The Effect of Perceived Streakiness on the Behavior of Basketball Players: How Defensive Strategy Leads Players to Change Their Shooting Behavior and Risk-Taking Propensity

Peter Csapo[1], Simcha Avugos[2], Markus Raab[1,3], and Michael Bar-Eli[2,4]

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[1] Institute of Psychology, German Sport University, Cologne, Germany.

[2] The Zinman College of Physical Education and Sport Sciences, Wingate Institute, Netanya, Israel.

[3] Department of Applied Sciences, London South Bank University, London, UK.

[4] Department of Business Administration, Guilford Glazer Faculty of Business and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel.

Correspondence should be addressed to Peter Csapo, Institute of Psychology, German Sport University, Am Sportpark Müngersdorf 6, 50933 Cologne, Germany. E-mail: peter.csapo@whu.edu. Phone: +49-1520-9769376.

Abstract

Objectives: Most researchers examining the hot hand, i.e. streaky performance of an individual, have neglected the effect of changes in task difficulty on performance although these changes can provide valuable insights into behavioral consequences arising from the hot-hand belief. In the current work, three proxies linked to shot difficulty in basketball, namely shot distance, shot type and shot angle, were identified and the effect of players' streakiness on these variables was measured.

Design: Changes of the variables were analyzed for various streak lengths – including cold streaks – in order to obtain a better understanding of how shooting behavior is altered.

Method: The play-by-play data of 1,216 games from the 2009-2010 NBA regular season was analyzed using conditional probabilities and correlational associations.

Results: The analysis revealed that all three variables significantly influenced shooting accuracy. Furthermore, the outcome of previous shots had a significant effect on the players' shot selection: The more consecutive shots players made, the more difficult shots became along the three dimensions and risk-taking propensity increased, while the opposite trend was observed for consecutive misses.

Conclusions: Several findings throughout this work implicitly underline that changes in shooting accuracy occur due to defensive pressure. The results also imply that most players' performance seemed to improve during hot streaks because they attempted more difficult shots while no significant decrease in shooting accuracy could simultaneously be observed. This might at least partially explain why convincing empirical evidence in favor of the hot-hand belief has been difficult to find when considering in-game field goal shooting. In the context of organizational behavior, the results indicate that task difficulty should be considered when assessing an agent's performance and that certain investment managers may indeed outperform their peers.

Keywords: hot hand, sport, basketball, decision making, behavioral, risk taking

1   Introduction

Over the past decades, psychologists have shown great interest in examining how people evaluate probabilistic events, as they systematically perceive non-existent patterns by mistake. A premier example of this discrepancy between perception and reality is the hot-hand phenomenon, according to which a basketball player is more likely to hit his next shot if he has made his previous shots than if he has missed them. Occurrences of the hot-hand phenomenon are by far not only limited to the sports domain but can also be found in managerial and economic contexts (e.g. Lehman & Hahn, 2013; Offerman & Sonnemans, 2004), and researchers from these fields have developed a strong interest in examining the hot hand, too.

A large amount of research focused on the question of whether the hot hand actually exists. For instance, the vast majority of basketball players, coaches and fans believe in the existence of the hot hand but Gilovich, Vallone, and Tversky (1985) could not find any statistical evidence for a positive correlation between consecutive shots. After analyzing field goal as well as free throw shooting data of professional basketball players and running a controlled shooting experiment, they concluded that shots were independent events. Since the publication of this study, most researchers have focused on trying to statistically validate the existence of the hot hand (e.g. Koehler & Conley, 2003; Larkey, Smith, & Kadane, 1989) but the majority of studies failed to produce results which could convincingly refute the findings of Gilovich et al. (1985) (for an overview, see Bar-Eli, Avugos, & Raab, 2006, and a meta-analysis by Avugos, Köppen, Czienskowski, Raab, & Bar-Eli, 2012). In particular, most of the scarce evidence in favor of the hot hand has come in individual sports. For instance, Abrevaya (2002) examined professional bowling tournaments where low-ranked bowlers first had to win several matches before being allowed to compete against high-ranked players who were waiting idly in the meantime. Abrevaya found that low-ranked bowlers beat high-ranked ones more often than expected by chance because they experienced a hot hand through their

previous wins. Similarly, Livingston (2012) found evidence in favor of the hot hand's existence among professional golfers and argued that the hot-hand effect has to be examined on an individual level as athletes have different characteristics and react differently to streaky performance. Thus, if the data are aggregated and the overall means are evaluated, no evidence in favor of the hot hand can be found.

When discussing the hot-hand phenomenon, most researchers refer to the actual belief, namely that a player is more likely to make a shot after several hits in a row. Yet, Burns (2004) suggested that a distinction between the hot-hand belief and behavior should be made, and found that a basketball team, whose players act according to the belief and allocate the ball to the perceived hot player, score roughly one extra point per seven games.

Consequences arising from the belief in the hot hand were discussed by several researchers (e.g., Gigerenzer, Todd, & The ABC Research Group, 1999), suggesting that the hot-hand belief should not be considered as a fallacy, but rather as being ecologically rational. According to this concept, the hot-hand belief should be evaluated relative to the respective situation, and behavior arising from it can be considered ecologically rational as long as it leads to the attainment of an agent's goals (Gula & Raab, 2004).

As previously mentioned, the hot-hand belief has also played an important role in management and economics. Specifically, most research in this area has focused on betting and investor behavior. For instance, Camerer (1989) examined the betting market for professional basketball games and found that gamblers behaved according to the hot-hand belief as the point spreads of teams on a winning (losing) streak were too high (low). Meanwhile, Offerman and Sonnemans (2004) pointed out similarities between financial and sports markets as investors tend to overvalue stocks of firms which have performed well in the past, while sports fans expect winning streaks of teams to continue. Similarly, investors tend to entrust their money with investment managers who have previously performed well as

they expect the hot streaks of these managers to continue (Patel, Zeckhauser, & Hendricks, 1994).

