compare the performance of NBA teams operating under heterogeneous technologies i.e.the East and

West conference frontier (Tsekouras et al., 2016) at the American technology level. The introduction of metafrontier analysis can be used in order to explain differences in production opportunities that can be attributed to available resource endowments, different ownership types (Casu et al. 2013) economic infrastructure, and organizational characteristics in which production takes place (O'Donnell et al. 2008; Kontolaimou et al. 2012).

3.2 Two-stage DEA Model: Variable returns to scale

Let us assume n DMUs (NBA teams), and that each DMUj (j = 1, 2,... n) has K inputs to the first stage, x_{ij}, (i = 1, 2,... m), which in our case is Salary Cap. It also has D outputs from this stage, z_{dj}, (d = 1, 2,... D), which is the Team Performance (Kourtzidis, 2015). These D outputs then become the inputs to the second stage and are referred to as intermediate measures. The outputs from second stage are denoted y_{qj}, (q = 1, 2,... s), and they represent team total Wins and Annual Attendance. We can establish the efficiency scores for the two stages by the following VRS output-oriented model (Banker et al. 1984):

$$maxE^1_{j_o} = \frac{\sum_{d=1}^{D} \eta_d^A z_{dj_o} + u^A}{\sum_{i=1}^{m} v_i x_{ij_o}}$$

s.t.

$$\frac{\sum_{d=1}^{D} \eta_d^A z_{dj} + u^A}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1, 2...., n$$

$$v_i, \eta_d^A \geq 0, , u^A : \text{free of sign}$$

and

$$maxE^2_{j_o} = \frac{\sum_{q=1}^{Ds} u_q y_{qj_o} + u^B}{\sum_{d=1}^{D} \eta_d^B z_{dj_o}}$$

s.t.

$$\frac{\sum_{q=1}^{Ds} u_q y_{qj} + u^B}{\sum_{d=1}^{D} \eta_d^B z_{dj}} \leq 1, j = 1, 2...., n$$

$$u_q, \eta_d^B \geq 0, u^B : \text{free in sign}$$

Using our approach, we have the VRS overall efficiency as using the weights defined under the CRS assumption

$$max \frac{\sum_{d=1}^{D} \eta_d z_{dj_o} + u^A + \sum_{q=1}^{Ds} u_q y_{qj_o} + u^B}{\sum_{i=1}^{m} v_i x_{ij_o} + \sum_{d=1}^{D} \eta_d z_{dj_o}}$$

s.t.

$$\frac{\sum_{d=1}^{D} \eta_d z_{dj} + u^A}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \tag{1}$$

$$\frac{\sum_{q=1}^{s} u_q y_{qj} + u^B}{\sum_{d=1}^{D} \eta_d z_{dj}} \leq 1$$

$$u_q, v_i, \eta_d \geq 0$$

$$u^A, u^B : \text{free in sign}$$

Note that this is an input-oriented model. If we use output-oriented VRS models, the weights will be defined as $w_1 = \dfrac{\sum_{d=1}^{D} \eta_d z_{dj_o}}{\sum_{q=1}^{s} u_q y_{qj_o} + \sum_{d=1}^{D} \eta_d z_{dj_o}}$ and
$w_2 = \dfrac{\sum_{q=1}^{s} u_q y_{qj_o}}{\sum_{q=1}^{s} u_r y_{rj_o} + \sum_{d=1}^{D} \eta_d z_{dj_o}}$

Model (13) is equivalent to the following linear programming program:

$$max \sum_{q=1}^{s} \mu_q y_{qj_o} + u^1 + \sum_{d=1}^{D} \pi_d z_{dj_o} + u^2$$

s.t.

$$\begin{gathered} \sum_{d=1}^{D} \pi_d z_{dj} - \sum_{i=1}^{m} \omega_i x_{ij} + u^1 \leq 0 \\ \sum_{q=1}^{s} \mu_q y_{qj} - \sum_{d=1}^{D} \pi_d z_{dj} + u^2 \leq 0 \\ \sum_{i=1}^{m} \omega_i x_{ij_o} + \sum_{d=1}^{D} \pi_d z_{dj_o} = 1 \\ \mu_r, \omega_i, \pi_d \geq 0, j = 1, 2, ..., n \\ u^1, u^2 : \text{free in sign} \end{gathered} \tag{2}$$

Once we obtain the overall efficiency, a model can be developed to determine the efficiency of each stage. Specifically, assume averting priority for stage 1, the following model determines that stage's efficiency ($E^1_{j_o}$), while maintaining the overall efficiency score at E$_o$ calculated from model (14),

$$E^1_{j_o} = max \sum_{d=1}^{D} \pi_d z_{dj_o} + u^1$$

s.t.

$$\begin{gathered} \sum_{d=1}^{D} \pi_d z_{dj} + u^1 - \sum_{i=1}^{m} \omega_i x_{ij} \leq 0 \\ \sum_{q=1}^{s} \mu_q y_{qj} + u^2 - \sum_{d=1}^{D} \pi_d z_{dj} \leq 0 \\ (1 - E_o) \sum_{d=1}^{D} \pi_d z_{dj_o} + \sum_{q=1}^{s} \mu_q y_{qj_o} + u^1 + u^2 = E_o \end{gathered} \tag{3}$$

$$\sum_{i=1}^{m} \omega_i x_{ij_o} = 1$$

$$\mu_q, \omega_i, \pi_d \geq 0, j = 1, 2, ..., n$$

$$u^1, u^2 : \text{free in sign}$$

4 Data and variables

In order to evaluate NBA team's productive performance we collect data on 30 teams (29 teams in the USA and 1 in Canada), grouped into two conferences (East and West) from the 2001-2002 season through 2018-2019 yielding an unbalanced panel of 536 observations.

We conceive of a NBA team as a two-stage acquisition and production operation. In the first stage we use salary cap as an input due to the limit for total amount of money that NBA teams have the ability to pay for their players instead of team payroll (Moreno and Lozano 2012; Young 2014). Because our study focuses on the efficiency of the teams, we preferred salary cap since it shows us the financial ability that teams have to buy players to reach the desired result. In the second stage total wins (Win) (Depken, 2000; Moreno and Lozano, 2014; Yang et al. 2014) of the teams in regular period and the number of spectators (Annual Attendance) (Moreno and Lozano, 2014; Yang et al. 2014) in each game are used as outputs. We acknowledged that the purpose of each team is to achieve the highest percentage of wins that can allow them to proceed in the next phase and to increase the number of spectators and to their revenues due to the tickets being sold.

Data on team performance, number of wins in regular season and the salary cap have been collected through the official site of the NBA whereas information on annual attendance come from the official site of Basketball Reference respectively. Tables 1 and 2 in the Appendix present some basic descriptive statistics for the panel and by conference as well. Moreover, Fig.1 depicts the relationship between salary cap (input) and team performance (intermediate) per conference and for each team, respectively. What we observe in this case is the positive relationship that appears between the 2 variables as well as a sharp increase in Salary Cap after the 2010-2011 season. It should be noted that, a common issue is that NBA teams often change their name as a result of a shift in franchising. We tackle this issue by using the current name of the team instead of the past one as in the case of the Oklahoma City Thunder (Seattle Supersonics 1967-2008), Brooklyn Nets (New Jersey Nets 1977-2012) and New Orleans Pelicans (2002-2013).

