Behavior and Patterns of Streaky Shooting in the Modern NBA

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Stats 406

Introduction

In basketball, when a player hits several difficult shots in a row, they are said to have a "hot hand", and the team will look to give that player more shots throughout the game. Video games such as the recent iterations of the *NBA 2K* franchise support this concept, where a player on a scoring streak is more likely to make the same shot as a player on a scoring drought. However, many in the basketball analytics community have proposed that this in fact an instance of the "hot hand fallacy", where a lucky start will cause coaches and players to overestimate the effectiveness of a certain player or set. A 1985 paper on this matter, titled "The hot hand in basketball: On the misperception of random sequences", found no evidence of streaky behavior among players on the Philadelphia 76ers in the 1980-1981 season (Gilovich, et. Al). However, since the introduction of the three-point to the NBA, the style of play has changed drastically. For example, In the 1980-1981 season, all teams collectively averaged 2.0 three pointers attempted per game. In the 2020-2021 season, all teams collectively averaged 34.1 three pointers attempted per game. Asking three-point shooting specialists to take the same shots more frequently may cause psychological effects that could cause non-random patterns in that players shooting record. For players who specialize in shooting, streaks and slumps may be more noticeable. If streaky shooting is in the modern NBA is in fact, as most research has suggested, a misperception of random sequences, then for each player in a set of players, that player's shooting percentage on shots following a streak of *n* misses or makes will be roughly the same for all values of *n*. The purpose of this paper is to examine whether shooting streaks and slumps have a significant impact on three-point specialists in the NBA.

Duncan Robinson of the Miami Heat, Ben McLemore of the Houston Rockets, and Kyle Korver of the Milwaukee Bucks were the NBA's leaders in three-point attempt rate last season (2019-2020). Each of these players took over 80% of their total field goal attempts from beyond the arc. These players are chosen as the best examples of "specialists" in the league.

For the three players who attempted the highest rate of three-point shots last season, we will test whether or not their shooting patters display signs of streakiness. Under the null hypothesis for the three players being tested, the differences between their shooting percentage when their streak is at a certain number will be very close to their overall shooting percentage. Under the alternate hypothesis, the players' field goal percentages will improve when they are on a streak of makes and worsen when they are on a streak of misses, so their field goal percentage at a certain streak will be further from their overall shooting percentage.

Data

The source of the data in this project was a CSV file found on Kaggle.com containing a full play by play log of the entire 2019-2020 NBA regular and playoff seasons (Schmadamco). This enormous file was reduced three times to three different tables containing all plays in games played by the Miami Heat, Houston Rockets, and Milwaukee Bucks, the teams of the players being studied. These tables were further reduced to only contain plays that were field goal attempts by Robinson, McLemore, and Korver respectively, keeping only the relevant columns, including "ShotOutcome" containing the values "make" and "miss" depending on the outcome of that shot, and the date of the game so it can be easily determined when a new game has started. The values of "ShotOutcome" were replaced with the Boolean values "TRUE" for a make and "FALSE" for a miss in order to simplify calculations. The following table shows some basic data about the individual shooting logs for the three players.

Figure 1

Player	Total number of shots	Number of games	Maximum shots in a game	Minimum shots in a game
D. Robinson	863	93	16	3
B. McLemore	585	81	18	1
K. Korver	340	66	15	1

All three players appear to have sufficient volume of shots across games.

Methods

In order to understand the methodology of this experiment we must define the concept of a shooting streak. A "streak" of makes or misses will only count shots attempted in the same contest. If a player ends one game on a streak of 4 misses, the streak will automatically be reset to zero at the start of the next game. For the purpose of this project a negative value of streak will be considered to be a streak of consecutive misses and a positive value will be a streak will be a streak of consecutive makes.

Iterating through the shooting logs for each player, that player's shooting percentage following any number consecutive makes or misses was calculated for every value of a shooting streak found in the data.

Theoretically, for each player, following *n* misses or makes, that players shooting percentage will be equal to their overall shooting percentage. However, even if streaks are in fact random, there will be some deviation from the expected distribution with the sample size in this example. A stochastic process drawing from the expected distribution will be performed and repeated to calculate a reasonable amount of deviation from the expected distribution of misses and makes. The test statistic for this experiment, which will be called “flatness”, is the average absolute value of the difference between a players’ field goal percentage at a certain streak and their overall field goal percentage for all values of shooting streaks where a player attempts at least 10 shots. A smaller flatness statistic will signify consistency in field goal percentage where a larger statistic shows deviation or streakiness.

