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Finally, Evidence for a Momentum Effect in the NBA

Jeremy Arkes and Jose Martinez

Abstract

No previous study on momentum in team sports has found any valid evidence for a momentum effect—i.e., an effect of success in the past few games, over and above the effect of team quality. We develop an econometric model to determine if there is a momentum effect in the NBA by examining how success over the past few games leads to a higher probability of winning the next game. The model takes into account the home vs. away strengths of the teams in the current game as well as their opponents in the previous games (to calculate measures of "adjusted success over the past few games"). Thus, success in previous games is adjusted for quality of the wins or losses. In addition, we account for rest days before the current game for both teams. Using data over three NBA seasons (2007-2009), we find strong evidence for a positive momentum effect.

KEYWORDS: momentum, basketball, NBA

1. Introduction

The concept of a "momentum effect" in sports is the situation in which a team has a higher probability of winning or success had the team been playing well in the last few games. Winning streaks are often described as a team having momentum. This is similar in nature to the "hot hand," which is mostly discussed for basketball and refers to a player having a higher probability of making a shot had he or she made the previous few shots.

Momentum is a deep-rooted belief in sports (Vergin, 2000). Like the hot hand, it is often discussed by players, coaches, and reporters/analysts as if there is no doubt on its existence. Yet, there is no valid evidence that there is such thing as a momentum effect. Winning streaks, as discussed below, have been mostly found to be statistically natural. Despite the lack of empirical evidence that a "momentum effect" exists, people continue to operate under the belief that it does exist or that other people believe it exists. Sinkey and Logan (2010) find that betting houses use biases in people's beliefs about momentum to set point spreads. They argue that betting houses do not make the point spread based on what the betting house thinks will happen, but rather based on what they think will split the bettors 50-50 so the betting houses can eliminate any risk and make their 10% profit (the vigorish). And because, as they argue, bettors are irrational in that they believe the momentum effect is larger than it really is, the betting houses skew the point spread in favor of the team with momentum. Thus, there are ways to make a profit by knowing the bias in point spreads put out by betting houses, which they make based on what Sinkey and Logan (2010) consider the bias by bettors.

The hot hand belief has attracted a lot of attention in the academic literature (see Bar-Eli, Avugos & Raab, 2006 for a comprehensive review). As these authors show, the majority of studies have not found empirical evidence to support the hot hand belief. However, a recent study improved on the previous studies by incorporating all players into one fixed-effects logit model (Arkes, 2010). With the significantly greater power, Arkes found evidence supporting the existence of the "hot hand" in that making the first free throw is associated with a significantly higher probability of making the second free throw. Still, the differences in methods, statistical assumptions, experimental designs, and situational factors for the various "hot hand" studies make it difficult to obtain a definitive response to the question of the existence of hot hand.

In contrast to the large literature on the "hot hand," research about "momentum" has not been so extensive. In some early studies, Iso-Ahola and Mobily (1980) examine a racquetball tournament and Silva et al. (1988) examine college tennis matches. Both find that winning the first game (in racquetball) or set (in tennis) leads to a greater probability of winning the next game or set.

However, both also find that when the players split the first two games or sets, the winner of the second game (i.e., the person with momentum) did not have a higher probability of winning the next game or set. Thus, this suggests that when ability is controlled for, then there is no evidence for a momentum effect. In a study on team play, Miller and Weinberg (1991) find that volleyball teams that score three or more consecutive points to tie a game (and thus, having momentum) had the same chance of winning the game as the other team. Goddard and Asimakopoulos (2004), in a study of games in the English Football League, find that success in the recent 4 or 9 games had no effect on the probability of drawing or winning, beyond the information the games provide on team quality. Vergin (2000) takes a different approach to examine momentum effects in team American professional baseball and basketball. He applies Wald-Wolfowitz runs test and chi-square test, in order to find streaks that were significantly different from what would be expected by chance. He does not find evidence for "momentum" in his analysis of baseball and basketball team's streaks, but he does not consider any of the systematic factors that could influence game results. Sire and Redner (2009) do consider such systematic factors by incorporating relative team strengths between teams in baseball games, but they ignored other important factors such as home-field advantage. Their results are similar to Vergin (2000), i.e., the observed long streaks are primarily statistical natural, so there is no evidence for momentum.