The implications of the current work are primarily relevant for organizational behavior and financial markets as we explore behavioral consequences, i.e. changes in basketball players' shooting behavior, resulting from the hot-hand belief. In the hot-hand literature, it has frequently been assumed that the opposing team might adjust its strategy once a player has been perceived as hot in order to minimize the number of points scored by the hot player and his teammates (e.g., Burns, 2004; Gilovich et al., 1985). For instance, a hot player might be guarded more closely or by several defenders, and thereby forced to take more difficult shots. Similarly, a player who experiences a cold streak, i.e. who has missed several consecutive shots, might not be pressured as intensively by defenders and given easier shot attempts.

In a managerial context, an agent improves his skills over time and may be asked by his principal to take on increasingly difficult challenges after the successful completion of several tasks. However, as argued by Aharoni and Sarig (2012), it is difficult to differentiate the performance of an average manager from that of a superior one from an outside perspective because one has to take into consideration the degree of task difficulty an agent is confronted with. Despite a high level of motivation and skill, a manager may for instance still fail to meet a certain target due to increases in task difficulty. Oftentimes, executive compensation schemes already account for the unobservability of managerial performance: Bebchuk and Fried (2005) found that the pay of top executives was uncorrelated to their observed performance while a significant correlation was found by Bebchuk and Grinstein (2005) between pay and the company's market capitalization, which can be interpreted as a proxy for managerial task difficulty.

Similarly, the performance of investment managers is difficult to observe but, as mentioned above, investors tend to entrust their money to managers who have performed well in the past. However, several studies (e.g. Jensen, 1969; Gil-Bazo & Ruiz-Verdú, 2008) found

that analyzing past information about stocks does not help individual investors to forecast the future more accurately as the past performance of an investment fund can at most be considered as a noisy signal. Berk and Green (2004) explain the performance of fund managers who follow up superior returns with mediocre performance by noting that superior fund managers are entrusted with more difficult tasks, which arise due to an increasing number of clients. Since highly profitable investment opportunities are limited, increases in managed accounts ultimately offset performance increases. Empirical evidence supporting Berk and Green's line of argumentation has been found by Ippolito (1992) who observed a large and highly significant correlation between fund growth and recent performance.

Furthermore, the implications of this study can be related to prospect theory (Kahneman & Tversky, 1979), according to which people become more risk-seeking in the domain of losses relative to one's reference point than in the domain of wins. In line with this work, Lehman and Hahn (2013) examined organizational risk-taking by analyzing how attitudes toward risk changed in professional football as a function of momentum, where momentum was very similarly defined to the hot hand as it was assumed to begin after the second consecutive event, i.e. after two unanswered scoring episodes. The authors concluded that risk-taking propensity depended significantly on (1) how an organization, i.e. a team or a business, was performing relative to its aspiration level and (2) whether it experienced positive or negative momentum before having to make a decision. For instance, an organization surpassing its performance targets but experiencing negative momentum is predicted to choose a less risky option relative to an organization with the same performance and positive momentum. While Lehman and Hahn (2013) considered risk attitudes on an organizational level, our study extends their findings by examining whether the propensity to take risk also changes on an individual level as a function of momentum.

This work closely ties in with two recently published studies by Aharoni and Sarig (2012) and Attali (2013) as they attempted to measure the effect of consecutive hits on the

shot selection of the hot player. The first two authors analyzed the shot difficulty of the offensive team and divided shots into "difficult" and "easy". They concluded that hot players tended to take more difficult shots while their teammates attempted easier ones but, as the authors acknowledged, their measures of shot difficulty and defensive adjustments were imprecise.

More recently, Attali (2013) used shot distance as a proxy for the perceived hotness of a player. Surprisingly, the analysis showed that long-range shots were generally followed by close-range shots and vice versa, regardless of the outcome. However, the core of Attali's analysis was solely based on how shot distance evolved after a single hit or miss. Although a single shot was enough to alter the behavior of players and coaches, it is generally accepted that three repeated events are needed for people to perceive streakiness (see Carlson & Shu, 2007). In other words, due to memory processing abilities, people tend to detect streak shooting following at least three consecutive hits, and vice versa for the cold hand.

Relative to Aharoni and Sarig (2012) and Attali (2013), the current study is based on a larger and more precise set of variables. We used three proxies, where we presumed a casual relationship with respect to shot difficulty: shot distance, shot type, and shot angle. Furthermore, this research incorporates changes of these three variables for various streak lengths – including cold streaks – in order to attain a better understanding of how the players' shooting behavior is altered depending on the number of consecutive makes and misses, respectively.

The current work includes two parts. In Section 2, we examine whether shot distance, type and angle could serve as proxies for shot difficulty. In Section 3, we analyze hot and cold spells in the performance record of the top 10 scorers of the 2009-2010 NBA regular season to investigate whether streaks have an effect on the three aforementioned variables. Furthermore, we use the number of turnovers as a proxy for defensive pressure to examine whether players are more (less) prone to turn the ball over during and after hot (cold) streaks.

Following the presentation and discussion of the results, we finally touch upon the implications of the study for hot-hand research as well as organizational and economic behavior.

2 The effect of shot distance, shot type and shot angle on shooting accuracy

2.1 Method

To examine the effect of shot distance, type and angle with respect to field goal percentage (FG%), we compiled the play-by-play data of 1,216 games from the 2009-2010 NBA regular season. This database included the outcome, type, and coordinates for each shot, which allowed us to calculate the distance and angle of 196,781 field goal attempts (FGA).

2.1.1 Shot distance

We analyzed the effect of distance on FG% for seven shooting intervals: five-foot steps were used for shots from less than 30 feet and one interval for distances of 30 feet or more.