Equation 1:

$$f = \frac{\sum |FG\%_s - \bar{FG\%}|}{n}$$

f: flatness, FG%: field goal percentage, s: streaks>=10 shots, n: number of streaks>=10 shots

An average is used because the total value might be dependent on the minimum and maximum lengths of streaks in different simulations and a minimum ten shots are required to consider the sample size large enough. The Simulations section details the stochastic process used to calculate hypothetical distributions under the null and alternate hypothesis. These hypothetical distributions are generated with a stochastic process, where outcomes are simulated chronologically to calculate a statistic, and the process is repeated to get a distribution of possible statistics (Rizzo 99).

Simulations

For each player being studied, 1000 simulated seasons were created under both the null and alternate hypothesis that the probability of making a shot was or was not dependent on the shooters current streak. For the purpose of the null hypothesis, each shot was independent, so each simulated shot is essentially a Bernoulli random variable. Under the alternate hypothesis, we will assume that the probability of making a shot is equal to the null value of the total field goal percentage, plus the streak (streaks of misses are negative) times 20%. If the new estimated field goal probability was greater than one or less than zero, it was handed as the nearest valid value

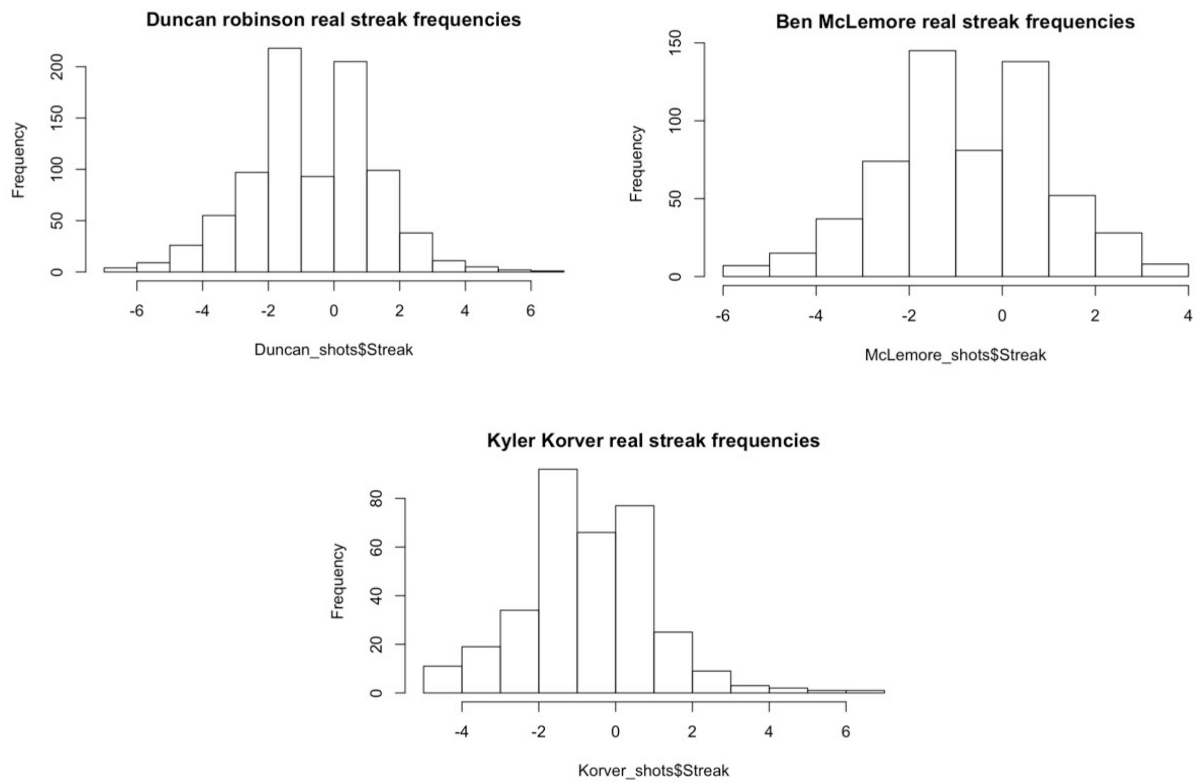
Equation 2:

$$H_0 : shot_i \sim Bern(FG\%)$$
$$H_a : FG\%^* = FG\% + (s_i \cdot 0.2), shot_i \sim Bern(FG\%^*)$$

