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Testing “hot hand” hypothesis at the individual athletes' level in soccer

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Abstract

The existence of a hot hand in individual athletes' performance in soccer under fantasy sports rules is investigated in this paper. It is also investigated whether fantasy sports users use this heuristic in selecting their squads. Using unique data of the performance of athletes and fantasy sports users' demand for them, the results show some existence of a hot hand, however, it fails to explain most future performance. Hot hand explains about 10 percent of the variability in future performance data. However, it explains more than 60 percent of the variability in fantasy sports user demand data. It is crucial to acknowledge that the outcomes often exhibit a higher level of noise compared to the expected results.

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1. Introduction

Sports fans, sports experts and even athletes themselves believe that athletes occasionally exhibit so-called streak shooting which means that an athlete's chance of hitting a shot is greater following a hit than following a miss on the previous shot (Bar-Eli et al. 2006; Gilovich et al. 1985). This belief is called a hot hand. Applications of this belief were first tested in basketball (Gilovich et al. 1985; Gula and Raab 2004; Koehler and Conley 2003; Morgulev et al. 2020) and baseball (Albright 1993), but now other sports such as hockey (Kniffin and Mihalek 2014), soccer (Parsons and Rohde 2015; Simmons and Wheeler 2017), volleyball (Raab et al. 2012), rugby (Pocock et al. 2018), golf (Cotton et al. 2019) and tennis (Meier et al. 2020) have been tested.

Soccer is the sport examined in this paper. However, previous papers (Parsons and Rohde 2015; Simmons and Wheeler 2017) have only examined soccer at the team level. This means whether a winning streak increases the probability of further victories. Generally, the results do not demonstrate this phenomenon (Albright 1993; Lantis and Nesson 2021) with a few exceptions (Brown and Sauer 1993; Green and Zwiebel 2018; Miller and Sanjurjo 2021). However, the debate has been reignited by the paper by Miller and Sanjurjo (2018), who use a coin flip to show that previous research may not have been well conducted methodologically and modify the results of Gilovich et al. (1985). Their results and mathematical proofs show the existence of a hot hand on the original data. However, it should be noted that this existence is relatively small. Additionally, Morgulev (2023) draws attention to the psychological aspects of the phenomenon under investigation by distinguishing between within-contest and across-contest dynamics. Furthermore, the author emphasizes the significance of developing a theoretical framework to guide research in this area. But all the papers agree that fans believe in this phenomenon, which has an impact, for example, on the sports betting market (Agha and Tyler 2017; Krčál et al. 2016; Legge and Schmid 2016), thus, bookmakers take it into account in their odds (Shank 2019; Wheatcroft 2020).

This paper aims to investigate hot hand at the individual player level, which is enabled by the use of data from fantasy sports (FS) that allows for the observation of player individual performance, as described in more detail in the following section on data and methodology.

It is important to note that in a team sport where so few goals are scored, it is not easy to determine momentum (Kniffin and Mihalek 2014), a term often used as a superset of the hot hand. The issue is whether past performance positively influences future performance. In the commentator's terminology, it is possible to talk about an athlete's good form. And FS is a unique tool to determine the good form of athletes, for example, regardless of whether they are offensive or defensive players. Similar patterns are investigated, for example, in financial markets for stock price movements (Anusakumar et al. 2014; Momani 2018). Authors examine whether a previous rise in the stock price has an impact on future growth (Su et al. 2007), and the behavior of traders in these markets (Koga 2016; Leal 2013).

FS is an online competition complementing traditional sports consumption (Karg and McDonald 2011), where users with a limited virtual budget select athletes for their squads and receive points based on the athletes' actual performance. Although many fantasy leagues are free and FS users can only win in-kind prizes such as tickets, jerseys or balls, FS users report competition as the most important incentive to participate. Winning the competition is therefore their most common goal (Davis and Duncan 2006; Dwyer et al. 2011). It is thus a game similar to sports betting but focused on individual athletes (Shapiro et al. 2020). Squad selection in FS is such a difficult and complex problem that its users often use heuristics (Bryson and Chevalier 2015; Smith et al. 2006) and hot hand is one of the possible ones. The application of the hot hand idea points to increased bets on the team in the winning streak (Camerer 1989; Simmons and Wheeler 2017), so in FS, athletes who have a point-scoring streak according to FS rules should be selected.