2.1.2 Shot type

The original play-by-play database included 50 different shot types. Since some types were highly similar, we established six categories: dunks, hook shots, other jump shots, regular jump shots, layups, and three-pointers. Roughly 23% of jump shots in the original database included more information about the way the shot was released, e.g. "turnaround jump" or "fade away jumper." Since we hypothesized that these types of jump shots may have a different degree of difficulty relative to straight-up jump shots, we differentiated between jump shots for which no detailed information was available (i.e. regular jump shots) and other jump shots. Furthermore, since tip shots occur fairly rarely in basketball, we included them in the "layup" category.

2.1.3 Shot angle

We used the shot coordinates to calculate the angle at which a player was standing relative to the basket and divided the court into six equally large sections, with the center being the basket and each section having an interior angle of 30 degrees (see Figure 1 for an illustration). We hypothesized that there might be individual differences with respect to FG% and the number of FGA relative to each shot angle, so that we examined the data of the top 10 scorers of the 2009-2010 NBA regular season in addition to the aggregate data of all players.

2.2 Results

2.2.1 Shot distance

As expected, a general decrease in FG% was observed as shot distance increased, and the results are visualized in Figure 2. Around one-third of all shots were attempted from less than five feet and this segment included the highest shooting percentage at 60.34% (mean distance: 1.21 feet). Meanwhile, a fairly sharp drop in shooting percentage was observed for the next segment (FG%: 42.30, mean distance: 7.64 feet), so that moving away from the basket by only a few feet seemed to have a considerable effect on shooting accuracy. In the following three distance sections, the average shooting percentages were fairly similar to the 5 to 10-foot segment but the increase in distance was generally paired with a small decrease in FG%.

Around 14% of all shots were attempted from 25 to 30 feet as FG% for this segment dropped to 35.08% (mean distance: 26.25 feet). The final section included shots from a distance of 30 feet or more: The average shooting percentage was very low, i.e. 7.59% (mean distance: 45.57 feet), and the standard deviation high (13.03 feet), since these shots were mostly attempted as time expired. An additional analysis revealed a statistically significant inverse relationship between shot distance and shooting percentage ($r = -.930$, $p < .01$).

2.2.2   Shot type

Large differences in FG% were observed for the six pre-defined shot types, as success rates ranged from 34.71% to 91.29%. The highest FG% was detected for dunks, while layups had a 35% lower chance of being successfully executed (56.12%), even though the average distance in both shot categories was quite similar – 0.95 feet for dunks compared to 1.21 feet for layups.

Surprisingly, a considerable difference in shooting percentages was found for regular jump shots (34.71%) and all other jump shots (57.23%), even though average distances were fairly similar (13.52 feet for regular and 11.25 feet for other jump shots). As for three-point shots, their mean distance was twice as large as that of regular jump shots (25.89 compared to 13.52 feet) but they were made with a slightly higher accuracy, namely at 35.58% as opposed to 34.71%. Overall, the relationship between shot type and FG% was statistically significant ($V = .286, p < .01$).

2.2.3   Shot angle

In general, all players displayed a strong tendency to attempt more shots from the middle of the court. Furthermore, some players displayed a preference for shooting from a certain side of the court. For instance, Dirk Nowitzki attempted more shots from the left corner (92 versus 62 from the right), while also successfully hitting 10% more of his shots relative to the ones attempted from the right corner (53.26% versus 43.55%). Furthermore, the number of FGA and FG% for each angle section were positively correlated ($r = .549, p < .01$).

Looking at the aggregate data for all NBA players, nearly half of all shots were attempted from the 60–90° section, where by far the highest shooting percentage could be found at 52.90%. An overview of the results for the shot type and shot angle analysis are

presented in Table 1. Similarly to the other two variables, shot angle was found to be a relevant proxy for shot difficulty ($V = .130, p < .01$).

2.3 Discussion

Based on the analysis, it can be concluded that shot distance, shot type and shot angle indeed affect shooting accuracy. Thus, it would neither be enough to merely look at the shot type when analyzing shot difficulty nor would it be sufficient to distinguish between only two shot types as done by Aharoni and Sarig (2012). Moreover, our findings show that the inferences made by Attali (2013) might have oversimplified the game of basketball, as it was suggested that a long-distance shot was "readily interpretable as evidence of hotness" (p. 2). Meanwhile, our analysis showed that the shot type was also of key importance for the assessment of shot difficulty as demonstrated through a comparison of jump shots and three pointers: Three pointers were accompanied by a higher FG% despite a nearly twice as large mean distance (13.52 versus 25.89 feet).

A key finding from the shot distance analysis is the sharp drop in FG% for shot attempts from 5 to 10 feet, which is followed by relatively constant values until players are 25 feet away from the basket. While uncontested shots from 5 to 10 feet are likely hit by players with very high accuracy, we hypothesize that intensive defensive pressure in games for shots near the basket leads to such a decrease in shooting percentage. Furthermore, defensive pressure decreases as shot distance increases, which ultimately leads to fairly constant shooting percentages.

As mentioned above, there were large differences in FG% when comparing layups and dunks (56.12% versus 91.29%). This finding might give another hint about the effect of defensive behavior. Professional basketball players are likely to hit uncontested layups with very high accuracy but this scenario changes in game situations, and layups can be altered more easily through defensive behavior than dunks.

The shot angle analysis revealed that the number of FGA from specific positions was positively correlated with the FG% in the respective angle range. In our view, an explanation could be that players tried to attempt as many shots as possible in areas from which they felt the most comfortable shooting.

Having confirmed the relevance of shot distance, shot type and shot angle with respect to shot difficulty, we next show how these three variables change in relation to a player's previous shots.

