2011-07-15

Do Gamblers Correctly Price Momentum in NBA Betting Markets?

Arkes, Jeremy

Do Gamblers Correctly Price Momentum in NBA Betting Markets?

Forthcoming in:
Journal of Prediction Markets

Abstract

There is little research on whether new information is correctly synthesized in prediction markets. Previous studies have found evidence consistent with, but have not proved, gambler misperceptions on the existence of momentum effects in the NBA. I use novel momentum measures that, unlike prior studies, incorporate the strengths of the opponent and the wins (or losses). With these measures, I test whether gamblers correctly synthesize information on momentum in the NBA. Contrary to previous studies, I find strong evidence for the existence of a momentum effect. Furthermore, gamblers incorporate momentum into their beliefs on the game outcomes. Gamblers, however, significantly overstate the importance of momentum. But, there is little evidence that the extent of this gambler misperception is large enough to generate market inefficiencies, or profit opportunity. Still, the gambler mis-pricing of the information has implications for how well new information is synthesized in other types of prediction markets.

I would like to thank Joe Price for providing me with data for this analysis and Ryan Rodenberg for his helpful comments on this paper.

INTRODUCTION

Numerous corporations have adopted internal prediction markets, including Best Buy, Chrysler, General Electric, Hewlett Packard, Intel, Microsoft, Nokia, and Pfizer. For example, Google has used prediction markets to forecast demand for various products such as gmail, predict performance such as meeting certain project deadlines, and predict external events relevant to Google such as industry mergers and acquisitions (Dye, 2008).

While there are some reports that prediction markets can be very accurate (e.g., Berg et al., 2008), other evidence suggests there can be biases in prediction markets. Cowgill et al. (2009) document several biases in the prediction markets at Google. For example, the prices on outcomes that were good for Google were over-priced slightly. In addition, Google's stock price, which had no bearing on these outcomes, typically led to the over-pricing. The company Best Buy also noted an optimism bias in the form of underestimating competitors (Dye, 2008).

While these studies have considered the accuracy of prediction markets, there has been little research on whether participants in prediction markets can correctly synthesize new information into the probability of certain outcomes occurring. The few studies that have examined this have used point spreads in gambling markets.

Gambling markets for professional sports are the most widely-used prediction markets. Although some evidence suggests otherwise (Levitt, 2004), the general theory is that oddsmakers set the odds or point spreads based on what the oddsmakers believe gamblers would have as the money-weighted median. Those expectations by gamblers could include irrational (or incorrect) assessments of what certain information means, and the oddsmakers aim to set point spreads to account for any gambler irrationality. Oddsmakers aim not to make money off of incorrect picks by the gamblers, but rather on the 10% vigorish they charge for losing bets. So, they aim to set the odds so that one-half of the money is bet on each of the two possible outcomes. If too many bets go to one outcome, they change the point spread to attempt to find that median expectation by gamblers. Thus, the final closing point spread can be considered a market price, representing gambler perceptions of the game outcome. As evidence for this, Gandar et al. (1998) find that, in the NBA, changes from the opening point spread to the closing point spread improves the accuracy of the point spread as a predictor of the game outcome. Still, there is room for gambler misperceptions.

Several authors have used point spreads for testing theories about how financial markets operate (e.g., Zuber et al., 1985; Gandar et al. 1988; Camerer, 1989; Brown and Sauer, 1993; Gray and Gray, 1997; Gandar et al., 1998). As Gandar et al. (1998) argue, whereas most assets lack an endpoint at which a fundamental value can be determined, betting markets have an ultimate fundamental value determined by the outcome of the game. That fundamental value can then be compared to the market-based forecast—the point spread.

At the same time, the determination of the fundamental value (the game outcome) has a potentially large random component to it. Game outcomes are often affected by an incorrect referee call, a play that is millimeters away from being in-bounds or out-of-bounds, or perhaps an unexpected strong performance by a normally weak player or an uncharacteristically poor performance by a normally strong player.

As a consequence, new information coming in the form of success in prior games (often called "momentum") could be a product of natural random variation. That is, just as flipping a coin many times would occasionally result in long streaks of heads or tails, the randomness to sporting outcomes could lead to a team having a nice winning streak even though the team may not be playing better than its normal abilities. Momentum is a curious concept. In the NBA, there are examples in which it appears that momentum had a large impact on a team's success—for example, the 8th-seeded New York Knicks in 1999 had a strong 6-week run in which they played well beyond their abilities, at least as proxied by their regular-season record, and made it to the NBA Finals. At the same time, there are other examples of what appeared to be momentum dying out fairly quickly. For example, the "Memorial Day Massacre" had the Boston Celtics crush the Los Angeles Lakers in Game 1 of the 1985 NBA Finals, 148-114. Boston went on to lose the next two games and lose the series in six games.

Obviously, when a team wins or loses a game by a certain number of points, that imparts some information on the quality of the team, as it contributes to their overall statistics. But, it is uncertain whether any abnormal success (or lack thereof) over the past few games has any extra information beyond just contributing to a team's overall statistics. Can gamblers separate that extra information from randomness correctly? Some evidence suggests that many fans don't understand randomness in sports (Berri and Schmidt, 2010), nor randomness in general (Nickerson, 2002). Rather, they take game outcomes as due entirely to skill and differences in the quality of the two teams. And, this could lead to a biased synthesis of new information. This raises the question of whether people who gamble on sports games also misperceive the role of randomness in a team's success or lack thereof.

