Assessing Performance Efficiency: A Case of Men's Professional Tennis Players

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ABSTRACT

This study strives to measure men's professional player's efficiency and explore the relationship between efficiency and year-end performance, including the number of tournaments won and total prize money. The authors used data envelopment analysis (DEA) to assess the efficiency score of each player. DEA result shows that men's professional players converted their inputs to outputs with an average efficiency of 76.1%. The eight players, including the 'Big 3', are most efficient in achieving desirable outcomes, while the other eight players record the least efficient score. The additional analysis uncovers that the efficiency score is positively related to the number of tournament-winning and prize money.

Keywords: efficiency, Data envelopment analysis (DEA), professional tennis, serve rating, return rating, under pressure rating

INTRODUCTION

Prior marketing research has emphasized uncovering the answer to the question, 'The more, the better?; The efficient salespeople do better?; and 'Efficient advertising creates more positive outcomes than others?. This research framework needs to extend to explain the relationship between sports players' efficiency and performance. Motivated by this, the authors attempt to unveil the answer to the two questions: Do sports players play efficiently?; and Do the efficient players outperform?

This study aims to measure the efficiency of men’s professional tennis players with DEA (Data Envelopment Analysis) analysis and explore how the efficiency score affects the number of tournament winning and total prize money. The authors provide a brief history and research background by reviewing the literature on efficiency and DEA and assess how efficiently each player transfers the performance inputs to outputs. Following a presentation of key results, the manuscript discusses research findings and concludes with future research directions.

RESEARCH BACKGROUND

Marketing scholars have searched for answers to 'Does Efficiency Matter?' with various topics and methodology. The 'efficiency' concept measured converting multiple inputs to multiple outputs in creating desirable outcomes, including retail productivity, marketing credibility, sales performance, and advertising productivity.

Retail Productivity

Salesforce size and productivity were evaluated through efficient frontier benchmarking. Boles, Donthu, and Lothia (1995) measured a salesperson’s efficiency to provide an overall ranking of the salesperson. They treated sales training, salary, management ratio, and territory potential as inputs for efficiency and percentage of quota attained, supervisor evaluation, and sales volume as outputs for efficiency (Boles, Donthu, and Lothia, 1995).

Horsky and Nelson (1996) suggested a procedure for evaluating the salesforce's size, allocation, and productivity by employing the more objective approach and benchmarking method. The use of multiple estimation results led to an improved understanding of the relationship between salesforce effort and profit. Unlike the past paper using only regression, the authors diagnosed the current optimal status and provided helpful insight for profit by utilizing an efficient frontier (Horsky, and Nelson, 1996).

Donthu and Yoo (1998) assessed retail productivity relative to best productivity using efficient frontier and DEA. The authors collected data from 24 stores of a fast-food restaurant chain in a metropolitan city over three years to calculate retail productivity scores. They regarded four inputs such as store size(squares yard), store manager experience(year), store location(in the mall or stand-alone), promotion expense($), and two outputs including financial output ($ sales), Customer-based output (satisfaction 5 point scale). In this study, customer satisfaction was considered an output variable not addressed in the past, eventually providing insightful information for employees to track productivity long-term (Donthu, and Yoo, 1998).

Marketing Communication Credibility and Efficiency

Luo and Donthu (2001) provided empirical efficiency of advertising and proposed ways to enhance advertising efficiency. The authors calculated 100 leading national advertisers' efficiency and 23 outdoor campaigns' efficiency showing there is also 'diminishing to marginal utility in advertising expenditure (Luo and Donthu, 2001).

Luo and Donthu (2006) also empirically showed that marketing expenditure positively impacts stock return using marketing communication efficiency. They combined advertising media expenditure and sales promotion expenditure as inputs and sales growth and corporate reputation as outcomes. Their study suggests that marketing effort is proven to have a still positive impact despite many critics and clarifies that "The more is, the better" cannot apply to marketing expenditure practice (Luo & Donthu, 2006).