3   The effect of hot and cold streaks on players' shooting behavior

3.1   Method

Similarly to the shot angle analysis above, we based the following analysis on the play-by-play data of the top 10 scorers of the 2009-2010 NBA regular season and considered streaks within each game, using at least three consecutive hits and misses as a measure of streak shooting.

3.1.1   Streak analysis

Shot sequences were analyzed using the so-called runs test where a player is considered to be streaky if he has fewer runs than expected by chance.

3.1.2   Analysis of changes in shooting variables conditional on streak length

For each player, we examined the effect of streak shooting on FG% as well as on the three shooting variables while considering hot and cold spells. The analysis of conditional probabilities relative to the players' FG% relates back to Gilovich et al. (1985), and we used the Durbin-Watson test to check for serial correlations and a t-test to analyze whether the players' FG% were statistically different for cold versus hot streaks. To examine changes in shot distance, type and angle in relation to streak length, we first calculated the distribution of

all shot attempts over the course the season for each player relative to the previously defined shot types and angles. Next, we examined how these proportions changed for different streak lengths. Finally, we examined the relationship between the variables and streak length, and evaluated their deviations relative to the season averages.

3.1.3   Turnover analysis

Since we hypothesized that opponents may react to both cold and hot streaks, we used turnovers as a proxy for defensive pressure and examined whether hot players turned the ball over more frequently than cold players. For the analysis, we classified every game of the ten players based on the streaks, if any, they experienced. Consequently, there were games in which players had both cold and hot streaks ("mixed streak") and others in which only cold or hot streaks occurred. We then calculated the number of minutes between the occurrence of the first streak and the end of the game. Next, we counted the number of turnovers attributed to the player within this timeframe. To render the number of turnovers more comparable, we normalized the figures based on a 48-minute game. Finally, we used an independent-samples Kruskal-Wallis test to examine whether there were differences in the distribution of turnovers for different streak types, i.e. cold, hot, and mixed.

3.2   Results

3.2.1   Streak analysis

As displayed in Table 2, six of the ten observed players exhibited fewer runs than expected by chance; however, only two players produced statistically significant results ($p <$ .05). Since streak shooting entails fewer runs, the results indicate that these players, namely Durant and Wade, were indeed prone to streak shooting. Meanwhile, none of the results for the other four players exhibiting more runs than expected was statistically significant.

3.2.2   Analysis of changes in shooting variables conditional on streak length

Overall, most players exhibited streaks of eight consecutive shots for both makes and misses at some point during the 2009-2010 regular season. The longest cold hand was experienced by Anthony and Ellis at twelve consecutive misses each, while Durant experienced the longest hot streak at eleven successive hits.

Serial correlations were negative for seven players, i.e. $d < 2$, but the values were non-significant for all ten players. Thus, they provided no evidence for the existence of the hot hand and were consistent with the literature. Furthermore, a t-test revealed that FG% were not statistically different during hot versus cold spells for nine of the ten players (see Table 3).

In the core part of our analysis, we first examined the effect of streak shooting on shot distance, and the aggregated results are displayed in Figure 3a. More precisely, we calculated the correlation coefficients for the top 10 scorers and, while all correlations were positive, seven values were statistically significant at the 1% level. Therefore, players tended to attempt shots from further away the more consecutive shots they had previously made and vice versa for misses.

Next, we analyzed how the distribution of shot types changed relative to streak length and found that players tended to attempt more shot types which were associated with lower FG% once they were on a hot streak and vice versa for cold streaks. During hot streaks, all players attempted more three-pointers relative to their season average. The opposite trend could be observed for cold streaks as eight players attempted fewer three-pointers and nine players tried fewer regular jumpers. Meanwhile, changes for the two shot types with the highest success rates, i.e. dunks and layups, were positive for most players during cold phases: Eight players attempted more dunks and the share of layup attempts increased for seven players. The aggregate results for the ten players are displayed in Figures 3b. and 3c. An independent-samples t-test was conducted to compare the means of the distribution of

dunks and layups to the ones of jump shots and three-pointers for cold and hot streaks, respectively, and statistically significant differences were found ($t = 5.180$, $p < .01$).

As for the shot angle analysis, recall that individual preferences could be observed for most ranges and universally valid generalizations were only feasible for the 60–90° range, so that we focused on this section for the analysis. The aggregate results are presented in Figure 3d. and, overall, seven players attempted more shots from the 60–90° range during cold streaks, while eight players displayed fewer attempts during hot spells relative to their season average. This finding was confirmed statistically when comparing the means of the shot distribution in the 60–90° section and the ones in all other angle ranges for cold and hot streaks, respectively ($t = 3.664$, $p < .01$).

Finally, we compared the magnitude of deviations from average performance and found that the absolute value of deviations tended to be larger for changes in shot types than for angle ranges, as well as for hot streaks compared to cold ones.

3.2.3 Turnover analysis

Overall, the ten players exhibited at least one streak in nearly all games. While the average number of games with cold- and hot-only streaks was fairly balanced at 19.1 (cold) and 15.1 (hot), players experienced mixed streaks in the majority of games (mean: 35.7).

When comparing the distribution in the number of turnovers between games with cold-only and hot-only streaks, only two players exhibited significantly more turnovers during hot streaks, namely Durant ($K = 5.745$, $p = .017$) and Bryant ($K = 4.032$, $p = .045$). Furthermore, Durant was the only player to have incurred significantly more turnovers during hot-only relative to mixed streaks ($K = 5.441$, $p = .020$).

