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Regular point scoring by professional basketball players

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Our research constitutes an advancement and attempts to answer an important question on basketball metrics: how to measure regularity in terms of points scored and which factors may influence this regularity. This question has been understudied in the specialised literature despite its importance. We employed the median absolute deviation (MAD) as a robust measure of regularity. After the analysis of the performance of 27 NBA players who played 82 games in the 2007 regular season, we have demonstrated that some players are much more regular in terms of point scoring than others, and when players are better scorers they become more irregular scorers, i.e. their performance is less predictable. In addition, some players at the half-level of regularity are "outliers" in the sense that some peaks in their performance may influence the variance of their respective distributions. Finally, the pattern of points scored per minute in a short series of games is very difficult to predict without taking into consideration additional information regarding influential variables; there is little evidence that NBA players are subject to a momentum effect.

keywords: NBA, basketball-metrics, regularity.

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1 Introduction

Basketball metrics, and indeed baseball metrics, is probably the branch of sports analytics which has grown most in recent years (Alamar, 2013), owing to the enormous quantity of data available and the possibilities this area offers for in-depth analysis (Fewell et al., 2012), which are not comparable with any other sport.

Player performance has been studied from different perspectives, from the more general (e.g. Kubatko et al. 2007; Piette et al., 2010) to the more specific (e.g. Casals and Martinez 2013), and global indexes of player performance (e.g. win scores, wins produced, adjusted plus-minus, PER) as well as indexes of focused statistics (e.g. points scored, steals/turnover ratio, true shooting percentages) have been studied.

However, very few studies have analysed one important indicator of player performance: regularity or consistency. The studies of Esteller-Moré and Eres-García (2002) and of Salmerón-Gómez and Gómez-Haro (2016) are the most outstanding. The former proposed using the Atkinson index to evaluate the performance of a player in any category of the game. Esteller-Moré and Eres-García (2002) applied it to the ranking of scoring leaders in the National Basketball Association (NBA), and evaluated consistency in empirical estimations of players' compensation. Regarding the latter, the authors proposed an index based on the sum of the mean and the inverse of the coefficient of variation in order to rank players in any category in the *Asociación de Clubes de Baloncesto* (ACB) Spanish League.

However, to the best of our knowledge, no in-depth research has been undertaken on the factors associated with the regularity of point scoring by basketballers. This is an important area for basketball analytics because as the regularity of players' point-scoring increases so their performance becomes more consistent and predictable. The notion of stability is particularly important in sports management when making decisions about future acquisitions ((Franks et al., 2016)). Some authors have defined stability as a metric which describes how much a single player metric varies over time (after removing chance variability).

The aim of this research is to examine in some depth the concept of regularity in basketball players, in terms of points scored. In this paper, we employ two different approaches to study the regularity of points scored by players in the NBA: (1) we use a full season evaluation, modelling regularity using a robust version of the median absolute deviation for variables (in order to explain variation), and we employed the Cochran variance outlier test in order to identify the players with the greatest variance in his performance; (2) we analysed the ordinal patterns of players' performance using short-term evaluations (three games per week).

We believe there is no single approach which should be used to study the regularity of basketball players; for this reason we undertook a multifaceted investigation. Our analysis has provided important results, which will act as a starting point for future studies on this topic.

2 Regularity

First, we should define regularity: it is a measure of consistency in player performance. This means that a player will be more regular to the extent that his performance becomes more predictable. This definition is in line with the definition provided by Franks et al. (2016).

This definition has important implications for measuring regularity. For example, indexes such as those of Gini or Theil, which measure inequality, may not be valid in short series of data (e.g. 10 games) because they do not provide an accurate picture of the regularity of players in terms of the presence of outliers; there are also issues with measures of dispersion as variants or coefficients of variation.

A robust measure of dispersion such as median absolute deviation (MAD) or Winsorised variance may also be useful. Casals and Martinez (2013) indicated that points scored per minute were associated with minutes played, the usage percentage and the difference in quality between teams; consequently, regularity is a variable which is subject to change.

However, in a large dataset of 82 games, Gini and Theil indices are less sensitive to outliers in terms of providing a regularity index consistent with our definition. Nonetheless, the MAD of the distribution was finally chosen as a regularity index for all the players in our dataset because of the robustness against extreme cases. This has previously been used by some sports analysts as a consistency index (e.g. Petersen 2013; Williams 2016).

