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Evidencia de buen y mal momentum entre partidos para el jugador de baloncesto

Evidence of good and bad player momentum between games in basketball

Evidência de bom e mau momentum entre os jogos para o jogador de basquete

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RESUMEN

La existencia de rachas en baloncesto ha sido estudiada en equipos (momentum del equipo) y jugadores (mano caliente/momentum del jugador), utilizando diferentes métodos y alcanzando resultados contradictorios. Sin embargo, investigación empírica reciente muestra que este tipo de fenómenos de rachas son reales y no un sesgo de la percepción. En esta investigación se analiza una forma de rachas de juego para el jugador que hasta ahora no había sido considerada: el momentum del jugador entre partidos. Empleando una muestra de 39 jugadores y 3483 partidos de las temporadas 2016/17 y 2017/18 en la NBA, se analiza los puntos anotados por minuto en situaciones de muy alto y también muy bajo rendimiento. Los resultados sugieren que hay una cierta tendencia que refleja el momentum, tanto para buenos como para malos rendimientos, pero ese resultado está influenciado por el porcentaje de uso del jugador, es decir, su capacidad para acaparar juego. La tendencia es ir hacia atrás (en torno a un 60-70%) en la distribución de anotaciones tras un partido muy bueno, y de ir hacia delante (en torno a un 30-40%) en la distribución de anotaciones tras un partido muy malo. Las implicaciones para la toma de decisiones son discutidas finalmente.

Palabras clave: baloncesto, momentum, estadísticas, rachas, rendimiento.

ABSTRACT

The existence of streaks in basketball has been studied for teams (team momentum) and players (hot hand/player momentum) using disparate methods and reaching some conflicting results. However, recent empirical research shows these types of streaks are real and not an artifact of perception. In this research, we analyze a form of player streak that has not been considered before player momentum between games. Using a sample of 39 players and 3483 games of the 2016/17 and 2017/18 NBA regular seasons, we studied the distribution of points scored per minute focusing on both tails of this distribution for each player, i.e., extremely high, and extremely low performance within the same season. Results suggest that there is a certain trend reflecting momentum (for both good and bad performances), but this outcome is influenced by the usage percentage. The trend is to jump back to

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around 60-70% of the distribution of scores after a very good game and to jump forward to around 30-40% of the distribution of scores after a very bad game. Implications for decision-making are discussed at the end.

Keywords: basketball, momentum, statistics, streaks, player performance.

RESUMO

A existência de sequências no basquetebol têm sido estudadas em equipas (momentum da equipa) e jogadores (mão quente/momentum do jogador), utilizando diferentes métodos e chegando a resultados contraditórios. No entanto, estudos empíricos recentes evidenciaram que esse tipo de fenômeno é real e não um viés de percepção. Este estudo analisou uma forma de sequência de jogo para o jogador que até então não havia sido considerada: o ímpeto do jogador entre as partidas. Para tal, participaram neste estudo 39 jogadores e 3483 jogos das temporadas 2016/17 e 2017/18 da NBA, e foram analisados os pontos marcados por minuto em situações de alto e baixo desempenho. Os resultados sugerem que existe uma certa tendência que reflete o momentum, tanto para as boas como para as más exibições, mas esse resultado é influenciado pela percentagem de aproveitamento do jogador, ou seja, a sua capacidade de dominar o jogo. As implicações para a tomada de decisão são finalmente discutidas.

Palavras chave: basquetebol, momentum, estatísticas, sequências, desempenho.

INTRODUCTION

During February 2003, the basketball player Kobe Bryant scored 40 or more points in nine straight games. Michael Jordan performed a similar feat between November and December of 1986. In the 2018/19 season, James Harden scored 30 or more points in 32 consecutive games. These are only a few examples of extraordinary streaks of performance which attracted the attention of both the mass media and fans, probably due to an implicit belief that some kind of momentum exists, such that these streaks are not purely due to the variability of the random variable that reflects points scored in 82 NBA games by a basketball player.

Therefore, conventional wisdom in basketball states that such streaks feed themselves, as a player is living in an almost trance-like state for several days (or weeks) at a time. And this fact is closely related to other similar concepts which have been studied in the sports science literature: team momentum and the so-called hot hand.