One omission of these authors is that they did not account for the strength of opponents. By not fully accounting for this, there could be a downward bias to the estimated momentum effect in these studies because of a regression to the mean in strength of opponents. That is, if a team plays against three weak opponents, it is a higher-than-average probability that the next opponent is stronger. Likewise, if a team has three home games in a row (for which they are more likely to win), there is a higher-than-average probability that the next game will be a road game (for which they are more likely to lose). Thus, not accounting for home vs. away or other aspects of team strengths in the previous games and the current game could bias the estimates towards a "negative momentum effect," perhaps counteracting any real positive momentum effect. This could contribute to the findings of no momentum effect in the literature.

In this paper, we use data from three NBA seasons (2007-2009) to test whether success over the previous 3 or 5 games increases a team's chance of winning the next game. Whereas previous studies examined momentum in the NBA by just looking at whether a team is more likely to win had they won previous games, or by analyzing if winning streaks were different from what would be expected by chance, we develop a model that takes into account differences in the quality of the opponents a team had in previous games as well as the quality of the opponent for the game of the analysis. This research is similar to the advancement in the "hot hand" literature that Arkes (2010) makes in that it combines teams into one model to provide sufficient power to detect a momentum effect, if one exists. We also account for differences in the number of days of rest before the game of analysis and we consider home-court advantage.

We find evidence for a positive momentum effect, in that stronger performance over the past 3 or 5 games is associated with a higher probability of winning the next game, with the estimated effect being stronger for home teams. Furthermore, the results are stronger when we use what are likely more precise measures of team strengths, suggesting that not fully accounting for team strengths could contribute to a downward bias in the estimated momentum effect.

2. Momentum vs. Team Strength vs. Randomness

Sports typically have a large amount of randomness that contributes to the determination of games' outcome. For example, there are wrong referee calls and plays that could be millimeters away from out-of-bounds or foul lines. Yet, people do not understand very well the role of randomness in sports (Berri and Schmidt, 2010), let alone random processes in general (see Nickerson, 2002). Empirical evidence shows that people interpret the results of their own sporting competitions as products of causality (e.g., McAuley & Gross, 1983).

A given winning streak by a team that includes more wins or better performance than would be otherwise expected from the team could be due to one of three phenomena: (1) the team is better than previously perceived; (2) a momentum effect; or (3) randomness—e.g. due to a missed referee call.

Given people's perspective of sports as determined almost entirely by causality, people would typically take a winning streak (or a series of games in which the team played well) as either a sign that the team is better than people had previously thought or a sign of a momentum effect. Either way, it would mean that people, in general, would expect a team with more success over the last few games to have a greater probability of winning the next game than had the team had less success over the past few games. On the other hand, if people were to interpret the winning streak or strong performance in previous games as being due to luck or randomness, then they would not expect the team to have any greater chance of winning the next game.

How much winning streaks or strong performances are used to re-calibrate perceptions on a team's strength would depend on the sport. In basketball, there are 82 games per season, so a given game, especially by the time the season is, say, one-quarter over, may not provide much new information. Furthermore, one bad call can turn a game, or one player having a good day can help a team win. With football, on the other hand, there are only about 13 games in a season for college and 16 games per season for the NFL. Skills are not as easy to measure as they are in other sports, and skills can deteriorate quickly among football players, especially as they wear down over the course of a season. Thus, a single win in basketball probably conveys much less information about the quality of a team than a football team winning a game.

Statistically and theoretically, one could separate the competing theories of team strength recalibration vs. momentum effect vs. randomness. Without adequate controls for team strengths (for the game of analysis and perhaps the previous games), a finding of a positive correlation between success in recent games and the probability of winning the current game could be due to either a momentum effect or just the previous wins conveying more information about the strength of the team. But, with adequate controls for team strengths, then such a positive correlation would be indicative of a positive momentum effect since the game outcome provides no new information on the team's strength.

