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The relationship between concentration of scoring and offensive efficiency in the NBA

Abstract: In this research we study the relationship between concentration of scoring production (measured with the Gini index of team points) and teams' offensive efficiency (measured as normalised team points per minutes played and possessions) in the game of basketball. We record the aggregate box-score statistics of all teams from the 1977/1978 to the 2010/2011 seasons in the NBA, together with each player's contribution to his respective team's offensive production. After applying a fixed effect regression model, we find evidence of a positive relationship between concentration of production and offensive efficiency, which contradicts some recent thesis (Skinner, Brian. 2010. "The Price of Anarchy in Basketball." *Journal of Quantitative Analysis in Sports* 6:Article 3) about the nature of this association. Our results suggest that that the well known mass-media concepts such as "big three" or "big four" to design successful teams make sense. Teams with more talent and with several big stars will (probably) increase its concentration of scoring, and this will be associated with an increase in its offensive efficiency.

Keywords: basketball; concentration of scoring; fixed effect regression model; offensive efficiency.

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1 Introduction

In a recent study, Skinner (2010) proposed a controversial way of improving the offensive performance of basketball teams. Based on studies of the price of anarchy in traffic networks, Skinner (2010) described a phenomenon called "Braess's Paradox." This paradox has apparently been observed in a number of major cities like New York, San Francisco and Stuttgart, where closure of a major road led to almost immediate improvements in traffic flow. Skinner (2010) suggested with his equations that the same principle can be applied to basketball, and that teams could maximize their offensive efficiency if they concentrate their shots less, i.e., if teams distribute their shots more equally among players. After using a network structure approach, a similar related result was recently found by Fewell et al. (2012); the more successful teams distributed decision making about ball movement beyond a centralized leader.

Although Skinner (2010) honestly admitted that his research provides no strong statistical evidence of his hypothesis, and even that his proposal does not necessarily reflect an actual basketball phenomenon, his study encouraged other investigators to empirically approach this phenomenon using real basketball data, in order to establish an association between concentration of production and offensive efficiency in the game. It is also important to note that, similar to Skinner (2010), Fewell et al. (2012), also admitted the inability of its study to empirically test the hypothesis suggested. Skinner's (2010) work is purely theoretical, and only constructs plausibility arguments by making ad hoc assumptions about the relationship between production and efficiency for a team and its "star player." The optimum level to which a star player should be used is therefore a function of that player's skill level and that of his teammates, and in principle the optimum usage for a star player can be arbitrarily larger. However, an extension of the corollary of his research could be that the offensive performance of basketball teams would increase if point concentration decreases, i.e., if many players score few points, instead of a few players scoring many points.

This form of planning a team's offensive performance is certainly unreal for professional basketball. In the 2010–2011 season of the NBA, for instance, the mean percentage of points scored and shots attempted by each team's most outstanding player was 19% and 18%, respectively, for the league's 30 teams. A single player was therefore responsible for nearly 20% of each team's production. Furthermore, if we consider each team's three most outstanding players, those percentages increase to 46% and 45%, respectively; only a few players per team hoarded a large portion of their offensive production during an NBA season. Berri and Schmidt (2010) performed a similar analysis that focused not on scored points but on the wins down to each particular player. They showed that, from 1978 to 1998, 80% of NBA wins came from only 22.6% of the players, which is practically consistent with Pareto's Law. If the analysis is restricted only to championship-winning teams, on average, 73.1% of all wins were attributed to only each team's 3 most outstanding players.

Although the wins produced metric (Berri 2008) is probably the player performance index most accepted in academic literature about the economy of sports (Berri and Bradbury 2010), it aggregates in a single index several player statistics other than points (rebounds, assists, steals, missed shots, fouls, turnovers, blocks) and has several limitations (Martínez 2012). Because wins produced combines numerous aspects of the game in a single metric, it mixes "apples and oranges," because it fails to properly separate production, i.e., points made, from the factors determining production. We therefore believe it is more appropriate to analyze the proposal by Skinner (2010) to only consider points scored by players. Consequently, we follow the perspective of Martínez (2012) about considering points made (scoring) as production, without diminishing other views of the concept of production referred to more complex measure of performance.

The objective of our research is to analyze the relationship between concentration of scoring production and offensive efficiency in basketball teams. We studied data from 33 NBA seasons (from 1978 to 2011), by the implementation of a fixed effect panel model to take team heterogeneity into account. Once controlled by different covariates, our research shows that there is a positive association between teams' concentration of production and offensive performance. We empirically show that the postulates made by Skinner (2010), and then reinforced by Fewell et al. (2012), do not match the evidence. Furthermore, our results strongly contradict Skinner's thesis (2010).