The presence of hot hand at the individual level in English Premier League (EPL) athletes is tested and then the consideration of this phenomenon by users playing FS is investigated.
The paper follows a structured format. Firstly, it presents the data, provides an overview of the rules of the specific FS, and outlines the methodology employed. Subsequently, it introduces specific models for investigating the existence of the hot hand phenomenon and explores the beliefs of FS users regarding this phenomenon, along with presenting their respective findings. The subsequent section focuses on testing the robustness of the results by partitioning the dataset into individual game positions, sensitivity analysis for different thresholds and using models with continuous scoring of performance. Finally, the paper concludes with a discussion that integrates previous literature, examines the implications of the findings, and proposes potential directions for future research.

2. Data and methodology

The dataset was provided by Seznam, Inc., which operated FS played by fans in the Czech Republic until the 2015-16 season. The investigation is based on the soccer EPL. The season contained 38 rounds of games. A total number of 11,096 FS users took part in the competition and filled in 134,682 squads in which they included 498 different athletes. The data is modified into a panel where one observation is a specific athlete in a specific round. The total number of observations in the complete dataset is 18,924.
One round of investigated FS typically corresponded to one round of EPL. FS users selected 11 athletes for their squad each round. They were required to select one goalkeeper and make a choice among several classical fielding configurations, namely 4-4-2, 4-3-3, 3-4-3, 3-5-2, 5-3-2, 4-5-1, and 5-4-1. The order of positions in each configuration always follows the pattern of defender, midfielder, and striker. If they did not complete their squad, they did not participate in the round. A FS user's point score was the sum of the points scored by the athletes in his or her squad. An athlete earns base points for playing in the match, specifically one point. The other two points are earned for playing at least 60 minutes. The three points earned are the most frequent value in the dataset, i.e. outside the value zero, where the athlete most often did not even play in the match. Additional positive points could be earned for scoring a goal, an assist, keeping a clean sheet (except for a striker). The goalkeeper earned points for every three saves and penalty caught. Minus points were earned for yellow and red cards and own goals. Defenders and goalkeepers earned minus points for goals received.
Based on the scoring, an athlete's success is measured by scoring four or more points. Therefore, he must have made a positive action in addition to entering the match and not have scored negative points. If he scored four or more points more rounds in a row, then he had a so-called point-scoring streak by which the hot hand is defined in this paper.
The present analysis is divided into two parts, the first examines the existence of the hot hand in individual athletes level. Model 1 takes the following form

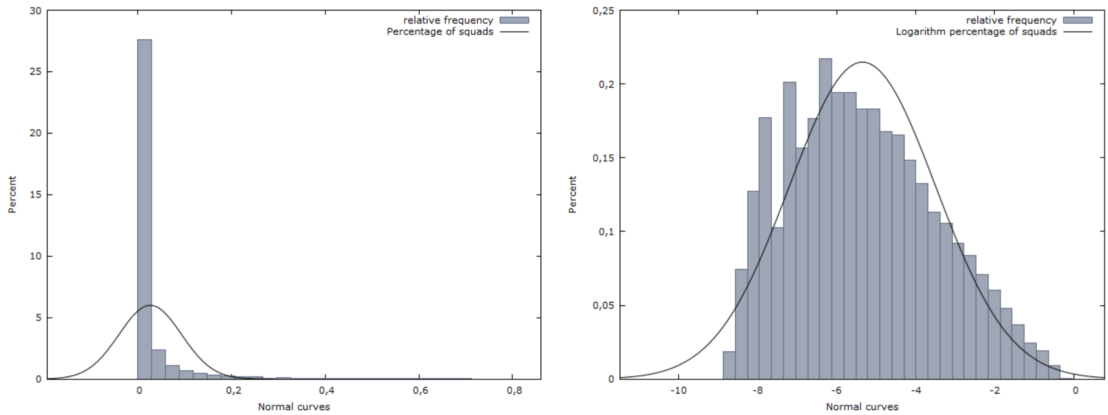
$$Hot\ hand_{i,t} = \alpha + \beta_1 \cdot Streak\ Duration_{i,t} + \beta_2 \cdot Streak\ Duration_{i,t}^2 + \varepsilon_{it} \quad (1)$$