An alternative finding of zero correlation between success in recent games and the probability of winning the current game would indicate that winning streaks or performance beyond what would be expected of the team are due to randomness. In that case, winning streaks (once team strengths are accounted for) are just statistically natural and not the product of momentum effects. That is, once a team's strength is accounted for, then a given win or loss is random, so success in the prior few games would have no causal effect on the probability of winning the next game. In this case, a given win would be more due to randomness (e.g., from bad referee/umpire calls) than a sign of team strength or a momentum effect. For example, suppose that a team has a 0.667 winning percentage. The team would be expected to win two out of every three games. If they had won the past three games, then they may be considered to have momentum (or that the team is better than its won-loss record would indicate). Thus, people would believe that they have a greater chance of winning the next game than had they only won two of the past three games. However, it may have been a blown referee call that gave them that third victory, so that the 0.667 winning percentage was a good indicator of the team's strength.

Another possibility is that there could be a negative momentum effect, or a "counter-trend effect," which occurs when the probability that a team wins the next game decreases with more success in the previous few games. This could occur, for example, if the players wear themselves out in the stretch of wins. There is a psychological basis to the belief in this pattern. Oppenheimer and Monin (2009) describe how a set of studies has found that after a coin flip results in three straight "heads," people tend to bet that that the next flip will be tails. Thus, people may believe that a team on a winning streak is "due for a loss," just as a batter in a slump is "due for a hit."

Being able to successfully distinguish between team strength recalibration, a momentum effect, and randomness requires being able to adequately account for team strengths. Thus, it would be important to distinguish between a team's home vs. away record, as some teams have greater success at home, relative to on the road, than other teams. Yet, team strengths can change over the course of a season, so accounting for such changes would also be important.

3. Methods

Econometric Model

A traditional approach to model game results in sports is the use of the Bradley-Terry model (Bradley and Terry, 1952). This model assumes that in a contest between any two teams, the odds that one of them beats the other depend on the ratio of their respective "abilities", i.e., the ratio of the teams' abilities. This model can be extended to consider home-field advantage and other systematic factors influencing team quality, together with a random component (Turer and Fith, 2010). Teams' abilities are parameters that have to be estimated from the model.

The Bradley-Terry model is simply one of the forms available to model game results, and it is subject to some criticisms. For example, if team strength is measured in a [0,1] scale, we could think that the probability that team A beats team B is not the same if team A is 0.7 and team B is 0.35, that if team A is 0.2 and team B is 0.1. If we consider the NBA context and we use winning percentage for the team strength, we would likely expect that the probability that team A beats team B would be higher in the first case.

Alternatively, we can think in terms of an econometric model, in which wins are explained by systematic factors (home-field advantage, difference in team strength, etc.) and a random component. In such a model, we could estimate the effect of independent variables on wins, i.e., the team strength variables would be an input of the model, and not parameters to be estimated, such as Bradley-Terry model implies.

We take this alternative approach and estimate the following empirical model:

$$Y_{i,t} = \alpha_h Q_{i,t}^{h} + \alpha_a Q_{i,t}^{a} + \beta_h' Ri_{,t}^{h} + \beta_a' R_{i,t}^{a} + \gamma_h S_{i,t}^{h} + \gamma_a S_{i,t}^{a} + \varepsilon_{i,t} \qquad (1)$$

where $Y_{i,t}$ is an indicator variable for whether the home team won game *i* in season *t*, Q^h and Q^a represent measures of the team strength for the home and away teams, R^h and R^a are vectors of variables representing the amount of rest between games for the home and away teams, S^h and S^a are variables representing the success over the past few games for the home and away teams, and ε is the error term. The variables on team success and team strengths are described in more detail below. A positive momentum effect for the home and away teams would be represented by a positive γ_h and a negative γ_a. Estimating the model based on whether the visiting team wins would produce the opposite coefficients, but the same interpretation as what would result in this model. Because the outcome is dichotomous, we estimate equation (1) as a logit model.