3.3   Discussion

The streak analysis provided several novel insights regarding changes in shooting behavior as a function of previous shots. The results of the runs test yielded non-significant results for most players and no statistically significant serial correlations were found while players attempted more difficult (easier) shots during hot (cold) streaks along the three dimensions. Therefore, players seemed to account for the outcome of their previous shots when deciding to shoot, which is consistent with the findings of Aharoni and Sarig (2012) and Attali (2013). Moreover, this trend was reported by Neiman and Loewenstein (2011) who suggested that reinforcement learning models could explain changes in shot selection. Similarly to Attali (2013), they found that a single shot was sufficient to alter a player's shooting behavior. While in certain situations, for instance towards the end of a close game, a single shot can change the outcome of a game and provide a team with momentum, the hot hand has traditionally been defined by streaks consisting of several, i.e. at least three, consecutive hits.

Since differences in FG% were non-significant for nine players during cold versus hot streaks and, at the same time, shot difficulty changed significantly, it can be hypothesized that most players' performance improved during hot streaks because they hit more difficult shots at a level similar to their average FG% during cold streaks. Therefore, researchers may have had difficulties to find evidence for the hot hand during in-game basketball shooting because the degree of shot difficulty offset the elevated performance during hot periods. This is a key finding since most evidence in favor of the hot hand has come in individual sports (e.g. Abrevaya, 2002).

Furthermore, it is important to examine why players seemed to alter their shooting behavior as a function of their previous performance. It might be, in case of a hot streak, a product of increased confidence or of defensive adjustments by the opposing team. As discussed in Section 2, there are several indicators that point towards the importance of

defensive strategy when it comes to increasing shot difficulty. In our view, the significant drop in FG% for shots from five to ten feet compared to those from zero to five feet is largely due to defensive pressure, as NBA players will likely hit these shots with high accuracy if they are uncontested. The same holds for the difference in FG% between dunks and layups, which is most likely due to the defense altering shots.

As for the turnover analysis, players experienced both cold and hot streaks in a large number of games which limited the data to work with. The findings indicate that most players did not seem to turn the ball over significantly more often during hot streaks while behavioral changes seemed to be more pronounced for cold streaks. However, we have to acknowledge that increased pressure by a defensive player can manifest itself in multiple ways beyond forcing turnovers and that the implications of this proxy should be interpreted with caution. A more in-depth analysis, e.g. through video analysis, would be needed to examine the impact of defensive behavior on streaky players.

4   Conclusion

A key finding of this work is that basketball players' shooting behavior is significantly altered as a function of streakiness because they attempt more difficult (easier) shots during hot (cold) spells. Moreover, the results provide a hint that shooting percentages and shot sequences are not necessarily the most important indicator when assessing a player's performance and streakiness. As our data have shown, a player's performance may become elevated during certain phases of a game but it may not be readily observable. Similarly, statistics from the NBA show that the best players and highest scorers are very rarely the ones who exhibit the highest FG% because players with the highest shooting percentage frequently attempt fewer and easier shots. For instance, it has only happened once since the 1965-1966 regular season that the player with the highest FG% led the NBA in scoring, namely when

Shaquille O'Neal averaged 29.7 points on 57% shooting during the 1999-2000 regular season ("All-Time NBA Stats," 2013).

Furthermore, several findings in Section 2 have pointed out the effect of defensive pressure on field goal percentage, so that we hypothesize that the largest driving force behind the observed variations in shooting behavior were defensive adjustments by the opposing team. Relating these findings back to the concept of ecological rationality, it can be concluded that an increase in defensive pressure was ecologically rational because the defenders' goal is to minimize the number of points scored by the opponents. The specific conditions, under which opposing teams alter their defensive strategy and the hot-hand belief can be considered as ecologically rational, should present a fruitful avenue for further research.

Transferring the findings of this study to an organizational and economic context, we posit that principals should take into consideration changes in the agent's task difficulty before concluding prematurely that the task was not solved adequately because of the agent's lack of skill and effort. Furthermore, our results provide empirical evidence for the model of Berk and Green (2004) indicating that high-performing agents become entrusted with more difficult tasks and that investment managers may indeed experience hot streaks which become unobservable due to an increase in the number of managed client accounts.

Considering the context of momentum and attitudes toward risk, we can finally examine the implication of changes in the players' risk-taking propensity as a function of cold and hot streaks. As the results in Section 2.2 have shown, there were significant differences in shot difficulty and hitting probability in each of the examined dimensions, namely shot distance, type and angle. For instance, a player attempting a shot from further away is, ceteris paribus, more risk-taking than one who attempts a shot from closer distance. As shown in Figure 3, the examined players attempted significantly more difficult shots during hot streaks, so that they made riskier decisions in phases during which they were in the gain domain relative to their reference point. Therefore, this behavior stands in contrast to the predictions

of prospect theory. While these findings are similar to the ones by Lehman and Hahn (2013), the underlying reasons for changes in risk-taking propensity are likely to be different: Lehman and Hahn's theory is based on behavioral changes due to the need for safety during cold streaks and overconfidence illustrated by relaxation during hot streaks, whereas our findings point towards the importance of defensive interference in causing a behavioral reaction. Further research could investigate the interplay of individual and organizational momentum as well as aspiration levels. For instance, it could be examined to what extent managers base risky decisions on their own momentum as opposed to the one of the organization. As previously mentioned, organizational performance is not necessarily indicative of a manager's skills and performance, and a manager with positive momentum might expose an organization, which is neither experiencing positive momentum nor meeting its aspiration level, to unwarranted and unnecessary risks.