2 Methods

2.1 Data

We collected data from www.basketball-reference.com, a free source of NBA statistics. We recorded the aggregate box-score statistics of all teams from the 1977/1978 to 2010/2011 regular seasons, together with each player's contribution to his team's offensive production. The reason for starting with the 1977/1978 season is because some box-score statistics, such as turnovers, are not available before that time. Turnovers are necessary to estimate team possessions. Also, the 1998/1999 season was dropped from the database because of the lock-out, as teams only played 50 games that season, instead of the 82 games played in the others. The final data set comprised 14,023 players nested in 879 teams along 33 seasons.

2.2 Variables

The aim of this research is to analyze the relationship between teams' concentration of production and offensive performance. However, we must consider other covariates in order to control by other factors which could potentially influence offensive efficiency. We now identify and explain the variables finally selected to implement our statistical model:

– *Offensive efficiency:* this variable, OE, reflects the offensive production of teams. To estimate the possessions of each team we employed the approximate formula explained by Berri (2008): points normalized by minutes played and possessions, i.e., Points/(Minutes played*Possessions). In order to improve the interpretation of this variable we multiplied by the mean number of minutes played by teams each season (19,818) and the mean number of possessions by teams each season (7807), and then we divided by 82 games. Therefore:

$$OE_{team}=\frac{Pts_{team}}{Minutes_{team}\cdot Possessions_{team}}\times\frac{Minutes_{League\ average}\cdot Possessions_{League\ average}}{82}.$$

This normalization makes this variable comparable among teams, because not all teams play the same number of minutes per season due to extra-time games, and all teams do not have an equivalent offensive pace as some teams play faster than others.

– *Concentration of production:* The Gini index, GI, is one of the most popular measures of concentration. GI is based on the Lorenz curve. It can be calculated as:

$$GI=\frac{2}{n^2\bar{y}_t}\sum_{s=1}^{n}s(y_{st}-\bar{y}_t)$$

where n is sample size (in our case is the number of players in a basketball team), y_{st} is the number of points scored by player s in year t (with $y_{st}<y_{s+1,t}$), and $\bar{y}_t$ is the mean number of points scored by the team (by simplicity we avoid the sub index i to differentiate teams). The Gini index is bound by $0\le GI\le 1$ being GI=0 in the case of equi-distribution

and GI=1 in case of maximum concentration of production.

- *Establishment of salary cap:* In the 1984/1985 season, the NBA approved new rules to try to balance both the competition and teams' profits. Before then, teams were free to spend money to sign and wage players. Although teams are not forced to respect the salary cap, they have to pay taxes to the league if it is exceeded. We believe that the salary cap could influence variations in teams' offensive performance, because the distribution of wages for players depends on changes in the collective bargaining agreement once the salary cap is applied (Hill and Jolly 2012). Thus, the competition is affected in a major or minor way by legislation concerning salaries and the work conditions of players and teams.
- *Presence of the 3-point line:* In 1979/1980, the NBA agreed to play with new offensive rules. Shots made behind this line would score three instead of two points. Obviously, this could influence teams' offensive performance. During the 1995, 1996 and 1997 seasons the 3-point line was drawn in a different form, shortened to homogeneous 6.70 m around the arc, in order to stimulate offensive playing. However, the NBA returned to the initial status in 1998 (with a non-homogeneous distance varying from 6.70 m at the sidle to 7.24 at the top).
- *Number of teams in the league:* The number of franchises in the NBA grew from 22 (1978) to 30 (2011). This led to a multiplication of players. Some analysts believe that this growth impoverished the league's global talent, while others believe that the use of foreign players has compensated for that hypothetical loss.
- *Legalization of zone defense:* In the 2001/2002 season, zone defense was legalized, and teams could implement other than individual defense strategies. Zone defense could affect the opponent's offensive performance regarding attempted 3-point shots, for instance, and hence the likelihood of high scores.

2.3 Model and estimation

Data about concentration of production and offensive efficiency were recorded for each team and season, in a classic panel structure. The cross-sectional part of the panel consists of *N* clusters (teams) and the longitudinal part consists of *T* years (seasons). This temporal dependency yields correlated residuals. The proposed model is as follows: We define Y_{it} (i=1, …, N=30; t=1, …, T=33), as the offensive efficiency of each team i in season t. In order to explain the variation of Y_{it} we use a set of p covariates X_j (j=1, …, p). The model can be written as:

$$Y_{it}=\sum_{j=1}^{p} X_{it}^{j} B_j+u_i+e_{it}$$

where X_{it}^{j} reflects the set of p covariates (j=1, …, p) for the team i and the season t, B_j reflects the effects of the p covariates (j=1,…, p) on the offensive efficiency, u_i reflects non-observable team effects (fixed or random), and e_{it} reflects the remaining non-systematic effects, also called white noise. e_{it} is assumed to be independent and normally distributed. Therefore, data pertaining to the different seasons are nested in each specific cluster (team).