It is important that the model accounts for differences in the strength of the two teams playing. Otherwise, the better teams would be more likely to have won the last few games and more likely to win the current game, so we would estimate a positive momentum effect that is mostly due to differences in team quality.

There are a few variants of the model, based on three dimensions: (1) measuring prior-game success based on the last 5 games or 3 games; (2) measuring that success over the past 5 or 3 games based on wins alone or incorporating the strength of the opponents; and (3) how team strengths are calculated for the strength-of-opponent measures.

For the first dimension, we use both 5-game and 3-game prior-game-success measures because, *a priori*, we do not know how long momentum would last. There is a trade-off in that fewer games would be closer in time to the game of analysis. However, more games would give more variation in strengths of opponents. For the second dimension, we aim to compare how the results would differ based on our new measure of prior-game success (considering the strength of the opponents) and just using the number of wins (how momentum has typically been measured).

The third dimension is how team strength is measured, which is used directly in the model for the current opponent and indirectly in the strength of opponents in the prior-game-success measures. One approach to controlling for the strength of current teams is to have fixed effects for the home team and away team. However, this is problematic because the fixed effects standardize the variables around the mean. Thus, if a team had won the last few games, then there is a higher probability they lost all other games, including the next game. For example, if a team has a 0.500 winning percentage (won 41 of 82 games) and it won its last 5 games, then its winning percentage for all other games would be 0.468 (36 of 77). Thus, assuming there was no momentum effect, if we set the model up this way, we would incorrectly estimate a negative momentum effect. For this reason, we do not use fixed effects.

Instead, in our first approach, team strength is based on the home winning percentage for the home team and the away winning percentage for the visiting team, both for the given season. These winning percentages exclude the outcomes of the current game and the previous 5 games (or 3 games) that go into the prior-game-success measure (described below). The second approach is the same, but we allow for changes in team quality during the season by dividing the season into two halves and calculating the home and away records for each team for the given half of the season. This takes into account changes in the team's strength, which could occur from trades or injuries affecting the roster, or merely from the existing team learning how to play better with each other or wearing down and playing worse over the course of the season. It would be ideal to break the season into smaller parts than halves, but then the sample size on the number of home or away games gets smaller, and the team-strength measure would be less precise.

By including controls for the teams' home and away records, the identification of any momentum effect comes from whether a team with a given record is more likely to win a home (away) game had they had relative success over the past few games than they would in other home (away) games in which they had less success over the prior few games. This holds the days rest for the two teams constant, as well as the strength of the opponent.

Measures of Prior-Game Success

To measure prior-game success, we first measure the home and away "adjusted team strength," or venue winning percentage, for each of the last 5 opponents, depending on where the game was. That is, suppose that in its last 5 games, Atlanta played Boston and Miami at home and Utah, Portland and Seattle on the road. We would then calculate the "adjusted team strength" for each of Atlanta's opponents by measuring the full season's (or half season's) away records for Boston and Miami and the home records for Utah, Portland, and Seattle—"adjusting" them by factoring out from these home and away records the outcome of the recent game against Atlanta. With the "adjusted team strength" (ATS) measures, we then calculate the "adjusted success" in the past 5 games as the sum of the ATS measures for teams Atlanta beat and subtract (1 – ATS) for teams Atlanta lost to.

Thus, beating a strong team adds more to the "adjusted success" score than beating a weak team. And, losing to a strong team takes away less from the "adjusted success" score than losing to a weak team. In addition, this model takes into account relative team strength for home vs. away games, as a road win would typically add more to the "adjusted success" score than a home win because opponents are stronger at home. We calculate this score for both the past 5 games and the past 3 games.

Data

The data come from nbastuffer.com, which provides a rich set of data on each game. We obtained data for the 2007 season through the 2009 season. The relevant information for this analysis was which team was the home vs. away team, what the game outcome was, and how many days of rest each team had before the given game. From that, we then constructed variables for season home and away records and how they did in their previous 3 and 5 games.