Managers may also be interested in identifying players who are regular point scorers over the full season, but who have some peaks of performance in specific games. Some players may achieve a very high or very low performance, i.e. they may be special players who perform unpredictably. We employed the Cochran variance outlier test in this work in order to identify the players with the greatest variance in performance. However, we also studied regularity in a short series of data. It should be kept in mind that the same regularity index can be obtained using a different pattern of data ordination. Some players may be more prone to influence by the variables identified by Casals and Martinez (2013); some players may even be subject to a momentum effect. In order to analyse the ordinal pattern representing the performance of players, we have employed raw data.

3 Data

We used the same database of Casals and Martinez (2013): statistical information about the NBA 2007 regular season from www.basketball-reference.com and www.nbastuffer.com. We had a complete set of variables for each NBA player linked to each game played. We direct readers to the study of Casals and Martinez (2013) for a complete description of all the considered variables, and the rationale of the variables' identification.

For our study, we selected points scored per minute as an indicator of the offensive performance of players. As Berri et al. (2007) have stated, the number of points scored has dominated evaluations of player productivity in the NBA. Player evaluation in the NBA seems overly focused on scoring in terms of salary and coaches' evaluation of player talent; the production of "team workers", as Martinez (2012) explained, should be noted here. Point scoring is the outcome of all the game processes, and the ultimate goal of the teams.

Regarding the filtering process, we followed exactly the same criteria of Casals and Martinez (2013). The database was composed of 458 players and 25,806 games. We used listwise deletion, so when a specific game did not fulfil the requirements we eliminated that player. First, we dropped players who had played less than 5 minutes in some of their games. We considered that playing less than 5 minutes did not allow players to fully develop their skills. Secondly, we removed players who had been traded that season because they changed teams, and hence they significantly changed their context of play (teammates, coaches, city, etc.). Thirdly, we only considered players who had played the entire season. The rationale behind this decision was to exclude the possible influence of injuries or sanctions, which can make players miss games. Consequently, we only considered players who played 82 games. Only 27 players passed this filtering process, and this result was the same as that of Casals and Martinez (2013).

Considering only those athletes who played all games of a season is the best way to assess regularity, at least in this first stage of development of this type of analysis, where we explore links with other performance variables. The next step of our research involved the two empirical studies, which are examined below.

4 Study 1. Modelling regularity for the complete season

4.1 Method

The dependent variable was the regularity index, and it was computed using the median absolute deviation. The covariates for the analysis were the team (cluster variable) and the player wage relative to team salary. As Casals and Martinez (2013) have pointed out, the salary is usually linked to the quality or value of a player. As teams possessing greater economic resources also spend much more money than other teams (the exceptions caused by the salary cap and the different size of the markets should be noted here), the salary of players can also be normalised considering the total budget of their respective teams. Therefore, we use the players' wages relative to teams' salary, which was highly correlated to the gross salary of each player ($r = 0.99$; $p < 0.001$).

In addition, we also considered two additional variables which were related to player skills; the mean of the points scored per minute and the mean of the win-score per minute. This latter measure was introduced by Berri (1999); Berri et al. (2007) in order to easily compute the "box-score" performance of a player in terms of points, missed shots, rebounds, assists, steals, turnovers, blocks and fouls.

Both variables characterise different type of players. For example, the mean of the points scored per minute differentiates shooters from other players who play a different role on the team. The same can be noted in relation to the mean win-score per minute, which differentiates players who contribute in different ways to team wins. The Pearson correlation r between both variables was not significant ($r = 0.26$; $p = 0.190$).

Moreover, we implemented a linear mixed model that took into consideration the team variable as random effect because some of the players were from the same NBA franchise. Thus, we accounted for repeated measures and the fact that the values of regularity could change from one game to the next. The random effect was presumed to be independent and normally distributed. The results of the Hausman test (Hausman 1978) were not significant, and thus we employed the more efficient random effect estimation, using the generalised least squares estimation. All statistical analyses were performed using the statistical software Stata 12.0. We estimated the model using ML xtreg procedure in Stata 12.0. Statistical significance was set at $\alpha < 0.05$.

In addition, we employed several control variables which were included in further runs of the initial model: height, body mass index (kg/height^2), player precedence (United States/rest of the world), age, experience as NBA player (number of previous seasons played), and position (guard/forward/centre).