5 Results and Discussion

5.1 Efficiency estimates for the NBA teams

The productive efficiency scores with respect to the specific technology (East and West conference) the metatechnology and the associated technology gaps are estimated for the 30 NBA teams in each of the 20 years. For our estimations we used R programme. At this point, it is crucial to note that the estimates are grounded on a cross-section basis, estimated separately for each year in the sample denoting an individual production set. Therefore, the values of the estimated productive efficiency and technology gaps for each conference and the metafrontier encompass two dynamic factors. The first is the change in distance from the metafrontier, while the second is the outward (technical change) or inward (technical regress) movement of the metafrontier itself. Under this logic, the estimated time-series for efficiency and technology gaps reflect the diachronic evolution of productive performance, taking into direct account any technological developments.

Tables 3 and 4 presents our results regarding salary cap, on-court and overall efficiency for the NBA teams for the distinct periods 2001-2002, 2006-2007, 2011-2012, 2016-2017 and the last championship of 2018-2019. The top and the bottom ranking teams in terms of overall efficiency varies season by season, because of the high competition that exists between NBA teams. Los Angeles Clippers, Chicago Bulls, Indiana Pacers, Utah Jazz and Toronto Raptors represent the highest efficiency during the 2001-2002, 2006-2007, 2011-2012, 2016-2017 and 2018-2019 seasons, respectively while New York Knicks, Portland Trailblazers, Phoenix Suns, Detroit Pistons and Atlanta Hawks the lowest ones. A more thorough inspection in our results reveals that for the first stage salary cap efficiency show that Los Angeles Clippers (92.1%), Atlanta Hawks (80.4%), Indiana Pacers (93.2%), Philadelphia 76ers (84.8) and Washington Wizards (91.2%) achieve high salary cap efficiency during the sample period. Some teams showed a specific trend toward wage efficiency. For example, we find that Washington Wizards and Toronto Raptors increased their salary cap efficiency from 59.9% and 62.2% during the 2001-2002 season to 91.2% and 85.4% during the 2018-2019 season, respectively. Noteworthy is the reverse trend followed by the Los Angeles Clippers who, from 92.1%, the highest in the 2001-2002 season, dropped to 57.6% in the 2016-2017 season.

Looking at the results of the second stage on-court efficiency some interesting findings are coming up. First, a wide variation of on-court efficiency is observed suggesting that, even though most players perform well on-court, it does not guarantee the winning of more games. There is a wide difference between teams in their ability to organize and to cooperate effectively. Moreover, the impacts of some unexpected factors could not be eliminated, which increase the uncertainty of games and attracts more spectators. In comparison with salary cap efficiency, we observe more teams achieving a higher efficiency score. Sacramento Kings (94.1%), Chicago Bulls (89.7%), San Antonio Spurs (98.6%), Golden State Warriors (97.7%) achieve high on-court efficiency during the sample period. In addition, Milwaukee Bucks need special mention for excellent performance in on-court efficiency (132%) during 2018-2019 season while New York Knicks witness a low on-court efficiency (53.4%) during 2001-2002 season and (49.6%) during the season 2006-2007. Also, Phoenix Suns (67.3%), Orlando Magic (67.2%) and Atlanta Hawks (64.5%) shows low on-court efficiency during 2011-2012, 2016-2017 and 208-2019 seasons, respectively. Boston Celtics, Los Angeles Lakers, San Antonio Spurs, Oklahoma City Thunder, Toronto Raptors and Houston Rockets demonstrates a steady course in on-court efficiency during sample data. In contrast, Memphis Grizzles normally witness a low on-court efficiency score during the sample period, reaching only 65.8, 69, and 66%, on average.

What is perceived in the first place is the gradual increase of overall efficiency over the season due to the increase in salary cap. Important reference should be made to the New York Knicks, who have a tremendous increase in overall efficiency of 53.4% reached close to

80%. The San Antonio Spurs, Los Angeles Lakers, Toronto Raptors, Washington Wizards are seen to have a steady course in the evolution of overall efficiency to near 75%, while the Toronto Raptors reaching the 2018-2019 season, their highest percentage 92.1%, which is also the highest for that season, which has led them to win the championship.On the other hand, Milwaukee Bucks, Philadelphia 76ers and Golden State Warriors are the teams with the greatest progress in overall efficiency, from 69% in the 2001-2002 season, the Golden State Warriors reached 85.4% in the 2016-2017 season conquering and the championship. The Milwaukee Bucks and Philadelphia 76ers in the 2018-2019 season reached 89%. Noteworthy is the reverse trend followed by the Los Angeles Clippers who, from 92.1%, the highest in the 2001-2002 season, dropped to 70% in the 2016-2017 season.

Lastly, the behaviour of the salary cap, on-court and overall efficiency for the NBA teams with respect to the US metafrontier are presented in Fig. 2. The distribution is mainly unimodal with small differentiations. The main result illustrated in Fig. 2 is that there is no noteworthy difference among the three efficiencies especially after the salary cap imposition.

5.2 Efficiency estimates by conference and Technology gap

In this section we have divided the teams based on the conference each belong, as this will create two sub-leagues from which will emerge in the end the two finalists who will claim the title of the NBA champion.Tables 5 and 6 presents our results revealing that the range of efficiency has diminished throughout the sample. In the Eastern conference the Detroit Pistons, during season 2001-2002, achieved the highest efficiency of 100% compared with other teams, suggesting that this team is the most efficient in transforming salary into the intermediate output of players' on-court performances, leading to the final outputs of winning games and generating revenue. Chicago Bulls (89.7%), Indiana Pacers (94.2%), Boston Celtics (93.1%) and Toronto Raptors (92.1%) represent the highest efficiency during the 2006-2007, 2011-2012, 2016-2017 and 2018-2019 seasons, respectively while the least efficient teams were the New York Knicks (62.6%), Detroit Pistons (69.4%) and Atlanta Hawks (63%).

As for the Western conference, Los Angeles Clippers (92.1%), New Orleans Pelicans (97.7%), Oklahoma City Thunder (94.8%), Utah Jazz (86.7, 97.3%) represent the highest efficiency during the 2001-2002, 2006-2007, 2011-2012, 2016-2017 and 2018-2019 seasons,respectively. During the same seasons, that mentioned before, the least efficient teams were the Portland Trailblazers (55.3, 77.9%), Phoenix Suns (70.3%), Memphis Grizzlies (66.7, 79.6%). The San Antonio Spurs, Los Angeles Lakers, Los Angeles Clippers, Sacramento Kings, Oklahoma City Thunder and Utah Jazz are seen to have a steady course in the evolution of overall efficiency to near 85%. Important reference should be made to the Portland Trailblazers and Huston Rockets, are the teams with the greatest progress in conference efficiency, from 55.3% and 61.9% in the 2001-2002 season to 96.5% and 88.5% in the 2018-2019 season, respectively.