The sample requirement for the models is simply that each team for a particular game must have had played 5 games or 3 games, depending on the "adjusted success" measure. There are 3452 games for the models based on 5-game momentum measures, and there are 3544 games for models based on 3-year momentum measures. They are almost perfectly evenly split across the three seasons, with differences just due to whether both teams would have had played 5 or 3 games for a given matchup.

Table 1. Descriptive Statistics.

Variable	Number of observations	Mean	Std. Dev.	Min. value	Max. value
Dependent variable					
Whether the home team won	3690	0.600	0.490	0	1
New Momentum variables					
5-game momentum for home team	3466	0.009	1.244	-3.425	3.350
5-game momentum for away team	3464	-0.025	1.255	-3.150	3.200
3-game momentum for home team	3551	0.001	0.901	-2.250	2.300
3-game momentum for away team	3559	-0.011	0.889	-2.225	2.475
Conventional momentum variables					
Wins in last 5 games for home team	3466	2.498	1.292	0	5
Wins in last 5 games for away team	3464	2.501	1.304	0	5
Wins in last 3 games for home team	3551	1.504	0.940	0	3
Wins in last 3 games for away team	3559	1.496	0.937	0	3
Variables representing team strength					
Home team's home winning %, excl. last 5 games	3466	0.600	0.175	0.184	0.974
Away team's away winning %, excl. last 5 games	3464	0.397	0.156	0.105	0.811
Home team's home winning %, excl. last 3 games	3551	0.600	0.175	0.184	0.974
Away team's away winning %, excl. last 3 games	3559	0.398	0.156	0.105	0.816

Table 1 shows the descriptive statistics for the variables used in the analyses based on models using full-season home and away records to calculate team strengths. The descriptive statistics are just slightly different for the models using home and away records for season halves to calculate team strengths, so we do not report them. The dependent variable, again, is whether the home team won, and this occurred in exactly 60% of all games. The "adjusted success" variables are all centered around zero, which should occur given that we add and

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subtract from the "adjusted success" score based on wins, losses, and the strength of the team playing. Note that the "adjusted success" variables have roughly the same standard deviation as the variables for the number of wins in previous games. Furthermore, each win would be, on average, equivalent for the two types of measures. For example, suppose that Chicago is playing a team with a 0.700 (adjusted) winning percentage. If it loses, the "adjusted success" variable loses 0.3, while the number of wins adds zero. If Chicago wins, then the "adjusted success" variable gains 0.7, while the number of wins adds one. For both variables (the "adjusted success" and the number of wins), winning contributes 1.0 to value. Thus, we can directly compare the coefficient estimates from the models using the "adjusted success" variable and just the number of wins.

4. Results

Table 2 presents the results of the models using prior-game success from the past 5 games. Model A (the first two columns of results) is based on measuring team strength based on the *full-season* home and away winning percentages; and Model B (the last two columns) are for models measuring team strength based on the *half-season* home and away winning percentages. In addition, for both Models A and B, the model in the top panel uses the "adjusted success" measure over the past 5 games, and the model in the bottom panel is based on using just the number of wins over the past 5 games.

The results show positive momentum effects. That is, the more success the home team had in the previous 5 games (based on adjusted success or the number of wins), the more likely the home team would win. The negative coefficient estimates for success of the away team indicates the same thing: the greater success in the past 5 games for the away team, the less likely the home team will win (and more likely the away team will win). All of these coefficient estimates are statistically significant at the 1% level. The marginal effects indicate that an extra win in the past 5 games, on average, increases the probability of winning by between 2.2 and 2.8 percentage points using Model A and between 3.3 and 4.0 percentage points using Model B. The marginal effects of the win or momentum variables are fairly steady for different values for the number of wins or the momentum variables. For example, in Model B for the number of wins in the past 5 games for the home team, going from 0 to 1 win increases the probability of the home team winning by 3.7 percentage points; going from 4 to 5 wins increases the probability of the home team winning by 3.3 percentage points.