In this paper, I gauge whether investors (gamblers in this instance) correctly synthesize momentum as to how it would affect the price of the outcome. I examine how several measures of success in prior games influence both betting point spreads and results for a given game. I use NBA data from the 1992 season through the 2010 season.

A few previous studies examined momentum in the NBA, but just analyzed the effects of winning streaks (Camerer, 1989; Sauer and Brown, 1993). I consider a wider range of momentum measures that take into account the strength of the victory—in terms of the strength of the opponent, the margin of victory, or some combination of the two. Whereas the previous studies found evidence suggesting (but not proving) that gamblers misperceive a mythical momentum effect, I find strong evidence that a momentum effect exists. However, gamblers significantly overestimate this momentum effect, indicating that the market players are not correctly synthesizing this information. This overestimation, however, is relatively minor, as there is no evidence that it leads to market inefficiencies, as indicated by the existence of profit opportunities.

PREVIOUS STUDIES

The initial studies using betting markets examined market efficiency by testing whether there were any arbitrage opportunities from systemic biases in point spreads. Zuber et al. (1985) and Sauer et al. (1988) used NFL team statistics and the number of wins to determine if there were any speculative inefficiencies. In both studies, the analysis was based on modeling the probability that a team beat the point spread. Whereas Zuber et al. (1985) found evidence for inefficiencies and profit opportunity, Sauer et al. (1988) found evidence consistent with the efficient markets hypothesis in that there was no profit opportunity. Gray and Gray (1997) took this test to the next level by examining whether it could be profitable to use certain strategies, such as betting on the home team, the underdog, or the team with the higher predicted probability of beating the point spread, based on probit models with team statistics. They found that certain strategies can be profitable (so that the market is inefficient), but they dissipate over time.

A few studies on professional basketball examined whether gamblers misperceive the role of team success in prior games (sometimes referred to as the "hot hand", although that is more often used in the context of an individual player). Camerer (1989) finds that bets placed on teams with winning streaks are more likely to lose, while bets placed on teams with losing streaks are more likely to win. He argues that this indicates that there is a "hot hand fallacy," but it is fairly small within the gambling market.

Brown and Sauer (1993) argue that Camerer (1989) does not account for changes in point spreads or changes in the assessment of teams' abilities from the winning streak. Brown and Sauer (1993) then present a test for momentum effects that jointly models the point spread and the actual game score difference in a Seemingly Unrelated Regression (SUR) model. They find that point spreads are clearly affected by winning and losing streaks, but the evidence is weak that streaks impact the score difference of the game. Standard errors are too large to conclude that the momentum effect (what they also call the "hot hand") is mythical. The lack of evidence for a momentum effect, which Vergin (2000) also finds, suggests that winning and losing streaks are statistically natural. This is consistent with the research on the individual "hot hand," which, with the recent exception of Arkes (2010), has found that streaks of makes and misses in games are statistically natural as well—see Bar-Eli et al. (2006) for a review of these papers.

A limitation of Brown and Sauer (1993), as well as Camerer (1989), is that winning streaks could have little meaning, as it could largely depend on the strength of the opponents. For example, a winning streak of two games could provide very little information on the ability of a team or any momentum the team may have if those games were against very weak opponents. In fact, winning the past few games would mean that it is more likely that the past few opponents were weak, which would mean that the next few opponents would more likely be stronger. That would bias the estimated effect of the winning streak on the point spread and the score difference downwards, perhaps counteracting a real momentum effect.

In this paper, I apply the same methods as Brown and Sauer (1993) to determine if new information gets properly synthesized, but consider a series of momentum measures. These measures account for the strength of the opponents over the past few games, which should eliminate any downward bias to a momentum effect.

METHODS

DATA

The data come from two sources: www.covers.com for data from the 1992 to 2004 seasons and Sports Insight for data from the 2005 to 2010 seasons. Both data sets indicate the date of the game, the point spread, and the final outcome. The Sports Insight data include the opening and closing point spread, whereas the covers.com data only include the closing point spread. Thus, the analyses will just use the closing point spread. From these data, I can construct all variables used in the analysis.

CONTROL VARIABLES

A key part of the model is to obtain accurate indicators of the strength of the two teams for their home and road games. I use two general approaches. The first approach, used by Brown and Sauer (1993), is measuring team strength based on the full-season record; the second approach is to measure up-to-date team strength at the time of the game. For a given game, the gambler and oddsmaker would only have the up-to-date statistics. However, they may have a better sense of the quality of the team than what the up-to-date statistics indicate, and the full-season statistics (while not observable to the gambler and oddsmakers at the time of a game) may be more indicative of how the gambler and oddsmakers perceive the team strength to be. When using the up-to-date statistics (at the time of the game), I only use games in which both teams have had at least 15 games at home or on the road, depending on whether the team is playing at home or on the road.

