Sentiment Bias in National Basketball Association Betting

Arne Feddersen[*] Brad R. Humphreys[†] Brian P. Soebbing[‡]

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Abstract

We develop evidence of bettors with sentiment bias in the betting market on National Basketball Association (NBA) games. We use novel measures of team popularity, arena capacity-utilization and team all star votes received, as proxies for the presence of biased investors. Analysis of point spreads and bet outcomes for more than 33,000 NBA games played in 1981-2012 shows that bookmakers offer favorable point spreads on games involving popular teams, an outcome consistent with sentiment bias. These favorable point spreads do not translate into higher returns for informed bettors, suggesting that bookmakers shade point spreads to increase their profits.

JEL Codes: L81, G14

Key words: sentiment bias, sports betting, NBA

[*]University of Southern Denmark, Department of Environmental and Business Economics, Niels-Bohrs-Vej 9, DK-6700 Esbjerg, Denmark; E-mail: af@sam.sdu.dk

[†]West Virginia University, College of Business & Economics, 601 University Ave., PO Box 6025, Morgantown, WV 26506-6025, USA; Email: brhumphreys@mail.wvu.edu

[‡]Louisiana State University, School of Kinesiology, 112 Long Field House, Baton Rouge, LA, 70803, USA; E-mail: bsoebb1@lsu.edu

I INTRODUCTION

A growing body of evidence supports the idea that investor sentiment affects outcomes in financial markets. Investor sentiment occurs when the actual price of a financial asset differs from the price that would be expected based on the present discounted value of future cash flows generated by the financial asset. In general, this mis-pricing can come from two sources: systematic forecast errors associated with the probability that some future outcome will occur (Baker and Wurgler, 2007), and systematic over-valuation of the value of the resolution of uncertainty about a future outcome, perhaps because of an emotional reaction to the resolution of this uncertainty (Hirshleifer, 2001). For example, consider an individual placing a bet on the outcome of a basketball game played by her favorite team. Economic theory predicts that this individual forms an expectation of the present value of the outcome of this game, compares this present value to the cost of the bet, and makes a bet if the expected present value of the bet exceeds the cost. The expected present value depends on both the expected probability that the team will win this game, and the total value of the win that will be realized after the uncertainty about the outcome of the game is resolved. In either case, the individual arrives at an ex post, or ex ante value of the future event that differs from the present discounted value implied by the objective probability of a win and an unemotional reaction to the resolution of the game. This difference is called sentiment bias in the literature (Avery and Chevalier, 1999).

Much of the evidence supporting the presence of sentiment bias in financial markets comes from sports betting markets outcomes. Avery and Chevalier (1999) reported evidence of sentiment bias, in the form of abnormally large losses on bets placed on "glamorous" National Football League (NFL) teams in point spread betting markets in the US. Forrest and Simmons (2008) found similar evidence for popular football teams in Spain and Scotland in fixed odds betting markets in Europe. Franck et al. (2011) found favorable odds on popular football teams in the UK in fixed odds betting markets, especially on weekends when biased bettors may participate in larger numbers.

Sports betting markets contain two complicating factors for analysis of sentiment bias compared to financial markets. First, the early sports betting literature contained the assumption that bookmakers attempted to balance bet volume on either side of wagering on individual games in order to earn a certain profit regardless of game outcomes (Woodland and Woodland, 1991). Levitt (2004) challenged this assumption, observing that betting on individual games did not appear balanced in some settings, and showing that the presence of bettors with behavioral biases generated increased bookmaker profits from unbalanced betting. Other empirical evidence confirmed Levitt's (2004) conclusion (Paul and Weinbach, 2008). Second, bettor heterogeneity may obscure evidence of sentiment bias in these markets. Makropoulou and Markellos (2011) identified three types of participants in sports betting markets: informed bettors who make profit-maximizing decisions based upon information available in the public domain; insider bettors who hold information about game or match outcomes unknown to bookmakers; and noise bettors who bet randomly (Makropoulou and Markellos, 2011). As an example of randomness, Makropoulou and Markellos (2011) observe that noise bettors may bet for their favorite team at any price. The presence of noise bettors with sentiment bias in the market can affect the odds or point spreads offered by bookmakers. but only if enough of them are present in the market. Also, bookmakers may adjust odds or point spreads to take advantage of bettors with sentiment bias but cannot adjust them too much because the informed or insider bettors could bet against the odds or lines reflecting sentiment, reducing the bookmaker's profit.