where *Hot hand* takes the value 1 when athlete i scored four and more points in round t. If he scored less, then it takes the value zero. *Streak Duration* is the number of consecutive rounds where athlete i has scored four and more points. Thus, if $Streak\ Duration_{i,t}$ were equal to two, then athlete i scored four and more points in rounds $t-1$ and $t-2$. A quadratic term $Streak\ Duration^2$ is also added to the model, following the previous literature (Pelster 2020).
The second part of the analysis examines the consideration of hot hand by FS users when selecting athletes for their squads. Model 2 takes the following form

$$Demand\ for\ player_{i,t} = \alpha + \beta_1 \cdot Streak\ Duration_{i,t} + \beta_2 \cdot Streak\ Duration_{i,t}^2 + \varepsilon_{it} \quad (2)$$

where *Demand for player* is the percentage of squads into which the athlete *i* got chosen in round *t*. This approach reflects the fact that a different number of FS users participated in each round. It is in a logarithmic form, following the previous research (Bryson and Chevalier 2015). The reason is that the percentage of selected athletes is skewed. As seen in Figure 1, the logarithmisation makes the distribution closer to normal distribution, allowing parametric statistics to be conducted. *Streak Duration* is consistent with model 1.

Figure 1. Percentage of squads in standard and log form.



Other specific characteristics of an athlete with an effect on squad selection that have been used in previous papers (Bryson and Chevalier 2015) are included as fixed effects in used regression.

3. Results

Given the nature of the data as a panel, the models were tested for the presence of fixed and random effects. The results of the Hausman test applied to model 1 (m-value = 560.22, p-value < 0.001) and model 2 (m-value = 508.13, p-value < 0.001) lead to rejecting the random-effects model. The results of the F test for no fixed effects applied to the model 1 (F-value = 4.38, p-value < 0.001) and the model 2 (F-value = 45.16, p-value < 0.001) lead not to rejecting the fixed effects model. Given the binominal dependent variable, fixed-effects logistic regression is used to estimate model 1. For model 2, the dependent variable may take multiple values, so the fixed-effects method is used. The results can be found in Table 1.

Table 1. Duration of streaks and the hot hand. In model 2, athletes who were not selected in a particular round by any of the FS users are omitted. According to the F-test, the models are significant at 1 per cent. Significance at 1 per cent is marked by ***. FE values are not shown for clarity.

	(1) Existence hot hand	(2) Taking hot hand into account
Streak Duration	.302***	.596***
Streak Duration^2	-.024***	-.044***
Observations	18,924	15,713
Adj. R^2	.126	.664
P-value (F)	<.0001	<.0001

First, the results show a non-linear effect of the point-scoring streak on both hot hand and FS user demand. Model 1 explains 13% of the variability of the dependent variable. Thus, a relatively large part of the dependent variable is unexplained. FS users are much more affected by the point-scoring streak, as Model 2 can explain 66% of the variability of the dependent variable. However, it is important to acknowledge that this phenomenon is not unique and can be observed in similar situations. Just like stock prices, game scores, and other related domains, there tends to be a higher level of noise in the outcomes compared to expectations. As a result, the coefficient of determination in the regression is typically lower (Admati 1985; Hubáček et al. 2019; Simmons and Wheeler 2017).

Thus, model 1 shows the significant presence of the hot hand in individual athletes' performances measured by specific FS rules, and model 2 shows that FS users take into account point-scoring streak duration in their decision to include an athlete in the squad. Given the results of model 1, the strategy of FS users taking the point-scoring streak into account appears to be sensible. Especially in a situation where the squad selection is difficult and time-consuming and FS users want some heuristics to help them. Given the large part of the dependent variable, which is not explained by model 1, this heuristic is certainly imperfect.

4. Robustness

The following lines will focus on testing the robustness of the results obtained from the baseline models. The testing will involve examining sub-datasets containing different game positions of athletes. This analysis aims to determine if there are significant differences between these positions. Additionally, the sensitivity of using a four-point threshold as the criterion for identifying the hot hand will be assessed. Specifically, two alternative thresholds, namely six and eight points, will be tested.

Furthermore, a model will be constructed to investigate the impact of the previous round's point total on the subsequent round's score, without differentiating the hot hand into distinct categories of 1 and 0. This approach will provide a more comprehensive understanding of the continuity of influence, albeit at the expense of examining streakiness.

4.1 Testing game positions

A logical extension of the analysis is the grouping of athletes by game position. This makes sense because of the different scoring systems for different positions in fantasy leagues, as well as the natural role distribution in soccer itself.