We decided to estimate a fixed effect model instead of a random effect model for the following reasons: first, u_i reflects the effect of a population of i teams instead of a sample of them (Rabe-Hesketh and Skrondal 2012); secondly fixed effects reflect the heterogeneity of teams, because of a previously known structural difference (Spanos 2011). For example, the size of each team's markets depends on the city where the team is located, and this affects ticket pricing and is also associated with players' wages. Thirdly, there are missing variables that reflect the specific characteristics of each team that do not vary over time, so variations in offensive efficiency depend on causes other than the fixed variables for each cluster (Stock and Watson 2007). These variables can be correlated with the model's covariates. For instance, some variables such as teams' historical importance or the size of their budgets are usually stable over time. These unmeasured variables are specific to each team, and may be correlated with concentration of production, because of their relevance for the composition of team rosters and wages paid.

3 Results

We first show the evolution of concentration of production and offensive efficiency over time (Figure 1A,B), together with the evolution of the mean values of the two variables (Figure 2)

These figures show that concentration of production and offensive efficiency are very heterogeneous among teams (Figure 1A,B), but, at the mean value, concentration of production has a slight tendency to grow with time (Figure 2). However, this pattern of growth is less evident for offensive efficiency, because mean offensive efficiency started to decrease in the mid-1990s. However, the mean value of teams' offensive production has started to grow again in the last few years.