Looking back at Tables 5 and 6 again, we see for each team the salary cap efficiency (1st stage) and on-court efficiency (2nd stage). The results for the first stage salary cap efficiency shows that in the Eastern conference the Detroit Pistons, during season 2001-2002, achieved the highest efficiency of 100% compared with other teams. Charlotte Hornets (87%), Indiana Pacers (94.2%), Philadelphia 76ers (91.6%) and Washington Wizards (91.2%) represent the highest efficiency during the 2006-2007, 2011-2012, 2016-2017 and 2018-2019 seasons, respectively. The same season, that mentioned before, the least efficient teams were the New York Knicks (45.8, 34.8%), Orlando Magic (54.9%), Cleveland Cavaliers (58.4%) and Atlanta Hawks (56.7%). Needs attention the course of the Detroit Pistons to the top of the efficient section the 2001-2002 season, drop second in the 2011-2012 season. We find that Washington Wizards and Toronto Raptors increased their salary cap efficiency from 74.8% and 77.6% during the 2001-2002 season to 91.2% and 85.4% during the 2018-2019 season, respectively. In the Western conference, Los Angeles Clippers (92.1%), New Orleans Pelicans (97.7%), Oklahoma City Thunder (92.2%), Denver Nuggets (84.5%) and Utah Jazz (97.3%) represent the highest efficiency during the 2001-2002, 2006-2007, 2011-2012, 2016-2017 and 2018-2019 seasons, respectively.

Looking in the results of second stage on-court efficiency some interesting findings are coming up. The impacts of some unexpected factors could not be eliminated, which increase the uncertainty of games and attracts more spectators. In comparison with salary cap efficiency, we observe more teams achieving a higher efficiency score. Detroit Pistons (100%), Boston Celtics (102%), San Antonio Spurs (96.9%), Golden State Warriors (93.3%) achieve high on-court efficiency during the sample period. Milwaukee Bucks need special mention for excellent performance in on-court efficiency (132%) during 2018-2019 season. New York Knicks witness a low on-court efficiency (49.6%) during season 2006-2007. Also, Phoenix Suns (66%), Orlando Magic (69.4%) and Atlanta Hawks (64.5%) shows low on-court efficiency during 2011-2012,206-2017 and 208-2019 seasons, respectively. Boston Celtics, Los Angeles Lakers, San Antonio Spurs, Oklahoma City Thunder, Toronto Raptors and Houston Rockets demonstrates a steady course in on-court efficiency during sample data. By contrast, Memphis Grizzles shows fluctuation on-court efficiency score which starts in season 2001-2002 with 65.8% reaching a historic high for the team 89.3% in season 2011-2012 and then drops again in season 2016-2017 at 74.9%

The results presented in Table 7 provide valuable information for the performance of the teams regarding the metatechnology ratios under the condition that all have access to common technology. Of the 28 teams during season 2001-2002, 14 are efficient. The relatively high scores can be explained as follows. Technology Gap is defined as the ratio of the conference efficiency score to overall efficiency score. Since the frontier is constructed assuming the conference efficiency, the data more closely than the frontier constructed using overall efficiency the ratio of these two distances leads to values very close or equal to one. Noteworthy is the fact that all teams belonging to the Western conference are efficient, while those belonging to the Eastern allocate their resources inefficiently and thus do not accommodate the effects of salary cap.

During season 2006-2007, 12 out of a total of 30 teams are the most efficient with a significant difference these twelve teams are from the Eastern conference. In season 2011-2012 the performance of all teams is close to the unit without anyone being able to utilize its resources effectively, but in averages their performance has increased compared to previous seasons. In the last two seasons 2016-2017 and 2018-2019 of our sample, we observe that the bandwidth of the team performances is relatively eliminated and approaching all the unit. In the 2016-2017 season there are 11 teams that have a performance equal to the unit and belong to the Western conference, with the rest ranging between 0.886 and 0.997. In contrast, for the 2018-2019 season there are 15 teams with a unit performance and belonging to the

Eastern conference, with the remaining ranging between 0.907 and 0.918.

Overall, the performance in terms of efficiency of NBA teams seems to increase on average during 2006-2007, 2011-2012 and 2018-2019 compared to 2001-2002 season. Furthermore, In each season there is a change of the conference that has the highest performing teams. A possible explanation for this increase may be attributed to rapid growth that has occurred in salary cap, as teams have managed to reach a unified market. Finally, this change in our regions indicates to which conference the champion belongs.

5.3 Technology gap convergence and conference team catch up

The use of convergence has been extensively used in the empirical literature while some new studies in efficiency and productivity analysis combine their performance results with convergence type of analysis (Bonasia et al. 2020; Camarero et al. 2013; Kounetas and Zervopoulos, 2019, Färe et al. 2006). In the current section we proceed with β and σ convergence tests defined by Barro (1991) and Sala-i-Martin (1996) to investigate if there exists a negative correlation between the initial level of NBA teams'technology gap and its growth rate. In addtion, we refer to σ convergence test as the path where the cross-sectional dispersion of technology gaps tend to decrease over time. The followign equation shows the regression for β-convergence of the technology gaps:

$$TG_{jt}^{MF} - TG_{j0}^{MF} = \alpha + \beta TG_{j0}^{MF} + \epsilon_{jt} \tag{4}$$

where TG_jt is the logarithm of technology gap for NBA team j in time t for each case, and TG_j0 is the value in the initial period, α_j and β_j are the parameters and ε_jt is the error term. The "half life" is calculated through the ratio $\dfrac{log2}{\beta_j}$.

Nevertheless, on the grounds of the vast criticism of β convergence (Quah, 1993; Barro and Sala-i-Martin, 1995; Sala-i-Martin, 1996) we further adopt σ convergence that measures the change in the value of the standard deviation over time (t=0, ..., T). Carree and klomp (1997) provided the extent of the statistical significance of the σ convergence assuming no σ convergence for the sample industries ($i = 1, \ldots, n$) (null hypothesis) using the following formula:

$$\sigma_{it} = \sqrt{N}\frac{\dfrac{\hat{\sigma}_{i0}^{2}}{(\hat{\sigma}_{it}^{2} - 1)}}{2\sqrt{1-(1-\hat{\beta}_{it})}} \tag{5}$$

The estimated results of the β regression are presented in Table 8. The results of this table indicate the existence of a process of unconditional convergence across all NBA teams for the period examined. More specifically, the estimated value for technology gap of the rate of convergence towards the common steady state is 8.11 and it is statistically significant. The time needed to halve the gap between initial and steady state level is equal to 3.711 periods. Table 6 reports the standard deviation and the coefficient of the two series for technology gap. To formally test the null hypothesis of equal variances the table also reports the t-test proposed by Carree and Klomp (1997). As it can be seen, there is a statistically significant variance decrease. In other words,we came across with unequivocal evidence in favor of both unconditional β and σ-convergence for our variable of interest.