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Table 1. Effect of shot type and shot angle on FG% of NBA players

Shot type	3 pointer	Dunk	Hook	Jump (reg.)	Jump (oth.)	Layup
FG%	35.58%	91.29%	52.75%	34.71%	57.23%	56.12%
FGA	43,832	9,325	6,305	64,509	18,899	53,911

Shot angle	0-30°	30-60°	60-90°	90-120°	120-150°	120-180°
FG%	40.57%	39.46%	52.90%	41.81%	38.00%	40.78%
FGA	11,098	23,992	93,630	31,367	24,668	12,026

Table 2. Analysis of runs for the top 10 scorers of the 2009-2010 NBA regular season

Player	# of shots made	# of shots missed	FG%	Observed # of runs	Z
Kevin Durant	803	885	47.57%	893	*2.440
LeBron James	729	730	49.97%	732	.079
Carmelo Anthony	685	799	46.16%	733	-.294
Kobe Bryant	658	766	46.21%	696	-.688
Dwayne Wade	711	796	47.18%	795	*2.218
Monta Ellis	631	766	45.17%	699	.325
Dirk Nowitzki	701	741	48.61%	717	-.234
Danny Granger	509	675	42.99%	611	1.758
Chris Bosh	579	563	50.70%	564	-.467
Amar'e Stoudamire	696	537	56.45%	616	.507

$* p < .05$ $** p < .01$

Table 3. Conditional probabilities of hits and misses for the top 10 scorers of the 2009-2010 NBA regular season

| Player | # of consecutive shots | | | | Serial corre-lation | t-test comparing means of FG% for cold and hot streaks | |
	≥ 3 misses	1 or 2 misses	1 or 2 makes	≥ 3 makes	d	t	Sig.
Kevin Durant	49.45%	50.68%	43.15%	50.00%	2.066	-.097	.923
LeBron James	52.08%	49.91%	50.54%	45.58%	2.000	1.108	.269
Carmelo Anthony	45.96%	45.57%	49.06%	38.33%	1.952	1.338	.182
Kobe Bryant	47.51%	44.87%	47.52%	49.60%	2.007	-.358	.721
Dwayne Wade	46.47%	50.44%	44.86%	36.70%	2.034	1.624	.106
Monta Ellis	39.38%	47.33%	45.82%	41.23%	2.042	-.319	.750
Dirk Nowitzki	52.70%	47.26%	49.71%	47.92%	1.965	.816	.415
Danny Granger	54.25%	42.65%	40.05%	38.81%	1.970	*2.135	.035
Chris Bosh	58.33%	48.55%	50.72%	52.42%	1.967	.927	.355
Amar'e Stoudamire	55.26%	57.67%	58.74%	53.80%	1.995	.212	.832

* $p < .05$ ** $p < .01$

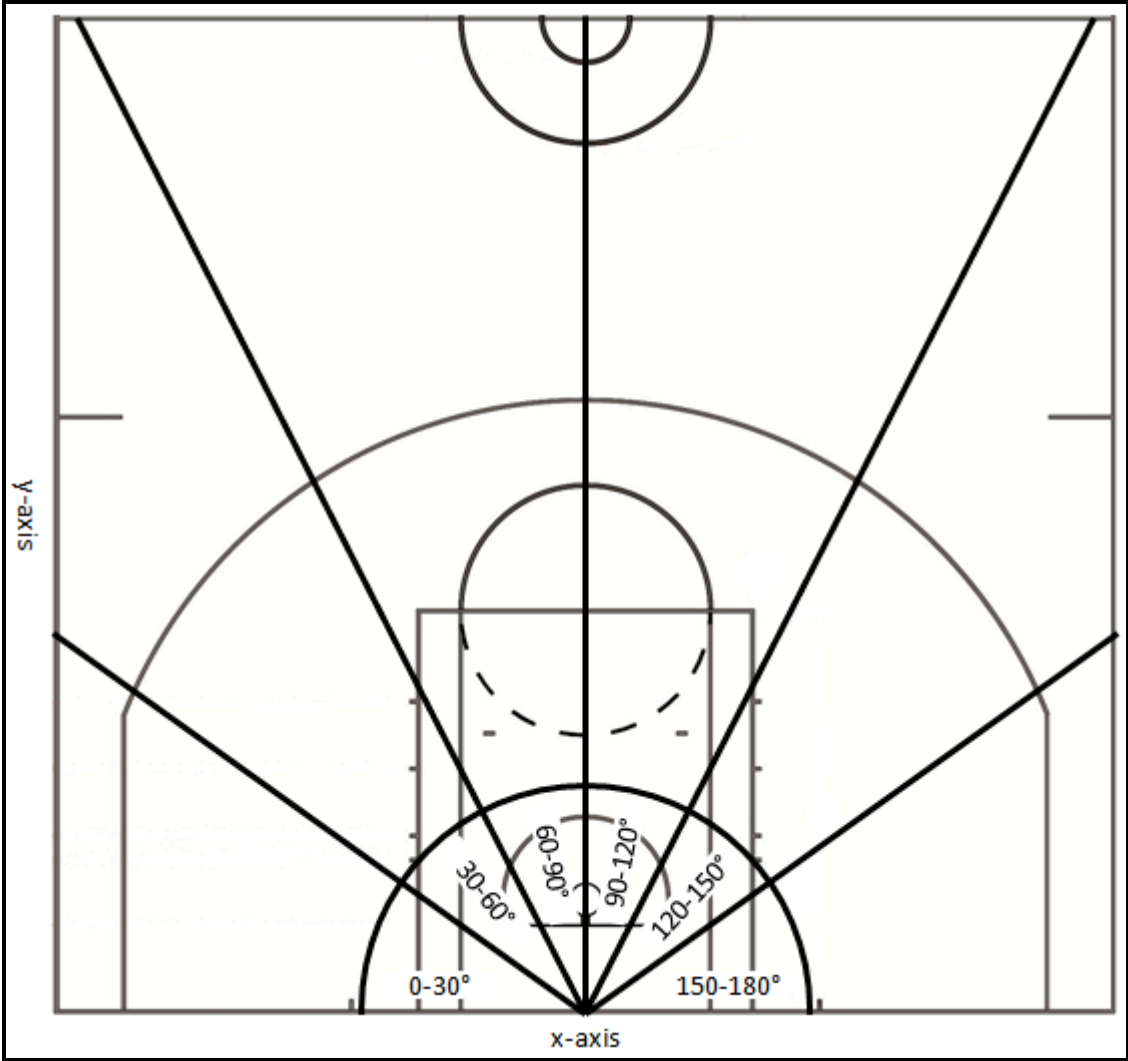**Figure 1. Illustration of the shot angle distribution**