We develop evidence that outcomes in betting markets for point spread betting on National Basketball Association (NBA) games appear consistent with the presence of bettors with sentiment bias in these markets. Point spreads are accurate predictors of game outcomes (Sauer, 1998) and efficiently aggregate information. Previous research on basketball betting has examined phenomena such as point shaving (Wolfers, 2006), referees' racial bias

(Larsen et al., 2008), and tanking (Soebbing and Humphreys, 2013). This paper contributes to this literature by examining other fundamental factors that influence point spreads on NBA games (Brown and Sauer, 1993b) and also show that individuals with sentiment bias exist in a wider number of financial markets.

Our sample contains regular season NBA games from the 1981-1982 season through the 2011-2012 season, an extensive sample period in which to examine sentiment bias among bookmakers. The results of a fixed effects OLS model explaining observed variation in point spreads find that bookmakers account for the popularity of NBA teams when setting point spreads, offering fans of these teams favorable point spreads, similar to Forrest and Simmons' (2008) result for football in Spain and Scotland. Moreover, these results are robust with regard to two different measures of popularity: relative attendance and team all star votes. However, estimates from a probit model explaining variation in bet outcomes shows that the favorable point spreads offered increases the probability that the observed team "covers" and a bet on that team wins, suggesting that the favorable point spread offered is not large enough to generate profitable betting strategies in this market.

II SENTIMENT IN THE SPORTS BETTING LITERATURE

Investor sentiment can be broadly defined as "any nonmaximizing trading pattern among noise traders that can be attributed to a particular exogenous motivation" (Avery and Chevalier, 1999, p. 493). Avery and Chevalier (1999) identified two major sources of sentiment, unanticipated and anticipated. Unanticipated sentiment can be attributed to an unanticipated demand shock, which results in the price of the asset shifting away from the true market value of that asset. Anticipated sentiment is known to the parties prior to the completion of trading and "merely shifts the position of the demand curve" (Avery and Chevalier, 1999, p. 498). They identified specific conditions that can affect the demand curve of an asset like a bet on a sporting event. These conditions included dynamic uncertainty, myopic pricing, irrationality of the market maker, defined in sports betting markets as bookmakers underestimating the power and degree that the particular sentiment has in the market, price discrimination, and composition of the market in terms of informed and uniformed bettors.

Sports, especially professional sports, is a good setting for examining economic phenomena that are difficult to detect in other settings (Kahn, 2000). In the literature, sports betting markets have been identified as “simple financial markets” (Sauer, 1998, p. 2021) containing well defined outcomes (wins and losses) and clear ending times (start of the game or match). In fact, Sauer (1998, p. 2021) stated, “wagering markets can provide a clear view of the pricing issues which are more complicated elsewhere.” The prices in sports betting markets are the point spreads and odds set by the bookmaker. Odds betting is common in lower scoring sports such as soccer and baseball, and point spread betting is common in high scoring sports such as basketball and American football. In odds betting, bettors take a position on the actual outcome of the match. Point spread betting is based on the difference in points scored by both teams in a match, not the actual outcome.

The prevailing assumption regarding bookmaking behavior was that prices set by the bookmakers balance the dollar value of bets of each side of the bet. Under this strategy, the bookmakers could pay the winning bets from the money collected from the losing bets. The profit that is left over is the commission, commonly called the “vig,” that was paid to the bookmaker by the bettors. Under the balanced book assumption, Levitt (2004) outlined three strategies that bookmakers can potentially implement in posting money lines or point spreads. Levitt (2004) and other previous research (Paul and Weinbach, 2008) challenged the traditional balanced book assumption. Rather than setting a point spread to maximize the total money bet on each side of a point spreads, this body of research has shown that bookmakers take a position regarding the outcome of the match and “exploit bettors’ biases” (Levitt, 2004, p. 226). However, bookmakers have to be careful not to adjust point spreads and money lines too much to exploit these biases as bookmakers would be taking a high risk on the outcome of the match or spread. As a result of bookmakers taking too high of a risk to exploit biases, informed bettors could bet a large amount of money against these biases.

