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A Note on the 'Linsanity' of Measuring the Relative Efficiency of National Basketball Association (NBA) Guards

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"A particular shot or way of moving the ball can be a player's personal signature, but efficiency of performance is what wins the game for the team." Pat Riley (ex-Knicks, Lakers, and Heat coach)

Abstract

This note examines the productive efficiency of 62 starting guards during the 2011/12 National Basketball Association (NBA) season. This period coincides with the phenomenal and largely unanticipated performance of New York Knicks' starting point guard Jeremy Lin and the attendant public and media hype known as *Linsanity*. We employ a data envelopment analysis (DEA) approach that includes allowance for an undesirable output, here turnovers per game, with the desirable outputs of points, rebounds, assists, steals, and blocks per game and an input of minutes per game. The results indicate that depending upon the specification, between 29 and 42 percent of NBA guards are fully efficient, including Jeremy Lin, with a mean inefficiency of 3.7 and 19.2 percent. However, while Jeremy Lin is technically efficient, he seldom serves as a benchmark for inefficient players, at least when compared with established players such as Chris Paul and Dwayne Wade. This suggests the uniqueness of Jeremy Lin's productive solution and may explain why his unique style of play, encompassing individual brilliance, unselfish play, and team leadership, is of such broad public appeal.

JEL codes: D19, C14, C61, M59, L83

Keywords: Data envelopment analysis, technical efficiency, basketball players, undesirable output, national basketball association

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1. Introduction

Jeremy Lin, New York Knicks starting point guard, Harvard economics graduate, and the first player of Taiwanese descent in the National Basketball Association (NBA), has thrilled the US and the world with an average of more than 27 points, 8 assists, and 2 steals per game in his first four starts. Leading his team to four successive victories in the 2011/12 season in his first week as starting point guard earned him Eastern Conference player of the week as well as two straight *Sports Illustrated* covers—joining the likes of Dirk Nowitzki of the Dallas Mavericks and Michael Jordan (former Chicago Bulls player) with dual distinctions. Dubbed *Linsanity* (currently with more than seven million Google hits), Lin has become a phenomenon since he made history by scoring 89 points in his first three starts. This is the most of any player since the NBA–American Basketball Association (ABA) merger in 1976/77, exceeding both LeBron James in his first three starts, and rivalling such legends as Michael Jordan and Larry Bird.

However, the fascination with *Linsanity* goes beyond mere playing statistics. Lin never received a basketball scholarship out of high school and went undrafted in the 2010/11 NBA draft. He was a benchwarmer in his previous teams, played minimal minutes, and was waived off the rosters of several teams after his first year in the NBA. Indeed, prior to the start of the 2011/12 season, Lin was playing in the NBA D-league. But since February 4, when he came off the bench and led New York to victory over New Jersey scoring 25 points and handing out 7 assists in 36 minutes of playing time, he has become the Knicks' starting point guard.

Linsanity has since moved beyond the basketball court into the world of business. Adubato (2012) at nj.com argues that leaders and professionals in all arenas can learn from Lin's can-do attitude, unselfishness, humility, and ability to recognize the achievements of his teammates. Gorrell (2012) in the *Huffington Post* maintains Lin's story is all about the importance of diversity in business and the infectious nature of success, while Crecenzo (2012) in *Entrepreneur* suggests "…the talent universe is full of overlooked people [like Lin], shunned for reasons of geography, status or background". Lastly, Jackson (2012) in *Forbes* asserts that Lin's success is proof that it is "…always better to be a first-rate version of yourself, instead of a second-rate version of somebody else", to believe in yourself, and to seize opportunity when it comes up.

