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Igan, Deniz and Pinheiro, Marcelo and Smith, John

International Monetary Fund, Research Department, Economic Consulting Services, LLC, Rutgers University-Camden, Department of Economics

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Racial Biases and Market Outcomes: "White Men Can't Jump," But Would You Bet On It?*

Deniz Igan† Marcelo Pinheiro‡ John Smith§

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Abstract

We identify a largely efficient market in which racial biases affect market outcomes. Examining data on NBA games, we show that teams with more black players tend to face larger point spreads and that these teams perform worse against the spread. These biased outcomes are significantly large and persistent so that we are able to identify profit opportunities. We also find evidence that the biased spread is set by the bookmakers rather than being moved as a result of excessive betting on the more black team. We examine several alternate explanations, and the racial bias remains significant in each of these specifications. This suggests that racial biases can persist even though they are financially disadvantageous, recognizable and correctable.

Keywords: Market efficiency, Racial biases, Belief-based discrimination

JEL Classification: D03, G00

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†Corresponding author: International Monetary Fund, Research Department, 700 19th St, NW, Washington, DC 20431. Phone: 202-623-4743. Fax: 202-623-4740. E-mail: digan@imf.org.

‡Economic Consulting Services, LLC; Email: marcelo@alumni.princeton.edu.

§Rutgers University-Camden, Department of Economics; Email: smithj@camden.rutgers.edu.

"Billy, listen to me, white men can't jump."

Sydney Deane

1 Introduction

Biases shaped by psychological dispositions and social norms or interactions are commonly recognized as important determinants of economic decision making and market outcomes. Becker (1957) and Arrow (1972) provide models depicting such biases in the context of discrimination while Akerlof (1980) and Romer (1984) study the persistence of customs. Most of the evidence on the effects of biases, comes from studies aiming to detect discrimination in labor markets (e.g., Bertrand and Mullainathan, 2004), in access to services (e.g., Page, 1995), and in access to resources, most notably credit (e.g., Munnell, Tootell, Browne, and McEneaney, 1996; Pope and Sydnor, 2011). But the study of biases go beyond discrimination: a related literature documents systematic deviations from standard assumptions underlying economic behavior and links them to psychological and social factors.[1] Challenges remain in both strands of the literature: documenting whether discrimination exists rather than the observed differences stemming from unobserved heterogeneity, distinguishing information-based discrimination (Phelps, 1972) from taste-based discrimination, and understanding whether and how behavioral biases carry over from laboratory experiments to real markets as well as whether and how they persist instead of market forces eliminating such biases.

This paper offers new insights into these challenges by studying the effects of psychologically-based, socially-reinforced beliefs in a financial market setting. In particular, we examine the relationship between National Basketball Association (NBA) betting outcomes and the race of the participants, in order to uncover how biases can affect market outcomes. This is an ideal setting to expand our knowledge on the economics of biases for several reasons.

First, the NBA betting markets provide advantages that other settings, including other financial market settings, cannot. Specifically, bettors pay for their biases à la Becker. Hence, decisions based on biases are punished with direct pecuniary losses. This is in contrast to

[1] See Camerer, Loewenstein, and Rabin (2004) and DellaVigna (2009) for a review.

studies of the impact of biases in psychology and sociology literatures, where most evidence relies on experiments or surveys with no immediate, explicit, pecuniary gains or losses for the participants. In addition, unlike most financial markets, the sports betting markets contain well-defined prices, well-defined outcomes, readily accessible information, and a finite time horizon. Therefore, the usual caveats associated with measurement problems (e.g., defining the horizon over which returns should be measured) and asymmetric information do not apply. Moreover, the actions and outcomes are repeated with a significant degree of frequency, providing an opportunity to test whether the bias persists or disappears as market participants strive to learn about biases and compete to grasp arbitrage opportunities.

Second, the bias in the market we study is easily recognized since some of the most deeply held ideas about race and racial difference are expressed in one of the most well-known stereotypes: the natural black athlete, and especially, the black basketball star.[2] The common stereotype of the black basketball player is so evident that the term "the black game" was coined to refer to the sport (George, 1999). What makes it so difficult to counter the argument that blacks have an innate ability to play basketball is that there appears to be evidence to support it: roughly 70% of NBA players are black. For economists, an interesting question is then whether such a stereotype affects economic decision making and market outcomes, thus challenging the rationality tenet in its standard form.

Hence, in our setting, market outcomes are objective, common knowledge, determined within a finite time, repeated regularly, and there exists a widely-familiar, biased view of the participants. Our data consists of the outcomes of NBA games and the Las Vegas point spreads on these games, from the 1993-94 season through the 2007-08 season.[3] Betting on NBA basketball generally involves a point spread wager, where the bet wins based on the relationship between the final score and the point spread. The team *covers* the spread if a bet on the team pays. To illustrate, if the spread is +3.5 for the home team, an $11 bet on

[2] For instance, see Biernat and Manis (1994) and Sailes (1996).