Thus, the data was divided by game position into sub-datasets containing only goalkeepers, defenders, midfielders and strikers. Models were then compiled as in the baseline analysis. In Table 2 you can see the results for testing the existence of a hot hand for each game position. In Table 3 you can see the results for testing taking hot hand into account in the demand for athletes also with a division for each game position.

Table 2. Testing game positions to the existence of hot hand. According to the F-test, the models are significant at 1 per cent. Significance at 1 per cent is marked by ***, at 5 per cent is marked by **. FE values are not shown for clarity.

	(3) Goalkeeper	(4) Defender	(5) Midfielder	(6) Striker
Streak Duration	.857***	.734***	.347***	.326***
Streak Duration^2	-.190***	-.180***	-.048***	-.016**
Observations	1,786	5,928	7,258	3,952
Adj. R^2	.162	.083	.143	.155
P-value (F)	<.0001	<.0001	<.0001	<.0001

Table 3. Testing game positions to take hot hand into account. According to the F-test, the models are significant at 1 per cent. Significance at 1 per cent is marked by ***. FE values are not shown for clarity.

	(7) Goalkeeper	(8) Defender	(9) Midfielder	(10) Striker
Streak Duration	.824***	.870***	.653***	.692***
Streak Duration^2	-.109***	-.159***	-.069***	-.043***
Observations	1,259	5,310	6,054	3,090
Adj. R^2	.643	.595	.701	.686
P-value (F)	<.0001	<.0001	<.0001	<.0001

The results of models 3 to 6 show a similar pattern to the results of model 1. For goalkeepers, midfielders and strikers, the models explain around 15% of the variability of the dependent variable, which is slightly more than in model 1. In contrast, for defenders, it is only around 8%. The effect of streak duration on scoring in the subsequent match is more non-linear for goalkeepers and defenders than for midfielders and strikers, where the squared coefficient is lower and significant only at 5%.

It is interesting to see that a similar consideration holds for models 7 to 10. Thus, the demand for goalkeepers and defenders is more non-linear than for midfielders and strikers. As in model 2, the coefficient of determination is substantially higher for models 7 to 10 compared to models 3 to 6. Streak duration explains between 60% and 70% of the variability of the FS users' demand for athletes. Thus, it cannot be said that FS users use this heuristic differently for different game positions.

4.2 Testing sensitivity

The next aspect to be examined is the sensitivity check for establishing a different threshold to determine the hot hand. In particular, thresholds of six and eight points will be tested. While these thresholds may not correspond directly to specific situations in a particular FS, they will help assess the sensitivity to higher athlete performance.

As a result, four new variables were created: *Hot Hand 6*, *Hot Hand 8*, *Streak Duration 6*, and *Streak Duration 8*. Models were then constructed using the same approach as the baseline analysis but with six- and eight-point thresholds. These variables were also employed to examine streakiness by considering their squared values. The results for testing the presence of a hot hand and incorporating the hot hand phenomenon in the demand for athletes using the six- and eight-point thresholds can be found in Table 4.

Table 4. Testing sensitivity to the existence of hot hand and taking hot hand into account. According to the F-test, the models are significant at 1 per cent. Significance at 1 per cent is marked by ***. FE values are not shown for clarity.

	(11) Existence hot hand – six-point threshold	(12) Taking hot hand into account– six-point threshold	(13) Existence hot hand – eight-point threshold	(14) Taking hot hand into account– eight-point threshold
Streak Duration 6	.340***	.745***		
Streak Duration 6^2	-.025***	-.063***		
Streak Duration 8			-.073	1.786***
Streak Duration 8^2			.112	-.465***
Observations	18,924	15,713	18,924	15,713
Adj. R^2	.146	.662	.025	.652
P-value (F)	<.0001	<.0001	<.0001	<.0001

The results of models 11 and 12 show a similar pattern to the results of models 1 and 2. The models explaining the existence of a hot hand demonstrate significantly higher coefficients on the variables and a greater coefficient of determination compared to the models analyzing the demand for athletes. Nevertheless, it is important to consider the presence of increased noise in real events relative to users' expectations.

At the eight-point threshold, it becomes evident, as illustrated in model 13, that this number is already too high to effectively detect a hot hand. The scarcity of athletes achieving such high scores makes it challenging to replicate such exceptional performances. Conversely, model 14 indicates that FS users tend to assume that if an athlete has previously achieved such high scores, they will continue to do so, leading to an overestimation in their squads. However, this strategy becomes less appropriate for athletes who consistently score at such high levels, as model 13 demonstrates.