Paradoxically, Lin is not without his critiques, as exemplified by Neil Paine at *Sports Illustrated*. Paine (2012), of course, lauds Lin's "…phenomenal ability to get to the basket" and natural playmaking ability, maintaining that his "…quick first step and attacking style naturally lead to a large number of free throws, which are great for enhancing offensive efficiency":

> [E]fficiency has definitely been the name of Lin's game during his recent run. His true shooting percentage, which measures the average number of points a player generates per possession when he shoots, compares favourably to that of other star players…only two players [Lakers' Kobe Bryant and the Thunder's Russell Westbrook] shoulder a greater proportion of their team's offensive burden than Lin has this season, and Lin's offensive efficiency is considerably better. The only players in the NBA to use more than 30 percent of team possessions and post better efficiency marks than Lin? Heat teammates [LeBron James and Dwyane Wade]. So, offensively, Lin is in elite company.

However, as Paine continues, "It's also fair to point out Lin's propensity for turnovers. This season, 21.8 percent of Lin's individual possessions have ended with him committing a turnover, 16th most among guards with at least 159 minutes. Lin's turnovers tend to come in bunches, too. He already has two eight-turnover games, to go with three more games in which he turned the ball over six times". Lin himself concedes as much. After the Knicks' win against

Sacramento, Lin said his greatest challenge thus far was to find ways to be efficient with the minutes given and to avoid turnovers. This is especially noteworthy in the Knicks' following game, which they lost to New Orleans 89–85, when Lin had nine turnovers, tying for the most in the 2011/12 season.

Inspired by these and other comments, the purpose of this note is to provide a timely and comprehensive assessment of Jeremy Lin's basketball playing efficiency. Fortunately, research in sports economics has recently embraced econometric and mathematical methods for the study of sporting efficiency, an important development as these empirical relationships are useful for making decisions on, among other things, hiring, play positions, and salaries. Beginning with work by Scully (1974) on baseball and Thomas *et al.* (1979) and Zak *et al*. (1979) on basketball, successive works have estimated team production functions in an effort to quantify the relationship between sporting inputs and sporting success. Subsequently applied to many sports, including soccer (Dawson *et al.* 2000a, 2000b; Carmichael *et al.* 2001; Hass 2003; Espitia-Escuer and Garcia-Cebrian 2004; Barros and Leach 2006a, 2006b, Barros *et al.* 2009), rugby league (Carmichael and Thomas 1995), baseball (Mazur 1994; Ruggerio *et al.* 1996; Einholf 2004, Kang *et al.* 2007; Lewis *et al.* 2007), and American football (gridiron) (Hadley *et al.* 2000; Hofler and Payne 1996) of particular relevance are those concerning basketball. These include Chatterjee *et al.* (1994), Hofler and Payne (1997, 2006), Berri (1999), McGoldrick and Voeks (2005), Lee and Berri (2008), Rimler *et al.* (2010) and Katayama and Nuch (2011). However, unlike nearly all of this research, we choose to focus on individual player efficiency.

The remainder of the note is structured as follows. Section 2 briefly describes the conceptual framework and the data used in the analysis. Section 3 explains the methodology, and Section 4 reports the results. Section 5 concludes the paper.

2. Conceptual framework and data specification

To measure the efficiency of a player, we need to specify an appropriate production process in which measurable inputs transform into measurable outputs. For instance, Lee and Berri (2008) considered the number of basketball wins as an output, which in turn is dependent on inputs such as points per possession employed and the points surrendered per possession acquired. Likewise, Berri (1999) measured a player's value by considering inputs such as points, rebounds, and steals, etc. and including the number of team wins. This model suggests that the number of wins influences a player's efficiency or value. However, unlike individual sports where a win is largely dependent on an individual's performance, basketball is a team sport, which suggests that the performance of all players must be included in the production model to determine a win. In our framework, we measure a player's contribution based on his own inputs and outputs, rather than those of the team. This may or may not correspond with team success.