We now turn our attention on the calculation of a catch-up index to measure the speed at which basketball teams, divided in the two conferences, catch up to the U.S technology. The catch-up hypothesis states that teams that lag furthest behind from the technology leaders would present higher rates of different types of efficiency measures and benefit the most from the diffusion of technical knowledge.Finally, we focus and implement our analysis taking into account two different periods before and after the lockout.
Taking each team as an observation, this hypothesis implies that the rate of growth of different types of efficiency performance is inversely correlated with the level of performance at the beginning of the period. In order to test whether there are any technical spillovers between the metafrontier and the frontier technology, we use means of panel unit root tests (Casu, 2016). The catch-up index is defined as the ratio of different types of efficiency measures $EP_{t,k}$ (overall, on-court and salary cap) of the metafrontier to that of the conference frontier[2]. Then,we determine the existence of convergence given that:

$$lnEP_{t,k} = \mu^k + \rho ln\left(\frac{EP^{MF}_{t-1,k}}{EP_{t-1,k}}\right) + lnEP_{t-1,k} + \varepsilon_{t,k} \tag{6}$$

and

$$lnEP^{MF}_{t,k} = \mu^{MF} + lnEP^{MF}_{t-1,k} + \eta_{t,k} \tag{7}$$

Combining both equations we have:

$$ln\left(\frac{EP_{t,k}}{EP^{MF}_{t,k}}\right) = \mu + (1-\rho)ln\left(\frac{EP_{t-1,k}}{EP^{MF}_{t-1,k}}\right) + \psi_{t,k} \tag{8}$$

where $\mu = (\mu^k - \mu^{MF})$. The existence of a unit root in Eq.(22) would suggest no catching up in terms of eco-efficiency and, hence, divergence towards the best technology.

Table 10 present the changes of catch-up index over the two different time periods before and after salary cap adoption. It is obvious that the majority of NBA teams show an increase in their catch up index after 2011 CBA agreement for both the three measures. More specifically, only two teams, Detroit Pistons form the East conference and Protland from the West, reveal a decrease in their catch up index regarding the salary cap efficiency. However, if we examine the change between the two separate periods, 2001-2011 and 2012-2019, it is observed that only five teams perform worts in terms of on-court efficiency. Those are Atlanta Hawks, Detroit Pistons, new York Knicks, Phoenix Suns and Portland Trailblazers.The specific result indicate a progressive decrease in the speed of convergence in terms of overall efficiency and on-court after the introduction of the new agreement and the implementation of salary cap.MORE HERE!!!

Table 11 reports the results concerning the tests for convergence for the efficiency measures under the two periods of examinations. We perform three separate tests from Levine, Li and Chu (LLC, 2002) , Handri LM test (2000) (LLC) and the Fisher-type test following to explore the presence of a unit root (Choi, 2001). These tests own the same null hypothesis of non-stationarity. However, their alternatives are contrary. The Fisher type allows

[2] We have to note that for the computation of the catch-up index we average across teams for each conference k at time t.

for different autoregressive coefficients, while the Levin-Lin-Chu test requires the same one (Levine et al. 2002). Finally, the null hypothesis of (HLM) test (Handri, 2000) is based on (trend) stationarity for all series against the alternative that some of the panels have a unit root. When referring to the LLC test, our results suggest that the null hypothesis of non-stationarity is strongly rejected in every scenario indicating a process of convergence towards the metafrontier. On the contrary, the Fisher-type test implies different outcomes fo the null hypothesis. As this test has the advantage of including various p-values obtained from different unit root tests performed on each panel[3], it holds a higher level of significance than the LLC test. Overall, the null hypothesis is rejected for the cases of overall, on-court and salary cap efficiency. Finally, with the utilization of the HLM test we strongly reject the null hypothesis and we conclude that convergence takes place for the majority of the teams.

6 Conclusions

The economics of sports and especially of NBA basketball clubs has received increasing attention during the last years due to the high profile of the basketball industry, the large number of spectators and the financial resources invested. More specifically, professional basketball in the U.S has experienced a boom the last few decades while its popularity expands to other markets including Europe and Asia. The last adoption and implementation of salary cap as an important contributing element for a competitive market that prevent from monopolizing phenomena and narrows the spread between NBA teams requires a further examination of its impact on their performance. Thus, combining resources to produce results is the main financial objective for the managers of professional sports teams. Understanding the overall team efficiency as well as the relative efficiency and importance of various stages' operation is a crucial and important issue from the perception of team management. As the production process of sports teams is essentially two stages, it is crucial to adopt an appropriate method to evaluate team efficiency and the two different stages, aiming to provide perceptive information for teams' decision makers.

In this paper we seek to improve upon previous studies estimating NBA teams productive performance. Unlike previous research efforts, we use salary cap as our main input while we adopt a metafrontier framework to detect possible organizational differences between the two conferences. Based on a panel dataset of 20 NBA teams during the 2001-2002 to 2018-2019 period seasons our empirical finding reveal that the average team efficiency scores has been increased especially the salary cap implementation. In addition, separating overall and conference efficiency into salary cap and on-court efficiency, empirical findings shows that wide variation of on-court efficiency suggests that, even though most players perform well on-court, it does not guarantee the winning of more games. There is a wide difference between teams in their ability to organize and to cooperate effectively. Moreover, the impacts of some unexpected factors could not be eliminated, which increase the uncertainty of games and attracts more spectators.

As for the estimations of individual team's different types of efficiency and can deduce

[3]The test uses four methods, two are based on an inverse x^2 where the second one is valid only if N goes to infinity (less relevant for our case), one of an inverse normal and one of an inverse logit.

that Detroit Pistons form East Conference and Golden State Warriors form th West on are the top efficient teams for the three measures. However, regarding salary cap efficiency Detroit Pistons, Indiana Pacers and Philadelphia 76ers and Utah Jazz, New Orleans Pelicans and Oklahoma City Thunder are the top three more efficient teams for the two conference. Moreover, again Detroit Pistons, Boston Celtic and Milwaukee Bucks from the East Conference and Golden State Warriors and San Antonio Spurs are the best performers in terms of on-court efficiency.Finally, in terms of technology gaps there is a significant reduction especially after 2011 and the salary cap adoption.