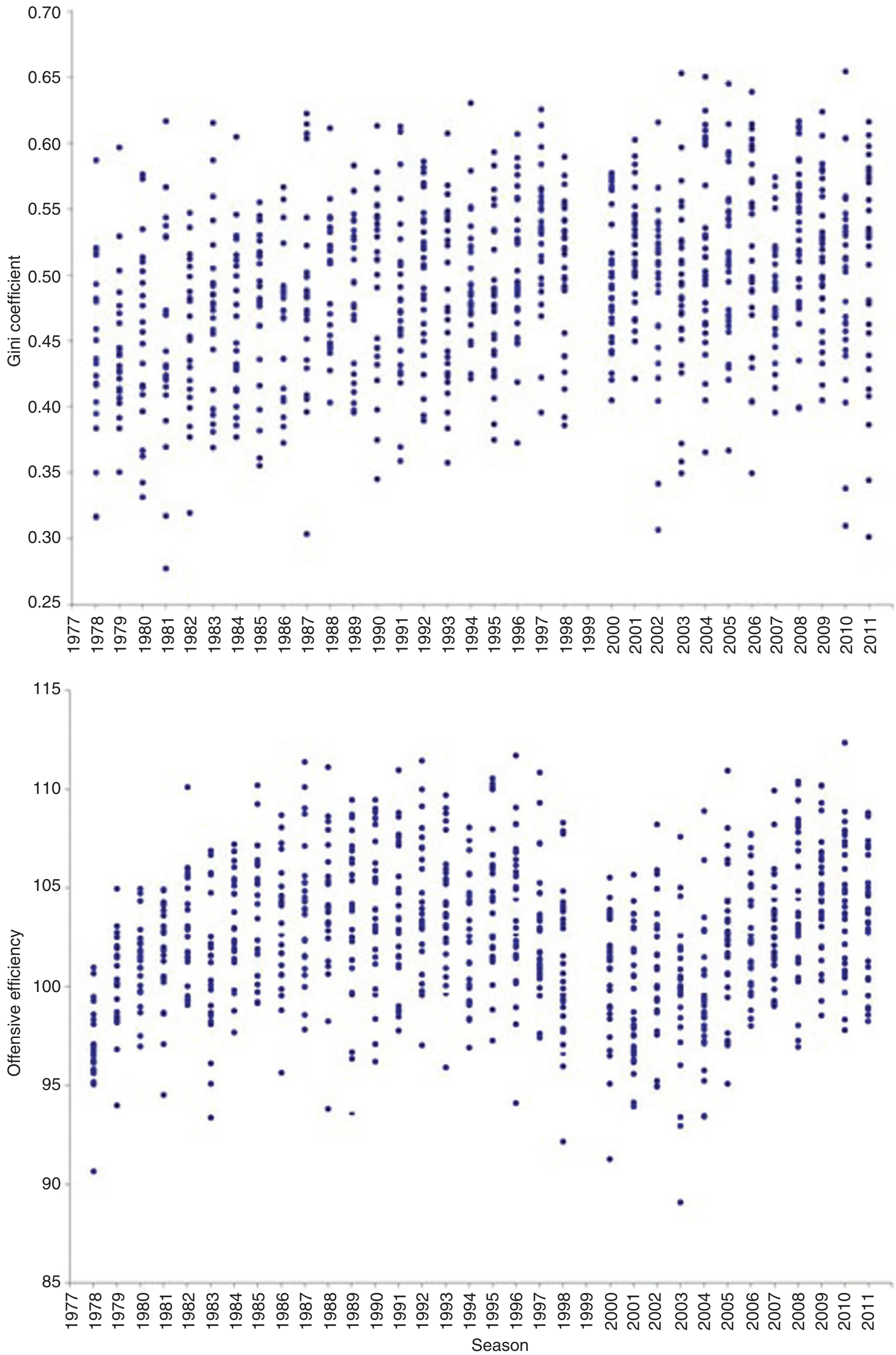

Figure 1 Evolution of concentration of production (Gini coefficient) and offensive efficiency along time.

Furthermore, a scatter plot was created (Figure 3) to explore the relationship between offensive efficiency and concentration of production. The association between the two variables seems difficult to find visually.

The next step of our analysis was the estimation of the fixed effect model via ordinary least squares. As the scatter-plot of Figure 3 did not show a clear pattern of association, we first hypothesized a linear relationship between concentration and efficiency. The variable “presence of the 3-point line” has 3 levels along time (no 3-point line; 3-point line at 6.70; 3-point line from 6.70 to 7.24). In order to estimate the effect of this discrete variable on

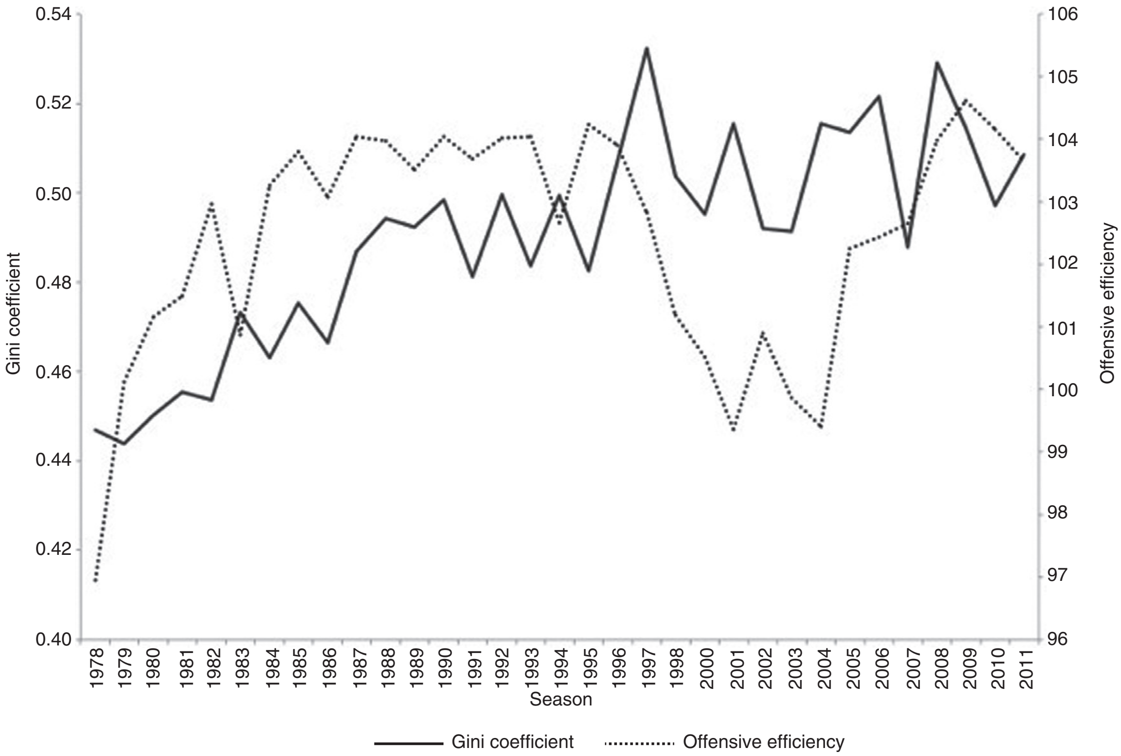

Figure 2 Evolution of the mean of concentration of production and offensive efficiency.