Kim and Richarme (2009) extended the efficiency concept to evaluate internet service businesses such as Amazon.com, Yahoo.com, eBay.com, and others. They measured internet business service efficiency with total assets and the number of employees as inputs and the number of visits and sales as outputs. They found that this service business efficiency is positively related to a firm's profit (Kim and Richarme, 2009).

Kim and Prater (2011) operationalized the service marketing productivity of 17 U.S. domestic airline companies with an efficiency concept. They included the firm's annual asset, total cost, number of employees, and on-time performance as efficiency inputs while treating the reciprocal number of mishandled bags and the reciprocal number of oversold booking situations as outputs. The result showed that service marketing productivity is significantly associated with a firm's profit (Kim, and Prater, 2011).

Kim, Freling, and Eastman (2013) measured Super Bowl advertising efficiency to examine the relationship between advertising efficiency and a firm's financial performance. Super Bowl advertising efficiency was calculated with advertising inputs, including total advertising expenditure, frequency, number of brands advertised, total length and multiple inputs and Ad Meter score, and Nielsen viewership score as multiple outputs. The findings include that the more efficient Super Bowl advertisers enjoy a higher abnormal stock return (Kim, Freling, and Eastman, 2013).

Consumer and Firm Efficiency

Kamakura, Ratchford, and Agrawal (1988) broadened the quality and price relationship using market efficiency and the concept of characteristics of space. They measured efficiency based on brand, including product category with two different involvement levels: (low involvement: 16 C-size battery brands) and high involvement (82 Automobiles) from Consumer Report, demonstrating that the purchase of inefficient brands links to customer welfare (Kamakura, Ratchford, and Agrawal, 1988).

Bosworth, Mehdian, and Vogel (2003) connected the banking industry's efficiency to executive compensation, asset size, and profitability, demonstrating that executives of bank holding companies have an incentive to expand the size of their organization beyond the scale efficient level. Their study found a relationship between efficiency and executive compensation and investigated differences in executive compensation in terms of asset size (Bosworth, Mehdian, and Vogel, 2003).

Dutta, Narashiman, and Rajiv (2005) measured firm-specific capabilities using extant conceptualization in the resource-based view literature. In particular, the authors focused on conceptualizing and measuring research and development (R&D) capabilities to examine the relationship between market performance measures such as Tobin's *q* and the R&D capabilities (Dutta, Narashiman, and Rajiv, 2005).

Compensation Efficiency

The efficiency concept was adopted to estimate the fair pay of professional major league baseball players. Howard and Miller collected 433 non-pitching professional baseball players from the 26 U.S. major league teams from the 1990 edition of Baseball Register. They analyzed underpayment and overpayment inequity for each group by position and all players. The authors extended DEA (data envelopment analysis) to the domain of pay equity, providing objective estimates of pay equity (Howard, and Miller, 1993).

The measure of efficiency has offered a different perspective on the impact of performance on managerial firings and managerial hirings on organizational performance. Fizel and D'Itri (1999) attempted to answer if firing and hiring processes are directly linked to managerial efficiency. They obtained data from 147 college basketball (NCAA Division I) teams from 1984 to 1991 and measured managerial efficiency by considering the player talent and opposition power as inputs and winning percentage as output. The authors found that college basketball coach firing or hiring decision is not based on efficiency (Fizel, and D'Itri, 1999).

METHODOLOGY

Method

DEA has been used to address efficiency-related questions and topics. Unlike the regular regression analysis, DEA estimates an efficient frontier with applied linear programming (Charnes, Cooper, and Rhodes, 1978). DEA efficiency score was considered a guideline and benchmark for maximizing outcomes and minimizing costs simultaneously. The calculation logic of the efficiency score allows multiple inputs and multiple outputs, providing great flexibility in application.