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APPENDIX A

Table 1: Summary statistics of empirical data

Variables	Mean	Std. Dev.	Correlation Matrix			
Inputs						
Team Salary Cap	73,789	21,478	1.000			
Intermediate Factor						
Team Performance	111.398	8.686	0.564	1.000		
Outputs						
Wins	40.544	12.349	0.165	0.588	1.000	
Annual Attendance	17,475.85	2,008.871	0.262	0.307	0.457	1.000

Table 2: Number of average wins, attendance and team performance by Conference

	East			**West**		
Season	**Wins**	**Attendance**	**TP**	**Wins**	**Attendance**	**TP**
2001-2002	39.2	17,218.86	104.979	42.57	17,134.79	109.771
2002-2003	37.7	16,962.86	103.185	44.06	16,808.27	108.518
2003-2004	37	17,120.14	100.901	44.73	16,983.27	107.084
2004-2005	38.9	17,330.73	105.743	43.06	17,296.73	109.193
2005-2006	39.2	17,720.27	105.739	42.8	17,393.8	106.628
2006-2007	38.84	17,887.47	105.483	43.13	17,626.33	110.819
2007-2008	38.8	17,717.8	108.444	43.2	17,070.93	113.971
2008-2009	41.4	17,563.07	109.906	40.6	17,430.4	111.682
2009-2010	39.6	17,067.07	109.036	42.4	17,231.27	113.649
2010-2011	38.6	17,226.4	107.886	43.4	17,411	113.396
2011-2012	31.68	16,905.73	104.083	34.4	17,640.53	110.110
2012-2013	38.46	17,148.53	107.333	43.46	17,547.87	113.527
2013-2014	37.06	17,015.87	108.458	44.93	17,798.73	116.482
2014-2015	38.46	17,760.93	108.974	43.53	17,856.87	114.552
2015-2016	40.53	17,874.4	113.922	41.46	17,823.67	116.319
2016-2017	39.6	17,956.67	117.443	42.4	17,811.53	119.737
2017-2018	40.2	18,098.4	119.485	41.8	17,877.87	120.224
2018-2019	39.28	17,978.73	124.167	42.8	17,735.13	127.721

Table 3: Overall team performance scores

		2001-2002				**2006-2007**			
Team	Conference	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins
Atlanta Hawks	East	0.622	0.622	0.622	33	0.804	0.804	0.804	30
Boston Celtics	East	0.778*	0.711	0.868	49	0.717	0.646	0.717	24
Brooklyn Nets	East	0.604	0.473	0.721	52	0.716*	0.669	0.736	41
Charlotte Hornets	East	-	-	-	-	0.870	0.870	0.870	33
Chicago Bulls	East	0.827	0.724	0.827	21	0.897*	0.814	0.897	49
Cleveland Cavaliers	East	0.717	0.717	0.717	29	0.792*	0.674	0.843	50
Dallas Mavericks	West	0.753*	0.655	0.875	57	0.677*	0.512	0.731	67
Denver Nuggets	West	0.653	0.589	0.653	27	0.732*	0.718	0.739	45
Detroit Pistons	East	0.839*	0.801	0.895	50	0.856*	0.748	0.856	53
Golden State Warriors	West	0.695	0.695	0.695	21	0.743*	0.723	0.743	42
Houston Rockets	West	0.619	0.619	0.619	28	0.742*	0.680	0.769	52
Indiana Pacers	East	0.695*	0.656	0.695	42	0.690	0.656	0.690	35
Los Angeles Clippers	West	0.921	0.921	0.921	39	0.782	0.735	0.782	40
Los Angeles Lakers	West	0.788**	0.682	0.924	58	0.681*	0.592	0.681	42
Memphis Grizzlies	West	0.658	0.618	0.658	23	0.690	0.690	0.690	22
Miami Heat	East	0.667	0.581	0.667	36	0.765*	0.653	0.765	44
Milwaukee Bucks	East	0.699	0.627	0.699	41	0.705	0.664	0.705	28
Minnesota Timberwolves	West	0.729*	0.672	0.800	50	0.682	0.637	0.682	32
New Orleans Pelicans	West	-	-	-	-	0.809	0.763	0.809	39
New York Knicks	East	0.534	0.367	0.534	30	0.496	0.348	0.496	33
Oklahoma City Thunder	West	0.773	0.773	0.773	45	0.749	0.749	0.749	31
Orlando Magic	East	0.760*	0.760	0.760	44	0.733*	0.660	0.733	40
Philadelphia 76ers	East	0.718*	0.564	0.718	43	0.643	0.598	0.643	35
Phoenix Suns	West	0.660	0.602	0.660	36	0.790*	0.774	0.810	61
Portland Trailblazers	West	0.553*	0.422	0.553	49	0.632	0.533	0.632	32
Sacramento Kings	West	0.805*	0.704	0.941	61	0.723	0.664	0.723	33
San Antonio Spurs	West	0.865*	0.761	0.865	58	0.775**	0.691	0.812	58
Toronto Raptors	East	0.749*	0.622	0.749	42	0.856*	0.856	0.856	47
Utah Jazz	West	0.738*	0.675	0.738	44	0.795	0.740*	0.821	51
Washington Wizards	East	0.747	0.599	0.747	37	0.758*	0.713	0.758	41
Mean	All	0.720	0.650	0.746	40.893	0.743	0.682	0.751	41

Notes: *Playof teams, **League Champion

Table 4: Overall team performance scores

		2011-2012				2016-2017				2018-2019			
Team	Conference	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins
Atlanta Hawks	East	0.750*	0.692	0.840	40	0.716*	0.649	0.776	43	0.630	0.567	0.645	29
Boston Celtics	East	0.728*	0.622	0.728	39	0.830*	0.755	0.907	53	0.729*	0.611	0.778	49
Brooklyn Nets	East	0.714	0.704	0.714	22	0.790	0.790	0.790	20	0.663*	0.576	0.696	42
Charlotte Hornets	East	0.774	0.728	0.774	7	0.706	0.644	0.726	36	0.709	0.622	0.745	39
Chicago Bulls	East	0.866*	0.763	0.866	50	0.803*	0.671	0.817	41	0.745	0.594	0.757	22
Cleveland Cavaliers	East	0.757	0.696	0.757	21	0.658*	0.506	0.697	51	0.750	0.601	0.762	19
Dallas Mavericks	West	0.777*	0.658	0.777	36	0.687	0.523	0.687	33	0.789	0.653	0.827	33
Denver Nuggets	West	0.844*	0.844	0.844	38	0.845	0.845	0.845	40	0.813*	0.712	0.980	54
Detroit Pistons	East	0.684	0.627	0.684	25	0.654	0.570	0.678	37	0.746*	0.640	0.792	41
Golden State Warriors	West	0.854	0.832	0.854	23	0.853**	0.774	0.977	67	0.846*	0.789	0.877	57
Houston Rockets	West	0.812	0.812	0.812	34	0.795*	0.736	0.855	55	0.806*	0.685	0.997	53
Indiana Pacers	East	0.932*	0.932	0.932	42	0.754*	0.719	0.767	42	0.778*	0.698	0.815	48
Los Angeles Clippers	West	0.819*	0.750	0.819	40	0.701*	0.576	0.798	51	0.791*	0.722	0.825	48
Los Angeles Lakers	West	0.696*	0.595	0.696	41	0.778	0.686	0.778	26	0.794	0.708	0.820	37
Memphis Grizzlies	West	0.774*	0.700	0.892	41	0.667*	0.559	0.749	43	0.724	0.660	0.753	33
Miami Heat	East	0.781**	0.676	0.942	46	0.735	0.605	0.775	41	0.806	0.675	0.844	39
Milwaukee Bucks	East	0.778	0.778	0.778	31	0.712	0.667*	0.752	42	0.889*	0.812	1.032	60
Minnesota Timberwolves	West	0.858	0.858	0.858	26	0.760	0.760	0.760	31	0.749	0.738	0.754	36
New Orleans Pelicans	West	0.740	0.717	0.740	21	0.704	0.666	0.717	34	0.760	0.760	0.760	33
New York Knicks	East	0.765*	0.641	0.765	36	0.724	0.608	0.724	31	0.788	0.666	0.788	17
Oklahoma City Thunder	West	0.916*	0.916	0.916	47	0.811*	0.747	0.835	47	0.840*	0.767	0.878	49
Orlando Magic	East	0.684*	0.537	0.684	37	0.672	0.563	0.672	29	0.816*	0.753	0.849	42
Philadelphia 76ers	East	0.790*	0.769	0.790	35	0.848	0.848	0.848	28	0.890*	0.818	0.930	51
Phoenix Suns	West	0.673	0.641	0.673	33	0.829	0.829	0.829	24	0.730	0.717	0.734	19
Portland Trailblazers	West	0.757	0.617	0.757	28	0.690*	0.571	0.725	41	0.884*	0.805	0.927	53
Sacramento Kings	West	0.855	0.855	0.855	22	0.729	0.657	0.737	32	0.814	0.793	0.825	39
San Antonio Spurs	West	0.840*	0.756	0.986	50	0.769*	0.625	0.891	61	0.869*	0.826	0.893	48
Toronto Raptors	East	0.856	0.856	0.856	23	0.752*	0.621	0.794	51	0.921**	0.854	0.960	58
Utah Jazz	West	0.883*	0.883	0.883	36	0.867	0.766*	0.907	51	0.893*	0.863	0.910	50
Washington Wizards	East	0.851	0.851	0.851	20	0.723*	0.642	0.793	49	0.912	0.912	0.912	32
Mean	All	0.794	0.744	0.811	33	0.752	0.673	0.787	41	0.796	0.720	0.835	41