$shot_i$: event a shot goes in, s_i: streak at the time of the shot

Under this extreme distribution, a shot will be guaranteed to go in for streaks of 3 or longer, which happen somewhat frequently, and guaranteed to miss for streaks of 3 or longer. While this may seem like problematic, such streaks are very rare in the real data, so if streakiness is a better predictor than overall field goal percentage, the player should be almost guaranteed when on such an extreme streak.

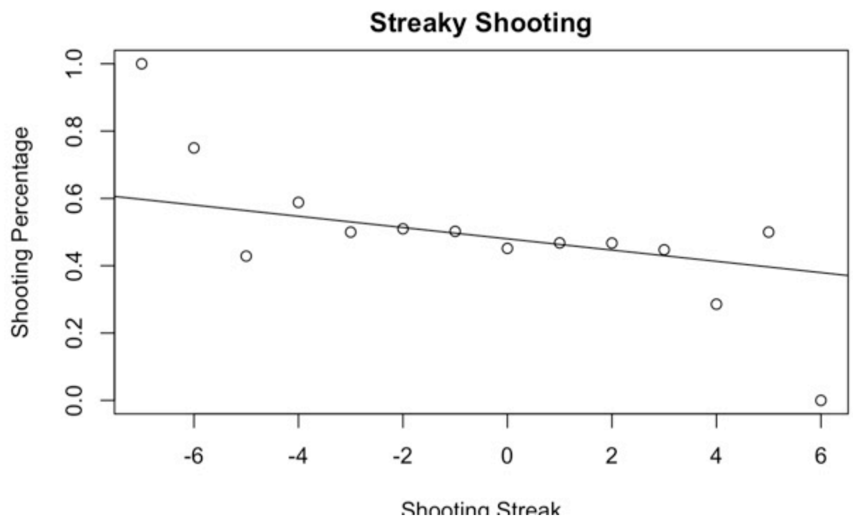
Figures 2, 3, 4:



Streaks of length 3 or longer are very rare so they are a sufficient metric of being "very hot"

For each individual simulated season, the streaks and field goal percentages at certain streaks are calculated along in order to generate a flatness statistic. The number of shots in each game by each player is kept the same. A graph showing one simulated season by Duncan Robinson is provided below.

Figure 5:



The graph features a regression line weighted by number of shots, which actually goes down slightly as the streak goes up in this simulation.

In order to maximize the power of the test while minimizing type I error, a one-sided alpha value of .1 was chosen. The null hypothesis would be rejected if the real flatness statistic was greater than the 90^{th} percentile value in the distribution of 1000 flatness statistics under the null hypothesis. In order to avoid excessive redundant graphs and reported figures, information about the simulated distributions for the null and alternate distribution will be included in the analysis section of this report as they are relevant to the hypothesis testing.

Analysis

The initial results for the summarized values of shooting percentages appeared to be in line with the expectations of the null hypothesis. The real shooting percentages at a given streak for all three players appear to be consistent with the null hypothesis that all of these values should be about the same.

Figures 6, 7, 8:

Duncan Robinson Summary

Streak	FG_Percentage	Makes	shots
-7	1.0000000	1	1
-6	0.3333333	1	3
-5	0.3333333	3	9
-4	0.5384615	14	26
-3	0.4545455	25	55
-2	0.3195876	31	97
-1	0.5045872	110	218
0	0.4731183	44	93
1	0.5219512	107	205
2	0.4040404	40	99
3	0.3421053	13	38
4	0.4545455	5	11
5	0.6000000	3	5
6	0.5000000	1	2
7	0.0000000	0	NaN

Ben McLemore Summary

Streak	FG_Percentage	Makes	shots
-6	1.0000000	1	1
-5	0.1666667	1	6
-4	0.4666667	7	15
-3	0.5675676	21	37
-2	0.4459459	33	74
-1	0.3655172	53	145
0	0.4814815	39	81
1	0.4420290	61	138
2	0.5576923	29	52
3	0.3928571	11	28
4	0.1250000	1	8

Kyler Korver Summary

Streak	FG_Percentage	Makes	shots
-5	0.6666667	2	3
-4	0.5000000	4	8
-3	0.3157895	6	19
-2	0.4117647	14	34
-1	0.5217391	48	92
0	0.3636364	24	66
1	0.3506494	27	77
2	0.5200000	13	25
3	0.3333333	3	9
4	1.0000000	3	3
5	0.5000000	1	2
6	1.0000000	1	1

All FG% values are close to eachotther when sample size is high, no trend apparent.