In addition, DEA provides meaningful criteria for benchmarking and comparing with the most efficient achievers based on relative efficiency performance against the set of Pareto-efficient frontiers. Howard, and Miller (1993) produced MLB (Major League Baseball) players' efficiency score by treating stolen bases, game played, official at-bats, runs scored, hits, doubles, triples, home runs, runs batted in, batting average, putouts, assists, errors, and fielding average as multiple inputs with pay(salary) as single output (Howard, and Miller, 1993).

In this study, 'men's professional tennis player's efficiency was defined as efficiently converting the offense skill, defense skill, and mental ability into winning percentage, the number of total matches won, and the number of tournaments won. The authors collected men's professional tennis performance data (the year 2021) from the ATP (Association of Tennis Players) website (https://www.atptour.com/en/stats). This DEA application selects five performance inputs and three outputs to measure men's top hundred professional tennis players. Five inputs include 'Serve rating,' 'Return rating,' 'Under pressure rating,' the total number of matches played, and the total number of tournaments played, demonstrating player's offense capability, defense capability, and mentality.

For example, the efficiency of one player is obtained as a solution to maximize its efficiency subject to the efficiency of all players being less than or equal to 1. The solution produces the weights which are most favorable to player 1 and provides a measure of efficiency for player 1. This study follows the algebraic model given below to assess the performance efficiency of men's professional tennis players:

$$Max\ h_0 = \frac{\sum_r \text{weight}_r \ \text{Output}_r \ \ \text{Player}_1}{\sum_i \text{weight}_i \ \text{Input}_i \ \ \text{Player}_1}$$

$$\text{Subject to} \quad \frac{\sum_r \text{weight}_r \ \text{Output}_r \ \ \text{Player}_j}{\sum_i \text{weight}_i \ \text{Input}_i \ \ \text{Player}_j} \leq 1 \quad \text{for each Player}_j$$

$$\text{weight}_r, \ \text{weight}_i \geq \varepsilon$$

Data and application

ATP database shows that Roger Federer's Serve rating was 300.5, Return rating was 145.5, and Under pressure rating was 145.5, while Rafael Nadal's 278.9, 173.7, and 266.5 Novak Djokovic's 282.1, 172.8, and 241.2 respectively. Compared with Rafael Nadal and Novak Djokovic, Roger Federer outperforms in his serve capability, but he is weak in his serve return capability and Under pressure mentality. Rafael Nadal is predominantly the best in Under pressure mentality, and Novak Djokovic's three scores are in the middle of Roger Federer and Rafael Nadal, as shown in Table 1 (Appendix).

The total number of wins, winning percentage, and the total number of tournament-winning are outputs equivalent to the experience of winning. 89 out of the top 100 players are considered because players with missing values are eliminated from the DEA analysis. For example, players that quitted because of injury during the 2021 season or players that started the season late are removed from the DEA analysis. Descriptive statistics and correlations of DEA inputs and outputs appear in Table 2 (Appendix).

FINDINGS AND DISCUSSION

Most tennis fans might have heard about the GOAT (The greatest of all time) debate in men's tennis: Who is the all-time best tennis player? John McEnroe, a tennis legend, discussed that Novak Djokovic would be a GOAT because of his outstanding performance records, including the longest year-end number one ranking. Other experts still believe that Roger Federer is still the emperor of tennis as he plays beautifully and elegantly. However, since Rafael Nadal, the King of Clay, won his 21^{st} Grand Slam title in the Australian Open in 2022, he is one of the strong candidates for GOAT.

The authors used DEA Excel Solver to evaluate the efficiency score of men's professional tennis players for the year 2021. The efficiency score estimation was based on the individual player's five inputs and three outputs compared to other players. Table 3 (Appendix) presents each descriptive statistic and range of the player's efficiency score. The mean efficiency score is 0.761, which means that players used their 23.9% of performance inputs inefficiently. John Isner, Matteo Berrettini, Rafael Nadal, Novak Djokovic, Alexander Zverev, Jenson Brooksby, Kei Nishikori, and Roger Federer were among the eight most efficient players with the score of 1.0 based on our input-oriented constant return to scale (CRS) DEA. These eight players efficiently utilized their performance inputs to create more outputs. All of the Big 3 players recorded an efficiency score of 1. In contrast, the three least efficient players, including Guido Pella (0.43), Radu Albot (0.48), and Adrian Mannarino (0.49), wasted more than 50% of their inputs to achieve their performance outputs.