As Arkes & Martínez (2011) explained, team momentum refers to the situation in which a team has a higher probability of winning or achieving success if the team had played well in the previous few games. Another concept of team momentum is also acknowledged in the literature, that is comprised within a game and not between games; teams who were performing well before and adversity will generally respond better to that adversity tan teams who were performed poorly (Roane et al., 2004). The concept of team momentum within a game has been proved in some instances (e.g., Mace et al., 1992; Roane et al., 2004). But there are more variations of this term. Morgulev et al. (2019) indicates that comeback during basketball games is perceived to be a catalyst for momentum. However, in their empirical study they did not find that teams came from behind to tie the game did have higher chances to win in overtime. On the other hand, Chen & Fan (2018) defined team momentum within a game in terms of the margin of one team outscores its opponent in a relatively short period. This flexible definition of team momentum allows researchers to choose the size of the margin and the lapse of time for the analysis. Under this latter definition, Chen et al. (2021) found that on the total of 12845 NBA games analysed, 12263 of them had momentum episodes.

The concept of momentum is similar in nature to the hot hand, which refers to a player having a higher probability of making a shot if he or she had successfully made the previous few shots. The terms hot hand and player momentum have sometimes been considered synonyms (e.g., Morgulev et al., 2020),

In spite of some decades of conflicting results, it seems that more recent empirical research has shown

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the existence of both phenomena (team momentum and hot hand) in basketball (e.g., Arkes, 2010; Arkes & Martínez, 2011; Bocskocsky et al., 2014; Dashlostrom, 2018; Munoz et al., 2019), However, we have to admit that there is also lack of evidence in other recent research (Morgulev et al., 2019; 2020).

In addition, as Salaga & Brown (2017) indicated, in sports betting marketing there is widespread evidence that bettors believe in positive momentum. Consequently, a generalized perception of momentum does exist.

Considering the previous definitions of team momentum and hot hand, it is highly plausible to hypothesize that player momentum between games also exists. The official NBA website, for example, as Martin (2018) pointed out, provides a player streak tool showing streaks from the 1983/84 season to the present, according to several box-score statistics.

However, a careful study of the real existence of these streaks is needed because snapshots of raw data may report a misleading interpretation of reality. For example, points scored should be reported per minute, because it is obvious that more minutes played means more opportunities to score. In addition, the usage percentage should also be considered, as it is an estimate of the percentage of team plays carried out by a player while on the court. Again, a higher usage percentage means more opportunities to score. Moreover, the concept of extraordinary performance should be relativized for each player, as it is related to a performance placed in the extreme of the right tail of the distribution of all the scores in a season for a given player, but these performance curves are player specific, i.e., they vary from one player to another. Therefore, a performance that is at the extreme of the tail for one player could lie around the mean value for another.

All these considerations are essential for the evaluation of the existence of player streaks. If we return to the Kobe Bryant case, only 2 of the 9 consecutive games in which he scored 40 or more points were within his best 5 performances that year, once points were normalized by number of minutes played. However, 4 of these 9 games were among the five games in which the player achieved his highest usage percentage. Moreover, 40 points is an arbitrary figure; why not put 39 or 41 (or any other number) to consider streaks? If we add that Bryant played 19 games that season in which he scored 40 points or more, and that his average was 30, we notice how difficult it is to speak of whether a consecutive performance is driven by a certain specific psychological state of flow, or whether it only appears to be this way. Moreover, other variables should also be considered, such as rest days, home/court advantage, and the difference in quality between teams.

Barnett et al. (2005) defined regression to the mean as a statistical phenomenon that can make natural variation in repeated data look like real change. As these authors indicated, this occurs when unusually large or small measurements tend to be followed by measurements that are closer to the mean. If no player momentum exists, then player performance would be expected to show a pattern compatible with the regression to the mean.

Knowing about streaks and the behaviour of players and coaches in these situations is important for decision making in sports. For example, rivals could change their defence strategy before a game as it is plausible to think that opposing players who performed well in the previous game will be likely to use a higher percentage of team plays in the following game.

