EXPLORING THE INFLUENCE OF COMMONLY CITED STATISTICS ON NCAA BASKETBALL TEAM EFFICIENCY USING DATA ENVELOPMENT ANALYSIS

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ABSTRACT

In the current study, we employ previously unexplored statistics as inputs to a data envelopment analysis (DEA) for National Collegiate Athletic Association (NCAA) basketball teams. These statistics have been popularized in the sports media and are widely relied on by college coaching staffs. We explore the efficiencies of 127 college basketball teams from 11 major conferences. Our results indicate which teams can be viewed as inefficient as well as which peer teams it would be useful for them to benchmark against.

Keywords: Data Envelopment Analysis, Efficiency Analysis, Strategic Decision Making, Performance, Benchmarking

INTRODUCTION

A quick glance at popular culture in the United States (US) shows the relative importance of sporting events to most of the populace. For many, the love of athletic competition is developed throughout childhood, in part, due to active participation in school sports. The High School Athletics Participation Survey conducted by the National Federation of State High School Associations (NFHS) reports that more than 7.6 million American high school students played sports during the 2009-2010 school year, which they estimate is approximately 55 percent of all high school students (Koebler, 2011). Participation in sports related activities continues for many Americans throughout adulthood. Approximately 2 million college students participate in club sports (Pennington, 2008), which does not include the number of athletes in teams under the auspices of the NCAA. The Pew Research Center survey found that 46% of adults in the United States follow sports (Center, 2012), with the majority of that interest surrounding the team sports of football, basketball and baseball. The interest in collegiate and professional sports can best be illustrated by examining the money inflows and outflows and attendance of sporting events.

Consider the National Basketball Association (NBA), where the average attendance for a team for games during the 2010-2011 season was 17,319 (ESPN.com, 2012b). The average player's salary in the NBA is $5.15 million US dollars a year (Aschburner, 2011). The NBA averages one of the higher player salaries in US professional sports, but according to the Pew Research Center survey (2006), is only the second favorite sport of American adults. Football ranks as the favorite sport of American adults and the average player salary for the National Football League (NFL) is $1.9 million (Aschburner, 2011). Attendance at NFL games averaged 1,062,948 per team in

2010-2011 (ESPN.com, 2012c). Baseball rounds out the top three and the average player salary for Major League Baseball (MLB) players is $3.34 million (Aschburner, 2011). The average 2010 attendance of an MLB team was 30,135 (ESPN.com, 2012a). All ten of the highest paid coaches in the US are from the NBA or the NFL and all make over $6 million a year (Van Riper, 2011). The average NFL team is worth $1.04 billion US dollars, with an average 2010 season revenue of $261 million (Badenhausen, 2011). The five most profitable NBA teams averaged $37 million US dollars in profit over the last five seasons (Smith, 2012). The average price of a ticket to an NBA game is $48.08 US dollars (Klayman, 2010) and to an NFL game $76.47 US dollars (Riley, 2010). Gambling is another high dollar related industry to both collegiate and professional sports. An astounding $93.9 million dollars was bet in Nevada on the NFL's Super Bowl XLVI (McCarthy, 2012).

Collegiate sports, unlike professional athletics in the US, do not pay their players, though many are supported through scholarship programs. Collegiate teams in the US can be considered the proving ground for athletes aspiring to professional careers, especially in football and basketball. Collegiate athletics are governed by the NCAA and are integrated within US academic institutions of higher learning. These institutions are not-for-profit and hence, all revenue generated by the sports programs is funneled back into the athletic or academic programs of the institution. However, the popularity of collegiate athletics in the US, especially of football and men's basketball, has led to very large athletic budgets at many colleges, large salaries for college coaches, and it has even been argued, an overshadowing of the primary focus of an educational institution (Pappano, 2012). The NCAA estimated that collegiate athletics had an overall annual revenue of $10.6 billion in 2008-2009 (Association, 2012). NCAA men's basketball home attendance for Division I schools was 25,147,122 in 2011 (NCAA, 2012b). In 2011, $256.6 million dollars was bet on college and professional basketball (McCarthy, 2012). The 2011 NCAA men's basketball Division I Championship Tournament alone drew 690,679 (NCAA, 2012b) and betting for this tournament is expected to exceed that of the Super Bowl this year (McCarthy, 2012). Total attendance for NCAA football (all divisions) was 49,670,895 for 2010 (NCAA, 2012a).

The discussion above illuminates the importance of athletics to the US culture and economy. The sheer scope of college and professional athletics warrants effective utilization of their resources. Many sports are viewed as a service that is consumed via a visual or emotional experience. A key part for sports service operations management is to enhance the overall experience of those paying for the service (McMahon-Beattie and Yeoman, 2004). As large service businesses, the application of management science tools to improve the efficiency and effectiveness of their operation is attractive. In this study, we apply a popular management science tool, DEA, to data from NCAA men's basketball teams in order to explore the functioning of these athletic teams. We use the results to illustrate where teams could improve and to give an indication of peer programs that could be used as benchmarks.