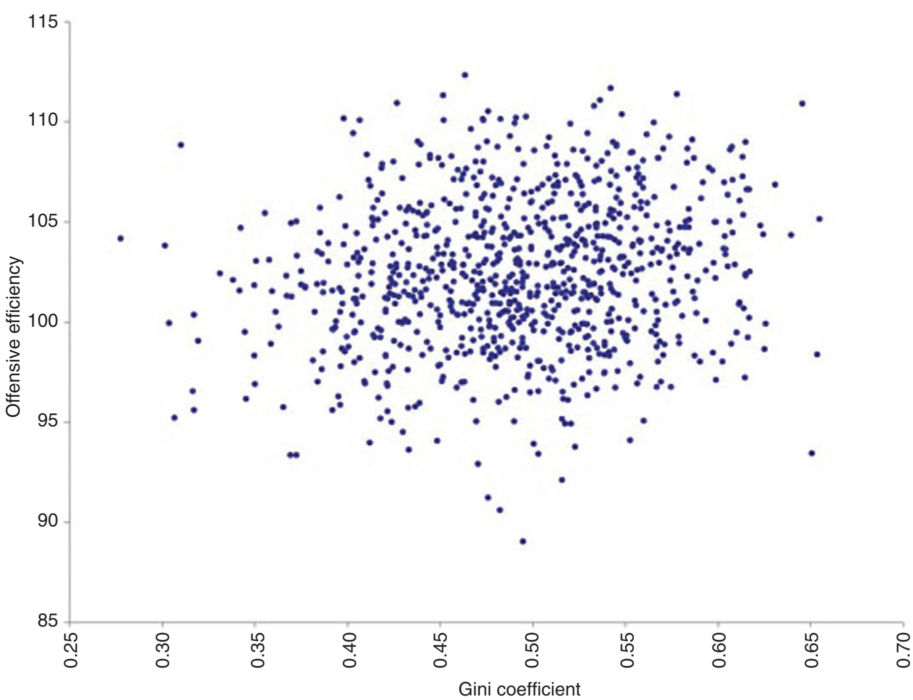

Figure 3 Scatter-plot of offensive efficiency vs. concentration of production (Gini coefficient).

offensive efficiency, we dichotomized it using the first category (no 3-point line) as a reference. We achieved a similar dichotomization for the variable "number of teams" (22, 23, 25, 27, 29 and 30 teams), creating six dummies and using the first category (22 teams) as a reference, in order to incorporate a non-lineal relationship between the number of teams and offensive efficiency. The variables: "establishment of salary cap" and "legalization of zone defense" are indicator (dummy) variables, where 1 indicates a season at or after the event occurred, and 0 would be assigned to seasons prior to the events. The results are shown in Table 1.

Under the hypothesis of a linear association, concentration of production and offensive efficiency would be positively and significantly related. Therefore, an extra decimal of concentration would be associated with an estimated increase of 6.74 points in expectation of offensive efficiency, controlling for other covariates. The global R-square of the model was 34.6%, and this was computed using the specification of the fixed effect model suggested by Antonakis et al. (2010). However, dropping the variable of interest (Gini coefficient) yielded an R-square of 33.4%. This would indicate that the concentration of production yielded a significant but small effect on the offensive efficiency (LRtest: $p<0.001$). In addition, we followed the indications of Tabachnick and Fidell (2007) to analyze residuals (Figure 4). We plot residuals vs. fitted values, showing an apparent random pattern, which support the validity of our model specification.

The remaining covariates were positive and significantly associated with offensive efficiency, except for the legalization of zone defense. Therefore, the creation of a salary cup, and the introduction of the three points line have contributed to the improvement of the offensive efficiency of teams. In fact, adding a three point line at 6.70 is associated with an increase in offensive efficiency of 4.60 points. This means that offensive efficiency has increased after the creation of the three point line in the 1979/1980 season. Enlarging the three point line, as the NBA made along three seasons in the mid 1990s was also associated with a positive increase in efficiency of 2.59 points. This means that the creation of the three point line (regardless the two different systems employed) has invigorated the offensive game.

Some of the team effects were significant (*F*-test <0.001), yielding an intraclass correlation (the fraction of variance due to the team effects) of 0.20, which supports the considered panel structure. Furthermore, the number of teams in the league also yielded a negative significant effect when comparing the situation of 29 teams against 22 teams. As the remaining effects were not significant, this could indicate that increasing the number of teams do not help to increase offensive efficiency, even in some cases might reduce it.

In addition, we achieved a new analysis, dropping these remaining co-variables and employing time as a covariate (recall that all the covariates employed correlates with time), yielded a slight increase in the effect of the concentration (8.06). However, the model had a lower R-square (17.5%). Therefore, we considered to maintain

Table 1 Model estimates of the fixed effect regression for the two hypothesized relationships.