The aim of this research is, therefore, to empirically analyse the existence of game streaks (player momentum), using a sample of 39 players and 3483 games for the 2016/17 and 2017/18 NBA regular seasons. We study the points scored per minute in situations of very high performance and very low performance, to analyse whether symmetry of effects appears.

METHODS

Study design

We conducted a non-experimental explicative study (Ato et al., 2013), using observable variables to explain the variation in the performance of players.

Participants

We obtained the statistical information about the NBA seasons from www.basketball-reference.com

Players who participated in all games for the 2016/17 and 2017/18 seasons were identified. Following Casals & Martínez (2013), we only considered those players who had played the entire season. The aim was to exclude the possible influence of injuries or sanctions, among others, which can make players miss games and lead to a possible influence on performance.

Forty-three cases met the criteria, with a total of 39 distinct players, as Andrew Wiggins, Karl-Anthony Towns, Marcin Gortat and Joe Ingles were present in both seasons. This sample encompasses a wide variety of profiles, with disparate ages, skills, and roles. In addition, the list shows high heterogeneity regarding scoring and minutes played, which we consider to be a good representation of NBA players (Table 1).

Ethical approval of the study was granted by the institutional research ethics committee of the author university and in accordance with the latest version of the Declaration of Helsinki.

Instrument

First, we computed the points per minute variable by dividing points per minute played for each game. Secondly, we ordered all these data from the highest to the lowest performance and assigned a consecutive number for each case. Therefore, the best game was labelled 1, the second best 2, etc., and thus the position variable was created. Thirdly, we computed the difference between consecutive positions; the aim was to quantify the difference in performance between consecutive games. Therefore, if, for a specific player, game number two had a position number of 20, and game number three had a position number of 30, then the difference variable was -10, so the performance was worse than in the previous game by a distance of 10 positions.

Difference was taken as the main variable of our analysis because it quantified the intensity of movement from an extreme position to the mean of the distribution. The next step was to build the main independent variables, i.e., two dichotomous variables representing the best and the worst games. To achieve this aim, we simply identified the 5 best games and the 5 worst games using the position variable and assigned a value of 1 to the next game (and 0 for the remaining games). It is important to stress that we were interested in studying a player's behaviour in the following game after an extraordinary good (and bad) performance. Consequently, the dichotomous variables after the best games and after the worst games were created.

Control variables were also considered. Casals & Martínez (2013) found the difference in team quality and usage percentages to be significant variables affecting player performance. Regarding team quality, we created a difference in team quality variable using two distinct procedures. For the first one, we simply subtracted the winning percentage of the rival team at the end of the season from the winning percentage of the player's team. As this variable could not consider notable differences in team quality during the season (for example, after trading some players) we achieved four partitions of the distribution of games: from 1 to 20, from 21 to 41, from 42 to 62, and from 63 to 82. We calculated the winning percentages for each partition in the following way; from 1 to 20 we assigned the winning percentage at game 20; from 21 to 41 we averaged the winning percentages at games 20 and 41; from 42 to 62 we averaged the winning percentages at games 41 and 62; and from 62 to 82 we averaged the winning percentages at games 62 and 82. Therefore, a more realistic team strength variable was computed for each team.

We then subtracted the winning percentage at each partition of the rival team from the winning percentage at each partition of the player's team. This second form of computing differences in team quality is also a proxy for measuring team momentum.

Recall that difference in team quality is a double difference variable because it first computes the difference between the qualities of both teams in a game (the player's team and the rival team), and the difference between these values is then computed between consecutive games.

Regarding usage percentage, this is an estimate of the percentage of team plays used by a player while on the court. The formula is 100 * ((field goals attempted + 0.44 * free throws attempted + turnovers) * (team minutes played/ 5)) / (player minutes played * (team field goals attempted + 0.44 * team free throws attempted + team turnovers)). We computed the difference in usage percentage between consecutive games.

Table 1
List of players.