4.3 Testing performance as a continuous variable

The final test for robustness involves constructing models that examine the impact of an athlete's specific point score on their subsequent match score. This approach replaces the binary values of 0 and 1 used in model 1. By doing so, it is possible to closely analyze the smaller differences between point scores, although streakiness is not taken into account. Only the momentum from one game to the next is observed in this context. To distinguish it from the hot hand, we will refer to this continuous performance as "momentum."

Models were then developed using the same methodology as the baseline analysis. In the momentum model, the dependent variable is the athlete's specific number of points scored in the observed round called *Points*. In both the momentum model and the demand for athletes model, the new independent variables, namely *Points Previous* and *Points Previous*^{2}, indicate the number of points an athlete scored in the previous round and the square of this value. The results for testing the presence of momentum and incorporating momentum in the demand for athletes can be found in Table 5.

Table 5. Testing the impact of past performance on future performance and user demand. According to the F-test, the models are significant at 1 per cent. Significance at 1 per cent is marked by ***. FE values are not shown for clarity.

	(15) Existence momentum	(16) Taking momentum into account
Points Previous	.334***	.279***
Points Previous^2	-.016***	-.009***
Observations	18,924	15,713
Adj. R^2	.288	.702
P-value (F)	<.0001	<.0001

The findings from models 15 and 16 yield similar conclusions to models 1 and 2. The significance and direction of the coefficients on the variables remain consistent. Notably, the coefficient of determination for model 15 surpasses that of the conventional hot hand model, indicating the importance of examining specific scoring patterns of athletes. While the absolute magnitude of the coefficients is higher in model 15 compared to model 16, this discrepancy arises from the wider range of values in the dependent variable *Points* compared to the percentage of athletes included in the squads.

In summary, all robustness tests confirm the initial trends observed in the baseline models. This includes some existence of the hot hand phenomenon and its evident influence on users'

squad formation strategies. However, it is worth noting that the real data exhibits greater noise compared to users' assumptions.
Fantasy leagues generally provide their users with a detailed record of the past performance of individual athletes, which is expressed in a specific scoring system. This is also the case in the fantasy league under study. This makes it relatively easy for FS users to find out whether a particular athlete has scored above standard in previous rounds. Thus, it is actually not surprising that FS users take this into account. However, if FS users want to win the competition, which is the most frequently cited motivation for playing in past research (Davis and Duncan 2006; Dwyer et al. 2011), they should also take into account other factors such as long-term performance (Bryson and Chevalier 2015), since streak duration does not have sufficient ability to explain future performance.

5. Conclusion

Given the ambiguous results of past literature regarding the existence of the hot hand fallacy across sports (Albright 1993; Brown and Sauer 1993; Lantis and Nesson 2021), this paper supports some existence of a hot hand in the form of a performance streak of athletes. However, the measured effect is weak. This conclusion is consistent with the research of previous papers focusing specifically on soccer (Parsons and Rohde 2015; Simmons and Wheeler 2017), but here individual performance streak is measured, which has not yet been investigated by another paper.
The consideration of the hot hand by FS users in their demand for athletes appears stronger, which past literature typically confirms and demonstrates fans' belief in the existence of the hot hand (Simmons and Wheeler 2017).
The conclusions presented have implications for various subjects in the sports market. First of all, bettors who are solving a similar optimization problem as FS users should be mentioned. The findings show that FS users overestimate the current short-term performance of athletes and it would therefore be appropriate for them to take into account not only current form but also other factors. Typically, for example, long-term performance can be mentioned, as shown by previous research (Kotrba 2020).
The implications for managers and coaches can also be mentioned. Of course, it cannot be argued that managers should not take into account the current form of a particular athlete. However, they should bear in mind that the current form is not the only factor and there may be regression towards the mean (Tversky and Kahneman 1974).
It is important to emphasize that FS is only one way of trying to assess an athlete's performance. Tracking the individual statistics of athletes is certainly a step up from tracking the performance of an entire team, but it could certainly go further. For example, the next step could involve tasks such as penalty kicking or evaluating an athlete's performance using the scoring system available on whoscored.com. These values have been used by past literature (Dendir 2016; Palacios-Huerta 2023; Sgro et al. 2016), but not to measure hot hand per se.

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