LITERATURE REVIEW

Table 1 illustrates that DEA has seen application to a variety of sports, including: basketball (Moreno & Lozano, 2012); (Bartholomew & Collier, 2011); (Cooper, Ruiz, & Sirvent, 2009); (Fizel & Ditri, 1996), American football (Einolf, 2004), soccer (Bosca, Liern, Martinez, & Sala, 2009); (Barros & Leach, 2006); (Garcia-Sanchez, 2007); (Espitia-Escuer & Garcia-Cebrain, 2006); (Haas, 2003), baseball (Lee, 2009); (Lewis, Lock, & Sexton, 2009); (Kang, Lee, & Sihyeong, 2007); (Sueyoshi, Ohnishi, & Kinase, 1999), golf (Fried, Lambrinos, & Tyner, 2004), and hockey (Leibenstein & Maital, 1992).

Table 1 - DEA Literature Regarding Sports

Reference	Context and Purpose	Variables Used
Moreno & Lozano (2012)	A network DEA approach applied to NBA players, offensive and defensive systems, teams.	2-point shots, 3-point shots, free throws, offensive rebounds, assists, inverse of turnovers, defensive rebounds, steals, blocked shots, budget, points, inverse of points, number of team victories
Bartholomew & Collier (2011)	Presentation of two new defensive performance metrics and an evaluation of their influence on defensive efficiency in basketball.	Contested pass, uncontested pass, forced turnover, field goal %, total opponent points
Bosca, Liern, Martinez, & Sala (2009)	Evaluating offensive and defensive efficiency of Italian and Spanish soccer teams.	Shots-on-goal, attacking plays made by the team, balls kicked into the opposing team's center area, minute of possession, goals scored
Cooper, Ruiz, & Sirvent (2009)	DEA theory paper with the evaluation of Spanish Premier League basketball players as empirical context.	Adjusted field goal, adjusted free throw, rebounds, assists, steals, inverse of turnovers, non-mad fouls own, fouls opposite
Lee (2009)	To evaluate the managerial efficiency in the Korean professional sporting leagues (Football, Basketball, and Baseball).	Total expenditure, player salary, number of average fan attendance, season win-loss percentage
Lewis, Lock & Sexton (2009)	Uses network DEA to examine efficiency of baseball teams.	Team's total bases gained/surrendered, number of walks received/surrendered, number of fielding errors, number of games played, games won
Barros & Leach (2006)	To evaluate the performance of English Premier League soccer teams.	Number of players, wages, net assets, stadium facilities expenditure, points obtained in the season, attendance, and turnover.
Garcia-Sanchez (2007)	To explore the operating efficiency, athletic or operating effectiveness, and social effectiveness of Spanish soccer teams.	Attacking moves, passes to the penalty area, shots at goal, ball recovery, goalkeeper's actions, number of goals scored, inverse of number of goals received, team rankings, number of spectators, stadium capacity, population of province
Kang, Lee, & Sihyeong (2007).	To examine the management efficiency of Korean baseball teams.	Total player salary, winning percentage, total fan attendance
Espitia-Escuer & Garcia-Cebrain (2006)	Evaluate Spanish soccer teams' performance.	Number of players used, attack moves performed, minutes of ball possession, shots at goal, number of points achieve throughout the season
Einolf (2004)	To examine franchise payroll efficiency in American football and baseball.	Team batting average, team earned run average, pitcher salaries, hitter salaries, defensive yards per attempt against, offensive yards per attempt, offensive salaries, defensive salaries, wins
Fried, Lambrinos & Tyner (2004)	Evaluate professional golfers.	Driving distance, drives in fairway, greens in reg., putts per green, scrambling, sand saves, earnings per event
Haas (2003)	Examine the efficiency of English Premier League soccer clubs.	Total wages and salaries, coach salary, home town population, points, spectators, revenue, international
Sueyoshi, Ohnishi & Kinase (1999)	Combines DEA with offensive earned-run average, to evaluate baseball players.	Bats, singles, doubles, triples, homeruns, walks, at bats, double plays, runs batted in, steals, sacrifices, walks
Fizel & D'itri (1996)	To examine the efficiency of American college basketball coaches.	Player talent, strength of each team's opponents, years of coaching experience, teams winning percentage
Leibenstein & Maital (1992)	Examines the X-inefficiency of hockey players.	Goals per game, assists per game, salary of player, shots on goal
Ruiz, Pastor, Pastor (2011)	Assess the performance of professional tennis players	ATP statistics as outputs, no explicit inputs used

Table 1 illustrates the multiple sporting contexts in which DEA has been applied. It is also interesting to note the difference in the units of reference. DEA has been used to evaluate individual players, for examples: golfers (Fried et al., 2004), baseball players (Sueyoshi et al., 1999), basketball players (Cooper et al., 2009), hockey players (Leibenstein & Maital, 1992). Another unit of reference at an individual level is the examination of coaches (Fizel & D'itri, 1996). The most common unit of reference is the team, see for example: (Espitia-Escuer & Garcia-Cebrain, 2006) examination of Spanish soccer teams; (Lewis et al., 2009) exploration of baseball teams; and (Barros & Leach, 2006) evaluation of English soccer teams.

While most studies have rather straightforwardly focused on the application of DEA to a particular context, some studies have used sporting contexts to explore more novel implementations or findings from DEA, see, for example: (Cooper et al., 2009) exploration of multiplier values, network DEA approaches (Moreno & Lozano, 2012), and (Garcia-Sanchez, 2007) three-stage-DEA approach.

The last column in Table 1 provides an overview of the different variables examined in the literature. The values used as inputs and outputs in DEA are, of course, specific to the particular sport being examined. However, it can be seen in the table that the choices may vary even within a sport. In many cases, this is due to the research question being explored or the ability to gain access to data.