For each approach, I then considered two alternative measures of the team's home and road strengths: the winning percentage and the average point difference (with the average *home* point difference, for example, being measured as the team's average points at home minus the opponents' average points). The team's winning percentage would be indicative of how well the team pulls out close games. At the same time, randomness could often determine the outcome of close games, and a 1-point win would count the same as a 20-point win. The average point difference would not capture how well the team pulls out close wins, but it does take into consideration the strength of the win. It turns out that using the point difference explained about 5 percentage points more of the variation in point spreads and about 2 percentage points more of the variation in score differences than using the winning percentage. Thus, all models use strength measures for the home and road teams based on the average points difference for home or road games, either for games up to that point or for the full-season. The momentum measures, described below, will use additional strength measures for the home and road teams' opponents over the last few games.

An alternative approach for controlling for the home and road team strengths would be to use team fixed effects. But, Arkes and Martinez (2010) argue that doing so would be problematic. Using team fixed effects would factor out the average points difference for each team. Thus, if a team does better than its average performance in the last few games, then by definition it would be more likely to do worse than average in the rest of its games.

Other control variables are indicators for the number of days of rest before the current game. The variables, for both the home and road teams, are for having no days and one day of rest, with the excluded category being two or more days of rest.

MOMENTUM VARIABLES

I consider several measures of momentum, some based on the past three games and some based on the previous game. Table I describes these measures. First, to be consistent with the previous studies, there are variables for having winning or losing streaks of three games or more.[1] Second, there are variables for the number of wins in the past three games.

The rest of the momentum measures capture the strength of wins and losses. The third set of measures, introduced in Arkes and Martinez (2010), represent "Adjusted momentum," which sums up the home or road winning percentage of each opponent the team beat in the past three games and subtracts "one minus the winning percentage" of the each team they lost to. For example, a home win against a team that has a 0.400 road winning percentage would add 0.400 to this measure; a loss to this team would subtract 0.600 to this measure. Thus, this measure is higher for teams that beat stronger teams, and it is lower for teams that lose to weaker teams. Also note that a given win would add 1.0 to the measure (0.400

[1] Camerer (1989) considered streaks of 1 to 9-or-more games, and Brown and Sauer (1993) considered streaks of two and four games. I split the difference of Brown and Sauer (1993) and, for the sake of parsimony, just use streaks of 3 games, which is consistent with the other measures based on the past three games.

– (-0.600)) relative to what a loss would have done to the measure. This is the primary set of momentum variables for this analysis.

The next set of momentum measures, "Adjusted points momentum," is similar to "Adjusted momentum" in that it gives greater points for beating stronger teams. The measure takes the point difference in the past three games and subtracts the opponents' average point differences for home or road games.

Finally, there are two sets of momentum variables that measure a strong win or a lopsided loss of just the prior game based on the score. One set of measures has indicators for whether the team won or lost by 15-or-more points in the prior game. The last set of measures has indicators for whether the team beat or lost to the point spread by 15-or-more points, thereby taking into account the strength of the opponent.

Table II shows the summary statistics for the two primary models, the first one using games in which both teams had played 15 home or road games (depending on whether the team is home or road) and the second one using all games in which both teams had played at least 3 games (to measure the momentum variables based on the past 3 games). For the first model, the score difference, in terms of the advantage of the home team, has an average of 3.4, while the point spread has an average of 3.5, giving an average forecast error of about -0.1. The home team beat the point spread about 48% of the time. As for the momentum variables, the Adjusted Momentum variables are essentially zero, as they add and subtract points based on the strength of the win or loss. The number of wins in the past 3 games averages to 1.5, as would be expected. In about 16% of the games, teams have a 3-game (or more) winning streak, and in another 16% of games, teams have a 3-game losing streak. Teams won or lost the prior game by

15-or-more points about 13 to 14% each. And, teams beat or lost to the point spread by 15-or-more points in the prior game by about 8 to 10% each.

EMPIRICAL MODEL

The model follows a similar set up as in Brown and Sauer (1993), in which the score difference and point spread in a given game are estimated as part of a Seemingly Unrelated Regression (SUR) model. The justification is that the error terms for both models would include factors known to the oddsmakers and gamblers, but not observable or quantifiable to the researcher. For example, if a major player for one of the teams is out with an injury, the oddsmakers and gamblers take that into account, but that is unobservable to a researcher examining thousands of games; and if it were observable, quantifying its impact would be very difficult. Because the unobservable factors would be relevant to both the score difference and the point spread, the error terms for the two equations would be correlated. Thus, a SUR model is appropriate.

The SUR model includes the following two equations:

$$D_i = \beta_1' S_i^H + \beta_2' S_i^R + \beta_3' X_i^H + \beta_4' X_i^R + \beta_5' M_i^H + \beta_6' M_i^R + \varepsilon_i^D \quad (1)$$

$$P_i = \gamma_1' S_i^H + \gamma_2' S_i^R + \gamma_3' X_i^H + \gamma_4' X_i^R + \gamma_5' M_i^H + \gamma_6' M_i^R + \varepsilon_i^S \quad (2)$$

where D_i is the score difference for game *i*, P_i the point spread, S_i^H is the strength of the home team for its home games, S_i^R is the strength of the road team for road games, X_i^H and X_i^R represent other observable factors that may affect the game outcome, and M_i^H and M_i^R represent measures of momentum. The score difference (D) and point spread (P) are both put in terms of the advantage of the home team. For example, a game in which the home team is favored by 5 and wins by 7 points would have D=5 and P=7. The point spread is typically the reverse, so that a team favored by 5 would have a point spread of -5. But, I reversed it so that it would be consistent with the score difference.