Consequently, our analysis measures the efficiency of point and shooting guards (collectively guards). The point guard and shooting guard, two of the five standard positions in a regulation basketball game are typically the team's best ball handlers and passers. The point guard is a position equivalent to that of the midfielder in soccer, the quarterback in American football (gridiron), the halfback in rugby league, or the centre in ice hockey, in that the player is responsible for directing plays and passing the ball as well as scoring. For this reason, the point guard should fully understand and implement the coach's game plan and the team's overall strategy and is a primary determinant of the team's ability to win games. By way of comparison, the shooting guard's main objective is to score points, but may also serve as the ball handler, exemplified, for example, by Kobe Bryant of the Los Angeles Lakers and Jason Terry of the Dallas Mavericks. Recent years have seen an increase in the number of shooting guards being point guards and vice-versa. Point guards as shooting guards include players like Derrick Rose of the Chicago Bulls and Russell Westbrook of the Oklahoma City Thunder. Because of the interchangeableness of the roles, it is difficult to ascertain which players are truly point guards and/or shooting guards, so our sample considers all guards.

All our data are from the official NBA website (www.nba.com). We specify the outputs based on a player's overall contribution to game play. These are points per game (PPG) (scoring with field goals or free throws), rebounds per game (RPG) (gaining possession of the ball after a missed field goal or free throw), assists per game (APG) (passing the ball to a teammate in a way that leads to a score), steals per game (SPG) (legally causing a turnover to gain possession of the ball), and blocks per game (BPG) (legally deflecting a field goal attempt). These five outputs are positive outputs associated with superior guard performance, though the weighting or emphasis placed on each output will of course vary throughout the game. For instance, points are a better indicator of offensive play while steals are a better measure of defensive play. In addition, we include turnovers per game (TOPG), which is a negative or undesirable guard output, as this is associated with the team turning from offensive to defensive play. The single input in our model is minutes per game (MPG). Actual play in the NBA comprises 12-minute quarters in a 48 minute game, but after including half-time, timeouts, fouls, and close games, a basketball game typically lasts around 2½ hours. Ideally, a guard would maximize the positive outputs and minimizing the negative output given the feasible resource limit of time in play.

Using this framework, we need to ensure that our dataset allows for an appropriate comparison. First, we include only guards in our analysis. This is because our behavioural assumption (i.e. the specification of inputs and outputs) differs markedly depending on the player's position and responsibilities, in turn depending on archetypical physical attributes and mental capabilities. This ensures we compare like with like. Second, we only include players who have played 19 games or more as a starter. We base this threshold on the number of games for which Lin has been a starter (that is, playing from the start of the game, and usually an indicator of the player's importance in the team). We only consider starters as it is only from when Jeremy Lin became a starter that he performed most outstandingly. Hence, of the 128 guards in the NBA, 62 are eligible for inclusion in our sample. Finally, as we focus on the *Linsanity* phenomenon that began in February 2012, we restrict ourselves to a cross-sectional analysis of the 2011/12 season.

<TABLE 1 HERE>

Table 1 provides selected descriptive statistics for the guard input and outputs as sampled. As shown, the typical NBA starting guard is on the court for 31.68 minutes, scoring 13.83 points, making 3.35 rebounds, providing 4.42 assists, 1.18 steals, and 0.29 blocks. The guard also turnovers the ball to the opposing team 2.15 times. Of the variables included, the most variable as measured by the coefficient of variation is blocks per game and the least variable is minutes per game. By way of comparison with the focus of our analysis, Jeremy Lin is in the upper quartiles for minutes (35.70), points (19.40), assists (8.40) and steals (2.40) per game. Less well, he is only in the next-to-upper quartile for rebounds per game (3.60) and the next-to-lower quartile for blocks per game (0.26). Most troublingly, Jeremy Lin also has the most turnovers (5.10) per game in the entire sample.

3. Methodology

We use a mathematical programming approach to calculate the productive efficiency of NBA starting guards, including Jeremy Lin. The mathematical programming approach seeks to evaluate the efficiency of a decision-making unit (here a player, but also an organisation or team) *relative* to other decision-making units in the same area (here other players, but also industries or sports). The most commonly employed version of this approach is a linear programming tool referred to as 'data envelopment analysis' (DEA). DEA essentially calculates the economic efficiency of our given player relative to the performance of other players producing the same outcomes, rather than against some theoretical or idealised standard of performance.