Covariate	Coef.	Std. Err.	Sig.
Concentration of production	6.74	2.06	0.003
Creation of the salary cap	1.44	0.52	0.009
Presence of the 3-point line at 6.70 (second category)	4.60	0.57	<0.001
Presence of the 3-point line from 6.70 to 7.24 (third category)	2.59	0.46	<0.001
23 Teams in the league (second category)	0.86	0.45	0.072
25 Teams in the league (third category)	0.65	0.82	0.113
27 Teams in the league (fourth category)	0.63	0.75	0.414
29 Teams in the league (fifth category)	−2.08	0.72	0.007
30 Teams in the league (sixth category)	1.31	0.90	0.165
Legalization of the zone defense	−0.62	0.55	0.261
Intra-class correlation	0.202		
Correlation between the fixed effect and the covariates[a]	−0.008		
R-square	34.6%		
Adjusted R-square	31.6%		
Wald test to detect heterocedasticity[b]	171.8		<0.001
Wooldridge test to detect autocorrelation	55.271		<0.001
Pesaran test to detect cross-sectional dependency	4.803		<0.001

[a]The Hausman test among the fixed and random effect estimates yielded a signification of 0.23. This means that, statistically, the implementation of random effects is plausible (the test is non-significant), and consequently, the assumption that the correlation between the fixed effect and the covariates is zero is plausible. However, we maintained the fixed effect estimation because of the theoretical arguments explained in the method section.
[b]We re-estimated the model using the procedure suggested by Hoechle (2007) to correct standard errors by heteroscedasticity, autocorrelation and cross-sectional dependency, but results did not change.

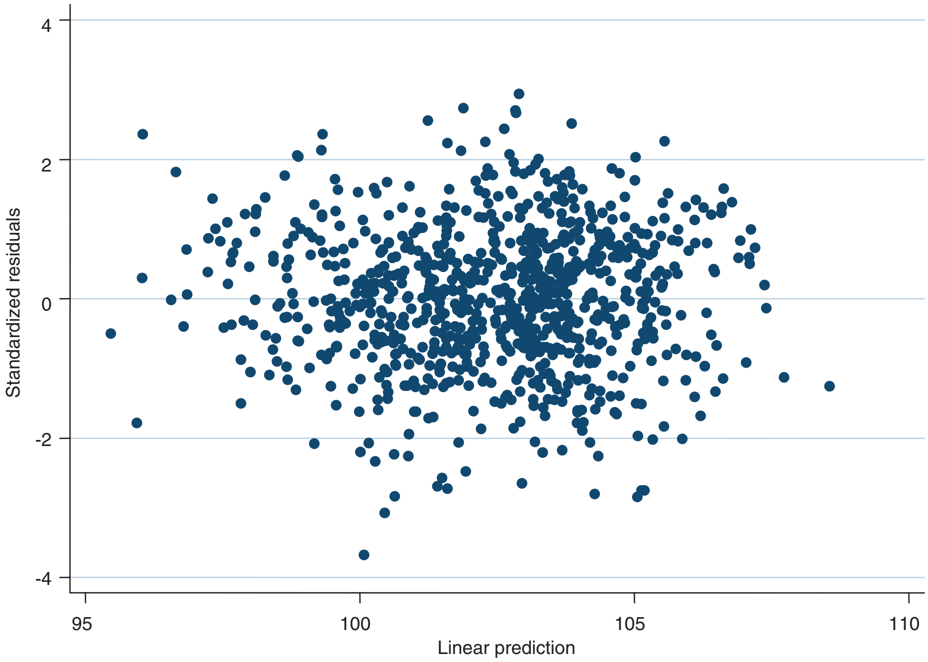

Figure 4 Residuals vs. fitted values for the model describing a linear association.

our original specification, employing the most informative covariates.

As the concentration of scoring production could be considered endogenous, then we also needed to re-estimate the model using instrumental variables. Recall that it would be plausible to think that teams that increase or decrease their concentration increase or decrease their offensive efficiency, and this could also influence the concentration of production for the following season. Therefore, offensive efficiency and concentration of production could be dynamically related. Consequently, we used a dynamic model with team-specific intercepts. We followed the suggestions of Rabe-Hesketh and Skrondal (2012) regarding estimation of the Arellano-Bond Generalized Method of Moments. Coefficient estimates of the concentration of production were very akin to the prior estimation, once controlled for the lagged response of offensive efficiency in the previous season. We employed lags of the level of the difference of the dependent variable to instrument the lagged dependent variable and the Gini coefficient lagged two periods as instruments for the hypothesized endogenous covariate. Again, results showed that the effect of the concentration of production on the offensive efficiency was positive and significant (6.01; $p<0.001$), similar to the prior and simple OLS estimation. In addition, we used a simpler two stage least squares estimation, employing the number of teams as an exogenous instrumental variable, and results were another time similar.

3.1 Alternative specifications

As our results supposed a great challenge to the corollary of Skinner (2010)'s thesis, we searched for other more complex specifications which could also explain data, in order to ascertain that our relatively simple linear model was correct.