Note that the outcome of the previous games contributes to both the team strength and the momentum measure. Thus, the effects of momentum are any effects of success (or lack thereof) in the past few games over and above what that information indicates for team strength.

If there were a positive momentum effect, then β_5 would be positive and β_6 would be negative for variables representing success in the prior games (e.g., winning streaks) and the opposite (a negative β_5 and a positive β_6) for variables representing the lack of success (e.g., losing streaks). If gamblers were to correctly synthesize how much information momentum conveys to the next game, then it would be the case that $\beta_5 = \gamma_5$ and $\beta_6 = \gamma_6$.

There are 12 models based on the set of equations constituting the SUR model. They are based on the two methods of using the current statistics at the time of the game (A models) and using the full-season statistics (B models), as described above. And for each of these methods, there is one model for each of the six set of momentum variables. These models indicate how much momentum affects subsequent game outcomes and gambler beliefs on those game outcomes.

This SUR model has been used more recently to examine whether NBA teams tank to better position themselves for the draft (Soebbing and Humphreys, 2010). In addition, an asymptotically-similar approach of modeling the forecast error (the score difference minus the point spread) and the probability of a team beating the spread has been used to show that there is racial bias among referees in the NBA (Larsen, Price, and Wolfers, 2008).

FINAL SAMPLE

The A models are based on the 12,606 regular-season games in which the home team had at least 15 home games and the road team had at least 15 road games in a given season. This makes it so the statistics for the average points difference for home or road games is a fairly accurate gauge of the strength of the team at home or on the road. The B models, using the full-season statistics, just require that the team played at least 3 games so that the momentum measures can all be calculated. There are 18,815 observations for the B models.

RESULTS

Table III shows the results from the primary models, based on the "Adjusted Momentum" measure. The first three columns are for Model 1A, which is based on up-to-date team strength measures, while the last three columns are for Model 1B, based on full-season team strength measures. The R^2 for the two equations are 0.20 to 0.21 for the score-difference equation and about 0.75 to 0.79 for the point-spread equation.

Unlike the previous studies, the results show strong evidence for the existence of a momentum effect, as success in the prior game(s) has an additional effect beyond just contributing to a team's overall statistics. The coefficient estimates, recall, are any effect of that success in the prior games beyond that game contributing to the team's strength (as measured by the up-to-date or full-season points difference for home or road games). An extra win in the past three games (which increases the momentum measure by one point) is estimated to increase the score difference in a team's favor by 0.56 points for the home team and 0.51 points for the road team in Model 1A and by 0.50 and 0.37 points for the home and road teams in Model 1B. All of the estimates are significant at the 1% level.

These effects of momentum, however, are less than what gamblers believe. In the point-spread equations, the estimates on the adjusted momentum variables all are around 0.85 for the home team and -0.85 for the road team. All of these estimates are significantly greater in magnitude than the corresponding estimate from the score-difference equations, with the difference being between 0.3 and 0.5.

Another mis-pricing by gamblers is that they understate the role of the teams' strengths, as measured here by home and road points differences. The difference in the estimates on the strength variables between the two equations are statistically significant at the 1% level for three of the four variables in Models 1A and 1B.

Having one day of rest for the home or road team, relative to having two or more days of rest, is not estimated to have any effect on the score difference. But, gamblers appear to understate the negative effect on the road team's score from having no days of rest.

Table IV shows the coefficient estimates for the momentum variables from separate models for each set of momentum variables in the 12 separate models. The results from Models 1A and 1B (from Table III) lead off the table. The first salient point from the results is that gamblers certainly perceive there to be a momentum effect, as almost all of the coefficient estimates on the momentum variables are statistically significant ($p < 0.01$) in the point-spread equations except for those in Model 6, for "beating the spread by 15+ points." But again, it appears that gamblers overstate the true impact of these factors, as in almost all cases, the estimates are much higher in magnitude in the point-spread equations than in the score-difference equations—in some cases by more than 100%. In the B models, these differences are statistically significant for all but one of the momentum variables based on the past three games (Models 1 to 4). In the A models, with the higher standard errors due to the smaller sample, fewer of the differences are statistically significant, but they all point to the same pattern of the gambler overstating the effect of success in the previous three games.

The estimates on the momentum variables in Model 2 ("number of wins in the past 3 games") can be compared to those on the "Adjusted momentum" variables in Model 1, as each win adds one point to the variable, relative to what it would have been with a loss. The estimates in Model 2 are slightly lower for both the score difference and the point spread, with the estimates being significantly lower in Model 2 than Model 1 for the point-spread equation. This suggests that gamblers do distinguish between wins and losses against strong and weak teams when considering momentum.

In Model 3, for every 10-points score difference a team beats its last three opponents over and above the opponents' normal score differences, the team will have an extra 0.23 to 0.28 points in the current game. The gamblers expect that difference to be 0.35 to 0.37, so again they overstate the effect.