One obvious problem with DEA is that in contrast to the econometric approaches to efficiency measurement it is both nonparametric and nonstochastic. Thus, we make no accommodation for the types of bias resulting from environmental heterogeneity, external shocks, measurement error, and omitted variables. Consequently, we assess the entire deviation from the productive frontier as being the result of inefficiency. This may lead to either an under or over-statement of the level of inefficiency. However, there a number of benefits implicit in DEA that makes it attractive on a theoretical level. First, given its nonparametric basis, it is relatively easy to alter the specification of inputs and outputs and thereby the formulation of the production correspondence relating inputs to outputs. Second, when using the econometric approach, we impose considerable structure upon the data from stringent parametric form and distributional assumptions regarding both inefficiency and, in the case of stochastic frontiers, statistical noise. These considerations, and the natural emphasis of DEA on the notion of 'best-practice' performance, make it an attractive choice in our chosen context.

More specifically, we employ Seiford and Zhu's (2002) data envelopment analysis (henceforth SZ-DEA) framework that deals with both desirable and undesirable outputs concurrently. SZ-DEA has been used in recent studies such as Lu and Lo (2007) on regional development in China, Chin and Low (2010) on port performance and Yeh *et al*. (2010) on comparisons of energy utilisation efficiency between China and Taiwan. Under basketball conditions, we can view individual efficiency in terms of the utilisation of ball possession with the aim of maximising points and other contributions while minimising the number of turnovers. This suggests increasing the desirable output (Y^g) while reducing the undesirable output (Y^b) which follows the linear monotone decreasing transformation in Seiford and Zhu (2002) based upon the classification invariance concept in Ali and Seiford (1990). Seiford and Zhu's (2002) approach helps preserve the linearity and convexity of the DEA model. Starting with the following DEA data domain:

$$\begin{bmatrix} Y \\ -X \end{bmatrix} = \begin{bmatrix} Y^g \\ Y^b \\ -X \end{bmatrix} \tag{1}$$

where Y^g and Y^b represent the corresponding desirable and undesirable outputs and X represents the input. To increase Y^g while reducing Y^b, Seiford and Zhu (2002) multiplied each undesirable output by negative one and then find a proper translation vector value w to convert all negative undesirable outputs into positives ($Y^{-b} = -Y_j^b + w > 0$) which results in the following domain:

$$\begin{bmatrix} Y \\ -X \end{bmatrix} = \begin{bmatrix} Y^g \\ Y^{-b} \\ -X \end{bmatrix} \tag{2}$$

Based upon (2), we then use Banker *et al.* (1984) model to modify the following linear program:

$$
\begin{aligned}
& \max \theta \\
& s.t. \quad \sum_{j=1}^{n} z_j y_j^g \geq \theta y_o^g, \\
& \qquad \sum_{j=1}^{n} z_j y_j^{-b} \geq \theta y_o^{-b}, \\
& \qquad \sum_{j=1}^{n} z_j x_j \leq x_o, \\
& \qquad \sum_{j=1}^{n} z_j = 1, \\
& \qquad z_j \geq 0, \quad j = 1, \ldots, n.
\end{aligned}
\tag{3}
$$

Here, θ is the efficiency score of the DMU, Y^g and Y^b are the j-th desirable and undesirable outputs, respectively, x_j is the j-th input and z_j is the weight of j-th player, and x_o and y_o represent the input and output vectors for all players.

To investigate better the impact of undesirable outputs on starting guard productive efficiency, we model two separate cases. All cases have the same set of inputs, but different sets of outputs. In the first case, we restrict the outputs to only the desirable outputs (PPG, RPG, APG, SPG, and BPG). The second case takes into account both desirable and undesirable outputs; that is, we also include TOPG.

4. Results

Table 2 provides the efficiency scores and ranks for each player using the above method. An efficiency score of one indicates that the player is efficient and therefore lies on the best-practice productive frontier. Note that the production frontier reflects different combinations of the inputs with the weights determined by the sample data, such that different players on the frontier are engaging in different productively efficient behaviour. For example, one player may be efficient because of a relatively large number of defensive plays while another may be efficient because of their offensive play in scoring points. In general, a larger number of outputs imply greater opportunity for efficient behaviour, and in turn, more players defining the frontier. A player with an efficiency score more than one indicates that a player can improve his efficiency by modifying his production process in order to reach the production frontier along the closest path defined by the direction vector.