[3] Note that the *Professional and Amateur Sports Protection Act of 1992 (PASPA)* imposes a federal ban on sports betting in all states with the exception of Delaware, Nevada, Montana, and Oregon. These four states already had sports betting laws on their books when the Congress passed PASPA and were permitted to offer parlay-type sports betting. Nevada, however, is the only state that allows all types of sports betting, on any professional or amateur sports games, in any capacity.

the home team would pay $21 if either the home team won the game or lost by 3 points or less. An $11 bet on the visiting team would pay $21 only if the visiting team won by 4 points or more. In this setting, the point spread is a market-based estimate of the realized margin (the final score of the home team minus the final score of the visiting team).[4]

Our analysis examines whether there is evidence that biases, embodied as stereotypes about a certain group of participants, have an impact on financial decisions by examining how the point spread and the performance against the spread in NBA betting markets varies with the racial composition of the teams.

We ask whether there is a bias on betting on teams that are "more black." If so, this bias would manifest itself such that the spread on the more black team would be higher than it should be, leading to a negative relationship between the fraction of black players and the performance against the spread. Further, if we make an auxiliary assumption that bettors are expected value maximizers, then such a bias would imply that, on average, bettors have (possibly subconscious) beliefs that "more black" teams are better than "less black" teams.

We find that the point spreads are higher for teams with a relatively higher fraction of black players. We also find that the probability of beating the spread decreases as the fraction of black players increases. Our results are robust to alternate measures of the racial composition of the team: the number of black players starting the game, the number of black players on the roster, and the minutes played by black players in recent games. Additionally, if we make the auxiliary assumption that bettors are expected value maximizers, then we can conclude that, all things equal, "more black" teams look better than "less black" teams. We refer to this as a *monetary bias*. However, without the auxiliary assumption, we cannot rule out the possibility of a non-monetary bias towards betting on more black teams. For instance, bettors could have a bias for betting on "popular" or "exciting" teams, or teams with "cool" or "style" or "it" and these are simply related to race. We refer to this as a *non-monetary bias*, since the bettors are not necessarily betting on the team that they deem more likely to win the bet.

[4] In terms of the timing of bets placed, the betting typically opens less than 24 hours before the start of the game and, needless to say, closes when the game begins.

There are two hypotheses for the cause of the relationship between race and the point spread. It could be that biased bettors place more money on the more black team, thus causing the spread to move from an unbiased spread to a biased spread.[5] Or it could be the case that the bookmakers are aware of the bias of bettors, and set the spread in order to extract more surplus. Why would bookmakers set a biased spread? Levitt (2004) shows that bookmakers can increase their earnings if bettors have a bias. This is because the bookmakers can set the point spread in a manner such that more than half of the money is bet on the outcome that wins less than half of the time. In order to distinguish between these hypotheses, we use a second data set containing the opening and closing point spreads, for the 2003-04 season through the 2009-10 season.

Our results show that the movement of the spread is not related to the racial composition of the teams in a robust manner. Hence, it appears to be the case that the bookmakers know of the bias towards more black teams and consider this when they set the spread. This is further supported by evidence that a larger fraction of money is bet on the more black team.

To gain intuition for our results, we offer the following discussion. Here we make the auxiliary assumption that bettors are expected value maximizers. In other words, they exhibit a monetary but not a non-monetary bias.[6] Consider two teams that are exactly as good as each other. Consequently both teams will win with a probability of 0.5. However, one team is "more black" than the other. Therefore, some people will have a, possibly subconscious, belief that the black team is better and deem their probability of winning to be greater than 0.5, despite that the "truth" is 0.5. To exploit this bias, rather than setting the spread as a pick-em (spread of 0), the bookmaker sets the spread in favor of the black team at a value different from 0. This means that (all things equal) the black team will cover the spread with a probability less than 0.5, making this a worse bet. This reasoning still holds

[5] Gandar et al. (1998) find that bettors move the initial point spread in a manner that improves the spread as a prediction of the outcome of the game.

[6] Here we make this assumption because, in our view, it makes the intuition easier to grasp. If, on the other hand, bettors do not have a non-monetary bias, the same sorts of arguments apply, except that the discussion is framed, not in terms of judgments of better or worse at basketball, but rather in terms of the nature of the non-monetary bias. It is for this reason that the assumption of expected value maximization renders this discussion more transparent.

when the teams are not as good as each other. In this case, there is a “true spread” where both teams will cover with probability 0.5. But the bookmakers do not set the spread at the true spread but rather the true spread adjusted by a few points for the black team. Again, the black team covers with probability less than 0.5.

Let us return to the case where both teams are equally good, so the expected final margin is zero. Further, let us assume that the spread at which an even amount of money would be placed both sides of the bet would be -3 for the more black team. In this case, since half of the money is on either side of the bet, the bookmakers' expected payoff is determined exclusively by the betting cost: for every $11 bet, the winner gets $21, that is, a return of $10 and not $11. Similarly if the spread is set at 0, the bookmakers' expected payoff is again determined exclusively by the betting cost.[7] The profit-maximizing spread is somewhere between 0 and -3. So, the bookmakers set the spread at, say, -2 and more money is bet on the black team because the median bettor thinks that the spread should be -3. Since more than half of the money is bet on the outcome that occurs less than half the time, the bookmakers earn extra profits.