DATA AND METHODS

Method - Data Envelopment Analysis (DEA)

Data envelopment analysis was proposed by Charnes, Cooper and Rhodes in 1978 (Charnes, Cooper, & Rhodes, 1978). The goal is to measure production efficiency by empirically estimating non-parametric production frontiers. The primary advantage of DEA is that it requires few assumptions and does not require any functional forms, as is the case in the majority of statistical modeling frameworks (Cooper, Seiford, & Tone, 2007a). To contrast DEA with common statistical modeling, consider the example of multiple regression analysis. In multiple regression analysis one obtains a best fit line by minimizing the sum of squared errors. This regression line provides an estimate of the central tendency of the response for various levels of the covariates. The nature of this type of modeling, either directly or indirectly, involves investigation of which statistically significant covariates influence the response and by how much (Kutner, 2005). DEA is not specifically concerned with how a variable on average influences a response, but rather what is the efficient frontier of output variable(s) to input variable(s) and where do our decision making units (teams) lie in respect to the frontier. This technique allows one to explicitly investigate multiple inputs to one or more outputs (Sherman & Ladino, 1995). DEA has been used in service operations, such as healthcare, banking, and sports. Many investigations where DEA has been employed in practice are in situations where management is trying to determine best practices that are too complex to define using traditional analytical methods (Sherman & Ladino, 1995). The goal of DEA is to determine which decision making units (DMUs) are most efficient based on their empirical levels of input and output compared to the entire set of DMUs. Also of importance is to determine which DMUs are inefficient and which efficient DMUs they should try to benchmark themselves against.

In envelopment modeling, there are several modeling options that may be implemented. Input-oriented, output-oriented, or Addititive/Slack-based (SBM) models all investigate the inefficiency of DMUs to the corresponding production frontier. Input-oriented models focus on reducing the inputs as much as possible whereby sustaining the current level of production (Cooper et al., 2007a). Conversely, output-oriented models focus on maximizing the output level(s) while not surpassing the observed input consumption. Additive and SBM models tackle both output deficits and input glut simultaneously. While all three approaches will tend to produce similar efficiency results, we performed an output-oriented investigation. We believe collegiate basketball management (i.e. athletics directors, coaches, or other such higher level administration) will strategically focus on maximizing their wins, while not necessarily focusing on minimizing costs. This approach is typically the primary goal of most high growth businesses and the consistent short-term hiring and firing of collegiate basketball coaches due to lack of winning suggests output-oriented is most appropriate here (Belzer, 2012). Winning percentage was used as our output.

A two-stage output oriented variable returns to scale (VRS) envelopment model was employed as shown below, allowing us to project any inefficient DMUs (teams) as a weighted convex combination of similar teams on the performance frontier (Zhu & Cook, 2007). All variables are assumed discretionary, implying they are under management control. This seems like a reasonable assumption because coaches and athletics administrators can focus on improving their shortfalls where necessary.

Stage 1

$$
\begin{aligned}
&\max \theta \qquad (1)\\
&\text{st.}\\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0} \quad i = 1,2,\dots,m\\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge \theta y_{r0} \quad r = 1,2,\dots,s\\
&\sum_{j=1}^{n} \lambda_j = 1\\
&\lambda_j \ge 0 \quad j = 1,2,\dots,n
\end{aligned}
$$

Data – NCAA Basketball

The data used in this study is for the 2011-2012 college basketball season. There are 345 Division I Men’s basketball teams, but only 127 were incorporated in this study. Even though teams are in the same division, there are vast differences in budgetary resources amongst the teams. With so much heterogeneity present, we set specific inclusion criteria of conferences to be included in this study. Conferences were chosen instead of specific teams, because one of the primary benefits of this analysis will be for coaches to be able to compare themselves with their peers. Conferences already tend to encompass similar type of programs, such as styles of play and players. Our homogenous inclusion criteria are teams that came from conferences that satisfied the following three conditions. First, they came from a conference that averaged at least one million dollars in men's basketball revenue. Second, they averaged a strength of schedule of at least .500 and, third, they had an average winning percentage of at least .500. This narrowed down the field to 11 conferences composed of 127 teams, as shown in Table 2 below. Army from the Missouri Valley conference was excluded from this study because their financial revenue was not available.

Table 2 – Conferences included in the study

Conference	Number of Teams	Minimum Revenue	Average Revenue	Average Profit	Average PythSOS	Average Winning %
Big Ten	12	$6,371,843	$12,638,477	$6,827,720	0.722	0.616
ACC	12	$5,535,773	$10,872,896	$4,841,122	0.634	0.574
Big East	16	$3,977,728	$10,453,340	$3,635,620	0.683	0.599
SEC	12	$6,914,565	$10,314,879	$3,454,235	0.655	0.596
Big 12	10	$5,448,009	$9,506,630	$3,153,612	0.691	0.603
Pac 12	12	$3,717,501	$7,595,855	$2,683,199	0.604	0.556
Mountain West	8	$1,689,770	$4,326,916	$1,105,418	0.554	0.624
Atlantic 10	14	$1,905,562	$4,070,811	$1,051,007	0.617	0.543
CUSA	12	$1,405,994	$3,157,407	($14,850)	0.558	0.555
Missouri Valley	10	$1,445,143	$2,631,211	$138,927	0.593	0.539
Horizon	10	$1,022,407	$1,979,553	($41,491)	0.510	0.503

Other basketball DEA studies such as (Cooper et al., 2009) analysis of efficiency of the Spanish Basketball league, used variables such as shooting and defense. We initially obtained similar statistics for inputs, but also incorporated others commonly used in media to evaluate team performance, as well as financial and team resources we argue are also relevant to the teams winning percentage.