Notes: *Playof teams, **League Champion

Table 5: Conference team performance scores

		2001-2002				2006-2007			
Team	Conference	Conference efficiency	Salary Cap efficiceny	On-court efficiency	Wins	Conference efficiency	Salary Cap efficiceny	On-court efficiency	Wins
Atlanta Hawks	East	0.745	0.745	0.745	33	0.804	0.804	0.804	30
Boston Celtics	East	0.934*	0.888	1.021	49	0.717	0.646	0.717	24
Brooklyn Nets	East	0.740	0.590	0.929	52	0.718	0.669	0.787	41
Charlotte Hornets	East	-	-	-	-	0.870	0.870	0.870	33
Chicago Bulls	East	0.937	0.904	0.937	21	0.897*	0.814	0.897	49
Cleveland Cavaliers	East	0.811	0.811	0.811	29	0.798*	0.674	0.970	50
Detroit Pistons	East	1.000*	1.000	1.000	50	0.856	0.748	0.856	53
Indiana Pacers	East	0.828*	0.818	0.839	42	0.690	0.656	0.690	35
Miami Heat	East	0.779	0.724	0.829	36	0.765*	0.653	0.765	44
Milwaukee Bucks	East	0.814	0.782	0.845	41	0.705	0.664	0.705	28
New York Knicks	East	0.626	0.458	0.626	30	0.496	0.348	0.496	33
Orlando Magic	East	0.904*	0.904	0.904	44	0.733*	0.660	0.733	40
Philadelphia 76ers	East	0.826*	0.703	0.830	43	0.643	0.598	0.643	35
Toronto Raptors	East	0.860*	0.776	0.943	42	0.876*	0.870	0.885	47
Washington Wizards	East	0.856	0.748	0.856	37	0.758*	0.713	0.758	41
Mean	-	0.833	0.775	0.865	39.214	0.755	0.693	0.772	38.867
Dallas Mavericks	West	0.753*	0.655	0.875	57	0.796*	0.661	0.796	67
Denver Nuggets	West	0.653	0.589	0.653	27	0.874*	0.874	0.874	45
Golden State Warriors	West	0.695	0.695	0.695	21	0.897*	0.897	0.897	42
Houston Rockets	West	0.619	0.619	0.619	28	0.865*	0.865	0.865	52
Los Angeles Clippers	West	0.921	0.921	0.921	39	0.946	0.946	0.946	40
Los Angeles Lakers	West	0.788**	0.682	0.924	58	0.835*	0.765	0.835	42
Memphis Grizzlies	West	0.658	0.618	0.658	23	0.832	0.832	0.832	22
Minnesota Timberwolves	West	0.729*	0.672	0.800	50	0.829	0.823	0.829	32
New Orleans Pelicans	West	-	-	-	-	0.977	0.977	0.977	39
Oklahoma City Thunder	West	0.773	0.773	0.773	45	0.901	0.901	0.901	31
Phoenix Suns	West	0.660	0.602	0.660	36	0.905*	0.905	0.905	61
Portland Trailblazers	West	0.553*	0.422	0.553	49	0.779	0.688	0.779	32
Sacramento Kings	West	0.805*	0.704	0.941	61	0.879	0.858	0.879	33
San Antonio Spurs	West	0.865*	0.761	0.865	58	0.904**	0.893	0.904	58
Utah Jazz	West	0.738*	0.675	0.738	44	0.950	0.950*	0.950	51
Mean	-	0.729	0.671	0.762	42.571	0.878	0.856	0.878	43.133