In order to test the regularity of the performance of the player, we conducted the Cochran variance outlier test, which is used to assess the homogeneity of variances. With the Cochran test, we tried to identify the player(s) with the greatest variance in performance, and thus the most unstable player(s).

The Cochran test for player i is computed as

$$C_i = \frac{s_i^2}{\sum\limits_{j=1}^{k} s_j^2} \tag{1}$$

where k is the number of players and s_i^2 is the sample variance of the performance of player i.

It is an upper-tailed test and the critical value at a confidence level of α can be computed as

$$CU_\alpha = \frac{1}{1 + \frac{k-1}{F_{\frac{\alpha}{k},n-1,(k-1)(n-1)}}} \tag{2}$$

where n is sample size for each player and $F_{\frac{\alpha}{k},n-1,(k-1)(n-1)}$ is the quantile $1 - \alpha/k$ of the F distribution with $n - 1$ degrees of freedom in the numerator and $(k - 1)(n - 1)$ degrees of freedom in the denominator.

4.2 Results and implications

We computed the MAD for the 27 players in our dataset. MAD was normal. The Shapiro-Francia W test for normal data was $W = 0.96$; $p = 0.26$. It should be noted that the Kendall $\tau - b$ correlation between Gini and MAD was $\tau - b = 0.05$, and between Theil and MAD $\tau - b = 0.10$. Therefore, the ranks of the players regarding regularity would have varied more if we had used the inequality measures.

Players were ranked by MAD, as Table 1 demonstrates. Rafer Alston was the most regular player of the dataset ($MAD = 0.105$), and Antonio McDyess was the last on the list ($MAD = 0.200$). The extent to which MAD increases the performance is more irregular. The Gini and Theil coefficients were also shown only for illustrative purpose, in order to ascertain that the ranks produced by inequality indices were very different from the robust measure of dispersion - MAD - which was chosen as an indicator of regularity.

The results of our calculations are depicted in Table 2. The salary of the player was not associated with variation in regularity. Only the mean of the points scored per minute was significantly linked to consistency in performance ($p < 0.001$). Therefore, when players are better scorers, they become more irregular in terms of their performance.

This is an interesting result because it reflects the uncertainty of performance increases to the extent that players have specific skills, such as being good scorers. Therefore, it would be more difficult to predict the points scored per minute of the leaders of each team.

This does not mean that being an irregular scorer is an undesirable feature for a specific player. Managers may prefer to have a more irregular player than another player who is a better scorer. However, if there is a choice between two high scorers, the managers would likely prefer the more regular scorer, and this is one reason this type of analysis is relevant.

We made an additional model using the control variables as covariates, and the results were almost identical (Table 2); therefore, control variables did not impact on the coefficients of the main model estimated.

Table 3 shows the results of the Cochran variance outlier test for the 27 players considered.

Tayshaun Prince and Mike James are outliers in terms of the variance of player's performance. Thus, their performance was unstable in comparison with that of other players.

The Cochran variance outlier test indicates that the performance of some players is significantly higher than others. Players may have peaks of performance in specific games, although the MAD indicated that they were not the most irregular.

5 Study 2. Describing regularity with ordinal patterns

5.1 Method

Let y_{it} denote the performance of player i at period t measured in points per minute. First we analyse what the structure of the player's performance is every three games. We divide the games played by each player into groups of three consecutive games (note that three is the average number of games per week). We consider the following vectors

$$u_{i1} = (y_{i1}, y_{i2}, y_{i3}); u_{i2} = (y_{i4}, y_{i5}, y_{i6}); \ldots ; u_{it} = (y_{i3(t-1)+1}, y_{i3(t-1)+2}, y_{i3(t-1)+3}); \ldots$$

The possible ordinal patterns of $\{u_{it}\}$ are as follows (Figure 1).

Thus, for instance, the first ordinal pattern represents that the performance of player i in three consecutive games improved in one game after another, while the opposite

Table 1: Regularity rank of analysed NBA players for points made per minute in the 2007 season