The basketball media statistics used in this study were obtained from kenpom.com, a website consisting of college basketball data and analysis (Kubatko, Oliver, Pelton, & Rosenbaum, 2007). Ken Pomery's blog and analysis has been referenced on ESPN and Sports Illustrated and is well-known within the college basketball community having co-authored The 2008-09 College Basketball Prospectus (Colman, DuMond, & Lynch, 2010; Wikipedia, 2012). Many collegiate coaches and staff have been cited as using this website as part of their game preparation and to scout upcoming opponents. Coach Mike Kryzewski who has won three national championships at Duke University has had Ken Pomeroy on his radio show, while Coach Brad Stevens of Butler University has stated he has used the site as well. A video coordinator for The Ohio State University basketball program even referred to the site as, "The Bible" for scouting (Thamel, 2011). We have found nobody who has used such commonly cited statistics in their DEA analyses, although some of the statistics provided by kenpom.com are composed of ones that have already been investigated in assessing NBA player efficiency such as two-point percentage, three-point percentage, etc. (Moreno & Lozano, 2012). However, we have found kenpom.com's statistics referenced in the sports and statistics focused literature (Colman et al., 2010; Fearnhead & Taylor, 2010; Phelps, Bourret, & Walters, 2011).

Data obtained from the 2010-2011 basketball season provided by the Department of Education Office of Postsecondary Education allowed us to obtain additional inputs we suggest influenced the winning percentage frontier (Education, 2011). The ratio of revenues to expenses and number of personnel on the team's coaching staff were incorporated. This ratio of revenue to profit was used as a proxy for profit since 11 of our included teams realized a negative profit and many others broke even. Making sure we used only non-negative input values was necessary so we did not violate the optimization routine. One should note that the ratio of revenue to expenses was for the 2010-2011 season, which gauged the resources that could be incorporated for the 2011-2012 winning percentage output. This has been done in other DEA studies investigating service production in banking to reduce cyclicality issues (Sherman & Ladino, 1995). The idea is that those who were financially successful the previous season will be able to use those additional resources to increase output the next season.

We found in many studies that justification of inputs and outputs were subjectively determined. However, DEA results rely greatly on the set of variables used in the analysis. Variable selection in DEA has not been greatly investigated in the literature as has been done in many other statistical approaches. Approaches used for variable selection have included expert panel screening, using regression and correlation analysis, adding variables in a step-wise fashion, using prior empirical evidence for inclusion in the analysis, as well as iteration techniques which remove variables based on average difference in efficiency (Wagner & Shimshak, 2007). Principal components analysis has also be investigated to reduce the data dimensionality (Adler & Yazhemsky, 2010). The only guidelines regarding which resources impact production is that the sum of inputs and outputs used should be less than or equal to one-third the number of DMUs used in the investigation. Cooper, et. al suggests using:

$$n \geq \max\{m \cdot s, 3(m+s)\} \tag{2}$$

where n is the number of DMUs, m is the number of inputs, and s is the number of outputs (Cooper, Seiford, & Zhu, 2004). We employed a combination of regression, correlation, and step-wise inclusion/exclusion and investigation of efficiency scores to determine the final inputs to be used in the analysis. Starting with all variables we found in previous studies, such as shooting percentages, etc. we ran an output-oriented VRS model and found nearly all teams were efficient. Typically output-oriented models with many inputs and or outputs will cause more of the DMUs to be efficient than input-oriented models, thus the variables included in the model should be carefully examined (Cooper, Seiford, Tone, 2007b). Some inputs were highly correlated since they were just combinations or derivations of other statistics. To determine which variables to include we performed multiple regression backward selection to remove the correlated redundancies. For example, offensive free throw rate was used instead of offensive free throw percentage as the regression analysis revealed offensive free throw percentage was highly insignificant with p-values over .90, while offensive free throw rate showed p-values of less than .10. This determination was not as straightforward with regard to defensive free throw percentage and defensive free throw rate, thus both were kept in the DEA analysis. Computational testing was then performed by iteratively excluded variables and investigating the difference in efficiency and slacks as discussed by Wager, et. al (Wagner & Shimshak, 2007) .

Fortunately, nearly all of the variables that the computational testing determined we should include in the model have not been investigated in past studies. The variables we considered in our model are shown in Table 2 along with formulas or explanations where applicable. Winning percentage is the lone output, while the remaining variables are inputs.