In Model 4, I find that 3-game winning and losing streaks do affect the game outcome, with the estimates being statistically significant for three of the four variables in both Models 4A and 4B. This stands in contrast to the previous studies on basketball (i.e., Camerer, 1989; Sauer and Brown, 1993; Vergin, 2000). Reasons for the difference could be due to this study having greater power from more observations and using more precise team-strength control variables by having both home and road statistics.

Model 5 has an interesting result. The home or road team winning the previous game by 15+ points leads to the current-game score difference being about 1 point more in their favor ($p < 0.01$). However, the home or road team losing the previous game by 15+ points has no significant effect on the game outcome. Yet, gamblers expect those large losses to have a negative effect on their performance. The differences are significant for three of the four outcomes, albeit only at the 10% level in one case.

In Model 6, either team beating the point spread by 15+ points in the previous game had no significant effect on the current-game score difference. In this case, it is the gamblers who perceive an effect for a team beating the spread by 15+ points, but not losing to the spread by 15+ points. However, none of the differences in estimates are significant. The finding that gamblers take into account a team beating the spread by 15+ points, but not losing to the spread by 15+ points is consistent with Gilovich's (1983) finding that bettors can "explain away" losses, but wins they take as confirmation of how strong they perceive a team's abilities to be.

One caveat of this analysis is that I assume that the point spreads are based on how gamblers price certain aspects. This viewpoint is further justified in that, if the point spread is different from what gamblers believe will occur, then the oddsmakers will adjust the point spread to try to move towards equal weighting on each side of the bet. However, it is possible that the oddsmakers, in some cases, do a poor job of predicting how the gamblers would price certain information, even with shifts in the point spreads. Thus, what I identify as mis-pricing by gamblers may partly be mis-pricing by oddsmakers.

DETECTING MARKET INEFFICIENCIES

The next question is whether gamblers' overstated perception of the momentum effect is large enough to create inefficiencies in the market, or profit opportunity for those who understand the mis-pricing by gamblers. To do this, I use logit models to predict the probability of the home team beating the spread given the momentum measures and other available information. I estimate this model excluding the 2009 and 2010 seasons, so that those seasons can be used for out-of-sample predictions, similar to Gray and Gray's (1997) analysis of betting strategies for the NFL. Furthermore, I only use the models with up-to-date statistics, as that would be what would be available to a gambler. For there to be profit opportunity in the market, one must be able to predict correctly 52.4% of the games, given the 11-for-10 rule (i.e., the 10% vigorish).[2]

Table V presents these success rates from various strategies based on these logit models. The logit models themselves are not included for the sake of saving space. In column (1), the simple strategy of betting on the road team yields a success rate of 51.7%. Columns (2) through (8) are then based on the predicted probabilities from various logit models. The first of these just includes the days-of-rest and team-strength measures (based on up-to-date calculations). The success rate increases to 53.0%, which is not significantly greater than 52.4%.[3] Adding the various sets of momentum variables, in columns (3) to (8), has hardly any effect on the success rate.

In the next row, I take all games in which one team has at least a 52.5% predicted probability of beating the spread and calculate the success rate from betting on that team. For the baseline model

[2] The 52.4% break-even point is calculated as follows: given that the gambler has to pay $11 to win $10, the return to the bet is 10p + (1-p)*11, where p is the probability of winning the bet; the break-even point where that equals zero is p = 0.524.

[3] The statistical significance is calculated based on the binomial probability distribution.

without any momentum variables, the success rate increases to 54.1%. In column (3), using the "Adjusted momentum" variables, the success rate increases to 55.1% (for 632 games), which is now significant at the 10% level. Using any of the other sets of momentum variables does not improve upon the success rate using the "Adjusted momentum" variables, and none of them are significantly greater than 52.4%. In the next row, I do the same but with games in which one team has a predicted probability of beating the spread by at least 55%. The success rate increases to as high as 56.0% (again, for the "Adjusted momentum" variables), but none of these are significantly greater than 52.4%.

DISCUSSION

Consistent with previous studies, the results of this paper indicate that gamblers incorporate information on momentum in their beliefs on the game outcome, which show up in point spreads. However, unlike previous studies, I find evidence indicating that momentum effects are real and not just the product of natural variation. The success in the past three games contributes positively to a team's performance beyond the information the past three games provides for the overall team strength. For just the previous game, I find evidence that wins help, but losses do not. Whereas, theoretically, measures of momentum incorporating the strengths of the opponents and the strengths of the wins/losses in the recent games should provide more information on the momentum of the team, there is only weak evidence, in the form of slightly higher R-squared's, that such measures better predict game outcomes or point spreads than the conventional measure of momentum—winning streaks. Perhaps this is an indication of the momentum effect, in general, being fairly weak.

It is not likely that gamblers (or oddsmakers) would do the calculations that I use in these models. But, if they are taking into account what occurred in the past few games, many would likely consider the strength of the team's victories or losses. Beating a strong team or winning big would count more than beating a weak team or just barely winning a game they should have won easily. The models that do incorporate the strength of the opponents into the momentum measures do have (slightly) higher R-squared's for both the score-difference and point-spread equations.