Notes: *Playof teams, **League Champion

Table 6: Conference team performance scores

		2011-2012				2016-2017				2018-2019				
Team	Conference	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins	Overall efficiency	Salary Cap efficiceny	On-court efficiency	Wins	
Atlanta Hawks	East	0.759*	0.708	0.842	40	0.799*	0.749	0.881	43	0.630	0.567	0.645	29	
Boston Celtics	East	0.738*	0.636	0.738	39	0.931*	0.872	1.045	53	0.729*	0.611	0.778	49	
Brooklyn Nets	East	0.723	0.719	0.723	22	0.854	0.854	0.854	20	0.663*	0.576	0.696	42	
Charlotte Hornets	East	0.784	0.745	0.784	7	0.772	0.744	0.788	36	0.709	0.622	0.745	39	
Chicago Bulls	East	0.876*	0.780	0.876	50	0.873*	0.775	0.873	41	0.745	0.594	0.757	22	
Cleveland Cavaliers	East	0.767	0.711	0.767	21	0.734*	0.584	0.805	51	0.750	0.601	0.762	19	
Detroit Pistons	East	0.694	0.641	0.694	25	0.723	0.658	0.757	37	0.746*	0.640	0.792	41	
Indiana Pacers	East	0.942*	0.942	0.942	42	0.830*	0.829	0.830	42	0.778*	0.698	0.815	48	
Miami Heat	East	0.791**	0.691	0.949	46	0.807	0.699	0.868	41	0.806	0.675	0.844	39	
Milwaukee Bucks	East	0.787	0.787	0.787	31	0.791*	0.770	0.826	42	0.889*	0.812	1.032	60	
New York Knicks	East	0.775*	0.655	0.775	36	0.792	0.702	0.792	31	0.788	0.666	0.788	17	
Orlando Magic	East	0.694*	0.549	0.694	37	0.737	0.650	0.737	29	0.816*	0.753	0.849	42	
Philadelphia 76ers	East	0.800*	0.787	0.800	35	0.916	0.916	0.916	28	0.890*	0.818	0.930	51	
Toronto Raptors	East	0.866	0.866	0.866	23	0.835*	0.717	0.904	51	0.921	0.854	0.960	58	
Washington Wizards	East	0.861	0.861	0.861	20	0.815*	0.741	0.944	49	0.912**	0.912	0.912	32	
Mean	-		0.790	0.739	0.806	31.600	0.814	0.751	0.855	39.600	0.785	0.693	0.820	39.200
Dallas Mavericks	West	0.794*	0.658	0.823	36	0.687	0.523	0.687	33	0.862	0.757	0.862	33	
Denver Nuggets	West	0.893*	0.893	0.893	38	0.845	0.845	0.845	40	0.893*	0.825	0.934	54	
Golden State Warriors	West	0.861	0.832	0.861	23	0.853**	0.774	0.977	67	0.925*	0.914	0.933	57	
Houston Rockets	West	0.857	0.857	0.857	34	0.795*	0.736	0.855	55	0.885	0.794*	0.938	53	
Los Angeles Clippers	West	0.857*	0.750	0.929	40	0.701*	0.576	0.798	51	0.867*	0.837	0.886	48	
Los Angeles Lakers	West	0.734*	0.595	0.846	41	0.778	0.686	0.778	26	0.870	0.820	0.898	37	
Memphis Grizzlies	West	0.799*	0.700	0.893	41	0.667*	0.559	0.749	43	0.796	0.765	0.812	33	
Minnesota Timberwolves	West	0.868	0.859	0.871	26	0.763	0.763	0.763	31	0.819	0.819	0.819	36	
New Orleans Pelicans	West	0.745	0.717	0.752	21	0.706	0.666	0.717	34	0.830	0.830	0.830	33	
Oklahoma City Thunder	West	0.948*	0.922	0.980	47	0.811*	0.747	0.831	47	0.919*	0.889	0.937	49	
Phoenix Suns	West	0.703	0.641	0.756	33	0.829	0.829	0.829	24	0.805	0.805	0.805	19	
Portland Trailblazers	West	0.763	0.617	0.763	28	0.693*	0.571	0.722	41	0.965*	0.933	0.986	53	
Sacramento Kings	West	0.864	0.864	0.864	22	0.732	0.657	0.753	32	0.889	0.889	0.889	39	
San Antonio Spurs	West	0.861*	0.756	0.969	50	0.769*	0.625	0.891	61	0.948*	0.948	0.948	48	
Utah Jazz	West	0.908*	0.895	0.918	36	0.867*	0.766	0.900	51	0.973	0.973*	0.973	50	
Mean	-	0.830	0.770	0.865	34.400	0.766	0.688	0.806	42.400	0.883	0.853	0.897	42.800	

Notes: *Playof teams, **League Champion

Table 7: Technology Gap

		Season				
Team	Conference	2001-2002	2006-2007	2011-2012	2016-2017	2018-2019
Atlanta Hawks	East	0.836	1.000	0.987	0.896	1.000
Boston Celtics	East	0.834	1.000	0.987	0.891	1.000
Brooklyn Nets	East	0.816	0.997	0.987	0.925	1.000
Charlotte Hornets	East	-	1.000	0.987	0.914	1.000
Chicago Bulls	East	0.882	1.000	0.988	0.920	1.000
Cleveland Cavaliers	East	0.884	0.994	0.987	0.897	1.000
Dallas Mavericks	West	1.000	0.851	0.979	1.000	0.915
Denver Nuggets	West	1.000	0.838	0.945	1.000	0.911
Detroit Pistons	East	0.839	1.000	0.987	0.905	1.000
Golden State Warriors	West	1.000	0.828	0.992	1.000	0.915
Houston Rockets	West	1.000	0.859	0.948	1.000	0.911
Indiana Pacers	East	0.839	1.000	0.989	0.908	1.000
Los Angeles Clippers	West	1.000	0.827	0.956	1.000	0.912
Los Angeles Lakers	West	1.000	0.816	0.948	1.000	0.912
Memphis Grizzlies	West	1.000	0.829	0.969	1.000	0.910
Miami Heat	East	0.856	1.000	0.987	0.912	1.000
Milwaukee Bucks	East	0.859	1.000	0.988	0.900	1.000
Minnesota Timberwolves	West	1.000	0.822	0.989	0.997	0.914
New Orleans Pelicans	West	-	0.828	0.992	0.997	0.916
New York Knicks	East	0.852	1.000	0.987	0.914	1.000
Oklahoma City Thunder	West	1.000	0.831	0.966	1.000	0.914
Orlando Magic	East	0.841	1.000	0.986	0.912	1.000
Philadelphia 76ers	East	0.869	1.000	0.988	0.926	1.000
Phoenix Suns	West	1.000	0.873	0.957	1.000	0.907
Portland Trailblazers	West	1.000	0.811	0.992	0.997	0.916
Sacramento Kings	West	1.000	0.822	0.989	0.997	0.916
San Antonio Spurs	West	1.000	0.858	0.976	1.000	0.917
Toronto Raptors	East	0.871	0.978	0.988	0.901	1.000
Utah Jazz	West	1.000	0.837	0.973	1.000	0.918
Washington Wizards	East	0.873	1.000	0.988	0.886	1.000
Mean	All	0.927	0.917	0.979	0.953	0.957

Table 8: Estimated results for β - convergence

Explanatory Variable	Coefficient	t-statistic	Prob
α	1.761***	17.263***	0.000
β	-0.0461***	-23.281***	0.000
Weighted Statistics			
R^2	0.542	Adjusted R-square	0.419
Half-life	1.812	(Durbin-Watson)	8.162

Table 9: Estimation Results for σ - convergence

Explanatory	Standard deviation		Variation coefficient		T3 test	
Variable	2001	2011	2001	2011	t-statistic	Prob.
Frontier						
DEA	0.215	0.274	-3.678	-3.914	17.185	0.000
DDF	0.244	0.310	-4.059	-4.294	17.856	0.000
Metarontier						
DEA	0.264	0.295	-4.411	-4.516	-18.145	0.000
DDF	0.347	0.354	-4.576	-4.854	-19.354	0.000