Research by Gandar et al. (1998) found that informed traders influenced the opening point spread set by bookmakers as well as the movement in the point spread from the opening line until the closing line. This large wager by informed bettors could result in large losses for the bookmakers and threaten their gambling operation. Thus, it is important for the bookmakers to recognize bettor biases that they could exploit for a larger profit or be able to balance the spread on each side of the wager.

Brown and Sauer (1993b) identified fundamental factors, like investor biases, that could influence point spreads and betting odds in professional sports betting markets. These various fundamental factors are all potential sources of investor sentiment bias. Much of the early research on sports betting markets focused on market efficiency (Sauer, 2005), in particular documenting the existence of the favorite/longshot bias. Golec and Tamarkin (1991) analyzed point spread betting on both professional (i.e., NFL) and college football games and found significant biases existed in the NFL betting market against home teams and for favorites. Over the sample period, both markets appeared to become more informationally efficient in that point spreads became bettor predictors of game outcomes. Evidence of biases were not found in the college football betting market. Furthermore, Vergin and Sosik (1999) found in a subset of NFL games that included Monday Night Football and playoff games that betting on the home team was a profitable betting strategy. In European football, Kuypers (2000) found that bookmakers offered lower odds against the team that was considered the favorite in the match in order to take advantage of biased bettors who miscalculated the strength of the favorite. Research in other professional sport settings also found evidence of biases associated with certain factors such as underdogs and home underdogs (Woodland and Woodland, 1994, 2001; Paul and Weinbach, 2005).

Research using data from betting on NBA games has examined bettor biases in the context of the efficient market hypothesis. Camerer (1989) examined the influence of the "hot hand" on point spreads for NBA games. The "hot hand" is a phenomenon where bettors misunderstand the randomness of events such as winning and losing streaks by sports teams.

Using point spread data from 1983-1986, Camerer (1989) hypothesized that teams with winning streaks would have point-spreads set too high, and teams on losing streaks would have point spreads set too low, by bookmakers. His results agreed with these two hypotheses. However, the changes in the point spreads were not large enough to be exploited by the betting public into a profitable betting strategy. Brown and Sauer (1993a) criticized these results, explaining that Camerer's (1989) conclusion was based on the incorrect premise that the "hot hand" phenomenon was a myth. However, Brown and Sauer (1993a) concluded that the hot hand phenomenon in the NBA was real in the sense that winning and losing streaks influenced the point-spreads set by bookmakers in the NBA. Research by Paul and Weinbach (2005) supported Brown and Sauer's (1993a) conclusions by showing that the betting public overbets NBA teams that are on winning streaks. More recent research by Arkes (2011) examined momentum with the point spread market and found that momentum was not just a factor of natural variation. However, bettors overestimate the momentum effect. Thus, betting markets still are efficient.

The NBA has been a popular setting for research on other sources of sentiment bias. Soebbing and Humphreys (2013) assessed the effect of tanking in NBA betting markets. Tanking occurs when a team eliminated from the postseason fails to supply effort to win the remaining regular season games. Their research indicated that bookmakers adjusted the point spread from 1 to 4 points when tanking was thought to occur in NBA regular season games. Larsen et al. (2008) investigated if the racial make-up of NBA referees compared to the composition of teams could lead to biases in betting market. Their results provided support for this hypothesis. Igan et al. (2012) examined racial bias by focusing on NBA team's racial composition. For Igan et al. (2012), their premise revolved around the belief that both bookmakers and the betting public believed that black basketball players were better than white basketball players. Thus, the point spread would exhibit this bias when one team had a higher composition of black players compared to its opponent. Results showed that the point spread betting markets exhibit evidence of racial bias by bettors.

Sentiment for popular teams and individuals can also affect bettors decisions and prices offered by bookmakers. Forrest and Simmons (2008, p. 120) defined this type of sentiment as "different returns to betting according to whether one wagers on more or less glamorous teams." Forsythe et al. (1999) developed evidence that bettors in political prediction markets purchased "shares" of the candidates of the political party in which they were affiliated. In sports betting, Avery and Chevalier (1999) found in their study of NFL games that bettors bet on teams that were covered more in the media. Later research by Strumpf (2003) examining illegal sports betting in New York City found that gamblers were more likely to bet on the local teams (e.g., New York Yankees) compared to teams outside of the New York City area. As a result, these illegal book makers offered higher prices to bettors betting on local teams.