Despite the gamblers being correct that a momentum effect exists, I find evidence indicating that gamblers systemically overstate the importance of momentum in how it affects the next game's outcome. When using the full-season team-strength measures, the differences between the actual momentum effect on game outcomes and gambler perceptions of the momentum effect on point spreads are statistically significant in all but one of the momentum variables based on success in the prior three games. However, in models using the up-to-date team-strength measures, which involve about one-third fewer observations, the differences are statistically significant in only about one-half of the cases.

These differences between the actual and gamblers' perceptions of the impact of momentum, however, may not be large enough to generate inefficiencies in the gambling market. There was no evidence that one could use misguided point spreads (due to gambler misperceptions) to make a profit gambling on NBA games.

Despite there not being evidence indicating market inefficiencies, the evidence does indicate that gamblers do not correctly synthesize information on momentum. What could cause gamblers to overstate the effects of momentum? One possible cause stems from the fact that gambling on sports often involve, for many people, emotional stakes as well as financial stakes. Thus, maintaining objectivity could be difficult. And, gamblers may take their team's wins as a sign of the team's strength, but explain away road losses, as Gilovich (1983) argues. Likewise, gamblers may take the lack of success among teams they root against and attribute that to the team being weaker than the truly are. This would be consistent with Nickerson's (2002) finding that people do not fully recognize the role of randomness in sports outcomes.

The emotional-bias story is consistent with the findings on Google's prediction markets that over-optimism biases prices. In other prediction markets, there could be similar emotional biases. For example, if there were a prediction market on the success of a drug at a pharmaceutical company, someone working on developing the drug may have an emotional stake in the outcome. Thus, they may overestimate the importance of positive indicators and perhaps underestimate the effects of negative indicators.

REFERENCES

Arkes, Jeremy (2010), Revisiting the hot hand theory with free throw data in a multivariate framework, *Journal of Quantitative Analysis in Sports*, 6(1), Article 2.

Arkes, Jeremy and Jose Antonio Martinez Garcia (2010), Finally, evidence for a momentum effect in the NBA, Working Paper.

Bar-Eli, Michael, Simcha Avugos, and Markus Raab (2006), Twenty years of "hot hand" research: Review and critique, *Psychology of Sport and Exercise* 7, 525-553.

Berg, Joyce E., Forrest D. Nelson, and Thomas A. Rietz (2008), Prediction market accuracy in the long run, *International Journal of Forecasting* 24, 283-298.

Brown, William O. and Raymond D. Sauer (1993), Does the basketball market believe in the hot hand - comment, *American Economic Review* 83, 1377-1386.

Camerer, Colin F. (1989), Does the basketball market believe in the hot hand, *American Economic Review* 79, 1257-1261.

Cowgill, Bo, Justin Wolfers, and Eric Zitzewitz (2008), Using prediction markets to track information flows: Evidence from Google," available at http://www.bocowgill.com/GooglePredictionMarketPaper.pdf

Dye, Renée (2008), The promise of prediction markets: A roundtable, *The McKinsey Quarterly*, *(2)*, 83–93.

Gandar, John M., William H. Dare, Craig R. Brown, and Richard A. Zuber (1998), Informed traders and price variations in the betting market for professional basketball games, *Journal of Finance* 53, 385-401.

Gandar, John M., Richard A. Zuber, Thomas O'Brien, and Ben Russo (1988), Testing rationality in the point spread betting market, *Journal of Finance* 43, 995-1008.

Gilovich, Thomas (1983), Biased evaluation and persistence in gambling, *Journal of Personality and Social Psychology* 44, 1110-1126.

Gray, Philip K., and Steven F. Gray (1997), Testing market efficiency: Evidence from the NFL sports betting market, *Journal of Finance* 52, 1725-1737.

Larsen, Tim, Joe Price, and Justin Wolfers (2008), Racial bias in the NBA: Implications in betting markets, *Journal of Quantitative Analysis in Sports*, 4(2), Article 7.

Levitt, Steven (2004), Why are gambling markets organised so differently from financial markets? *The Economic Journal*, 114, 223–246.

Nickerson, Raymond S. (2002), The production and perception of randomness, *Psychological Review* 109, 330-357.

Sauer, Raymond D., Vic Brajer, Stephen P. Ferris, and M. Wayne Marr (1988), Hold your bets - another look at the efficiency of the gambling market for national-football-league games, *Journal of Political Economy* 96, 206-213.

Soebbing, Brian and Brad Humphreys (2010), Do gamblers think that teams tank? Evidence from the NBA, *Univ. of Alberta Working Paper* No. 2010-13.

Vergin, Roger C. (2000). Winning streaks in sports and the misperception of momentum. *Journal of Sport Behavior*, 23 (2), 181-197.

Wolfers, Justin and Eric Zitzewitz (2004), Prediction markets, *Journal of Economic Perspectives* 18, 107-126.

Zuber, Richard A., John M. Gandar, and Benny D. Bowers (1985), Beating the spread - Testing the efficiency of the gambling market for national-football-league games, *Journal of Political Economy* 93, 800-806.