Then, the authors compared performance efficiency scores by tournament-winning experience. Figure 1 (Appendix) displays the efficiency score of players with winning tournament experience and players with no winning tournament experience during the 2021 season. The average efficiency score of 16 players winning at least two times is 0.90338, and that of 30 players winning at least once is 0.85315. Players with no tournament winning experience show their tournament efficiency score of 0.71737. Additional *t*-test result shows that the efficiency score of players with tournament winning experience (winning the tournament at least once) is significantly different ($p < .001$) from the efficiency score of players with no tournament winning experience.

The additional analysis was conducted to explore the relationship between the performance efficiency and the average total prize money. Table 4 (Appendix) displays the average total prize money in 7 different efficiency ranges. The most efficient group's average total prize money was $3,223,713, while the least efficient group's average total prize money was $665,574. Interestingly, the second most efficient group of players earned $171,944 more than the most efficient group. The least efficient group of players achieved $97,364 more prize money than the second least efficient group. Rather than a positive linear relationship, a more complicated relationship, for example, a quadratic relationship is expected between the performance efficiency and the player's compensation.

CONCLUSION

This study is the first to evaluate how efficient men's professional tennis players are in creating favorable performance outcomes. The DEA application demonstrates that not all men’s tennis players efficiently created desirable performance outcomes using their input capabilities. Roger Federer, Rafael Nadal, and Novak Djokovic, The Big 3 players, show the most efficient conversion of their performance inputs to performance outputs. The average efficiency score of players with tournament-winning experience in 2021 was significantly higher than that of players with no tournament-winning experience. The result illustrates a more considerable difference between the average efficiency score of players who won the tournament at least two times and the average of players who did not win the tournament, demonstrating that efficient players have a higher potential to win the tournament than inefficient ones. Therefore, the efficiency of men's professional tennis players is closely related to the number of tournament-winning experiences.

The next best efficient group of players, such as Stefanos Tsitsipas and Daniil Medvedev earned more prize money than the most efficient group in terms of efficiency score and the total prize money. This result demonstrates that being not too efficient may be more beneficial in earning prize money. The least efficient group won more prize money than the second least efficient group of players. Thus, the answer to the question 'More efficient, the higher prize money?' may not always be yes.

In spite, future research should investigate the relationship between the efficiency score and performance with the increased number of observations. This study can be extended to investigating how efficiency score affects performance outcome variables such as winning prizes, the number of tournament-winning, and the year-end ranking.

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APPENDIX

Table 1. Big 3 and other players' serve, return, and under pressure ratings

	Serve Rating	Return Rating	Under pressure Rating
Big 3 Players			
Roger Federer	300.5	145.5	225.7
Rafael Nadal	278.9	173.7	266.5
Novak Djokovic	282.1	172.8	241.2
The average score of other players than the Big 3	266.5	139.3	202.7
Highest player and his score	John Isner 317.2	Rafael Nadal 173.7	Rafael Nadal 266.5
The player with the lowest score and his score	Mikael Ymer 245.1	John Isner 101.0	Jaume Munar 165.3