We consider various non-racial bias alternate explanations for our results, however the racial bias remains significant in each specification. Our results imply that biases can indeed influence behavior in financial settings. Hence, we contribute to the literature by providing evidence that economic decision making is altered by conscious or subconscious categorization based on observable characteristics, e.g., race and gender. Additionally, the association between the point spread ("the price") and the racial composition of the teams (a variable that is not systematically related to the winning ability of a team and is observable prior to the bets being placed) creates profitable opportunities that involve betting on the "whiter" team.[8] In other words, the bias is sufficiently large and persistent that we are able to identify a means of profiting from the biased market outcomes.

[7] For more on this, see Levitt (2004).

[8] Perhaps with slight abuse of the term, we use "white" to refer to all non-black players.

2 Background

Our paper relates to several strands of literature. The first of these strands examines biases and their impact on economic outcomes. A large number of studies look at discrimination, where outcomes are affected by characteristics such as gender and race. Because of the inefficiencies discrimination can create and the potential policy implications, it is of great interest to identify settings in which biases exist and, once they are identified, to specify the mechanism that is causing the bias.[9] Often, it is very difficult to find unambiguous evidence of biased outcomes, mostly due to the omitted variables problem. That is, ruling out the possibility that the observed variation may be a consequence of unobserved heterogeneity, which is also correlated with the object of study (in many cases, gender or race), is a difficult task.[10] In response to this problem, some researchers have used audit studies whereby the investigators send identical treatments into the field, with the exception that they differ on the basis of, say, race. Then the researchers seek to observe differences in behavior that could only have been driven by race. For instance, in their influential study, Bertrand and Mullainathan (2004) sent otherwise identical resumes to potential employers, where some applicants had "white" names and some had "black" names. The authors found that applicants with black names were less likely to receive a callback for an interview than were the applicants with white names.

Audit studies, such as this one, have proven to be useful in identifying bias.[11] There are however, some drawbacks.[12] First, it is argued (Heckman, 1998) that these studies overstate the effect of discrimination because they do not account for the effects of unbiased people on the market outcomes. In other words, these audit studies can identify that some behave in a biased fashion, however it is possible that the unbiased people can behave in a way that

[9] For more on discrimination literature, see, among others, Altonji and Blank (1999), Ross and Yinger (2002), and Charles and Guryan (2008).

[10] There is a literature that examines whether there is racial discrimination in the salaries of professional basketball players. For instance, see Kahn and Sherer (1988), Hoang and Rascher (1999), Hill (2004), Kahn and Shah (2005), Groothuis and Hill (2011), and Ajilore (2014). Of course, it is difficult to measure individual productivity in a team setting and therefore the results in this literature are not uncontroversial. However, our paper does not suffer from the same difficulty as a team either covers the bet or it does not.

[11] See Ayers and Siegelman (1995) for another example of this type of technique.

[12] For more on the difficulties with audit studies, see Yinger (1998).

mitigates the effects of the behavior of the biased people. Our paper is not vulnerable to this criticism because the object of our study is not individual behavior but rather market outcomes and we find that the market outcomes are biased. Second, to our knowledge, audit studies are not repeated whereby the decision maker can learn about the unobserved heterogeneity of the subject. Again, we are not vulnerable to this objection because we have a considerable number of observations for the same players and teams, whereby the effects of the unobserved heterogeneity could be learned. We find that the market is systematically biased though there are learning opportunities and there are pecuniary costs to behaving in this biased fashion.

Of particular relevance to our paper, Stone, Perry and Darley (1997) directed subjects to listen to an audio clip of a basketball game after viewing a picture of the player whom they were instructed to judge. The subjects who were shown a picture of a black player rated the performance as better than those subjects who were shown a picture of a white player.[13] While existing experiments are suggestive of biases in judgments involving race and athletic performance, since the accuracy of these judgments are not related to the material incentives of the subjects, it can be difficult to interpret these results. However, our study is not vulnerable to this critique because obviously betting on the outcome of a basketball game is indeed related to a person's material incentives. On the other hand, this literature is consistent with the monetary bias explanation for our results, in that it provides laboratory evidence of a racial bias in the assessment of talent and performance in basketball.

Our paper also relates to the literature documenting and explaining market anomalies in finance. Closely related to our premise of studying the impact of perception in a financial market setting, Hong and Kacperczyk (2009) and Hong and Kostovetsky (2012) look at case of the "sin stocks" and political values in investment decisions. Wolfers (2006a) examines the stock market returns of companies with female CEOs.

Sports betting markets, in particular, provide an attractive ground for testing market efficiency because, unlike most financial markets, the sports betting markets contain well-defined prices, well-defined outcomes and a finite time horizon. In particular, sports betting mar-

[13] Also see, Stone, Lynch, Sjomeling, and Darley (1999).

kets have outcomes that are realized within a short time frame, are observable by all market participants, and are unambiguous (no measurement error or uncertainty about the horizon over which outcomes should be measured). Finally, due to the widespread availability of information, these markets are unlikely to have uninformed traders. Therefore, the questions related to the efficiency of the sports betting markets are of interest to economists in testing market efficiency hypotheses.