Table 3 – Variables Used in this Study

Variables	Description	Formula
AdjOffEff	Adjusted Offensive Efficiency	http://kenpom.com/blog/index.php/weblog/national_efficiency/
AdjDefEff	Adjusted Defensive Efficiency	http://kenpom.com/blog/index.php/weblog/national_efficiency/
AdjTempo	Adjusted Tempo: The number of possessions per 40 minutes.	Possessions = FGA-OR+TO+.475*FTA
Avg Hgt	Average Height: Average listed height of every player on the team, weighted by minutes played.	Average listed height of every player on the team, weighted by minutes played. Players that have played less than 10% of their team's minutes are not included.
Bench Minutes	Bench minutes: Assumes starters five are players who played the most minutes on the season.	The minutes of remaining players are all assumed to be bench minutes. Players that have played less than 10% of their team's minutes are not included.
Off 3PA%	Offensive 3-Point Field Goal Attempted Percentage	$\frac{3PA}{2PA\ +\ 3PA} * 100$
Def 3PA%	Defensive 3-Point Field Goal Attempted Percentage, but for opposing team	
Def FT%	Defensive Free-Throw Percentage: Free throw percentage for opponents played	FTA/FTM
Experience	Experience: Number of years of college experience determined by a player's eligibility class.	Freshman=0, Sophomore =1, Junior=2, Senior=3, weighted by the experience of each player on the roster based on minutes played. Players that have played less than 10% of their team's minutes are not included.
Off FT Rate	Offensive Free Throw Rate: Measures a player's ability to get the line relative to how often he attempts to score.	FTA/FGA
Def FT Rate	Defensive Free Throw Rate: Same as offensive free throw rate, but for opposing team	FTA/FGA
Off eFG%	Offensive Effective Field Goal Percentage: Same as regular field goal percentage, except that made three-pointers are appropriately given 50% more credit.	(FGM + 0.5*3PM)/FGA
Def eFG %	Defensive Effective Field Goal Percentage: Same as Off eFG%, but for opposing team	(FGM + 0.5*3PM)/FGA
Off TO%	Offensive Turnover Percentage: Turnovers divided by possessions.	Turnovers/Possessions
Off OR%	Offensive Offensive Rebounding Percentage: The number of possible offensive rebounds a player gets. The denominator is scaled based on the percentage of a team's minutes played by the player.	PlayerOR / [%Min * (Team OR + Opp. DR)]
PythSOS	Pythagorean Strength of Schedule	http://kenpom.com/blog/index.php/weblog/ratings_explanation/
NCSOS	Non-Conference Pythagorean Strength of Schedule	http://kenpom.com/blog/index.php/weblog/ratings_explanation/
Total Staff	Total Staff: Total number of head coaches, assistant coaches, part-time staff, etc.	
Rev/Exp	Revenue/Expenses: Ratio of revenues to expenses for the entire season	$\frac{Revenue}{Expenses}$
Win%	Won-Lost Percentage	$\frac{W}{W+L}$

Results

After reducing the number of inputs down to 19, we found 106 out the 127 teams to be 100% efficient, thus lying on the production frontier. There were no teams from the Horizon League and Missouri Valley Conference that were found to be inefficient as shown in Table 4 below. The condition $n \geq \max\{m \cdot s, 3(m+s)\}$ as discussed above was satisfied in our model.

Table 4– Variables Used in this Study

Conference	No. 100% Eff.	No. teams	Pct. of teams 100% Eff.
Horizon	10	10	100.0%
Missouri Valley	10	10	100.0%
Big East	15	16	93.8%
Conference USA	11	12	91.7%
Big 12	9	10	90.0%
SEC	10	12	83.3%
Pac 12	9	12	75.0%
Mountain West	6	8	75.0%
Atlantic 10	10	14	71.4%
ACC	8	12	66.7%
Big Ten	8	12	66.7%

Table 5 shows the 21 inefficient teams and their corresponding "best-practices" teams they should use as their relative benchmarks. In the output-oriented VRS model, efficiencies > 1 indicate that a team is inefficient as shown in column two, indicating that each of these teams should be able to increase their winning percentages given their respective input levels (Zhu & Cook, 2007).

Table 5– 2011-2012 inefficient teams and their corresponding benchmark teams

Inefficient Teams		Best-Practices Team Reference Set								
Team	O-O VRS Eff.	Team1	Team2	Team3	Team4	Team5	Team6	Team7	Team8	Team9
Arizona	1.08688	Tulane	Houston	Young. St.	St. Louis	Virginia	Missouri	Kentucky	Wisconsin	
Arizona St.	1.74559	Tulane	Boston College	Butler	Virginia	Utah				
Charlotte	1.24896	Tulane	Sou. Cal	ND	Butler	Sou. Miss	Colorado	SDSU		
Dayton	1.21850	Cleve. St.	Cincinnati	Stanford	Virginia	Kentucky	Wisconsin	Syracuse		
East Carolina	1.26899	Tulane	Sou. Cal.	Butler	DePaul	Sou. Miss	St. Louis	Virginia	LSU	Wisconsin
Illinois	1.09021	Sou. Cal	Cleve. St.	Seton Hall	La Salle	Fordham	Cincinnati	Virginia	LSU	Texas
Indiana	1.06573	SDSU	Stanford	California	Kentucky	UNC				
Iowa St.	1.10090	ND	Cincinnati	SDSU	Missouri	Kentucky	UNC			
Maryland	1.18176	Tulane	ND	Cincinnati	SDSU	Virginia	LSU	Kentucky	UNC	
Miami FL	1.17818	Sou. Miss	St. Louis	Missouri St.	Cincinnati	SDSU	Virginia	Syracuse	UNC	Louisville
Minnesota	1.18320	Tulane	Butler	Virginia	Alabama	Kentucky				
North Carolina	1.12590	Providence	California	Kentucky	Wisconsin	UNC	Louisville			
Penn St.	1.11181	Tulane	Sou. Cal.	ND	Butler	Seton Hall	Fordham	Rutgers	Cincinnati	Clemson
Rhode Island	1.90618	Tulane	Wisc. GB	Butler	St. John's	Fordham	Rutgers	Cincinnati		
St. Bonaventure	1.18929	Tulane	Creighton	Sou. Miss	Virginia	Kentucky				
Tennessee	1.08522	Tulane	Sou. Cal.	Wisc. GB	Butler	DePaul	St. Louis	Virginia	Kentucky	Wisconsin
Texas Christian	1.16528	Tulane	Sou. Cal	Butler	Sou. Miss	St. Louis	Virginia	Wisconsin		
Vanderbilt	1.13526	ND	Creighton	St. Louis	Wichita St.	Virginia	Kentucky			
Villanova	1.47070	Butler	St. John's	Cincinnati	LSU	Kentucky	UNC			
Virginia Tech	1.16548	Tulane	Sou. Cal.	Butler	Rutgers	Virginia	LSU	Alabama	Kentucky	Wisconsin
Washington St.	1.48555	Wyoming	New Mexico	Virginia	Kentucky	Syracuse				