Table 2. The effects of adjusted success and wins in the past 5 games on the probability of winning a game (N=3452 games)

	Model A: Using **full**-season home & away records for team strengths		**Model B**: Using **half**-season home and away records for team strengths	
	Coef. Est.	Marg. Eff.	Coef. Est.	Marg. Eff.
Using "Adjusted Success"				
Adjusted success in past 5 games for home team	0.119*** (0.036)	0.028	0.151*** (0.034)	0.036
Adjusted success in past 5 games for away team	-0.116*** (0.035)	-0.027	-0.170*** (0.033)	-0.040
Home team's home winning %, excl. last 5 games	3.494*** (0.262)	0.827	2.730*** (0.223)	0.647
Away team's away winning %, excl. last 5 games	-3.167*** (0.283)	-0.749	-2.214*** (0.238)	-0.525
Home team had 1 day's rest	0.017 (0.090)	0.004	0.029 (0.089)	0.007
Home team had no day's rest	-0.210* (0.122)	-0.050	-0.190 (0.121)	-0.046
Away team had 1 day's rest	-0.173 (0.107)	-0.041	-0.170 (0.106)	-0.040
Away team had no day's rest	0.034 (0.115)	0.008	0.022 (0.113)	0.005
Using "Number of Wins"				
Wins in last 5 games for home team	0.111*** (0.034)	0.026	0.151*** (0.033)	0.036
Wins in last 5 games for away team	-0.093*** (0.033)	-0.022	-0.141*** (0.032)	-0.033
Home team's home winning %, excl. last 5 games	3.514*** (0.261)	0.831	2.723*** (0.222)	0.645
Away team's away winning %, excl. last 5 games	-3.274*** (0.281)	-0.775	-2.331*** (0.237)	-0.552
Home team had 1 day's rest	0.013 (0.090)	0.003	0.023 (0.089)	0.005
Home team had no day's rest	-0.207* (0.122)	-0.050	-0.189 (0.120)	-0.045
Away team had 1 day's rest	-0.172 (0.107)	-0.041	-0.174 (0.106)	-0.041
Away team had no day's rest	0.034 (0.115)	0.008	0.021 (0.113	0.005

Note: Standard errors are in parentheses. The model also includes a constant (not reported). ***, **, * indicate statistical significance at the 1, 5, and 10% levels.

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An interesting result here is that the momentum effect is roughly the same magnitude for the home and away teams. So, based on these results, there is no apparent added momentum effect for home teams. In addition, the estimates on the “adjusted success” and win variables are consistently larger for Model B than for Model A. Given that Model B uses team strength measures that are likely more representative of the team strength at the time of the game, this suggests that the estimates are downwardly biased when team strengths are not adequately accounted for.

The other coefficient estimates are generally as they would be expected or statistically insignificant. Higher winning percentages for the home and away teams are associated with a higher probability of their own winning of the game. For the variables on the number of days’ rest, the excluded variable is two-or-more days’ rest. Thus, we would expect “one day’s rest” or “no day’s rest” to have negative effects on the probability of winning for the home team (and positive effects for the away team). All of the estimates are insignificant other than the coefficient estimate on “no day’s rest” for the home team, which is significant at the 10% level.

Table 3 is the same as Table 2 except that the models are based on success over the past 3 instead of 5 games. The results are generally the same, except the estimated momentum effects are consistently larger in magnitude for the home team than for the away team, albeit not by statistically significant amounts. In Model A, the estimated momentum effect for the away team decreased and its significance level dropped, but still remained significant at the 5% and 10% levels. The estimated marginal effects from an extra victory in the past 3 games are now, for Model A, about 3.3 and 2.0 percentage points for the home and away teams, respectively. For Model B—what is likely the more accurate model—the estimated marginal effect remains high and is now about 4.2 and 3.3 percentage points for the home and away teams.

In all of the models, the estimated momentum effects are consistently larger for the “adjusted success” than for the “number of wins”, but only by a slight amount. This suggests that the “adjusted success” measures of performance over the past few games has little or no advantage over just using the “number of wins” over the past few games to measure team performance.