Echoing findings in other financial markets, several studies have found inefficiencies in the sports betting markets.[14] For instance, studies have found evidence consistent with the explanation that bettors erroneously place bets for sentimental reasons (Avery and Chevalier, 1999; Braun and Kvasnicka, 2013; Forrest and Simmons, 2008), on teams that are deemed "hot" (Brown and Sauer, 1993; Camerer, 1989), on teams that are "popular" (Feddersen, Humphreys, and Soebbing, 2013), and on teams that are favorites (Golec and Tamarkin, 1991; Grey and Grey, 1997). Levitt (2004) finds, using data on the wagers placed by bettors as part of a handicapping contest offered at an online sports book, that the amount of money placed on each side of the bet is not equal and this imbalance is related to observable information. In particular, Levitt finds that the proportion of money bet is higher for favorites and road teams. The author argues that the bookmakers set the spread in order to exploit common biases: people like favorites and people do not sufficiently account for the home field advantage.[15]

Others have also looked at the effect of race on outcomes in sports. Again, this literature is significant beyond the sports context because it involves decisions that exhibit large incentives for success or accuracy, and the outcomes can be objectively measured. Price and Wolfers (2010) find a negative relationship between the personal fouls assessed against NBA players and the number of own-race referees who officiated the game. Similarly, Parsons, Sulaeman, Yates, and Hamermesh (2011) find that the likelihood of a called strike in baseball is related to the agreement of the pitcher's and umpire's race. Although these judgments are made by well-trained and experienced professionals, they are also made under great duress and

[14] See Barberis and Thaler (2002) for a general overview and Sauer (1998) for applications in sports betting.

[15] Paul and Weinbach (2011) corroborate this finding using the percentage of bets actually placed on NFL games. Our analysis shows that the bets on NBA games are also distorted by racial stereotypes. Also see Kuypers (2000). Snowberg and Wolfers (2010) discuss the evidence that, in the odds betting of horse racing, bettors have a bias towards betting on longshots rather than on favorites.

must be made almost instantaneously. Therefore, it is possible that these biases, while of great significance, would be attenuated if they were made under different circumstances. By contrast, the decisions that comprise our data are made by individuals who have the opportunity to reflect on the merits of their decisions. Hence, our findings imply that racial stereotypes may affect decisions, even when they are made under an extended period of deliberation.

Finally, Larsen, Price, and Wolfers (2008) find that the relationship between race and fouls documented in Price and Wolfers (2010) is significant enough so that, given information about the race of the referees and the relative racial composition of the teams, one could improve their chances of placing a winning bet against the spread. By contrast, we focus primarily on the racial composition of the teams. Hence, the bias we examine emerges from a more simple bias for betting on the more black team, rather than the less visible notion that the referees exhibit an own-race bias. Finally, as does Larsen, Price, and Wolfers (2008), we offer an analysis of a simple betting strategy. The simple betting strategy proposed by Larsen, Price, and Wolfers (2008) involves the interaction of the differences in the race of the teams and the referees, and in our case it is exclusively a function of the racial composition of the teams. Hence, arguably, our strategy requires less information and is less computationally-intensive than theirs. Our betting strategies prove to be at least as profitable, and often more so, than the ones analyzed in Larsen, Price, and Wolfers (2008). We view our work as offering a complementary investigation into the relationship between race and market outcomes.

3 Data

Our baseline dataset combines box score information on all regular season NBA games played from the 1993-94 season to the 2007-08 season. We exclude the playoff games since the outcomes for these games tend to be path-dependent, not only across games in the same series but also across rounds, thus accentuating the survivorship bias in that the number of player or team observations would depend on their past performance. The box score information is obtained at the player-game level from www.basketball-reference.com, which also keeps track of draft picks and other background information of the players, such as the height and weight. The ultimate team-game level dataset is constructed from these player-by-player observations.

One crucial variable for our analysis that is missing from the www.basketball-reference.com website is the race of the players. In some cases (mostly for players who are still active), a picture of the player accompanies the statistics but this happens only at a small fraction of the overall player universe during our sample period. Hence, we conduct an extensive search to obtain information on the race of the players, navigating www.nba.com, www.hoopedia.nba.com, www.draftreview.com, and images found via Google. This information enables us, by visual inspection, to characterize the racial membership of the players. Admittedly, we use a rather coarse definition of race by assigning players into two broad categories of black and white, where white includes Caucasians, Asians, and Latinos. Yet, in order to ensure robustness of the results, we use several measures of the racial composition of the team. Further, we also double-check our classification of the racial membership of the players against that used in Price and Wolfers (2010). The discrepancy between the racial classification exists for a mere 31 out of 1128 matched players. This difference corresponds to only 2.5 percent of the more than a quarter of a million player-game observations used in our dataset.

The data for the point spreads are obtained from www.goldsheet.com. We verify the accuracy of the spreads from this source against other sources commonly-used in the academic studies of sports betting, such as www.covers.com, and find no significant discrepancies. In fact, information on the ultimate outcomes of the games tends to be more accurate in www.goldsheet.com than it is in www.covers.com. Of the 41 cases when a discrepancy between the two sources exists, the cross-check with www.espn.com confirms that the former has the correct information 80 percent of the time. In the absence of an obvious third source to check the point spreads against, we ultimately use the two data sources as cross-checks against each other in constructing our final dataset and eliminate the observations in which a discrepancy exists.

A total of 18,450 regular-season games were played during the sample period. After excluding games for which there is a missing box score or racial composition data, we are left with 17,178 games. Further, after excluding games for which there was either no betting information or contradictory betting information, or where the betting outcome was a push, leading to cancellation of all bets (which occurs approximately 1.3 percent of the time), we are left with 14,785 games in the sample. Before we move to the formal analysis, we present some descriptive statistics of this final dataset.