The slacks were obtained via a two-stage process. In the first stage, Stage 1 was run to obtain the maximum efficiency θ^* which did not use slacks. In the second-stage, θ^* is held constant while running Stage 2 (Zhu & Cook, 2007).

Stage 2

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \tag{3}$$

st.

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0} \quad i = 1,2,\dots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \theta^* y_{r0} \quad r = 1,2,\dots,s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \qquad j = 1,2,\dots,n$$

Table 6 shows the relative weight λ_j for each inefficient team to their corresponding benchmark team. For example, Arizona has a 59% weight of Virginia (Team 5). This means for Arizona to increase their winning percentage they should focus more on the operations/ game play of Virginia, followed by Saint Louis (Team 4) and so on. The usefulness of this will be discussed in more detail later in the paper.

Table 6– 2011-2012 inefficient teams and their corresponding benchmark teams' λ_j^*

Inefficient Teams		Best-Practices Team Reference Set								
DMU Name	O-O VRS	Team1	Team2	Team3	Team4	Team5	Team6	Team7	Team8	Team9

	Eff.									
Arizona	1.08688	0.0532	0.0037	0.0036	0.2713	0.5922	0.0004	0.0669	0.0087	
Arizona St.	1.74559	0.3291	0.0294	0.2388	0.3285	0.0742				
Charlotte	1.24896	0.2468	0.2181	0.0050	0.1454	0.0338	0.0203	0.3306		
Dayton	1.21850	0.2185	0.1429	0.2705	0.1025	0.1043	0.0787	0.0827		
East Carolina	1.26899	0.1677	0.0093	0.0709	0.1092	0.0187	0.1141	0.4504	0.0399	0.0198
Illinois	1.09021	0.1308	0.0693	0.2541	0.2665	0.0154	0.1708	0.0804	0.0071	0.0056
Indiana	1.06573	0.2585	0.1980	0.2000	0.2970	0.0464				
Iowa St.	1.10090	0.2866	0.2446	0.1731	0.2127	0.0261	0.0570			
Maryland	1.18176	0.1924	0.0180	0.0999	0.0162	0.0088	0.4751	0.1448	0.0448	
Miami FL	1.17818	0.0459	0.1955	0.1314	0.2379	0.0348	0.1871	0.0596	0.0767	0.0309
Minnesota	1.18320	0.1321	0.0954	0.2218	0.2555	0.2952				
North Carolina St.	1.12590	0.0986	0.4932	0.1494	0.0072	0.0012	0.2505			
Penn St.	1.11181	0.0482	0.2273	0.0822	0.0679	0.0103	0.2903	0.1153	0.1003	0.0583
Rhode Island	1.90618	0.0224	0.2202	0.1458	0.1353	0.4499	0.0221	0.0043		
St. Bonaventure	1.18929	0.1659	0.0588	0.1575	0.3368	0.2810				
Tennessee	1.08522	0.0009	0.1436	0.0854	0.0359	0.0921	0.3505	0.1844	0.0315	0.0757
Texas Christian	1.16528	0.2870	0.0531	0.0222	0.0540	0.4166	0.1560	0.0111		
Vanderbilt	1.13526	0.3102	0.1432	0.0638	0.1921	0.0499	0.2407			
Villanova	1.47070	0.3543	0.2487	0.1029	0.1487	0.0918	0.0536			
Virginia Tech	1.16548	0.0355	0.2372	0.0986	0.0698	0.1138	0.0697	0.0394	0.1328	0.2033
Washington St.	1.48555	0.2223	0.1108	0.3825	0.2712	0.0132				

The non-zero slacks in Table 7 show the amount of waste of input resources for their corresponding inefficient output, winning percentage (Du, Wang, Chen, Chou, & Zhu, 2011). For example, Arizona could reduce its adjusted defensive efficiency by 5.11 from their current input level and expect to realize the same number of wins.

Table 7 shows the input slacks. Since the model used was output-oriented, which maximizes winning percentage while not surpassing the observed input levels, each value in the table below depicts where those teams had excess in resources but fell short in output. For example, Arizona could have had a lower adjusted defensive efficiency of 88.7 instead of their realized efficiency of 93.8 (-5.11 change) and still produced the same 2011-2012 season winning percentage of 65.7%. More interestingly, they could also have had about 2 (1.81) less staff members or a revenue to expense ratio of only $1.23 million from the previous season, instead of the $3.06 million recognized.