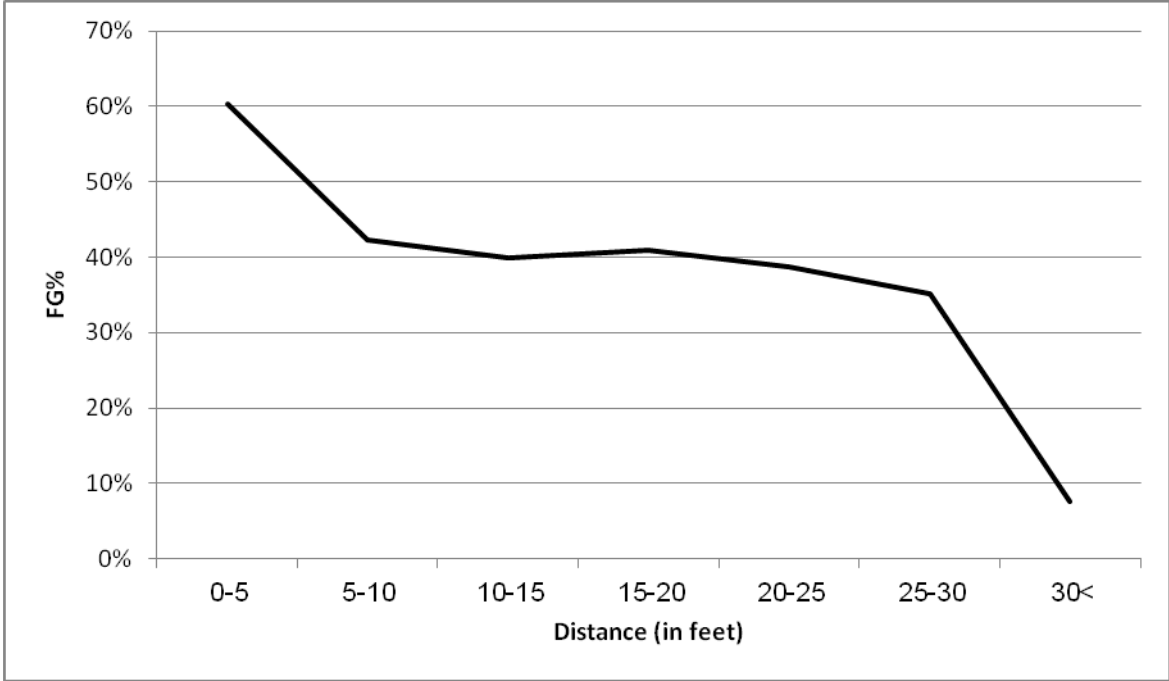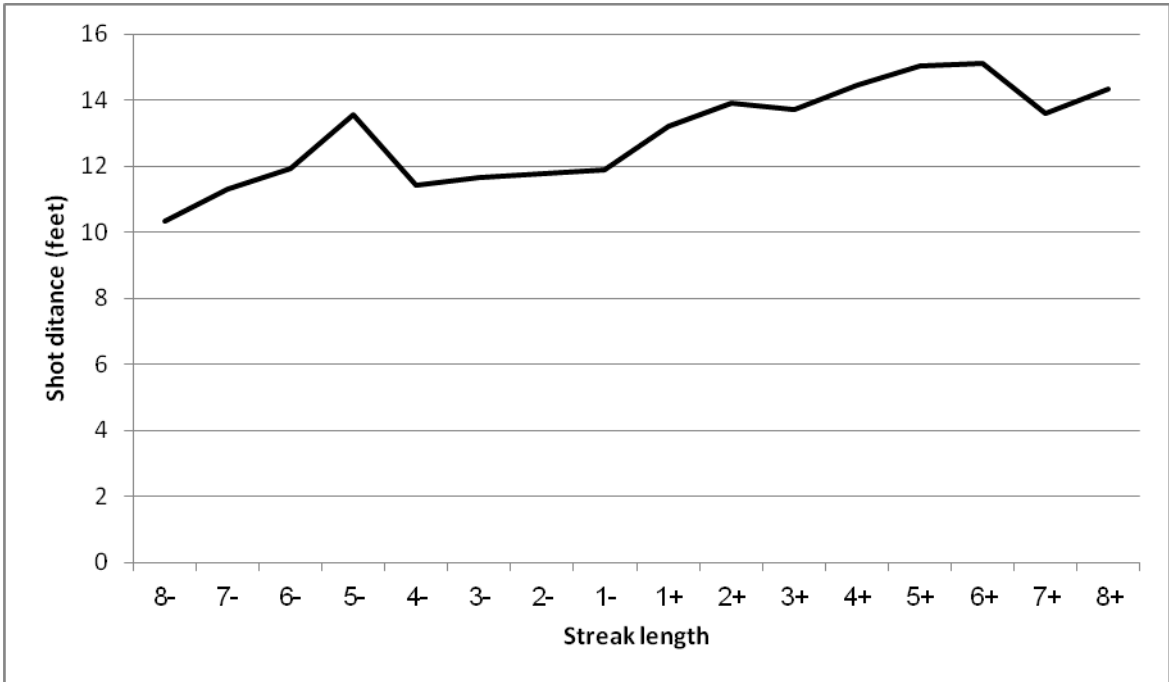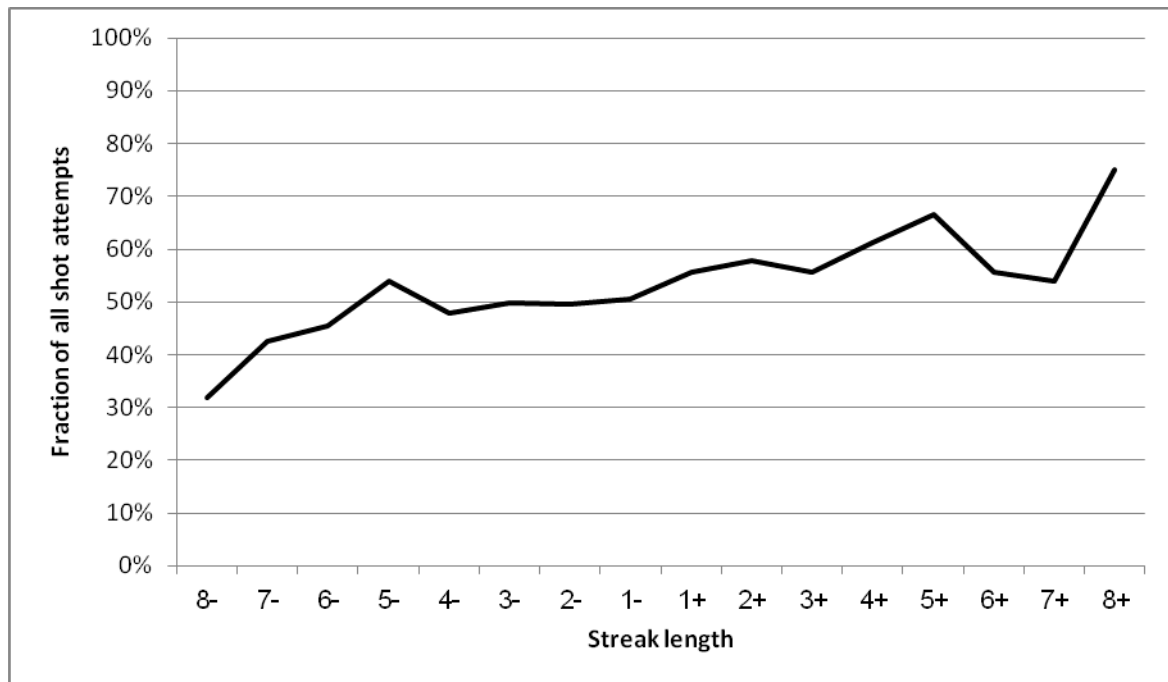**Figure 2. Effect of shot distance on FG% of NBA players**