APPENDIX B

Figure 1: Relationship between Team Salary Cap and Team Performance

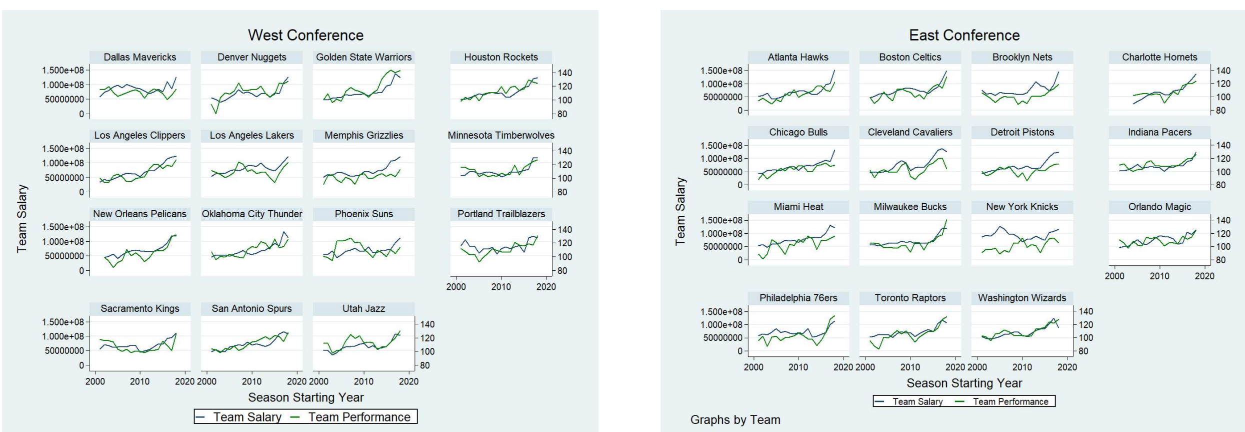

Table 10: Catch up indices of NBA team performance scores

	2001-2011 (a)		2012-2019 (b)						
Team (Conference)	On-court(a)	On-court(b)	salary cap(a)	Salary cap(b)	Overall(a)	Overall(b)	Change SC	Change On-court	Change
Overall									
Atlanta Hawks (East)	0.134	0.112	0.292	0.322	0.398	0.364	↓	↑	↓
Boston Celtics (East)	0.743	0.778	0.647	0.716	0.876	0.917	↑	↑	↑
Brooklyn Nets (East)	0.889	0.914	0.999	1.021	0.882	0.916	↑	↑	↑
Charlotte Hornets (East)	0.657	0.715	0.763	0.821	0.917	0.997	↑	↑	↑
Chicago Bulls (East)	0.997	1.097	0.924	1.002	0.921	1.001	↑	↑	↑
Cleveland Cavaliers (East)	0.564	0.617	0.717	0.797	0.829	0.902	↑	↑	↑
Dallas Mavericks (West)	0.698	0.753	0.655	0.775	0.917	1.001	↑	↑	↑
Denver Nuggets (West)	0.567	0.653	0.589	0.653	0.727	0.815	↑	↑	↑
Detroit Pistons (East)	0.453	0.419	0.511	0.495	0.650	0.665	↑	↑	↑
Golden State Warriors (West)	0.643	0.695	0.695	0.745	0.743	0.789	↑	↑	↑
Houston Rockets (West)	0.587	0.619	0.619	0.619	0.628	0.743	↑	↑	↑
Indiana Pacers (East)	0.562	0.599	0.616	0.695	0.642	0.691	↑	↑	↑
Los Angeles Clippers (West)	0.761	0.801	0.821	0.888	0.798	0.832	↑	↑	↑
Los Angeles Lakers (West)	0.917	1.088	0.982	1.024	0.918	1.002	↑	↑	↑
Memphis Grizzlies (West)	0.789	0.858	0.718	0.808	0.723	0.812	↑	↑	↑
Miami Heat (East)	0.617	0.667	0.581	0.667	0.636	0.701	↑	↑	↑
Milwaukee Bucks (East)	0.712	0.799	0.727	0.809	0.856	0.912	↑	↑	↑
Minnesota Timberwolves (West)	0.689	0.719	0.702	0.800	0.765	0.850	↑	↑	↑
New Orleans Pelicans (West)	0.324	0.412	0.478	0.521	0.599	0.674	↑	↑	↑
New York Knicks (East)	0.598	0.514	0.467	0.384	0.378	0.301	↓	↓	↓
Oklahoma City Thunder (West)	0.734	0.773	0.713	0.803	0.765	0.812	↑	↑	↑
Orlando Magic (East)	0.697	0.760	0.811	0.896	0.756	0.843	↑	↑	↑
Philadelphia 76ers (East)	0.789	0.818	0.864	0.918	0.865	0.913	↑	↑	↑
Phoenix Suns (West)	0.345	0.298	0.502	0.415	0.547	0.496	↓	↓	↓
Portland Trailblazers (West)	0.632	0.553	0.422	0.353	0.487	0.391	↓	↓	↓
Sacramento Kings (West)	0.754	0.805	0.704	0.841	0.812	0.889	↑	↑	↑
San Antonio Spurs (West)	0.789	0.848	0.761	0.806	0.789	0.845	↑	↑	↑
Toronto Raptors (East)	0.912	1.019	0.922	1.014	0.876	0.976	↑	↑	↑
Utah Jazz (West)	0.698	0.712	0.694	0.748	0.758	0.876	↑	↑	↑
Washington Wizards(East)	0.698	0.734	0.699	0.747	0.768	0.861	↑	↑	↑

Table 11: Panel unit root tests for efficiency measures convergence

Test	Specification	Statistic	p-value
2001-2011-Overall Performance			
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -3.452	0.009
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 121.241	0.000
		Inv. Norm Z: -11.107	0.000
		Inv. Logit L*: -8.958	0.000
		Mod. Inv. X^2: -6.785	0.006
Hardi LM	No time trend, het. Robust	Z: -36.488	0.000
2001-2011-Salary cap Performance			
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -18.928	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 934.187	0.000
		Inv. Norm Z: -3.564	0.000
		Inv. Logit L*: -3.518	0.000
		Mod. Inv. X^2: 4.582	0.000
Hardi LM	No time trend, het. Robust	Z: 33.480	0.000
2001-2011-On-court Performance			
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -6.605	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 617.812	0.000
		Inv. Norm Z: -7.369	0.000
		Inv. Logit L*:-6.368	0.000
		Mod. Inv. X^2:4.553	0.000
Hardi LM	No time trend, het. Robust	Z: 120.246	0.000
2012-2019-Overall Performance			
Levin-Lin-Chu	1 lag, no time trend	Adj t*: 3.192	0.001
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 214.919	0.0001
		Inv. Norm Z: -9.176	0.000
		Inv. Logit L*: -7.908	0.000
		Mod. Inv. X^2: 3.815	0.0002
Hardi LM	No time trend, het. Robust	Z: 41.988	0.000
2012-2019-Salary cap Performance			
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -21.018	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 534.214	0.000
		Inv. Norm Z: -4.109	0.000
		Inv. Logit L*: -3.981	0.000
		Mod. Inv. X^2: 6.582	0.000
Hardi LM	No time trend, het. Robust	Z: 41.198	0.000
2012-2019-On-court Performance			
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -4.302	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 117.812	0.000
		Inv. Norm Z: -6.014	0.000
		Inv. Logit L*:4.698	0.000
		Mod. Inv. X^2:4.132	0.000
Hardi LM	No time trend, het. Robust	Z: 120.246	0.000