<TABLE 2 HERE>

If we consider the model including only desirable outputs, 19 of the 62 players (30.6 percent) are efficient with a mean level of inefficiency of 19.2 percent (= 1.192 – 1). As our model is output-orientated, focus is on the equiproportionate augmentation of outputs relative to inputs. Accordingly, the average NBA starting guard would have to increase his desirable outputs by 19.2 percent to place him on the best-practice productive frontier. The most inefficient player is Ray Allen (1.645 or 64.5 percent inefficient). However, when we include undesirable output (turnovers) in the model, 26 players are efficient, including all of the players judged efficient with only desirable outputs. By considering undesirable outputs in the model, eight additional players are efficient largely because while their input and desirable output numbers may not be as high, their undesirable output is sufficiently low to place them on the frontier. The mean level of efficiency is lower when we take account of the undesirable outputs, with the typical NBA point guard being 3.7 percent inefficient relative to best practice.

This can work both ways. For example, Arron Affalo's efficiency substantially improved after we considered the undesirable output from 61.9 percent inefficient to just 1.2 percent inefficient, increasing his rank from 60th to 31st. In contrast, the efficiency of Tyreke Evans improved in terms of level (3.9 to 2.3 percent) but his ranking fell (from 25th to 37th). Similar to Färe *et al.* (1989), our results confirm the same findings that standard DEA method fails to credit DMUs for undesirable output reduction, and this potentially distorts the true measured efficiency. We can see that Jeremy Lin is fully efficient in both models.

<TABLE 3 HERE>

Table 3 details the potential improvements for each inefficient player needed to achieve overall efficiency using the model including the undesirable output of turnovers per game (the model more favourable to players). This shows the percentage changes required to reduce the undesirable output or/and increase the desirable outputs relative to the level of input. For example, Deron Williams can improve his overall efficiency by increasing his minutes played (MPG) by 14.7 percent (= 1 – 0.853), reducing his turnovers (TOPG) by 2.5 percent (= 1 – 1.025) and increasing his blocks (BPG) by 82 percent (= 1 – 0.180). Alternatively, Anthony Parker could maintain the same level of input in terms of minutes played, and focus instead on increasing his outputs in terms of points (by 62.1 percent), rebounds (by 60.3 percent) and steals (by 89.5 percent). Obviously, some of these improvements may be feasible in theory, but infeasible in practice, given the player's endowments and game conditions.

Table 4 provides information on the benchmark players used to determine the efficiency improvements needed for the inefficient players in Tables 2 and 3. Note that the benchmark players are not equally weighted. For example, Deron Williams' benchmarks (percentage of target needed) are Derrick Rose (77.8 percent), Chris Paul (10.3 percent), Jeremy Lin (10.7 percent), and Steve Nash 1.2 percent). Note 77.8 + 10.3 + 10.7 + 1.2 = 100 percent. Clearly, of the benchmark players needed for Deron Williams to improve his performance, the most important to observe and target is Derrick Rose as his (efficient) combination of inputs and outputs is closest to Deron Williams' existing (inefficient) combination and therefore the easiest to imitate in terms of an efficiency improvement.