Player	Age	Season	Team	Games started	Minutes played	Points
Bradley Beal	24	2017-18	WAS	82	2977	1857
Dragan Bender	20	2017-18	PHO	37	2069	531
Bismack Biyombo	25	2017-18	ORL	25	1495	468
Dillon Brooks	22	2017-18	MEM	74	2350	898
Pat Connaughton	25	2017-18	POR	5	1488	441
Raymond Felton	33	2017-18	OKC	2	1365	565
Yogi Ferrell	24	2017-18	DAL	21	2282	838
Taj Gibson	32	2017-18	MIN	82	2726	999
Marcin Gortat	33	2017-18	WAS	82	2075	690
Joe Ingles	30	2017-18	UTA	81	2578	940
LeBron James	33	2017-18	CLE	82	3026	2251
Tyus Jones	21	2017-18	MIN	11	1467	416
Cory Joseph	26	2017-18	IND	17	2210	649
Khris Middleton	26	2017-18	MIL	82	2982	1652
Darius Miller	27	2017-18	NOP	3	1944	637
Patty Mills	29	2017-18	SAS	36	2107	819
E'Twaun Moore	28	2017-18	NOP	80	2586	1022
Patrick Patterson	28	2017-18	OKC	3	1270	318
Jakob Pöltl	22	2017-18	TOR	0	1524	567
Julius Randle	23	2017-18	LAL	49	2190	1323
Ish Smith	29	2017-18	DET	35	2043	894
Lance Stephenson	27	2017-18	IND	7	1850	757
Karl-Anthony Towns	22	2017-18	MIN	82	2918	1743
P.J. Tucker	32	2017-18	HOU	34	2281	502
Taurean Waller-Prince	23	2017-18	ATL	82	2464	1158
Andrew Wiggins	22	2017-18	MIN	82	2979	1452
Corey Brewer	30	2016-17	TOT	11	1281	371
Marquese Chriss	19	2016-17	PHO	75	1743	753
Jordan Clarkson	24	2016-17	LAL	19	2397	1205
Jamal Crawford	36	2016-17	LAC	1	2157	1008
Gorgui Dieng	27	2016-17	MIN	82	2653	816
Marcin Gortat	32	2016-17	WAS	82	2556	883
Tobias Harris	24	2016-17	DET	48	2567	1321
Buddy Hield	24	2016-17	TOT	55	1888	866
Justin Holiday	27	2016-17	NYK	4	1639	629
Ersan İlyasova	29	2016-17	TOT	52	2142	1071
Joe Ingles	29	2016-17	UTA	26	1972	581
Jamal Murray	19	2016-17	DEN	10	1764	811
Elfrid Payton	22	2016-17	ORL	58	2412	1046
Marreese Speights	29	2016-17	LAC	2	1286	711
Jeff Teague	28	2016-17	IND	82	2657	1254

Karl-Anthony Towns	21	2016-17	MIN	82	3030	2061
Andrew Wiggins	21	2016-17	MIN	82	3048	1933

The literature also suggests that rest days (e.g., Reed & O'Donoghue, 2005) and home advantage (e.g., Winston, 2009) be considered. We computed the difference in rest days between consecutive games. Regarding home advantage, and because of the features of our data base, we had to slightly elaborate the construction of this variable. Therefore, when a player played two consecutive home games, we took this as a reference category. We then built three dichotomous variables representing the following situations: when the previous game was played at home and the following game was played away; when the previous game was played away, and the following game was played at home; and when the previous game was played away, and the following game was played away.

Procedure

We proposed the following linear model:

$$Y_{ij=}\sum_{k=1}^{p} X_{ij}^{k}\beta_k + u_i + e_{ij}$$

Where Y_{ij} is the difference in the positions of points per minutes calculated for the player *i* and the game *j*. We employed a set of *p* covariates, where X_{ij}^{k} represents the set of *p* covariates (*k=1,...,p*) for the player *i* and the game *j*. The parameters β_k reflects the effects of the *p* covariates on Y_{ij}, u_i represents non-observable individual effects, and e_{ij} represents the remaining non-systematic effects, which are assumed to be independent and normally distributed. Consequently, points per minute are nested in each specific player, which acts as a cluster variable. Stata 13.0 was employed for statistical analysis.

RESULTS

After estimating the fixed effect model using the ordinary least squares method, we found a similar difference in position after the best games and after the worst games (-22.23 and 23.24, respectively). This means that the effect size of the jump from an extremely good game or from an extremely bad game was, statistically, of equal magnitude, because 95% IC were (-25.98; -18.47) and (19.52; 26.95).