Of the 1021 players who were active in the NBA during our sample period, 71.8 percent are black. Black players are even more over-represented in the starting line-up of the teams: on average, only one out of five starters is white. In a typical game, each team utilizes 9 to 11 players, 8 of which are, on average, black. As a result, at the player-game level, 76.7 percent of the minutes are played by black players. These statistics confirm the casual observation of the dominance of black players in the NBA, not only by sheer number but also by the visibility they obtain by playing more minutes.

At the player-game level, some differences between black and white players are statistically significant. However, it is not always the case that black players have "more desirable qualities" and the magnitudes of these differences are not *economically* meaningful. For instance, while, on average, black players score roughly two points more than their white counterparts, they are not as efficient, as demonstrated by their slightly lower field goal percentages. According to these metrics, black players overall do not appear to be much better than their white peers. If the quality of the team is related to the individual quality of the players, there seems to be no statistical reason to deem more black teams to be better.[16]

We summarize the information on betting spreads and the racial composition at the team-game level (on which we conduct the primary analysis) in Table 1. Racial composition is measured by three alternative metrics: the number of black starters, the number of black players on the team roster regardless of whether they actually play in a game, and the minutes played by black players. This final metric is calculated as the average of the past five games the team has played and is expressed as a percentage of the total minutes in the game. To avoid duplication, all variables are expressed from the home team's perspective. Simple statistics point to a slight advantage for the home team as they win the game 60 percent of the time, by an average margin of approximately 4 points. Point spreads appear to take this

[16] A summary of this analysis is available from the corresponding author upon request.

into account, at least partially, because the home team is the favorite about 70 percent of the time and beats the spread 51 percent of the time.[17]

We complement this information on the closing spreads with information on the opening spreads and the percent of bets placed on each side of the bet from the 2003-04 season through the 2009-10 season. These data were obtained, at a fee, at www.sportsbetting.com. This website compiles information from Las Vegas and online sports books, and reports the opening and closing lines and percent of money wagered on home versus the visiting team. The reported figures are the median for the opening and closing lines while the percent of money wagered is computed by summing the individual book numbers. From this data set we have 7977 observations of opening lines and 8011 observations of the fraction of money bet on the teams.

4 Analysis

4.1 Accuracy of point spreads and the link between race and winning probability

Our empirical approach rests on a baseline specification where the probability that the home team beats the spread is a function of the racial composition of the team relative to its opponent. This relies on two assumptions and, before moving on to the main analysis, we confirm that these assumptions hold.

The first assumption is that basketball betting markets are, in general, efficient, in that any observable information should be reflected in the spread. So, we begin our analysis by looking at the accuracy of point spreads in forecasting the game outcome. We find that the "forecast errors," defined as the realized margin minus the point spread[18] closely resemble a normal distribution with zero mean.[19]

[17]Note that the *partial* offset of the home court advantage is in line with earlier studies showing a similar bias in NFL betting markets (Levitt, 2004).

[18]See Wolfers (2006b) who examines the distribution of errors in college basketball games and finds evidence of point shaving in games with a large point spread.

[19]Kolmogorov-Smirnov equality-of-distributions test as well as skewness and kurtosis test for normality

The second assumption is that the probability of winning a game does not increase in the relative blackness of the teams. Table 2 presents the results of a regression analysis where the more black team in a match-up is shown not to have a systematically higher probability of winning a game. The sign on the variables of interest, i.e., blackness of the home team relative to the visiting team, varies from one specification to the next and is not always significant and positive when the dependent variable is the realized margin on the game (upper panel in Table 2). Therefore, there is little evidence of a positive association between the blackness of the teams and the decisiveness of the final scores. A quick glance at the table would suggest a somewhat robust *negative* relationship between the blackness of the teams and the probability of winning (lower panel in Table 2).[20] It should be noted that this is not necessarily a sign of lower quality or generally worse performance of teams composed of more black players against teams with more white players. Rather, in these specifications, the relative blackness of a team may be capturing the effect of other factors that determine the performance of one team against another. Indeed, once factors such as the record of the team up to a specific game in a season is controlled for, the magnitude and significance of this coefficient is weakened.[21] In summary, our assumption that the probability of winning a game does not *increase* with the differences in racial composition towards blackness has support in the data.

The verification of these two assumptions are important since it confirms that the NBA betting markets incorporate all observable and unobservable factors that help predict the outcome of a game and that the blackness of a team does not increase its chances of winning. Hence, concerns that the blackness may be related to unobserved skill levels that determine the outcome of a game do not appear to find support in the data. With these two assumptions verified, we now proceed to the regression analysis of point spreads.

further verify that forecast errors are normally distributed. Results of these tests are available from the authors upon request.

[20]Notice that the team with more black starters is likely to have a larger realized margin but a lower probability of winning. While this seems a bit curious, it is consistent with a few outliers where the team with more black starters had a blowout when they won. Also note that the association between the differences in the blackness of the teams and the realized margin of the game is not robust as the positive significant coefficient disappears when alternative measures of blackness are used.

[21]These results are not presented here, but are available from the corresponding author upon request.