Table 1. Measures of momentum

Momentum measures	Definition and notes	Takes into account the strength of the opponent(s)	Takes into account the strength of the win	Success measured over the past 1 or 3 games
3-game winning and losing streaks	0-1 indicator variables for both winning and losing streaks	No	No	3
Number of games won in the past 3 games	Ranges from 0 to 3	No	No	3
Adjusted momentum (primary outcome)	Add up the home or road winning percentages for the team(s) the subject beat and subtract the home or road winning percentages for the team(s) the subject lost to.	Yes	Yes	3
Adjusted points momentum	Sum up the points difference minus the expected points difference based on home and road average point differences	Yes	Yes	3
Won/lost by 15+ points	0-1 indicator variables for both winning or losing by 15 or more points	No	Yes	1
Beat/lost to spread by 15+ points	0-1 indicator variables for both beating and losing to the spread by 15 or more points	Yes	Yes	1

Table 2. Descriptive statistics.

	Models based on up-to-date team strengths measures (n=12,606)		Models based on full-season team strength measures n=18,815	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Outcomes				
Score difference (for home team)	3.399	13.037	3.339	13.017
Point spread	3.495	6.482	3.433	6.392
Forecast error	-0.096	11.380	-0.093	11.465
Whether home team beat the spread	0.483	0.500	0.485	0.500
Control variables				
Home-team average points difference (up-to-date)	3.352	5.253		
Road-team average points difference (up-to-date)	-3.325	4.828		
Home-team average points difference (full-season)			3.295	5.187
Road-team average points difference (full-season)			-3.316	4.711
Home team had 1 day's rest	0.611	0.488	0.581	0.493
Home team had 0 day's rest	0.153	0.360	0.156	0.363
Road team had 1 day's rest	0.500	0.500	0.476	0.499
Road team had 0 day's rest	0.331	0.471	0.337	0.473
Momentum variables				
Adjusted momentum				
For the home team	0.005	0.901	0.000	0.898
For the road team	0.002	0.914	0.005	0.898
Wins in the past 3 games				
For the home team	1.497	0.940	1.495	0.942
For the road team	1.511	0.952	1.520	0.945
Adjusted points momentum				
For the home team	0.049	24.226	-0.129	24.014
For the road team	0.123	24.696	0.226	24.266
3-game winning/losing streaks				
Winning streak for home team	0.156	0.362	0.156	0.363
Losing streak for home team	0.161	0.367	0.162	0.369
Winning streak for road team	0.166	0.372	0.164	0.370
Losing streak for road team	0.162	0.369	0.157	0.364
Won or lost last game by 15+ points				
Home team won	0.136	0.343	0.131	0.338
Home team lost	0.128	0.335	0.129	0.335
Road team won	0.136	0.342	0.135	0.342
Road team lost	0.137	0.344	0.133	0.339
Beat or lost to the point spread in last game by 15+ points				

Home team beat spread	0.084	0.277	0.085	0.279
Home team lost to spread	0.097	0.296	0.098	0.297
Road team beat spread	0.084	0.278	0.087	0.282
Road team lost to spread	0.101	0.301	0.098	0.298

Table 3. Results for the primary SUR models.

	Model 1A (n = 12,606) (based on up-to-date team strengths measures)			Model 1B (n = 18,815) (based on full-season team strength measures)		
	Score-difference equation	Point-spread equation	Difference in estimates	Score-difference equation	Point-spread equation	Difference in estimates
Momentum variables						
Home-team Adjusted Momentum	0.556*** (0.131)	0.858*** (0.034)	0.302**	0.500*** (0.107)	0.871*** (0.030)	0.371***
Road-team Adjusted Momentum	-0.511*** (0.130)	-0.864*** (0.034)	-0.353***	-0.368*** (0.107)	-0.847*** (0.030)	-0.479***
Team-strength variables						
Home-team average points difference (up to that point)	0.780*** (0.023)	0.711*** (0.006)	-0.069***			
Road-team average points difference (up to that point)	-0.742*** (0.025)	-0.730*** (0.006)	0.012			
Home-team average points difference (full-season)				0.819*** (0.019)	0.683*** (0.005)	-0.136***
Road-team average points difference (full-season)				-0.776*** (0.020)	-0.711*** (0.006)	0.065***
Days of rest variables (2 or more days' rest is excluded category for both home and road team)						
Home team had 1 day's rest	0.395 (0.255)	-0.118* (0.066)	-0.513**	0.166 (0.202)	-0.154*** (0.056)	-0.320
Home team had 0 day's rest	-1.547*** (0.345)	-1.053*** (0.089)	0.496	-1.374*** (0.274)	-1.147*** (0.076)	0.227
Road team had 1 day's rest	0.114 (0.296)	0.110 (0.076)	-0.004	0.126 (0.234)	0.024 (0.065)	-0.102
Road team had 0 day's rest	1.971*** (0.315)	1.299*** (0.081)	-0.672**	1.913*** (0.247)	1.224*** (0.069)	-0.687***
Constant	-2.398*** (0.319)	-1.571*** (0.082)		-2.516*** (0.245)	-1.326*** (0.068)	
R-squared	0.201	0.786		0.210	0.748	

Note: Correlation between "score difference" and "point spread" equations: Model 1A=0.226, Model 1B=0.188
Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table 4. Coefficient estimates on the momentum variables for the various models.