Table 2. Descriptive Statistics of DEA Inputs and Outputs

	Mean	SD	X_1	X_2	X_3	X_4	X_5	Y_1	Y_2	Y_3
DEA inputs										
Serve (X_1)	266.9	13.9	1	-.344**	.311	0.136	-.391**	.303**	.488**	0.281
Return (X_2)	140.2	13.1		1	.400**	.242*	0.001	.366**	.383**	.396*
Under pressure (X_3)	204.3	19.9				0.198	-.223*	.402**	.544**	.407*
Total number of matches played (X_4)	41.2	14.8				1	0.183	.926**	.560**	.642**
Total number of tournament played (X_5)	30.5	8.6					1	-0.007	-.300**	-0.241
DEA outputs										
Total number of matches winning (Y_1)	22.9	12.1						1	.770**	.808**
Winning percentage (Y_2)	0.53	0.13							1	.728**
Total number of tournament winning (Y_3)	1.93	1.23								1

* $P < 0.05$
** $P < 0.01$

Table 3. Men's professional tennis player's performance efficiency score

Player	score	Player	Score	Player	Score
Adrian Mannarino	0.49	Felix Auger-Aliassime	0.85	Mikael Ymer	0.71
Albert Ramos-Vinolas	0.71	Filip Krajinovic	0.63	Miomir Kecmanovic	0.52
Alejandro D. Fokina	0.75	Frances Tiafoe	0.78	Nick Kyrgios	0.75
Alex de Minaur	0.73	Gael Monfils	0.72	Nikoloz Basilashvili	0.73
Alexander Bublik	0.75	Grigor Dimitrov	0.79	Novak Djokovic	1.00
Alexander Zverev	1.00	Guido Pella	0.43	Pablo Carreno Busta	0.94
Alexei Popyrin	0.81	Hubert Hurkacz	0.85	Pablo Cuevas	0.70
Aljaz Bedene	0.78	Ilya Ivashka	0.84	Pedro Martinez	0.64
Andrey Rublev	0.87	James Duckworth	0.77	Peter Gojowczyk	0.84
Arthur Rinderknech	0.77	Jan-Lennard Struff	0.66	Radu Albot	0.48
Aslan Karatsev	0.87	Jannik Sinner	0.87	Rafael Nadal	1.00
Botic van de Zandschulp	0.87	Jaume Munar	0.66	Reilly Opelka	0.74
Brandon Nakashima	0.83	Jenson Brooksby	1.00	Ricardas Berankis	0.66
Cameron Norrie	0.93	Jiri Vesely	0.67	Richard Gasquet	0.72
Carlos Alcaraz	0.78	John Isner	1.00	Roberto Bautista Agut	0.75
Casper Ruud	0.94	John Millman	0.65	Roberto Carballes Baena	0.64
Cristian Garin	0.74	Jordan Thompson	0.70	Roger Federer	1.00
Daniel Evans	0.70	Karen Khachanov	0.78	Sam Querrey	0.62
Daniil Medvedev	0.99	Kei Nishikori	1.00	Sebastian Korda	0.86
David Goffin	0.79	Kevin Anderson	0.82	Soonwoo Kwon	0.85
Denis Shapovalov	0.82	Laslo Djere	0.68	Stefano Travaglia	0.58
Diego Schwartzman	0.81	Lloyd Harris	0.83	Stefanos Tsitsipas	0.97
Dominic Thiem	0.72	Lorenzo Musetti	0.69	Steve Johnson	0.73
Dominik Koepfer	0.61	Lorenzo Sonego	0.75	Taylor Fritz	0.82
Egor Gerasimov	0.60	Mackenzie McDonald	0.76	Tennys Sandgren	0.57
Emil Ruusuvuori	0.66	Marco Cecchinato	0.62	Thiago Monteiro	0.68
Fabio Fognini	0.63	Marcos Giron	0.73	Tommy Paul	0.71
Federico Coria	0.63	Marin Cilic	0.85	Ugo Humbert	0.76
Federico Delbonis	0.71	Marton Fucsovics	0.78	Yoshihito Nishioka	0.66
Feliciano Lopez	0.59	Matteo Berrettini	1.00		
				Mean	0.761
				S.D.	0.129