Table 2 shows the results of three estimated models; Model 1 estimated a fixed effects regression model with the difference in team quality computed using four partitions of the winning percentage; Model 2 estimated a fixed effects regression model with the difference in team quality computed as the winning percentage at the end of the season; and Model 3 estimated a linear regression model with clustered robust standard errors with the difference in team quality computed using four partitions of the winning percentage. All three models yielded equivalent estimates, because the intraclass correlation was non-significant, so we chose the simplest linear regression model (Model 3) to interpret and to validate the analysis.

Table 2
Model estimates of the model.

	Model 1		**Model 2**		**Model 3**	
	Coef	*p*-value	Coef	*p*-value	Coef	*p*-value
After the best 5 games	-22.23	<.001	-22.45	<.001	-22.23	<.001
After the worst 5 games	23.24	<.001	22.21	<.001	23.24	<.001
Difference in team quality (82 games)			3.71	.081		
Difference in team quality (4 partitions)	3.95	.04			3.94	.17
Difference in usage %	-2.34	<.001	-2.33	<.001	-2.34	<.001
Home advantage (Home-Away)	-1.25	.31	-1.24	.32	-1.25	.37
Home advantage (Away-Home)	-.31	.80	-.31	.80	-.31	.79
Home advantage (Away-Away)	-1.98	.11	-1.95	.12	-1.9	.04
Rest days	.40	.35	-.41	.35	-.40	.34
Constant	1.32	.19	1.31	.20	1.31	.05
Intraclass correlation	.00	1.00	.00	1.00		

Model 1: Fixed effects regression model with the difference in team quality computed using four partitions of the winning percentage.
Model 2: Fixed effects regression model with the difference in team quality computed as the winning percentage at the end of the season.
Model 3: Regression model with clustered robust standard errors with the difference in team quality computed using four partitions of the winning percentage.

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Therefore, after an extraordinary game (good or bad), the subsequent performance moves towards the mean but, importantly, not to the mean itself, because the expected jump to the mean would be about -40 in the case of good games and +40 in the case of bad games. Consequently, the data says that there is a trend towards a good performance after a very good performance and a bad performance after a very bad performance, which could be interpreted as a momentum effect.

This preliminary momentum effect must be analyzed together with the role played by the difference in usage percentage variable, which was also significantly and negatively associated with the difference in position. This means that players who performed exceedingly well generally decreased the usage percentage in the next game, and a player who performed badly incremented the usage percentage in the next game. As points per minute are highly correlated with usage percentage (Pearson correlation: .74, p < .001, in this sample), the momentum effect was therefore partially disturbed by the modification in the usage percentage. And this distortion was highly significant, as Table 3 shows:

Table 3

Usage percentage (Usg %) after very good and very bad games.

	Usg %	95% CI	*p*-value
Five best games	26.24	(25.28; 27.20)	
The games after the 5 best games	19.59	(18.59; 20.58)	<.001
Five worst games	13.14	(12.23; 14.05)	
The games after the 5 worst games	19.11	(18.01; 20.21)	<.001

Note: The mean of the whole sample for the Usg % is 19.24

Therefore, it would be expected that, if players had employed a similar usage percentage after their best or worst games than that used in these best or worst games, the momentum effect would have been even stronger.

Consequently, the distributions of points per minute highly depends on the usage percentage. However, although usage percentage regresses towards the mean after a very good or a very bad game (as shown in Table 3), the difference in position does not (as shown in Table 4); at least not completely, showing a trend towards keeping the position of the performance of the previous game.

As shown in Table 4, the number of minutes played remained the same in the games after the five best games (p = .87), and slightly increased in the game after the five worst games (p = .004). These results reinforce the idea that minutes played did not contaminate the momentum effect analysis.

Table 4

Minutes played after very good and very bad games.