However, when applying the simulations and hypothesis testing,, the flatness of the alternate test statistics were not as far away from the null test statistics as anticipated. Finding a rejection value with a usable power but a responsibly low type one error was particularly difficult for Kyle Korver, and to a lesser extent Ben McLemore, who did not have as many long streaks to cause large deviation from their overall field goal percentages. As a result, the powers of their tests, provided in the following table will be low. The power was calculated as the percentage of flatnesses in the alternate distribution that were less than the 90th percentile value in the null distribution. The p-value for the individual test statistics is the percentage of values in the null distribution that are less than the actual test statistic. The following table provides basic information that is also shown in the resulting density plots of the experiment.

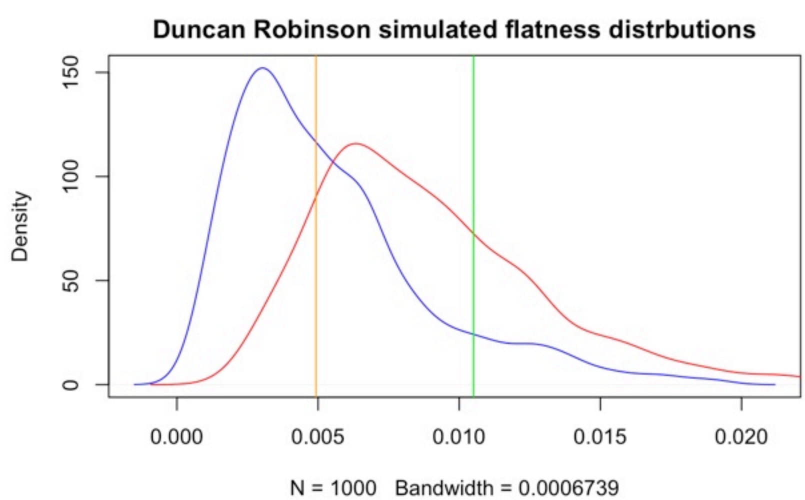
Figure 9:

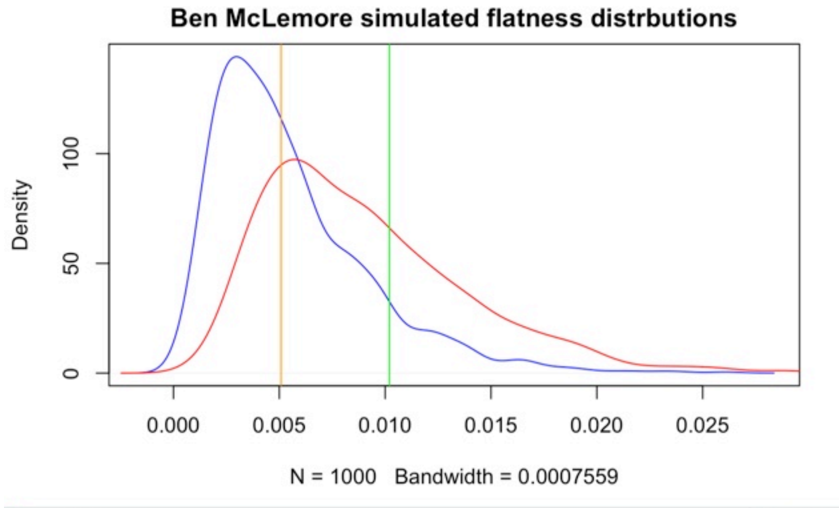
Player	Flatness	p-value	90th percentile rejection value	Power
D. Robinson	0.004927297	0.458	0.01050887	0.286
B. McLemore	0.005080413	0.437	0.01020782	0.335
K. Korver	0.005783134	0.383	0.0117193	0.284