Player	MAD	Gini	Theil
Alston Rafer	0.105	0.221	0.089
Snow Eric	0.108	0.460	0.500
Dalembert Samuel	0.113	0.231	0.100
Battier Shane	0.114	0.287	0.138
Deng Luol	0.116	0.161	0.043
Biedrins Andris	0.120	0.265	0.119
Fisher Derek	0.122	0.236	0.091
Blount Mark	0.123	0.219	0.072
Parker Smush	0.126	0.245	0.101
Granger Danny	0.127	0.218	0.078
Collison Nick	0.132	0.279	0.128
Stevenson DeShawn	0.134	0.249	0.104
Wilcox Chris	0.134	0.214	0.071
Prince Tayshaun	0.135	0.241	0.092
Howard Dwight	0.140	0.209	0.072
Bell Charlie	0.152	0.269	0.138
Foye Randy	0.153	0.265	0.139
James Mike	0.156	0.297	0.202
Stoudemire Amare	0.156	0.185	0.063
Webster Martell	0.159	0.378	0.312
Bibby Mike	0.161	0.222	0.078
Warrick Hakim	0.161	0.235	0.100
Finley Michael	0.166	0.298	0.183
Pargo Jannero	0.167	0.284	0.180
Carter Vince	0.170	0.182	0.054
Gordon Ben	0.193	0.215	0.079
McDyess Antonio	0.200	0.368	0.270

occurred with the last ordinal pattern. Ordinal patters 2, 3, 4 and 5 are called changing patterns since they exhibit a change in the behaviour of the player performance in three consecutive games and therefore provide us with a sign of irregularity.

Table 2: Model estimation results

	Research Model			Expanded Model		
Covariable	Coef.	Std. error	p-value	Coef.	Std. error	p-value
Intercept	0.094	0.016	0.000	0.001	0.279	1.000
Player wage relative to team salary	-0.033	0.079	0.671	-0.133	0.105	0.205
Mean of the points scored per minute	0.146	0.041	0.000	0.171	0.047	0.000
Mean of the winscore per minute	-0.054	0.050	0.271	-0.006	0.110	0.952
Height				-0.001	0.001	0.934
BMI				0.003	0.003	0.349
Age				0.001	0.002	0.600
Procedence				-0.100	0.012	0.406
Experience				0.001	0.003	0.811
Position				0.001	0.014	0.965

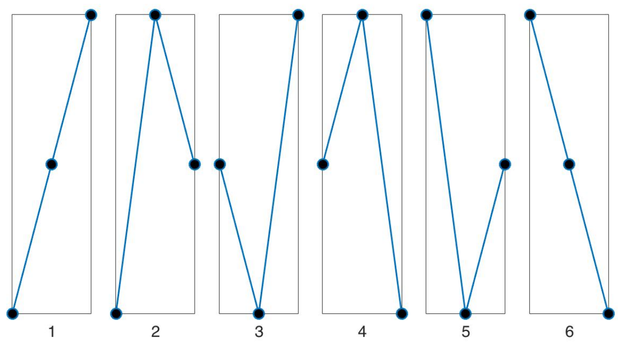

Figure 1: Possible ordinal patterns in 3 games

5.2 Results and implications

Figure 2 shows the distribution of the ordinal patterns observed in one season for the 27 players considered in this study:

It should be noted that the case in which the ordinal patterns are equally distributed (with probability 1/6; flat histogram) correspond with the case in which the player's performance is more *chaotic*. The distribution of the relative frequencies of each ordinal pattern indicates that, depending on the player, there are some patterns which appear more than one would expect and some others appear less frequently than expected. Nevertheless, the sample size is not large enough (n =27 sample ordinal patters per player) to permit the detection of differences between the frequencies of ordinal patterns. Despite this, we have computed in the following table the chi-square test in order to check

Table 3: Test for the stability of the performance employing the Cochran variance outlier test. $CU_{0.1} = 0.0540; CU_{0.05} = 0.0557; CU_{0.01} = 0.0592$

Player	Cochran statistic
Alston Rafer	0.0221
Snow Eric	0.0225
Dalembert Samuel	0.0369
Battier Shane	0.0426
Deng Luol	0.0274
Biedrins Andris	0.0253
Fisher Derek	0.0524
Blount Mark	0.0288
Parker Smush	0.0230
Granger Danny	0.0232
CollisonNick	0.0477
Stevenson DeShawn	0.0283
Wilcox Chris	0.0444
Prince Tayshaun	0.0655***
Howard Dwight	0.0274
Bell Charlie	0.0349
Foye Randy	0.0464
James Mike	0.0738***
Stoudemire Amare	0.0484
Webster Martell	0.0286
Bibby Mike	0.0325
Warrick Hakim	0.0213
Finley Michael	0.0300
Pargo Jannero	0.0471
CarterVince	0.0465
Gordon Ben	0.0438
McDyess Antonio	0.0280

whether the six ordinal patterns of players' performance are equally distributed (Table 4).