Table 3. The effects of adjusted success and wins in the past 3 games on the probability of winning a game (N=3544)

	Model A: Using **full**-season home and away records for team strengths		**Model B**: Using **half**-season home and away records for team strengths	
	Coef. Est.	Marg. Eff.	Coef. Est.	Marg. Eff.
Using "Adjusted Success"				
Adjusted success in past 3 games for home team	0.138*** (0.046)	0.033	0.176*** (0.044)	0.042
Adjusted success in past 3 games for away team	-0.091** (0.046)	-0.022	-0.147*** (0.044)	-0.035
Home team's home winning %, excl. last 3 games	3.665*** (0.247)	0.865	2.923*** (0.213)	0.692
Away team's away winning %, excl. last 3 games	-3.462*** (0.269)	-0.817	-2.565*** (0.229)	-0.607
Home team had 1 day's rest	0.024 (0.089)	0.006	0.036 (0.088)	0.008
Home team had no day's rest	-0.214* (0.121)	-0.051	-0.197** (0.119)	-0.047
Away team had 1 day's rest	-0.177* (0.106)	-0.042	-0.185* (0.105)	-0.044
Away team had no day's rest	0.032 (0.114)	0.008	0.009 (0.112)	0.002
Using "Number of Wins"				
Wins in last 3 games for home team	0.136*** (0.044)	0.032	0.175*** (0.043)	0.041
Wins in last 3 games for away team	-0.077* (0.043)	-0.018	-0.130*** (0.042)	-0.031
Home team's home winning %, excl. last 3 games	3.666*** (0.245)	0.866	2.925*** (0.212)	0.692
Away team's away winning %, excl. last 3 games	-3.510*** (0.266)	-0.829	-2.618*** (0.229)	-0.619
Home team had 1 day's rest	0.022 (0.089)	0.005	0.033 (0.088)	0.008
Home team had no day's rest	-0.203** (0.121)	-0.049	-0.182 (0.119)	-0.044
Away team had 1 day's rest	-0.176* (0.106)	-0.041	-0.187* (0.105)	-0.044
Away team had no day's rest	0.031 (0.114)	0.007	0.009 (0.112)	0.002

Note: Standard errors are in parentheses. The model also includes a constant (not reported). ***, **, * indicate statistical significance at the 1, 5, and 10% levels.

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5. Discussion

As mentioned above, no previous study had found any statistically valid evidence for a momentum effect, instead concluding that winning streaks were statistically natural. We improved upon the previous studies by developing a model that offers greater power than the previous studies and perhaps by more precisely accounting for the strength of the previous opponents and the current opponent. With this new method, we find that, after holding team strengths constant, greater success in the past few games leads to a higher probability of winning the next game. Likewise, poor play over the past few games leads to a lower probability of winning the next game

While some winning streaks may be due to randomness, this finding indicates that many winning streaks or periods of strong performance beyond how a team normally performs are at least partly due to a momentum effect. Assuming that we adequately controlled for team strength, we can rule out that periods of stronger-than-normal performance are signs of a team being better than they were previously perceived. While this finding of a momentum effect stands in contrast to what previous researchers have found, it confirms what most people involved with sports believe: that playing well in the past few games leads to playing well in the next game.

One caveat of the results is that they could be due to differences over the course of the season in the composition of the team. The team's composition could change from injury or trades, causing a big shift in winning probabilities over the course of the season. Of course, previous studies failing to find any evidence for momentum suffered from the same potential bias. We attempt to address this by measuring team strengths for home and away games for each half of each season. The estimated momentum effects actually grow stronger with this model attribute.

The results are not necessarily applicable to other sports. In baseball, team strength can vary considerably depending on who the starting pitcher is. Football is more of a game of physicality than a game of skill, so momentum could be different, as it would be based mostly on energy and not much on sharpened skills. Also, in football, we conjecture that team strength can change more rapidly over the course of a season than in basketball due to more devastating injuries and player simply getting worn out over the course of a season. Thus, each game in football may convey greater information on the team strength than would a basketball game, so it would be difficult to distinguish a momentum effect from an effect of learning more about the team strength.

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