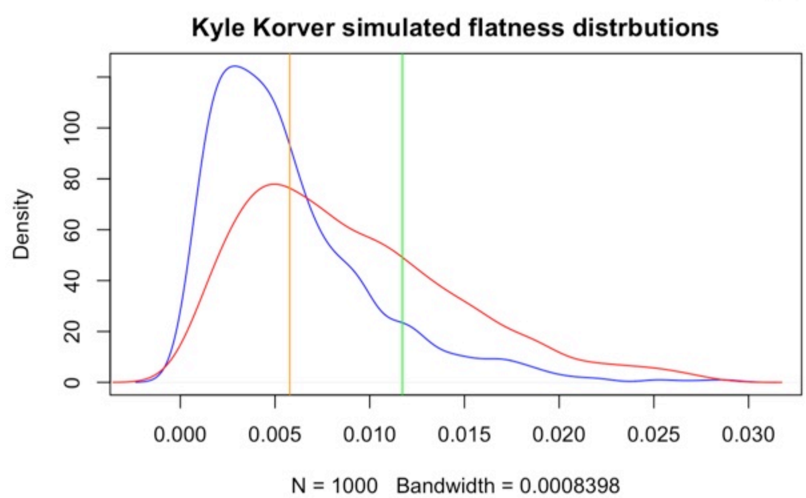
For all three tests, the p-value seems to support the null hypothesis, but the low power of the tests is problematic.

Figures 10, 11, 12:

--Null Dist. –Alt. Dist. –Actual value –Rejection value







The null distribution appears more likely but the low power of the test causes uncertainty.

The fact that the orange test-statistic line crosses the blue null distribution line higher than the red alternate distribution line is consistent with the high p-values – given that the null hypothesis is true and streak is irrelevant to the shooters expected field goal percentage, the calculated test statistics from the real data are not at all unlikely. The problem lies in how much overlap there is between the null and alternate distributions. Even if the alternate hypothesis were true that streak is very important in determining expected field goal percentage, we would still not be likely to reject the null hypothesis under the current test. For Kyle Korver, the test statistic being larger than the modal value of the smoothed alternate distribution appears to be particularly problematic given that the null hypothesis cannot be rejected. Even with a very aggressive calculation for FG%* under the alternate stochastic process, the flatness statistics were not high enough to conduct a very effective test. We cannot strongly reject the null or alternate hypothesis without a better metric to compare the simulated seasons than the flatness statistic designed for this experiment.

Discussion

Given the limitations of the flatness statistic used in this study, no strong conclusions can be made about the subject matter. There is very weak support for the null hypothesis found in similar research that shots are independent and that the shooting percentages for a given streak value are roughly the same and that all shots are practically independent from one another. Tentatively, this hypothesis appears to hold for three-point specialists as well as it does for other types of basketball players

Further research is certainly required. A larger sample size incorporating more players and more seasons of data would certainly be useful as there are very few long streaks found in the data used, which is the behavior that I am most interested in exploring. Of course, the lack of these long streaks is itself support that streaky behavior is rare amongst the three-point specialists being studied. A better metric to define streakiness could potentially be found than the one arbitrarily chosen for this project. The psychological effects of a make can potentially last from game to game or several consecutive makes can provide psychological benefits even after a miss. A logistic regression model predicting whether a shot will go in based on the presence of several different patterns of makes in the previous shots both in that game and in others might yield better results at finding some significant example of streaky behavior. While this approach may be more expensive in computing power, the results may be more powerful. Ultimately, any possible explanation or pattern of streaky behavior that could have been proposed before reading this paper cannot be fully dismissed as a result of the experiments conducted.

Works Cited

1. Gilovich, Thomas, et al. "The Hot Hand in Basketball: On the Misperception of Random Sequences." *Cognitive Psychology*, vol. 17, no. 3, July 1985, pp. 295–314., doi: https://doi.org/10.1016/0010-0285(85)90010-6Get.
2. Rizzo, Maria L. *Statistical Computing with R, Second Edition*. Chapman and Hall, 2019.
3. Schmadamco. "NBA_PBP_2019-20.csv." Kaggle.com, 21 Jan. 2021.

Supplemental Materials

1. Final Code.rmd – Code for all calculations and plots in the report
2. NBA_PBP_2019-20.csv – Play-by-play dataset used to find player shooting logs