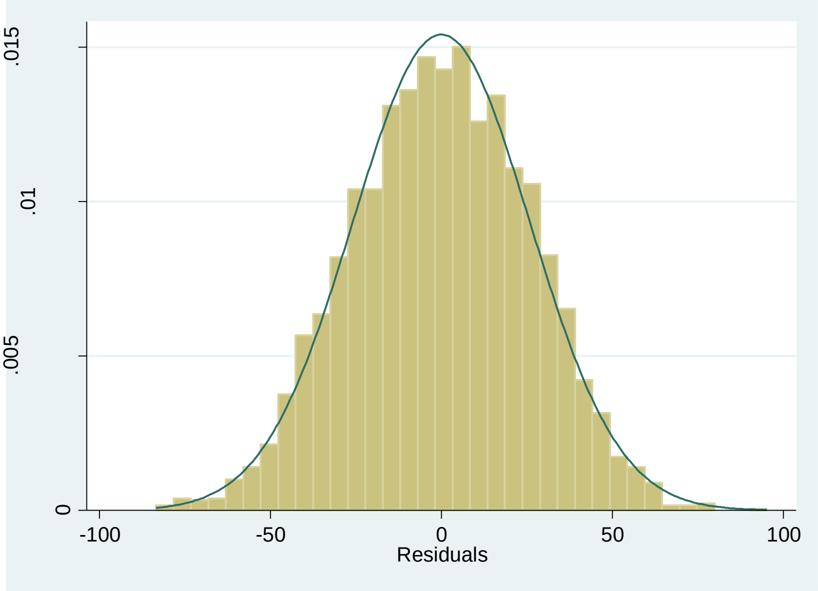
	Minutes played	95% CI	*p*-value
Five best games	26.19	(24.96; 27.42)	
The games after the 5 best games	26.34	(25.09; 25.60)	.87
Five worst games	23.38	(22.18; 24.60)	
The games after the 5 worst games	25.91	(24.72; 27.10)	.004

Note: The mean of the whole sample for minutes played is 26.78

Model validation

Model 3 was subject to different miss-specification tests (Spanos, 2018). The Breusch-Pagan/Cook-Weisberg test supported homocedasticity: χ^2 (1) = .07; p = .79. The Skewness/Kurtosis tests for normality of residuals showed deviation from normality: χ^2 (2) = 10.15; p = .006. However, this was mainly due to the large simply size, and was considered negligible after viewing the histogram of residuals (Figure 1).

Figure 1
Histogram of the residuals with normal curve for Model 3



Although the Ramsey RESET test provided significant results, *F* (9.3465): 6.77; $p < .001$ this was probably caused by the sensibility to the large sample size, and we believe this is not truly important. Moreover, we estimated an alternative model with the squared terms and all the possible interactions between all the continuous covariates. The explained variances were practically the same: .3870 for the simplest model vs .3880 for the more complicated model, i.e., a negligible change.

The run test for independency of residuals, considering the sign of unstandardized residuals, did not support independency, $z = 18.52$; $p < .001$, but this was to be expected in this kind of model with data registered by time. Therefore, although autocorrelation was present, its effect on the results was not significant. To show this, we estimated a fixed effect regression with Driscoll-Kraay standard errors (Hoeche, 2007), since they are robust to very general forms of cross-sectional and temporal dependence. The standard errors for the variables after the best games and after the worst games were slightly reduced, and 95% IC were (-25.37; -19.08) and (20.00; 26.47), but the interpretation of the results did not change.

Regarding sensitivity analysis, as some of the sampled players played less than five minutes in some games, we decided to apply the cut-off criteria of Casals & Martínez (2013) and discarded all these cases as it is plausible to think that playing less than 5 minutes did not allow players to adequately develop their skills. The following players were excluded: Pat Connaughton, Darius Miller, Jakob Pöltl, Corey Brewer, Buddy Hield, Justin Holiday, Joe Ingles (season 2016/17) and Jamal Murray. Model 4 was estimated with a sample of only 2754 cases after a listwise deletion. In addition, we estimated an additional model (Model 5) using the 4 best and worst games instead of the 5 original ones to see if the estimates were sensible to small variations in these variables. As Table 5 shows, all the results were equivalent, so our Model 3 was considered robust.