Figure 3. Evolution of shooting variables as a function of streak length for the top 10 scorers of the 2009-2010 NBA regular season
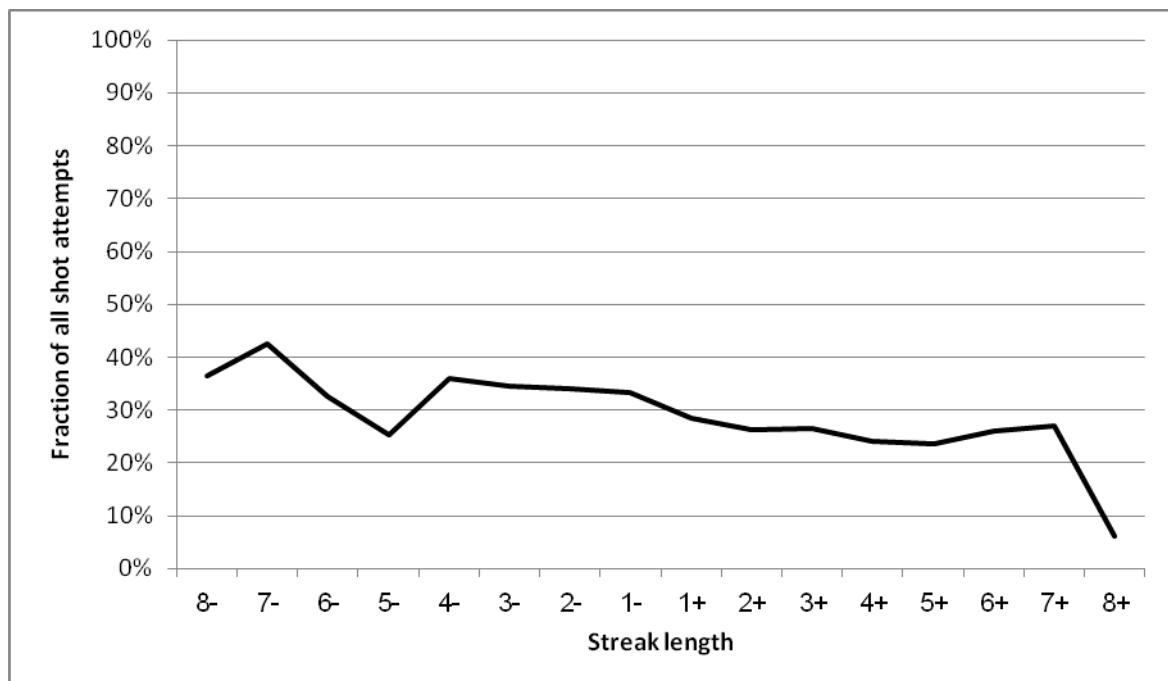
3a. Shot distance

3b. Two shot types with lowest average FG%: 3 pointers and regular jump shots (fraction of all shot attempts belonging to these two shot types)

3c. Two shot types with highest average FG%: dunks and layups (fraction of all shot attempts belonging to these two shot types)

3d. Shot angle range with highest average FG% and largest number of FGA: 60-90° (fraction

of all shot attempts belonging to this angle range)