Figure 1. Comparison of efficiency score by tournament-winning experience

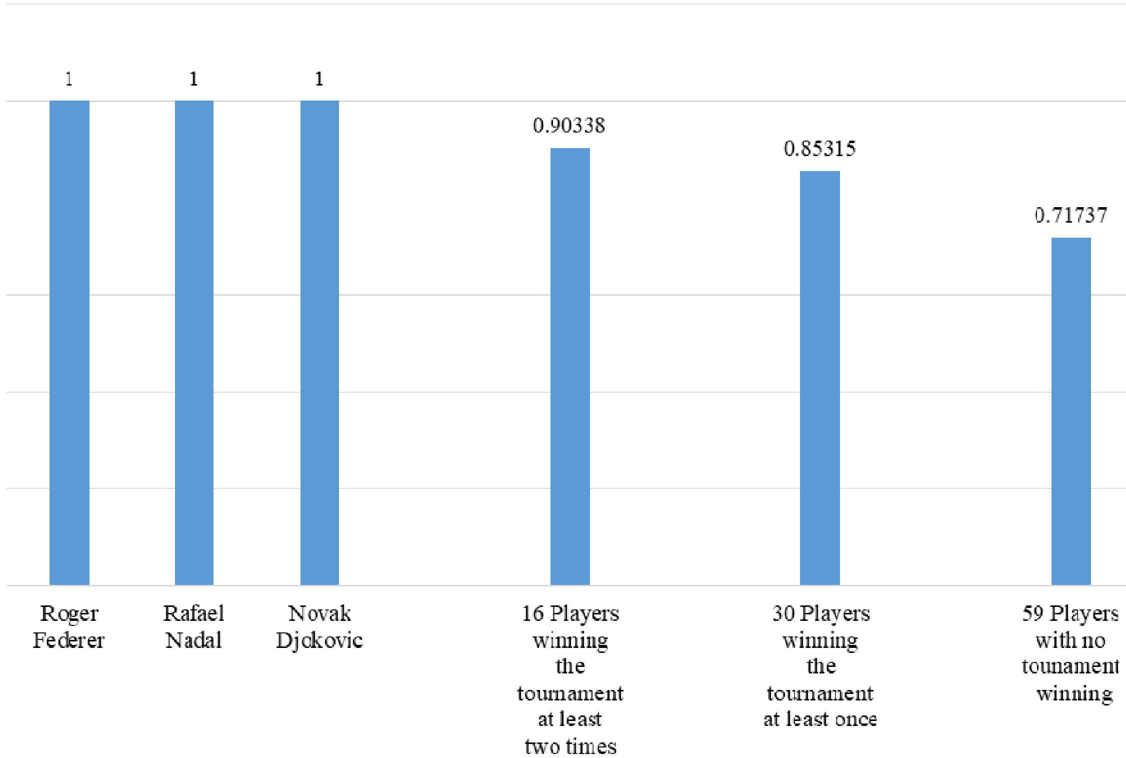

Table 4. Performance efficiency and the average total prize money

Efficiency Rage	N = 89	Examples of players	Average of total prize money
1.00	8	John Isner, Matteo Berrettini, Rafael Nadal, Novak Djokovic, Alexander Zverev, Jenson Brooksby, Kei Nishikori, Roger Federer	$3,223,713
0.9 ~ 0.99	5	Cameron Norrie, Stefanos Tsitsipas, Daniil Medvedev	$3,395,657
0.8 ~ 0.89	18	Diego Schwartzman, Andrey Rublev, Denis Shapovalov	$1,307,959
0.7 ~ 0.79	30	Carlos Alcaraz, Dominic Thiem	$863,857
0.6 ~ 0.69	20	Fabio Fognini, John Millman, Lorenzo Mussetti	$740,389
0.5 ~ 0.59	5	Feliciano Lopez, Adrian Mannarino, Tennys Sandgren	$568,210
0.4 ~ 0.49	3	Guido Pella, Radu Albot, Adrian Mannarino	$665,574