<TABLE 4 HERE>

While any efficient player can potentially serve as a benchmark, in practice only a smaller subset typically comprise the optimal benchmark solution. This is quite telling in that the most important point guards in terms of defining efficiency improvements (number of player benchmarks set) are Chris Paul (29), Dwayne Wade (22), Jared Dudley (16), Daequan Cook (14) and Jose Calderon (14). We could then say with some justification that the productive behaviour of these five point guards epitomises the NBA at its best. Surprisingly, Jeremy Lin with just four benchmarks accounts for only a small percentage of the optimal lambdas, suggesting that in both absolute and relative terms his unique performance as defined by *Linsanity*, while technically efficient, is neither feasible nor desirable for the majority of inefficient point guards in the NBA. The exceptions are Deron Williams (10.7 percent), Russell Westbrook (22.6 percent), Stephen Curry (5.9 percent), and Monta Ellis (1.6 percent). This possibly emphasises the uniqueness of his productive solution, encompassing as it does exemplary performance in points, assists and steals, moderate performance in rebounds and blocks, and rather lacklustre performance in turnovers. A study by John Hollinger (ESPN) also showed similar results that Lin was in the top ten most efficient NBA point-guards in the 2011/2012 NBA season based on the Player Efficiency Rating (PER)[1].

[1] The PER sums up all a player's positive accomplishments, subtracts the negative accomplishments, and returns a per-minute rating of a player's performance.

As DEA is non-parametric and lacks statistical inference, we test the reliability and robustness of our results by employing Spearman's correlation rank test similar to Friedman and Sinuany-Stern (1998). The ranking for each model is based on the efficiency scores derived for each player from the models DEA and SZ-DEA. In essence, the correlation coefficient (r_s) is derived from the ranks of the observations between the two models. The r_s has a range between 1 and -1, whereby a value of 1 (-1) indicates perfectly positive (negative) rank-order association, while $r_s = 0$ indicates no association exists. Our coefficient was 0.676 (t-statistic = 7.11) and statistically significant at 5 percent level which suggests a strong positive correlation between these two models indicating consistency in rankings.

5. Concluding remarks

This note examined the individual player performance of starting point guards in the NBA during the 2011/12 season, a period personified by the *Linsanity* phenomena. Using DEA, we measured the productive efficiency of 62 guards using an input–output specification encompassing both desirable and undesirable inputs. The results indicate that between 29 and 42 percent of NBA guards are fully efficient, including Jeremy Lin, with a mean inefficiency of 3.7 and 19.2 percent. However, while the phenomena that is Jeremy Lin and that spawned *Linsanity* is technically efficient, he seldom serves as a benchmark for inefficient players, at least when compared with players such as Chris Paul and Dwayne Wade. This necessarily reinforces the uniqueness of Jeremy Lin's productive behaviour and perhaps highlights why his unique style of play, encompassing individual brilliance, unselfish play, and team leadership, is of such broad public appeal.

Of course, the analysis does have some limitations and these provide useful directions for future research. First, due to the input–output specification, the study is limited to Spearman's correlation rank test, although bootstrapping as suggested by Simar and Wilson (1998) would have been more appropriate. It is also likely that a smaller number of outputs would mean that fewer players define the efficient frontier. With some qualifications, this could more finely distinguish between efficient and inefficient players given that the broad specification used in this analysis permits such a wide range of potentially productive behaviour. Second, we focused only on individual player efficiency compared with the more common analysis of team-level efficiency with its natural focus on win and losses. One future direction would be to integrate these two hitherto separate areas such that individual player efficiency would nest within team efficiency in much the same manner as the performance of a business division or group nests with overall corporate performance.

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Table 1. Selected descriptive statistics

Statistic	Input	Outputs					
		Positive					Negative
	MPG	PPG	RPG	APG	SPG	BPG	TOPG
Mean	31.682	13.827	3.355	4.427	1.177	0.286	2.148
Std. dev.	4.224	5.104	0.938	2.565	0.506	0.223	0.957
Coef. of variation	0.133	0.369	0.280	0.579	0.430	0.780	0.446
Minimum	22.400	3.200	1.500	0.300	0.400	0.030	0.400
First quartile	29.450	10.500	2.700	2.200	0.800	0.133	1.600
Median	32.600	13.500	3.300	4.100	1.000	0.265	2.000
Third quartile	35.100	17.100	3.775	6.150	1.500	0.350	2.700
Maximum	38.900	29.000	5.700	11.100	2.500	1.300	5.100

Notes: MPG – minutes per game, APG – assists per game, PPG – points per game, SPG – steals per game, RPG – rebounds per game, BPG – blocks per game, – TOPG turnovers per game.