Table 5
Model estimates (sensitivity analysis)

	Model 3		Model 4		Model 5
	Coef	*p*-value	Coef	*p*-value	Coef
After the 5 best games	-22.23	<.001	-21.97	<.001	
After the 5 worst games	23.24	<.001	22.83	<.001	
After the 4 best games					-20.43
After the 4 worst games					23.04
Difference in team quality (4 partitions)	3.94	.17	3.35	.32	3.75
Difference in usage %	-2.34	<.001	-2.51	<.001	-2.40
Home advantage (Home-Away)	-1.25	.37	-.63	.70	-1.37
Home advantage (Away-Home)	-.31	.79	-.36	.80	-.37
Home advantage (Away-Away)	-1.9	.04	-1.06	.33	-1.81
Rest days	-.40	.34	-.12	.76	-.41
Constant	1.31	.05	.58	.45	1.25
R-squared	.387	<.001	.398	<.001	.373

DISCUSSION

This research empirically analysed the existence of game streaks (player momentum) in basketball, employing a sample of 3483 NBA games, using the points scored per minute in situations of very high performance and very low performance. Results suggest that there is a certain trend reflecting momentum for both good and bad performances, but that this outcome is influenced by the usage percentage.

Player streaks (player momentum) exists, but maybe not with the conventional interpretation of long streaks of extraordinary performance. When a player performs very well, he tends to maintain such a high level of performance in the following game but with a reduction in points per minute. The size of this reduction is not compatible with a regression to the mean effect, because it is placed (using approximate figures) around 60-70% of the distribution and does not approach 50% of the distribution. Similarly, for very bad performances, players tend to maintain such a low level of performance in the following game but with an increase in points per minute. The size of this increase is, again, not fully compatible with a regression to the mean effect, because it is placed (again using approximate figures) around 30-40% of the distribution and does not approach 50%. These results challenge the conclusions of Martínez (2013), which were obtained with partial data, using a less robust empirical method.

It is important to note that, for players performing very well, minutes played does not vary for the following game. This means that the coaches probably did not consider giving more minutes to players that performed well in a previous game. However, usage percentage clearly decreased and, in fact, regressed towards the mean. The interpretation of this result is not easy to ascertain, but it could be related to the higher attention that rival coaches and players placed on the specific player who performed well in the previous match, as Csapo et al. (2015a) found within games. Usage percentage decreased from 26.24% to 19.59%, about 20% of its value, which means that, in the following game, the player is not so active in the offensive play. Observational studies (e.g., Morillo-Baro et al., 2021) could be achieved for analysing in detail the behaviour of players and opponent defences after a player performs a highly notable game.

On the contrary, after a very bad game, usage percentage increased from 13.14% to 19.11%, which is about 50% of its value. This could mean that rival players are not so worried about the specific player who performed poorly in the previous match and/or that this player tried to improve his performance by playing a more leading role in the offensive play. The slightly significant increase in minutes played after a poor game did not explain the high increase in usage percentage.

Csapo et al. (2015b) studied the behavioural changes of basketball players arising from the hot hand. They found that the more consecutive shots a player makes

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(or misses), the more difficult (or easier) the shots become. On the other hand, Attali (2013) found that even a single successful shot was sufficient to increase the likelihood of a player taking the next team shot, increasing the average distance from which this next shot is taken and decreasing the probability that the coach will replace the player. These results reinforce the idea that players (and coaches) believe in player momentum in a game (the hot hand). Our results show that momentum from game to game also exists but with different characteristics, as players significantly decreased their usage percentage. In other words, this means that if, within a game, player momentum appears by increasing the number of shots made and their difficulty, player momentum between games is present, although the offensive activity significantly decreases. This is an important difference that our results suggest.

The practical implications of this research are diverse. For example, rival coaches and opponent players may focus on the player that has achieved a great performance in the previous game. This could explain the decrease in usage percentage. In addition, coaches of the team of that player could redefine the offensive tactic for the next game, acknowledging that player may be in the spotlight of the opponent team. This depends, of course, of the role of the player and its importance for the team. For sports bettors, knowing that momentum between games exists is a powerful tool to design their betting strategy for the next game. For fans and analysts, it is also a way of understanding fluctuations of player performance.