Firstly, we employed the fractional polynomials approach to fit non-linear functions (see Royston and Altman 1994), using OLS estimation with teams as dummies and also the generalized estimating equations (Gelman 2008). Both analyses yielded similar results; the best powers of the Gini coefficient were (–2, –2), with a deviance of 4416.2 and –256.5, respectively. However, these deviances were almost identical to the deviance obtained with the simpler linear model (4416.9 and –256.5, respectively). In addition, adjusted R-square was similar (31.5% vs. 31.6%), so that the non-linear approach did not significantly improve the linear one. Figure 5 shows the fitted curve.

On the other hand, we have also conducted a categorical regression spline with the "crs" package in R (see Nie and Racine 2012, Racine and Nie 2012). This package provides a method for nonparametric regression that combines the (global) approximation power of regression splines for continuous predictors with the (local) power of kernel methods for categorical predictors. When the predictors contain both continuous and categorical (discrete) data types, the approach offer more efficient estimation than the traditional sample splitting (i.e., "frequency")

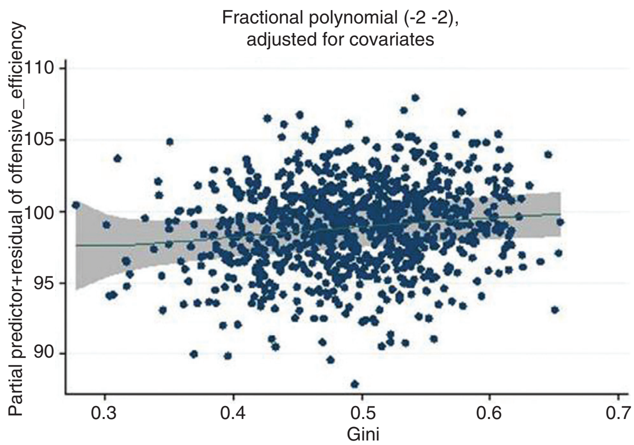

Figure 5 Fractional polynomial regression between offensive efficiency and concentration of production adjusted for covariates.

approach where the data is first broken into subsets governed by the categorical variables. Categorical regression splines have the ability to automatically remove irrelevant regressors by smoothing them out of the model completely thereby avoiding the need for pre-testing.

We took the same dependent variable and independent variables as with the other explained methods. With the analysis method provided by the categorical regression splines we observe an increase in the Offensive Efficiency when concentration, measured by the Gini index, increases up to 0.40, remaining essentially constant from this point. The conditional mean of Offensive Efficiency is shown in the Figure 6.

This indicates a positive relation between Offensive Efficiency and concentration (Gini index), although it might be weak one. Moreover the adjusted R-squared was 24% and significant.

4 Discussion

In a highly celebrated paper, Skinner (2010) suggested that teams would be better at offense if they distributed their shots more equally, so removing a key player from a team can improve its offensive efficiency. Although Skinner (2010) does not explicitly refer to concentration of offensive production, the claim that concentrating the offensive game in a few players instead of distributing shots more uniformly among teammates would be a bad strategy for teams, could be inferred as a corollary of his research.

Skinner's research (2010) heightened our interest to further study the effect of distributing scores more equally. It is true that Skinner (2010) defined concentration as "the fraction of the team's shots that [the player] takes while on the court," whilst our measure of concentration is related to the distribution of points made at the end of a season. However, considering the impossibility of collecting data with these features from the seventies, we think that our measure of concentration is a good proxy of how evenly the team spreads the offense over the players on the court.

We therefore attempted to study the association between offensive efficiency and concentration of production using a large set of empirical data from the NBA [overcoming the important empirical limitations of the studies of Skinner (2010) and Fewell et al. (2012)], estimating a fixed effects regression model to treat team heterogeneity, and controlling for a set of covariates. Our results contradict Skinner's theory (2010), because we found that concentration of scoring production is positively related to offensive efficiency. Therefore, it seems that the well known mass-media concepts as "big three" or "big four" to design successful teams make sense. Teams with more talent and with several big stars will (probably) increase its concentration of scoring, and this will be associated to an increase in its offensive efficiency. Recall that in our first model (fixed effect regression model) an extra decimal of concentration would be associated with an increase of 6.74 points in offensive efficiency, and this can be interpreted as a non-trivial change. There are multiple examples in the data base where teams have increased their concentration of scoring by 0.1 from 1 year to the following. So it is possible to increase, for example, from 0.3 to 0.4 from one season to the following. And this would