As can be noted in the previous table, except for the pattern of Derek Fisher all the

Table 4: Chi-Square test to check whether the six ordinal patterns of player's performance are equally distributed.

Player	χ^2-test	p-value	Sample needed to reject at 5%
Alston Rafer	7.00	0.220	16
Snow Eric	4.77	0.443	36
Dalembert Samuel	5.66	0.340	26
Battier Shane	0.77	0.978	357
Deng Luol	0.77	0.978	357
Biedrins Andris	3.88	0.565	50
Fisher Derek	15	0.0104	-
Blount Mark	5.66	0.340	26
Parker Smush	3.88	0.565	50
Granger Danny	7.00	0.220	16
Collison Nick	3.88	0.565	50
Stevenson DeShawn	6.55	0.255	19
Wilcox Chris	10.11	0.072	3
Prince Tayshaun	6.11	0.295	22
Howard Dwight	5.22	0.389	30
Bell Charlie	2.11	0.833	115
Foye Randy	4.33	0.502	42
James Mike	3.44	0.631	60
Stoudemire Amare	3.44	0.631	60
Webster Martell	1.22	0.942	218
Bibby Mike	8.33	0.138	9
Warrick Hakim	6.55	0.255	19
Finley Michael	3	0.699	73
Pargo Jannero	2.55	0.768	90
Carter Vince	3.88	0.565	50
Gordon Ben	1.66	0.893	152
McDyess Antonio	8.77	0.118	7

ordinal patterns are equally distributed at a 5% level for all players. As stated above, this may be due to the fact that the sample size is not large enough to permit the rejection of the null of equal distribution of ordinal patterns of players' performances. The last column of the previous table reports, by keeping constant the probability distribution of ordinal patterns, the sample size needed to reject the null. Those players who have rejected the null or need a greater sample size to reject the null are those who perform more regularly (more structured performance). This is because rejecting the null means that some ordinal patterns of the player performance dominate the distribution.

Globally, results derived from the chi-square test reflect the fact that the pattern of points scored per minute in a series of three games is very difficult to predict without taking into consideration additional information regarding influencing variables, as Casals and Martinez (2013) have demonstrated.

6 Concluding remarks

Although there has been an increase in the availability of highly advanced mathematical tools which can be used in basketball metrics, basic concepts on measuring player performance should not be forgotten if we are to balance the high number of possibilities of analysis and the practical implications for improving our understanding of the game (Pelton 2016).

Our research constitutes an advancement and attempts to answer an important question on basketball metrics: how to measure regularity in terms of points scored and which factors may influence this regularity. This question has been understudied in the specialised literature despite its importance.

We have demonstrated that some players are much more regular in terms of point scoring than others, and when players are better scorers they become more irregular scorers, i.e. their performance is less predictable. In addition, some players at the half-level of regularity are "outliers" in the sense that some peaks in their performance may influence the variance of their respective distributions. Finally, the pattern of points scored per minute in a short series of games is very difficult to predict without taking into consideration additional information regarding influential variables; there is little evidence that NBA players are subject to a momentum effect.

Other measures of regularity have also been employed in basketball literature previously, such as the Atkinson index (Esteller-Moré and Eres-García 2002), the sum of the mean and the inverse of the coefficient of variation (Salmerón-Gómez and Gómez-Haro 2016). However, the Atkinson index requires the incorporation of a sensitivity parameter which can range from zero to infinity, and this should be subjectively chosen by researchers in function of the sensitivity to inequalities at the bottom of the distribution. Regarding the sum of the mean and the coefficient of variation, these can be influenced by extreme cases. Therefore, we believe our index of consistency is more objective and robust than the aforementioned ones.

One of the major limitations of our study is the possible existence of reverse causality with respect to the unique significant covariate: mean of points scored per minute. We attempted to test the control variables, which were clearly exogenous, as instruments with which to apply a two-stage least square estimation (2SLS). However, all the instruments were weak (low correlation with the covariate). This, together with the small sample size, make the 2SLS procedure inefficient.

However, we do not think that regularity influences players' offensive performance. Shooters in the NBA fully assume their roles, and they know they are responsible for most of the shots for their teams. Regularity is a measure of how all these players do during the NBA season. We believe that our model is accurate and useful, but we acknowledge the limitations caused by not empirically testing for reverse causality because of the lack of good instrumental variables.