	Models based on up-to-date team strengths measures (n = 12,606)			Models based on full-season team strength measures (n = 18,815)		
	Score-difference equation	Point-spread equation	Difference in estimates	Score-difference equation	Point-spread equation	Difference in estimates
		Model 1A			**Model 1B**	
Home-team adjusted momentum	0.556*** (0.131)	0.858*** (0.034)	0.302**	0.500*** (0.107)	0.871*** (0.030)	0.371***
Road-team adjusted momentum	-0.511*** (0.130)	-0.864*** (0.034)	-0.353***	-0.368*** (0.107)	-0.847*** (0.030)	-0.479***
R^2	0.201	0.786		0.210	0.748	
		Model 2A			**Model 2B**	
Home-team number of wins in past 3 games	0.599*** (0.124)	0.742*** (0.032)	0.143	0.458*** (0.098)	0.776*** (0.027)	0.318***
Road-team number of wins in past 3 games	-0.387*** (0.123)	-0.754*** (0.032)	-0.367***	-0.296*** (0.097)	-0.793*** (0.027)	-0.497***
R^2	0.198	0.780		0.208	0.747	
		Model 3A			**Model 3B**	
Home-team adjusted points momentum	0.028*** (0.005)	0.035*** (0.001)	0.007	0.025*** (0.004)	0.037*** (0.001)	0.012***
Road-team adjusted points momentum	-0.028*** (0.005)	-0.035*** (0.001)	-0.007	-0.023*** (0.004)	-0.036*** (0.001)	-0.013***
R^2	0.200	0.787		0.211	0.753	
		Model 4A			**Model 4B**	
Home-team 3-game winning streak	0.748** (0.298)	0.899*** (0.078)	0.151	0.565** (0.236)	0.928*** (0.067)	0.363
Home-team 3-game losing streak	-1.109*** (0.301)	-1.322*** (0.078)	-0.213	-0.867*** (0.233)	-1.390*** (0.066)	-0.523**
Road-team 3-game winning streak	-0.467 (0.294)	-1.062*** (0.077)	-0.595**	-0.261 (0.231)	-1.106*** (0.065)	-0.845***
Road-team 3-game losing streak	0.783*** (0.299)	1.281*** (0.078)	0.568*	0.760*** (0.235)	1.255*** (0.066)	0.495**
R^2	0.197	0.778		0.208	0.736	

		Model 5A			**Model 5B**	
Home team won last game by 15 points or more	0.987*** (0.311)	0.481*** (0.084)	-0.506*	0.980*** (0.246)	0.681*** (0.071)	-0.299
Home team lost last game by 15 points or more	0.165 (0.318)	-0.587*** (0.085)	-0.752**	0.147 (0.234)	-0.604*** (0.068)	-0.751***
Road team won last game by 15 points or more	-1.050*** (0.310)	-0.737*** (0.083)	0.313	-0.754*** (0.241)	-0.820*** (0.070)	-0.066
Road team lost last game by 15 points or more	0.195 (0.310)	0.430*** (0.083)	0.235	0.093 (0.234)	0.461*** (0.068)	0.368*
R^2	0.197	0.765		0.207	0.724	
		Model 6A			**Model 6B**	
Home team beat spread by 15 points or more	0.380 (0.375)	0.199* (0.102)	-0.181	0.102 (0.290)	0.141* (0.084)	0.039
Home team lost to spread by 15 points or more	0.310 (0.350)	0.014 (0.095)	-0.296	0.236 (0.256)	0.087 (0.075)	-0.149
Road team beat spread by 15 points or more	-0.579 (0.373)	-0.206** (0.101)	0.371	-0.401 (0.286)	-0.246*** (0.083)	0.155
Road team lost to spread by 15 points or more	0.226 (0.344)	-0.126 (0.093)	-0.352	-0.111 (0.258)	-0.092 (0.075)	0.019
R^2	0.196	0.761		0.207	0.719	

Note: Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels.

Table 5. Proportion of 2009 & 2010 season games picked correctly and statistical significance of difference from 0.524

		Predicted probabilities from logit models, with the indicated momentum variables included						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Just pick road team	No momentum measure	Adjusted momentum	# wins in past 3 games	Adjusted points momentum	Winning and losing streaks	Won/lost last game by 15+ points	Beat/lost to spread last game by 15+ points
Correctly classified (n = 1542)	0.517	0.530	0.532	0.529	0.530	0.536	0.531	0.518
Correctly classified for teams with 52.5% or greater predicted probability	--	0.541 (612)	0.551* (671)	0.548 (694)	0.544 (651)	0.531 (686)	0.539 (686)	0.542 (668)
Correctly classified for teams with 55% or greater predicted probability	--	0.556 (133)	0.560 (159)	0.524 (164)	0.525 (160)	0.553 (179)	0.556 (153)	0.530 (166)

Note: For the last two rows, the number in parentheses is the number of games with a team identified as having at least 52.5% or 55% predicted probability of beating the spread. The logit models, based on data through the 2008 season, include the days-of-rest variables, the up-to-date home or road team-strength measures based on the average points difference, and any indicated sets of momentum measures. The * indicates that the proportion of games correctly classified is greater than 0.524 by an amount that is statistically significance at the 10% level.