4.2 Race and point spreads

Table 3 presents our main findings. Our analysis shows that teams that are more black tend to face higher point spreads and that these teams exhibit a worse performance against the spread. In each regression, team fixed effects and season fixed effects, as well as team-season interactions are employed.[22] Hence, neither the time-invarying team characteristics nor the team-invarying time effects are driving the results.[23]

In the upper panel, the dependent variable is the spread faced by the home team. According to our three measures of the racial differences between the teams, we see that there is a positive relationship between the spread and these measures. In the middle panel, the dependent variable is the realized margin of the home team minus the spread. Based on the three measures of the racial differences between the teams, we see that there is a negative relationship between the blackness of the team and the realized margin minus spread. In the lower panel, the dependent variable is a dummy that takes the value of 1 if the home team beats the spread and zero otherwise. Again, according to our three measures of the racial differences between the teams, we find a negative relationship between the blackness of the team and the probability that they cover the spread.

To summarize, we find evidence that teams that are more black tend to face a larger point spread and that these teams perform worse against the spread. The evidence so far supports part of the conjecture we introduced at the beginning: point spreads, even as they control for all relevant and available information about the two teams, are disproportionately higher for more black teams. This suggests a bias towards betting on more black teams. With an auxiliary assumption that bettors are expected value maximizers, we can infer that bettors think that more black teams are better.

[22] We have also conducted the analysis without the team-season interactions. Our results are robust to this specification and are available from the corresponding authors upon request.

[23] The results presented in the tables are estimated using probit when the dependent variable is a binary variable, e.g., the probability of beating the spread. To ensure that the results do not suffer from the incidental parameters problem, we also estimate these specifications using ordinary least squares. The sign and significance of the coefficients of interest are indeed robust to the choice of estimation method. The reported standard errors are robust to the usual sources of misspecification provided that the observations are independent, as likely to be the case in our setting. In any case, we also confirm the significance of the results allowing for intragroup correlation across teams and seasons.

4.3 Robustness checks and alternate explanations

How robust are our results? We perform several robustness checks where we investigate plausible alternate explanations. One concern is that our results no longer hold when we also account for the racial composition of the referee crew. For instance, Larsen, Price, and Wolfers (2008) find that the racial composition of the referee crew, together with the racial composition of the teams, is relevant and can affect the probability of a team winning the game and, hence, beating the spread. We perform a series of regressions with the dependent variable as the probability of beating the spread, however, we restrict attention to the following categories: an all-white crew, a crew with at least one black referee, a crew with at least one white referee, and an all-black crew. We also consider the case where the crew is neither all black nor all white. Finally, we add the proportion of white referees as an additional control variable in our baseline specification. Table 4a presents the results of these regressions. Even when accounting for the racial composition of the referee crew, our results remain significant in each case, with the exception of an all-black crew. However, note that an all-black crew is an extremely rare occurrence as it accounts for only 126 games out of 14,694 in our sample. Hence, in the majority of the games in our sample, it holds that the more black team is less likely to beat the spread.

Second, our results might not survive if performance criteria of the teams or the factors that may be affecting each team's performance against specific opponents are explicitly included in the specification. Here we include the difference in the records of the team and the difference in the recent performance of the teams. These variables could be regarded as a measure of popularity, since teams with better records and better recent performance are likely to be more popular. Additionally, there are possibly match-up issues when specific teams play each other. Therefore, we also include specifications that capture these possibilities. Another issue could be that bookmakers correct any systemic mistakes that might occur in setting the spread as the same two teams face each other again. Table 4b presents the results obtained when the difference in the records and recent performance (the number of games the team won out of the last five games played) of the teams are added to the specification. Table 4b also presents specifications that account for the margin of the previous match of the teams, the spread of the previous match, and match-specific fixed effects. Our finding that more black teams have a lower probability of beating the spread is robust to these specifications.

Whereas the previous analysis showed that differences in popularity (as measured by recent or overall success) and match-specific issues could not explain our results, there remain several other plausible alternate explanations for our results. Here we include specifications with two additional measures of the difference in popularity, a measure of the difference in star power, and the difference in the number of foreign players.[24] In particular, we measure the difference in popularity as the difference between the number of nationally televised games within the season and the difference in home attendance within the season. We measure the difference in star power as the difference in the number of players selected to the all-star team within the season. Finally, we include the difference in the number of players on the roster who are not U.S. citizens.[25] These specifications are shown in Table 4c. Our finding that the more black team has a lower probability of beating the spread is robust to these specifications.[26]

4.4 Biased bettors or biased bookmakers?

A natural question then is, what is driving the relationship between the racial composition of the teams and the performance against the spread? There are two main competing hypotheses. The first hypothesis is that the bookmakers are aware of the racial bias of bettors and they set the spread in order to exploit the bias à la Levitt (2004). The second hypothesis is that the bookmakers are unaware of the bias of the bettors and set the spread to be the expected final score of the game. In this case, the biased point spread is caused by

[24] See Eschker, Perez, and Siegler (2004), Yang and Lin (2012), and Hoffer and Freidel (2014) for papers that investigate whether foreign players, all things equal, earn less than non-foreign players.