Table 7– Input slacks

Team	*Input Slacks*																	
	Adj Off Eff	*Adj Def Eff*	*Adj Tempo*	*Avg Hgt*	*Bench Minutes*	*Off 3PA%*	*Def 3PA%*	*Def FT%*	*Player Exp.*	*Off FT Rate*	*Def FT Rate*	*Off eFG%*	*Def efg%*	*Off TO%*	*Off OR%*	*Pyth SOS*	*NCSOS Pyth*	*Total Staff*	*Rev/Exp*
Arizona	0.64	5.11	3.67	-	-	0.060	-	-	0.067	0.084	-	-	0.001	0.006	0.011	-	0.081	1.8	1.832
Arizona St.	-	10.17	0.09	1.9	5.3	0.021	0.024	0.043	-	0.032	0.024	0.039	0.025	0.059	-	0.052	-	0.3	0.311
Charlotte	-	1.90	3.62	0.3	1.2	0.042	0.042	0.008	0.057	0.030	-	-	0.013	0.013	-	0.061	0.051	-	-
Dayton	2.42	8.93	0.37	0.1	2.1	0.079	-	-	0.618	-	0.014	-	0.047	0.009	0.016	-	-	0.3	1.283
East Carolina	-	6.94	2.18	0.8	3.6	0.087	-	-	0.354	-	0.031	-	0.035	0.014	-	0.006	-	-	0.042
Illinois	-	-	0.16	1.0	2.4	0.021	0.021	-	-	-	0.022	-	0.027	0.019	0.010	0.098	-	-	1.664
Indiana	8.49	4.15	0.18	0.4	4.4	-	-	0.018	0.211	0.068	0.053	0.036	0.029	0.008	0.009	0.101	-	-	0.797
Iowa St.	-	0.55	2.54	-	1.2	0.073	0.008	0.007	0.091	0.034	-	0.014	0.017	0.016	-	0.042	0.066	0.3	-
Maryland	-	7.90	1.58	0.9	0.8	-	-	0.035	-	0.123	-	-	0.018	0.011	-	0.020	-	-	0.406
Miami FL	1.55	5.24	0.57	0.5	6.4	0.057	0.030	-	-	-	0.012	-	0.020	-	-	0.015	0.047	-	-
Minnesota	-	4.39	0.54	0.1	11.0	-	0.032	0.047	-	0.003	0.035	0.012	0.033	0.039	0.032	0.092	-	0.7	1.393
North Carolina St.	0.65	4.80	1.15	0.5	-	-	0.025	0.028	0.461	-	0.033	-	0.019	-	0.016	0.013	0.101	1.2	0.889
Penn St.	3.84	-	-	0.4	9.1	0.060	0.108	0.039	-	-	0.105	-	0.037	-	0.020	0.113	-	-	0.903
Rhode Island	4.41	4.49	1.05	0.7	8.3	0.024	-	0.012	-	-	-	-	0.049	0.003	0.042	0.022	-	-	-
St. Bonaventure	1.08	4.53	-	0.4	2.7	-	0.019	0.036	0.399	0.032	0.055	0.001	0.014	0.037	0.049	-	0.060	0.7	-
Tennessee	-	1.51	2.32	1.2	4.4	0.016	-	-	-	0.053	0.007	-	-	0.023	0.031	0.052	-	-	0.824
Texas Christian	1.14	11.98	6.00	0.2	0.6	0.023	-	-	0.443	0.018	0.055	-	0.078	0.010	-	-	0.001	1.6	-
Vanderbilt	0.74	-	1.28	0.8	3.6	0.083	0.029	0.008	0.753	0.023	-	0.013	0.018	0.030	-	0.072	0.081	-	-
Villanova	4.12	4.34	2.09	1.2	6.6	0.047	0.026	0.029	-	0.016	-	-	0.005	0.012	0.024	0.094	-	0.9	-
Virginia Tech	2.08	6.03	-	1.3	1.8	-	0.016	0.009	-	-	0.018	-	0.007	0.007	0.026	-	-	-	0.187
Washington St.	-	10.64	-	0.2	4.0	0.019	0.053	-	0.352	0.057	0.055	0.010	0.052	0.020	0.004	-	0.024	2.2	0.111

Table 8 shows the actual winning percentage for the inefficient teams compared to what their efficient target winning percentage should be based on the input resources used. Teams such as Washington State, Arizona State, Rhode Island, and Villanova significantly underperformed having a difference of nearly 20 percent or more.

Table 8– Input slacks

Team	Actual Win %	Efficient Target Win%	Difference
Washington St.	51.4%	76.3%	24.9%
Arizona St.	32.3%	56.3%	24.1%
Rhode Island	22.6%	43.0%	20.5%
Villanova	40.6%	59.7%	19.1%
Dayton	60.6%	73.8%	13.2%
East Carolina	48.4%	61.4%	13.0%
St. Bonaventure	62.5%	74.3%	11.8%
Minnesota	60.5%	71.6%	11.1%
Miami FL	60.6%	71.4%	10.8%
Charlotte	43.3%	54.1%	10.8%
Maryland	53.1%	62.8%	9.7%
Vanderbilt	69.4%	78.8%	9.4%
Texas Christian	54.5%	63.6%	9.0%
North Carolina St.	64.9%	73.0%	8.2%
Virginia Tech	48.5%	56.5%	8.0%
Iowa St.	67.6%	74.5%	6.8%
Arizona	65.7%	71.4%	5.7%
Indiana	75.0%	79.9%	4.9%
Illinois	53.1%	57.9%	4.8%
Tennessee	55.9%	60.6%	4.8%
Penn St.	37.5%	41.7%	4.2%