Limitations and strengths

This study has several limitations. Firstly, only the following game after a very good or a very bad game was considered. Other research analysing team momentum (not player momentum) considered a wider buffer; for example, Arkes & Martínez (2011) analysed 3 and 5 consecutive games. However, other studies regarding player momentum within a game considered the next action after a shot, i.e., Attali (2013).

Secondly, although we employed a large sample size, larger samples would be desirable to obtain a more complete list of players. As we have justified, the players we studied represent a wide range of different player profiles but are not a random sample of players and are only circumscribed to the two seasons considered.

Thirdly, the concept of good or bad performance is relative for each player. This fact is certainly positive for relativizing and comparing results but could also be a shortcoming if we think about the concept of good performance in an absolute way, i.e., for the top scorers of the league. The examples shown at the beginning of this paper included names such as Kobe Bryant, Michael Jordan, and James Harden, all of whom were extraordinary scorers. Many of these players are clutch players whose performances improve in the most decisive phases of the game (Solomonov et al., 2015). And fourthly, classical definitions of psychological momentum or simply momentum include notions such: tension-excitement can be either gradually built-up or dramatically sparked, effecting a positive propulsion toward a goal; adrenaline rush is marked by a feeling of confidence and determination; a tidal wave on which to ride; added or gained psychological power; athletes in a psychological momentum state will experience various cognitions, affects, and motivations related to the elements of control, confidence, optimism, energy, and synchronism; increased arousal associated with the activity; change in cognition, affect, and physiology (e.g. Alder & Alder, 1978; Iso-Ahola & Mobily, 1980; Taylor & Demick, 1994; Vallerand et al., 1998). These notions regarding momentum imply that originally it was viewed as a short-lived psycho-physiological phenomenon. However, it is true that the term momentum has been generalized to explain across game effects (e.g., Arkes & Martínez, 2011; Munoz et al., 2019), and this latter approach is what we have employed in this research.

Despite these limitations, this research also has several strengths. It employs a large sample size with a statistical model which has been validated and is robust to slight departures from the initial conditions, as the sensitivity analysis has shown. In addition, the inclusion of all the covariates considered guarantees the control for several confounding variables, with the most important being the usage percentage variable, which plays an essential role in the results. If usage percentage had not been considered, all the regression models estimated would have shown a

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clear regression towards the mean effect, therefore refuting the conclusion that momentum exists.

Finally, this research adds new empirical evidence to studies into the momentum concept applied to teams between games and players within a game. The most recent research shows that conventional wisdom about states of flow (or trance) of players and teams was right, or at least, had an empirical basis. Our research is in line with this evidence.

Further research

We think that our design is valid for studying player momentum between games, acknowledging that it would be interesting for further research to extend this approach for a set of consecutive games, and to then compare the results. Further research could try to analyse momentum in previous NBA seasons and during play-offs.

We encourage other researchers to advance the study of player momentum between games using only a sample of high scorers to ascertain whether their behaviour is similar to the results obtained here.

In addition, further research is needed in order to analyse the role of emotional regulation and impulsivity (e.g., Millán-Sánchez, et a., 2023) in basketball, because of its possible association with the concept of momentum. And more broadly, studies in basketball should deepen into identify factors that could trigger momentum (see Briki & Zoudji, 2019)

Sometimes, even in the sport science literature "hot hand" is also identified with "gaining momentum" (e.g., Iso-Ahola & Dotson, 2016), so some confusion may arise in defining the concepts. We have employed the term "player momentum between games" to clearly differentiate it from the concepts of "team momentum" and "hot hand".

Qualitative studies with players could help to understand their perspective about player momentum between games. Like the study of critical moments in basketball within a game (e.g., Navarro et al., 2017), the player confidence could be a variable analyse.

CONCLUSION

This research has empirically shown the existence of game streaks (player momentum) in the NBA. Our results suggest that there is a certain trend which reflects momentum (for both good and bad performances), but this outcome is influenced by the usage percentage. The trend is to jump back to around 60-70% of the distribution of scores after a very good game, and to jump forward to around 30-40% of the distribution of scores after a very bad game. Therefore if, within a game, player momentum appears by increasing the number of shots made and their difficulty, player momentum between games also appears although the offensive activity significantly decreases. Coaches, players, the media, fans, and bettors may interpret these results for decision making purposes.

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