[25] We define foreign players as those that are reported to be non-U.S. citizens in the source websites. Note that this designation may or may not correspond to the popular perception that the player is foreign. When a foreign-born player gets citizenship, he would be coded as non-foreign. On the other hand, a U.S.-born player may choose to change his nationality and play for another national team and he would be coded as foreign.

[26] We do not report additional regressions involving the race of the coaches and the racial composition of the location of the teams. Again, our results are robust to these specifications and are available from the corresponding author upon request.

bettors who systematically bet on the more black team, thus moving the spread. In order to distinguish between these hypotheses, we investigate whether there is a relationship between the movement of the spread and the racial composition of the teams. Before we proceed, we confirm that the movement of the spread is normally distributed with a mean of zero.[27]

Table 5a presents the results of our regressions involving the movement of the spread.[28] In our first specification, we do not account for team- and season-specific factors, or team-season interaction terms. There we find a significant relationship between race and the movement of the spread. However, for the three specifications in which we account for these fixed effects, we do not find a significant relationship between the race of the teams and movement of the spread. This evidence favors the explanation that the bookmakers, rather than the betting of the bettors, are responsible for the biased point spread.

Now we investigate the relationship between the fraction of money bet and the racial composition of the teams. As shown in Figure 1, there appears to be more money bet on the home team if it has more black players than the visiting team. To further explore this point, we conduct an econometric analysis to test this conjecture. We also account for other alternate explanations, such as whether there is a difference in the teams considered to be *hot*, whether there is a difference in the popularity of the teams, and whether there is a difference in the *star power* of the teams. Table 5b shows the results of this exercise.

There appears to be a positive, albeit statistically weak, relationship between the racial composition of the team and the fraction of money bet on the home team. In other words, the spread is set in a way that the resulting bets are skewed in favor of the more black team. Note that the well-known home court advantage is already embedded in the left-hand-side variable. Additionally, when we also account for other known biases, measured by recent performance,[29] nationally televised games, and all-star players, the racial bias remains significant.[30] Based

[27] This is available from the corresponding author upon request.

[28] In the remainder of the tables, for the sake of brevity, we only show the results involving the difference in black starters. The results are virtually identical when the other two metrics are used and are available from the authors upon request.

[29] We admit to being surprised at the significant, negative coefficient of the recent performance variable. One possibility is that bookmakers excessively adjust the spread of a team currently performing well, so that many bettors take the contrary position.

[30] In unreported regressions, we use other measures: winning record and average home attendance. The

on the regressions in Tables 5a and 5b, we favor the explanation that bookmakers are aware of the bias of bettors and set the spread to exploit this bias.

4.5 Profit opportunities

So far, we have presented evidence that there is a negative relationship between the relative blackness of a team and its probability of beating the spread. The question then is whether there are profitable strategies that consistently yield returns over the break-even hurdle. Accounting for the cost of betting, the break-even hurdle requires a winning percentage higher than 52.4 percent. We consider three simple strategies in Table 6: betting on the team with more black players, betting on the team with more white players, and betting on the home team only when it has more white players than the visiting team.[31] The reason for distinguishing between the home and visiting team is to exploit the possibility that the home court advantage may not be fully accounted for by the bettors. Betting on the whiter team, regardless of location, yields a winning percentage of 51.7 with a return of -1.3 percent. For the case where we consider betting on both home and visiting teams, we must restrict attention to teams with at least two fewer black starters. Here we observe a winning percentage of 53.1 percent with a return of 1.3 percent. However, if we restrict attention to betting on the whiter home team, then we do not need to consider the size of the difference in the composition of the starters. Here, betting on the whiter team yields a winning percentage of 53.3 percent with a return of 3.6 percent.

Across seasons, the profits obtained by following the "bet on the white home team" strategy are persistent over time. Table 7 presents the results of adopting this strategy over our whole sample period. In the 2007-08 season, as a result of the strategy of only betting on the home team when it has 1, 2, 3, or 4 more white players in the starting line-up than the visiting team, we observe the probability of a winning bet to be as high as 75 percent and net returns (accounting for the cost of betting) ranging from 8 percent to 43 percent. Indeed,

results are similar to the ones reported here and are available from the corresponding author upon request.

[31] One could, of course, design betting strategies based on the roster of the teams or the minutes played by black players. We obtain similar results using such strategies but prefer the results involving the black starters because this is the most easily-accessible and least computationally-intensive variable.

this strategy of betting on the home team, when it has more white players, delivers positive net returns that not only increase with the starkness of the racial difference between the two teams but also broadly persist from one season to the next. This suggests that, although learning opportunities abound in this incentivized setting, the bettors are biased for betting on the team with more black players. Further given the auxiliary assumption that bettors are expected value maximizers, this is indicative of a persistent and mistaken belief that teams with more black players are better.[32]

5 Conclusion

This paper examines the impact of the stereotype of the black basketball star on financial decisions, as revealed in the market outcomes, using evidence from the basketball betting market. We find that teams with more black players face higher point spreads and these teams perform worse against the spread. We find evidence that these biased point spreads are being set by the bookmakers rather than the result of excessive betting on the teams with more black players. We have explored many specifications that account for alternate explanations for our results. The racial bias that we find survives these alternate specifications. While we are not able to rule out every possible non-racial explanation, we interpret our results as evidence of a bias in NBA betting markets based on race. Further, with the auxiliary assumption that bettors are expected value maximizers, our findings can be interpreted as indicating that bettors regard black teams as better.