Since Washington State had the largest difference in inefficiency of 24.9 percent, we'll use them as an example. Their coach and athletics administration could look at their corresponding benchmark teams from Table 5 above. Table 9 shows Washington State's input and output variables compared to its benchmarked teams. Those teams might have more or less input production from each input variable, but using the weights in Table 6, they could obtain their target efficiencies for each input, which in theory would have helped them realize an efficient output winning percentage of 76.3%. The largest input slack or input inefficiency for Washington State was adjusted defensive efficiency. As an example, from the second column in Table 9 we can derive the input target of 89.2 by taking a weighted average for each variable: (0.22*92.5)+(0.11*89.7)+(0.38*87.7)+(.27*88.2)+(0.01*90.3) = 89.2.

Table 9– Input slacks for Washington State

Team	*Adj Off Eff*	*Adj Def Eff*	*Adj Tempo*	*Avg Hgt*	*Bench Minutes*	*Off 3PA%*	*Def 3PA%*	*Def FT%*	*Player Exp.*	*Off FT Rate*	*Def FT Rate*	*Off eFG%*	*Def efg%*	*Off TO%*	*Off OR%*	*Pyth SOS*	*NCSOS Pyth*	*Total Staff*	*Rev/Exp*	*Win %*
Washington St. (Actual)	108.6	99.8	62.9	77.5	30.1	0.3354	0.3734	0.6724	1.94	0.4386	0.3651	0.5287	0.4958	0.2046	0.3073	0.5977	0.4745	10.00	1.39	51.4%
Washington St. (Target)	108.6	89.2	62.9	77.3	26.1	0.3164	0.3200	0.6724	1.59	0.3812	0.3104	0.5183	0.4438	0.1843	0.3031	0.5977	0.4508	7.80	1.28	76.3%
Efficient Benchmarks																				
Wyoming	99.2	92.5	61.0	76.0	25.6	0.3850	0.3274	0.7083	2.33	0.3837	0.3702	0.5098	0.4674	0.1895	0.2405	0.4978	0.3135	8.00	0.93	63.6%
New Mexico	111.0	89.7	66.3	77.1	34.7	0.3708	0.3598	0.6787	1.67	0.3876	0.3149	0.5277	0.4440	0.2010	0.3439	0.5491	0.4498	9.50	1.20	80.0%
Virginia	102.9	87.7	60.6	76.9	26.7	0.2976	0.3241	0.6343	1.71	0.3541	0.3115	0.5067	0.4471	0.1875	0.2750	0.5892	0.3945	7.00	1.31	68.8%
Kentucky	122.9	88.2	66.2	78.8	21.6	0.2647	0.2896	0.6938	0.77	0.4173	0.2581	0.5376	0.4197	0.1698	0.3746	0.7061	0.6361	8.00	1.50	95.0%
Syracuse	118.1	90.3	65.2	78.6	33.9	0.3098	0.3619	0.6761	1.68	0.3288	0.3096	0.5206	0.4421	0.1595	0.3615	0.7068	0.5925	9.50	2.52	91.9%

This information could aid Washington States' coaching staff in considering improvements to their basketball operations. However, as with any mathematical model, the results should aid in the decision-making process, not replace the decision maker (Bazaraa et al.). Assuming model inputs such as strength of schedule remain the same, Washington State should consider ways to improve their adjusted defensive efficiency (10.64), followed by reducing their bench minutes (4.05), as well as consider reducing their total staff from 10 to 8 (2.2). The average number of staff for all teams under investigation was 7.5, so they would still be above average in that regard.

Lastly, athletics staff and administrators may argue that inefficiency in the way we describe it is not relevant if their team wins big games. In other words, wins in the NCAA tournament may outweigh their teams winning percentage. However, two of our 21 2011-12 inefficient teams had a respectful performance in the NCAA tournament with Indiana and North Carolina State both making it to the Sweet 16. While Indiana's target winning percentage last year was 80%, a National Championship was not out of reach. A five percent increase from what was realized may have made that a possibility. Moreover, Indiana has been projected by many experts to be the favorite team to win the national championship going into the 2012-13 season, therefore improving in the mentioned areas would appear extremely advantageous to their athletics department (Katz, 2012). Similarly, had North Carolina State played slightly weaker competition, they may have won more which would have made up some ground at achieving their target winning percentage of 73%, an 8.2% difference from what was realized. North Carolina State is projected as a top ten team as well for the next season. These two examples provide some insight into how the DEA results could be interpreted and used.

CONCLUSION

This paper uses data envelopment analysis, a technique that has been used in many realms in service industries for comparison of efficient decision making units. While DEA has been applied using various inputs and outputs in sports, there have been none that have applied it to college basketball using both statistics typically regarded from collegiate coaching staffs as more insightful as well as using financial data. Given the importance of athletics to the US culture and economy and the sheer scope of college and professional athletics, this analysis provides additional information to help coaches and athletic administrators make better decisions in regard to the effective utilization of their resources (Adler and Yazhemsky, 2010). Future work may include the examination of other variables such as game attendance and player recruiting that might also be incorporated into the model.

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