Researchers using data from European (football) soccer also concluded that bookmakers account for bettor sentiment, in terms of the popularity of certain teams or countries. Forrest and Simmons (2008) found evidence of bettor sentiment in their examination of betting on Spanish and Scottish football leagues. Using the difference in average attendance from each team's previous season as their measure of sentiment, Forrest and Simmons (2008) concluded that betting odds were more favorable for the more popular team in the match. Based on an analysis of betting on English football matches, Franck et al. (2011) developed evidence supporting the findings of Forrest and Simmons (2008). In addition, Franck et al. (2011) examined the impact of weekday versus weekend matches on investor sentiment. These results showed that more favorable odds are offered on weekend matches. The authors attributed this difference to the amount of casual bettors participating in the betting market for weekend games compared to weekend games. Finally, Braun and Kvasnicka (2013) examined the sentiment from national football club matches across Europe. Using data from football matches from across Europe, Braun and Kvasnicka (2013) found evidence of biases in the prices that bookmakers offer for a country's national football clubs. They explained their result as perception bias, the confidence of the bettors that their home country will win, and loyalty bias, wagers strictly on the national team to win due to the loyalty of bettors.

In summary, bookmakers have to recognize various biases in order to set a point spread or betting odds to offer on a game or match. Recent research suggested that bookmakers try to exploit these various biases, which can be interpreted as a form of investor sentiment. Academic research has examined many biases including favorites, underdogs, the "hot hand" phenomena, and the popularity of teams. The NBA has been a popular setting for research on on betting biases. The present research focuses on the degree in which the popularity of NBA teams is priced into the point spread of NBA games, adding to the growing literature from Brown and Sauer's (1993b) research on additional fundamental factors that affect the point spread for NBA games.

III EMPIRICAL ANALYSIS

Background and Strategy

Following the general practice in this literature, the present research identifies observable factors likely to be associated with the presence of bettors with sentiment bias and include variables capturing these factors in regression models of the determination of prices and bet outcomes in this market. Recall that point spreads can be interpreted as prices in these financial markets (Sauer, 1998). The key decision for empirical research on sentiment bias involved identifying observable factors that can be plausibly linked to the presence of bettors affected by sentiment bias in the market. Avery and Chevalier (1999) used expert opinions, performance in the previous year, and conference affiliation as proxy variables for the presence of bettors with sentiment bias in NFL betting markets. Forrest and Simmons (2008) used the difference in average attendance at home matches in the previous season for each team in a football match in La Liga, the top Spanish football league. The measure of popularity used here is the difference in the percent of seating capacity filled in the two team's home arenas in the previous season. This measure of the number of bettors with sentiment bias wagering on games is similar to the one used by Forrest and Simmons (2008).

Like Forrest and Simmons (2008), the present research looks for evidence of sentiment bias in both the prices set by bookmakers in this market, and in game outcomes. We estimate reduced form models of the determination of point spreads in NBA games using Ordinary Least Squares (OLS), and reduced form models of the outcomes of bets, based on a dichotomous dependent variable the is equal to one if a bet on that team paid, using a probit model. Both models include variables the proxy for the presence of bettors with sentiment bias in the market. The sign of the estimated parameters on these variables will be statistically significant if bettors with sentiment bias bet on these games, or if bookmakers believe such bettors are present.

Data

We analyze point spreads and game outcomes from NBA regular season games played in the 1981-1982 season through the 2011-2012 season. Point spreads from recent seasons were collected from various online websites for Las Vegas sports books. Older point spreads were gathered with the assistance of Richard Gandar.[1] Game and arena data were collected from a variety of websites including *ESPN* and *Basketball Reference.* The unit of observation for the present research is side-game-season. There were a total of 34,105 NBA games played during the sample period. Out of the 34,105 games, there were approximately 0.01% (254) of the observations that point spreads either could not be found or were not offered. As a result, the sample contains data from 33,851 games. Bettors can place a bet on one of two "sides" in each game: the home team to win by more than the point spread, or the home team to win by less than the point spread or lose. Table 1 presents the summary statistics for these sides.

[1]We are tremendously indebted to Richard Gandar and Andy Weinbach for their help in locating older NBA point spread data.