Our research should be viewed as the first stage of more in-depth studies on the regularity of basketball players. The limited scope of our data and the small sample size are major limitations which should be addressed in future research.

Our methodology can be applied to any other sport structured in seasons with a defined number of games, such as football, baseball or volleyball. We believe that this method is not feasible for sports such as tennis, athletics or other individual sports.

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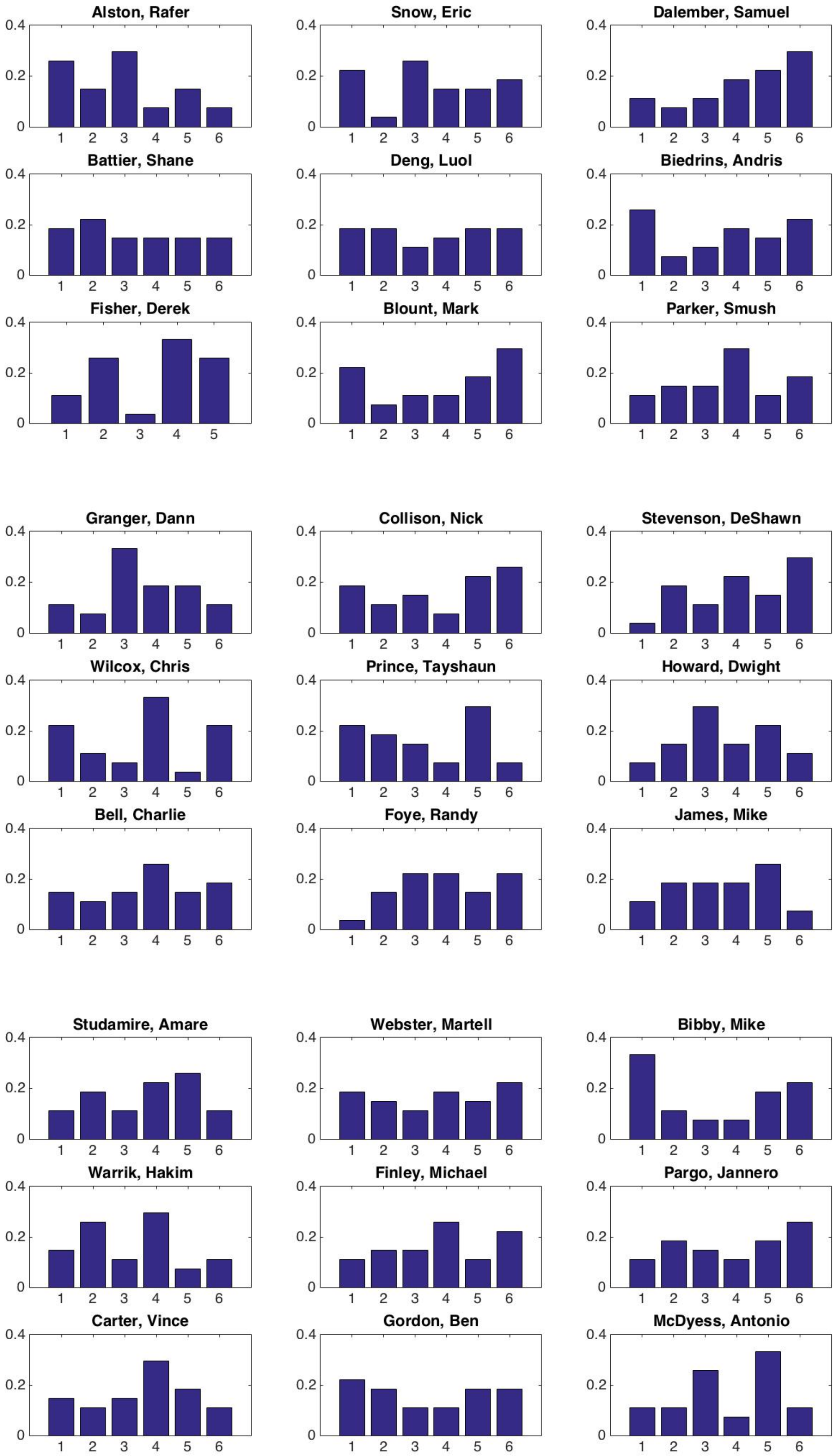

Figure 2: Distribution of the ordinal patterns observed in one season for the considered 27 players.

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