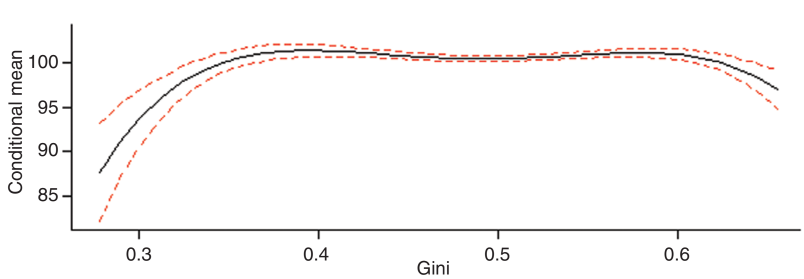

Figure 6 Conditional mean of offensive efficiency in spline regression.

increase the expectation of offensive efficiency by almost seven points, which is a considerable effect size, because the offensive efficiency variable has been built to be interpreted similarly (but not exactly the same) to the team points scored per game.

Skinner (2010) suggested that players' offensive efficiency decreases with their percentage of team shots, providing a unique example: Ray Allen. It is true that the correlation between offensive efficiency (measured by True Shooting Percentage) and the percentage of team plays a player uses when he is on the court (measured by Usage Percentage) is negative for Allen's career (–0.49). However, we have found many examples of other All-Star players with a long NBA career (like Allen), where this correlation is positive; they include LeBron James, Dirk Nowitzki, Kobe Bryant, Dwayne Wade, Steve Nash, Manu Ginobili, and other players. This means that it is not clear that players' efficiency decreases when they increase usage, and a deep understanding of this question is needed for further research.

Although the work of Skinner (2010) inspired our research, our conclusions go beyond depicting the relationship between offensive efficiency and concentration of production. Therefore, we also show that the salary cap has helped to increase teams' offensive efficiency, as did the establishment of the 3-point line. These were therefore two successful managerial decisions, because increasing offensive efficiency generally means more attractive games for the NBA audience. However, the legalization of zone defense had no significant impact on teams' offensive efficiency.

In this respect, further research could analyze the impact of international players becoming part of the NBA. Indeed, zone defense was legalized at a time when large numbers of foreign players were being signed (2001/2002). The international expansion of the NBA started in the late 1980s, with some of the best European players. Until the mid-1980s, international players had to give up playing for their respective country teams in FIBA tournaments. The presence of international players (especially from Europe) could enhance team's offensive performance, as they are traditionally viewed as less individualistic than American players. In addition, some of these foreign players have extraordinary offensive skills. Consequently, the effect of zone defense legalization could be masked by a structural change derived from the incorporation of talent from other countries. This could also explain why concentration of production has interrupted its tendency to grow since the 1980s, because international players added offensive talent and therefore provided more shooting options. In any event, more research is required in this respect.

We have not considered structural changes in the physical and technical level of the players, and this is a limitation of our research. Obviously the height, force, power and other athletic features have evolved with time, and these features influence the offensive but also the defensive performance of teams. We have taken into account a "time" variable to consider these structural changes in an additional analysis, and results were very similar. However, this variable was highly correlated with other covariates of the model. Therefore, we decided to maintain the initial covariates selected in order to provide more specific information about policy changes in the league.

Another limitation is related with the range of data analyzed (0.27–0.63 for the Gini coefficient) and the inference accomplished from these data. We cannot claim that, increasing the concentration beyond the range considered to estimate the model will enhance offensive efficiency. Obviously, teams cannot make concentration grow without limits, so there has to be some saturation point. We have not detected such a point with some of our analyses (we also estimated some diminishing return curves using the half-logistic transformation), and we suspect the reason is coaches know that, beyond some point, to increase concentration hurts their team. However, the results coming from the categorical regression spline, seem to suggest that that saturation point could be at the very close end of the range of the Gini coefficient. Therefore, beyond a concentration of production of 0.6, offensive efficiency could slightly decrease. This result was not detected with the other methods employed, so we are prudent about this claim. Consequently, this is also an attractive topic for further empirical research.

Finally, a major limitation of the study is that it does not consider changes of coaches and modifications in teams' rosters from one season to another, which influences team quality and playing style. Fixed effects take team heterogeneity into account, but assume that this heterogeneity is time-invariant. Certainly, it is a challenge for further research to consider these factors. Anyway, we took each team's winning percentage as a proxy of its quality, and re-estimated the model. As expected, winning percentage was positively and significantly associated with offensive efficiency but, more importantly, the model's other coefficients were very similar to the results showed in Table 1. Therefore, and with caution, we believe that our results are highly consistent with the changes in coaches and rosters year by year.

In sum, after a large and comprehensive analysis of historical data of the NBA, we find evidence of a positive relationship between concentration of scoring production and offensive efficiency. This breaks with some recent academic contributions regarding this topic, and provides a new understanding of the relationship between the concentration of scoring and team success.

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