Both the mean home and away team winning percentages prior to playing the observed game was around 0.500. The home team won close to 62 percent of the games during the sample time period reflecting the strong home court advantage that has been repeatedly cited in the literature for the NBA (Smith et al., 2000). The average point spread was -3.787, meaning that the home team was just under a four point favorite to win the matches during the sample period. The home team covered just over 49% of the time and 2% of the sample games were a push, meaning that the score differential was equal to the point spread set by the bookmaker. There was about a 16.5% percent average of the absolute values of the difference in the percent filled to capacity variable.

Table 1: Summary Statistics, NBA Games 1981-1982 to 2011-2012

Variable	Mean	Std. Dev.	Min	Max
Home team win percent	0.497	0.188	0	1
Away team win percent	0.503	0.189	0	1
Home Team Win	0.617	0.486	0	1
Point Spread	-3.787	6.306	-25	49
Bet on Home Team Wins	0.487	0.500	0	1
Game outcome was a Push	0.022	0.147	0	1
Absolute difference in % Capacity Filled	16.467	14.769	0	82

Analysis of Point Spread Data

In order to determine how the popularity of NBA teams affects the point spreads set by bookmakers, the present research estimates the following reduced form model of the determination of point spreads by OLS:

$$PS_{hvik} = \beta_0 + \beta_1 Winpct_{hik} + \beta_2 Winpct_{vik} + \beta_3 Popular_{hvi(k-1)} + \theta_j + \alpha_{j,k} + \gamma_k + \epsilon_{hvik}. \quad (1)$$

In equation (1), h indexes NBA home teams, v indexes visiting NBA teams, i indexes games, and k indexes seasons. θ_j $(j = h, v)$ are team specific effects for home and visiting teams, γ_k is a season fixed effect, $\alpha_{j,k}$ $(j = h, v)$ is a team×season fixed effect for home teams and visiting teams, and ϵ_{hvit} is the equation error term. The regression model controls for unobservable heterogeneity in teams over the sample, seasons in the sample, and unobservable team-season heterogeneity. We assume that ϵ_{hvit} is a mean zero, constant variance, identically and independently distributed random variable. PS, the dependent variable in equation (1), is the point spread for game i played by home team h and visiting team v in season k. $Winpct_{hik}$ is home team h's win percent prior to game i in season k. $Winpct_{vik}$ is visiting team v's win percent prior to game i in season k.

Popular is the variable of interest since it proxies for the presence of bettors with sentiment bias in the market. It is equal to the difference in the average fraction of the seating capacity filled in each team's home arena in the previous season. For example, if the LA Lakers play the Denver Nuggets in LA and the Lakers averaged 90% of the capacity of their arena in the previous season and the Nuggets averaged 80% of the capacity of their arena, then $Popular = 10$ for that game. Recall that Forrest and Simmons (2008) used a similar variable, the difference in per game average attendance from the previous season in their study. The popularity and support for NBA teams can be reflected in both the size of the team's home arena and the number of fans who attend games. Popular teams will have both large home arenas and large numbers of tickets sold; unpopular teams will have both small arenas and low numbers of tickets sold. In addition, team popularity can vary in the short run even though arena capacity does not. So an unpopular team could have a large home arena and not sell many tickets. We use the average fraction of each team's home arena filled in the previous season as a measure of the popularity of each team, and the difference in this value as the relative difference in the popularity of each team. As this difference in the fraction of the team's home arena filled in the previous season increases, there will be more bettors with sentiment bias toward the team with the largest attendance relative to capacity in the betting market.

Table 2: OLS Regression Results, Equation (1)

Variable	Coefficient	Standard Error	p-value
Home team win percent	-5.670	0.148	< 0.001
Visiting team win percent	5.459	0.149	< 0.001
Difference in % capacity filled	-1.323	0.204	< 0.001
R^2	0.855		
N	32,664		

Table 2 presents the parameter estimates, estimated standard errors, p-values, and other summary statistics. Estimates of the various fixed effects parameters are available upon request from the authors. Equation 1 explains nearly 86 percent of the observed variation in point spreads in these games. The estimated parameter on the home team's winning percentage going into the game indicates that an increase in the home team's winning percentage decreases the point spread for the game, meaning that the home team becomes a bigger favorite or a smaller underdog. As expected, the stronger the visiting team, the less of a favorite the home team is, other things equal. The difference in the capacity of each team's arena filled in the previous season is negative and significant. Specifically, for every one percent increase in the difference in the percent filled to capacity, the spread favors the home team by an additional 0.4 points. This result means that the larger the difference in the percent filled to capacity, the more the spread moves in favor of the home team. Bookmakers appear to adjusting the point spread based upon the relative popularity teams in each game, where popularity is measured by how much each team filled their home arenas in the previous season. This result can be interpreted as evidence that bettors with sentiment bias are present in NBA betting markets.

Analysis of Bet Outcomes

The results in the previous section suggest that point spreads reflect both the relative strength of the teams in the match as well as the popularity, measured by the difference in percent filled to capacity of the arena compared to the visitors. To determine how this change in point spreads influences the likelihood of a bettor winning a bet placed on team i, the following probit model is estimated

$$Cover_{hvik} = f(Winpct_{hik}, Winpct_{vik}, Popular_{hvi(k-1)}) \tag{2}$$

where h indexes home teams, v indexes visiting teams, i indexes games, and k indexes seasons. The dependent variable is equal to one if a bet placed on home team h playing visiting team v won, or was a push in game j in season k.

Table 3 presents the results from the probit model and the corresponding marginal effects, which are generated using the "mfx compute" command in STATA 12. From Table 3, the strength of the home team, as measured by the home team's winning percentage before the game, has no relationship to the probability that a bet on the home team wins. The strength of the visiting team has a positive and statistically significant relationship to the probability that a bet on the home team wins. This result is consistent with the bookmaker offering favorable point spreads to bettors wagering on home teams when the opponent is stronger. Finally, the sentiment bias variable has a positive and statistically significant parameter estimate, meaning that an increase in the difference in the percent the team's home arena was filled to capacity between home team h and visiting team v last season increases the probability that a bet on the home team wins in game i in season k. However, the marginal effect of this variable shows that the effect is quite small – less than one percent. Thus, even though sentiment bias is present in the point spreads, reflecting the presence of bettors who want to bet on popular teams, this sentiment bias does not increase the probability of winning a bet by much.

Table 3: Probit Results (Marginal Effects), Equation (2)

Variable	Coefficient	Standard Error	p-value	Marginal Effect
Home team win percent	0.0026	0.0387	0.818	0.0010
Visiting team win percent	0.1472	0.0387	< 0.001	0.0587
Difference in % capacity filled	0.0011	0.0003	0.001	0.0005

Robustness Checks

One difficulty of identifying sentiment bias in betting markets is to find a good measure of a team's popularity. Like in previous research, our main empirical strategy is based on differences in attendance figures of the individual clubs or, more precisely, the difference in capacity filled. This kind of measure seems to be criticizable for two main reasons. First, the capacity filled might be just a local measure of the popularity of the team, i.e. it is strongly depending on the market potential of the surrounding region, while biased bettors might exist in a broader area or even national-wide. Second, the utilization of the arena can – to a given degree – be influenced more or less directly by the team. For example, reducing the ticket price or intensifying promotional activities might have an influence on attendance, which might not reflecting a team's popularity.

To check whether the previous findings are robust, an alternative measure of popularity should be used in this section. Based on the stated criteria of being a) not only a local measure but also b) not under control of the team, data from social media (e.g., Facebook "likes" or Twitter followers) seems to be an obvious measure of team popularity. Since social media did not exist for most of the sample period and social media figures are not available for the past, we collected data from NBA all star voting. In most seasons, the NBA organizes an All Star game of the best players from the Eastern and Western Conference.[2] To determine the starting team for each conference, fans can vote for the most popular

[2] Only in the 1998-99 season, the All Star game was canceled since the season did not start until February 5, 1999, due to a lockout.

players for each position for each conference: Two guards, two forwards, and one center. Our hypothesis is that the share of a team's all star votes compared to the total number of all star votes cast by fans is reflecting the team's popularity, even if the fan votes are strictly speaking only an expression of player popularity. Nonetheless, this seems to be an appropriate measure considering data availability and assuming that team popularity is a function of the individual popularity of the team's players.

Since the complete list of all star votes for all players is not available, all star votes for the top 25 players (ten guards, ten forwards, five centers) from each conference were collected from the *Basketball Reference* website.[3] In total, voting data is available for 1,419 player–season observations throughout our observation period. If one of these players was traded within the actual season (56 out of the 1,419 cases), his votes have been included with the team he completed the most of the season's games. Further, the absolute number of available all star votes has been summed up for every season to be able to calculate a team's share of all star votes for a given season. Consequently, in the context of this robustness check, the variable *Popular* is defined as the difference in the share of the all star votes for each of the two competing teams. Since the voting is available mid-season just in front of the all star game, all matches following the all star game are augmented by the respective team shares of all star votes until the next all star game.[4]

Table 4: OLS Regression Results, Equation (1)

Variable	Coefficient	Standard Error	p-value
Home team win percent	-5.729	0.147	< 0.001
Visiting team win percent	5.481	0.177	< 0.001
Difference in All Star votes	-0.215	0.007	0.003
R^2	0.857		
N	33,378		

[3]From 1981-82 until 1984-85 season, voting data is only available for the top 15 players (five guards, five forwards, five centers).

[4]Consequently, the team shares based on the All Star voting for the 1997-98 season have been used until the all star game of the 1999-2000 season, since the 1998-99 All Star game was canceled.

Table 4 presents the estimated parameters, corresponding standard errors, and p-values, while – again – the fixed effects are available upon request. Using the team all star votes as a proxy for the popularity of the teams instead of the capacity filled, reveals almost the same results. First, the explanatory power of the model remains high at around 86 percent. Other things equal, the stronger the home team, the bigger a favorite or the smaller an underdog the home team is. Accordingly, the stronger the away team – measured by the team's winning percentage going into the game –, the smaller a favorite or the bigger an underdog the home team is. Moreover, these parameters show very similar values than shown in Table 2. Our alternative measure of relative popularity, the difference in the team's share of all star votes, displays a highly significant and negative coefficient. This means that the larger the difference in the shares of all star votes between the teams, the more the spread is in favor of the home team. This result supports the findings from the previous section in the way that it can be stated that bookmakers appear to adjusting the point spread based upon the relative popularity of the participating teams in the observed game.

Again, we examine how this change in point spreads influences the likelihood of a bettor winning a bet placed on team i by means of the probit model displayed in equation (2). The results and the corresponding marginal effects are presented in Table 5.

Table 5: Probit Results (Marginal Effects), Equation (2)

Variable	Coefficient	Standard Error	p-value	Marginal Effect
Home team win percent	-0.0041	0.0390	0.915	-0.0017
Visiting team win percent	0.1395	0.0389	< 0.001	0.0556
Difference in All Star votes	0.0023	0.0015	0.124	0.0009

Similar to the results presented in Table 3, the strength of the home team has no relationship to the probability that a bet on the home team wins, while the strength of the visiting team shows a significantly positive relationship to the probability that a bet on the home team wins. Again, this result confirms that bookmakers offering favorable point spreads to bettors wagering on home teams when the visiting team is stronger. However, the sentiment bias variable appears to be statistically insignificant meaning that the difference in the team's share of the all star votes from the last election, which should cover the difference in the popularity and not in the abilities of the two teams, have no influence on the probability of winning a bet on the home team.

Discussion

The results indicate that sentiment bias exists in NBA betting markets. The popularity of a team, as captured by both differences in average attendance relative to arena capacity at games in the previous season and the differences in the team's share of all star votes based on the last voting, affects both the price of the asset in this financial market and the return on this asset in a way that bookmakers offer more favorable point spreads on popular home teams, making these teams bigger favorites. However, this favorable price does not translate into greater returns on bets on the more popular team. At the 90th percentile of the popularity variable, the home team averaged 26% more of its home arena capacity filled compared to the visiting team. Based on the marginal effect reported on Table 3, this is only associated with a 0.1% increase in the probability that a bet on a more popular home team wins; this would be unlikely to generate excess returns to bettors following a strategy of betting on only popular teams.

The results of betting simulations confirm the result of the inability to generate excess returns. Betting on the home team when the difference in percent of arena capacity filled (difference in team's all star voting shares) was in the top 75% of the distribution of this variable provided 4,630 (4,299) wagering opportunities in this sample. A strategy of betting on the home team in these games resulted in only 51.42% (50.80%) of these bets winning; this would not be a profitable betting strategy under the standard "risk 11 to win 10" Las Vegas style point spread betting rules (Sauer, 1998). Betting on the home team when the difference in percent of capacity filled was in the top 95% of the distribution of this variable provided

1,235 (830) wagering opportunities. A strategy of betting on the home team in these games resulted in only 51.85% (51.23%) of these bets winning. Even though bookmakers offered more favorable point spreads to bettors wagering on more popular teams, this had no affect on the return on the bets. Forrest and Simmons (2008) reported identical results for betting on football matches in La Liga.

Clearly, the reason bookmakers offer more favorable point spreads to bettors wagering on popular teams must be to increase profits. Offering more favorable point spreads on popular teams may induce more fans of these teams to bet on the game, and generate imbalanced betting on some popular teams. Paul and Weinbach (2008) showed that unbalanced betting existed on NBA games, and Humphreys (2010) showed that unbalanced betting on NFL games lead to higher bookmaker profits than balanced betting on either side of games.

Since the probit results show that this point spread shading cannot be exploited as a profitable betting strategy, an increased volume of bets on these popular teams would increase the commission earned by the bookmaker in the long run. Why would bettors continue to bet on their team, even when this approach does not yield above average returns? The utility of gambling model developed by Conlisk (1993) provides one explanation. If bettors derive utility from betting on their team, then they would continue to place bets no matter what the financial return on those wagers. Sometimes the opposite behavior, where bettors with a strong affiliation to a given team bet against that team, a form of "emotional hedging" has been observed in experimental settings (Bosman et al., 2005). In this context, bettors wagering against their favorite team to win offset the immediate loss in utility with financial gains from bets on the opposing team. Since our results contain evidence of bettors with sentiment bias in this market, these bettors with sentiment bias may be present in larger numbers than bettors undertaking emotional hedging.

IV CONCLUSIONS

Previous research found evidence of bettors with sentiment bias in sports betting markets. We develop new evidence suggesting that the popularity of certain NBA teams, as reflected by both the fraction of the seats in each team's home arena filled on average, and the team's share of all star votes, influenced the point spreads set by bookmakers over the period 1981-2012. Our results support the idea that bookmakers adjust the point spread based on the difference in popularity of NBA teams. However, these changes in point spreads cannot be exploited by bettors to earn excess profits in the market. Our findings confirm previous evidence of sentiment bias that has been found in other settings, including betting on NFL games and European football matches.

The presence of sentiment bias in these simple financial markets has broader implications for other financial markets. The recent financial problems experienced by economies around the world raise important questions about the operation of financial markets, and their propensity to undergo upheavals. Sentiment bias represents a market inefficiency, as it reflects factors affecting the price of financial assets not related to fundamentals like expected future revenues generated by the financial asset. The results here suggest that sentiment bias exists, but is not large enough to generate opportunities for excess profits for investors. These sports betting markets contain inefficiencies generated by sentiment bias, but they are not too large, suggesting that asset prices in this market do not drift too far from their fundamental values. If these results generalize to other financial markets, then sentiment bias is unlikely to lead to bubbles in other asset prices that could generate turmoil in financial markets.

Future research on sentiment bias in professional sports, both in the United States and in Europe, could include alternative measures of team popularity. With the popularity of social media around the world, provides opportunities for researchers to study phenomena that was unavailable in the past (Edelman, 2012). Future research examining sentiment bias could measure team's popularity in terms of Facebook "likes" or Twitter followers. These measures might better examine the reach of the team's sport brand around the world, not confining to the local residents who consume the live sporting event. Since these measures cannot be influenced by team actions, such as the reduction in ticket price to encourage people to attend games or other promotional event to encourage attendance, social media can potentially provide a more accurate measure of a team's popularity. In addition, the use of social media measures for proxies of investor sentiment presents an opportunity for researchers to more accurately measure investor sentiment and its effects in the market.

Finally, the presence that sentiment bias exists but cannot be exploited to earn excess profits by bettors raises interesting questions about the operation of bookmakers. If bettors cannot exploit the changes in point spreads set by bookmakers, then bookmakers may be earning higher profits by "shading" the point spread to favor popular teams. Although the probability of a bet placed on a team that benefits from sentiment bias is not more likely to win, sentiment bias could also affect bet volumes. If the point spread shading done by bookmakers leads to increased betting on games involving popular teams, then bookmakers could earn higher profits, even if the change in the point spread is small. Additional research should focus on betting volume, and not simply point spreads or betting odds, to better understand the effect of sentiment bias in this market.

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