Regardless of whether the racial bias that we find is monetary or non-monetary, our findings add to the literature showing the importance of biases in economic decision making and market outcomes. In particular, we demonstrate that market makers process the available information efficiently but at the same time, when setting the prices, allow for the fact that the participants have a (possibly subconscious) bias, which they do not correct, even though not doing so leads to direct pecuniary losses. We also provide evidence that biases do indeed

[32] See Pope and Schweitzer (2011) for another example of a persistent bias in a setting with many possibly correcting factors.

carry over from audit studies and laboratory experiments to real markets, even when stakes are high and the agents have the opportunity to learn.

What do these findings mean for other markets? If we find persistently-mistaken, financially-disadvantageous beliefs in a market with obviously- and immediately-realized financial costs and many opportunities to learn, then we would expect there to be such in other markets barring the limitation that participants in sports betting markets may be markedly different than those in other markets. Most straightforwardly, do presumptions about intellectual or athletic ability based on stereotypes increase or decrease the odds of success for certain groups in certain fields? Another socially and politically uncomfortable question that may arise from this analysis is, if people are prone to making suboptimal sports betting decisions due to racial stereotypes, do people make similar costly judgment errors in other economic decisions? For instance, are employers more likely to hire engineers with a background from a particular region, expressing a bias that these individuals have an innate ability for quantitative tasks? Is provision of health, education, and other social services affected by subconscious attitudes towards groups? These and other interesting questions are left for future research.

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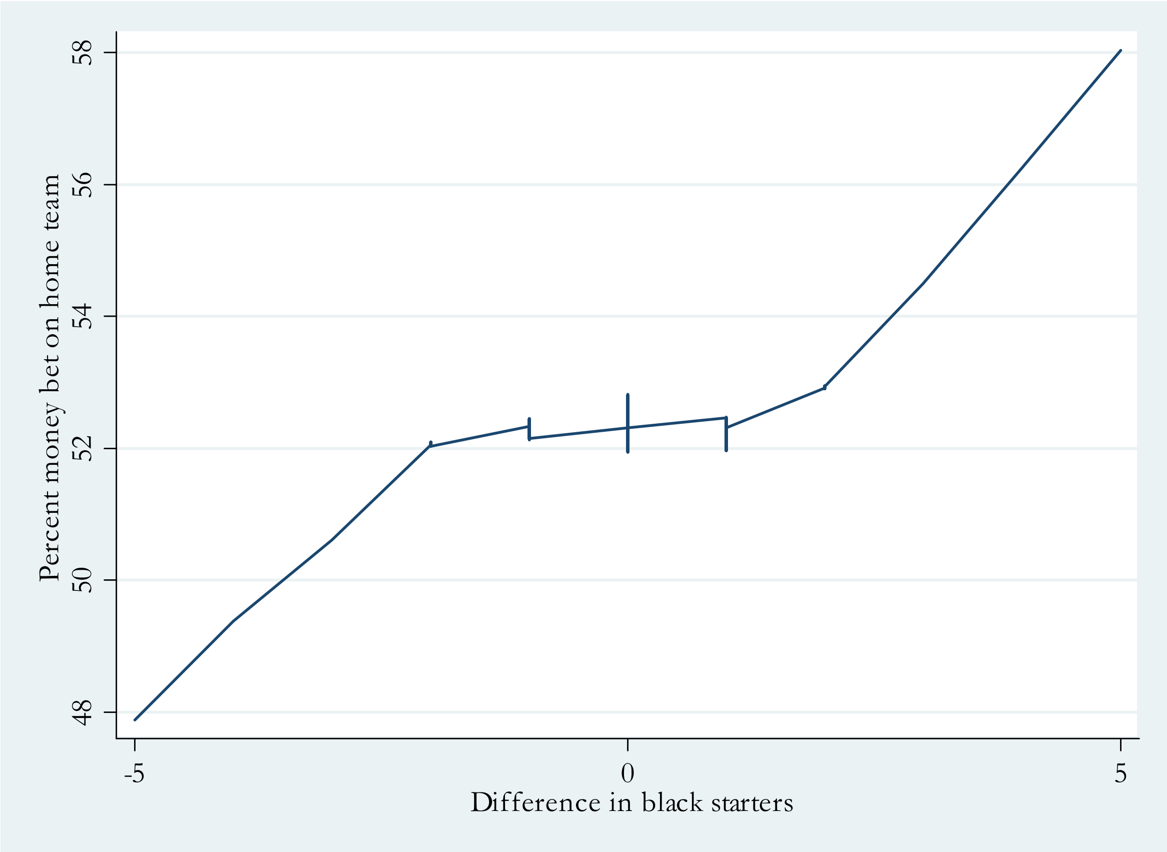

Figure 1: Percent of money bet on the home team and the difference in black starters.

Notes: The actual values of the difference in black starters are discrete. The line shown is continuous because it is constructed using locally weighted scatterplot smoothing (LOWESS). See Cleveland (1979) for details on the LOWESS methodology.

Table 1. Summary Statistics at Team-Game Level

	Obs	Mean	St. Dev.
Point spread	14785	-1.86	5.07
Realized margin	17178	3.36	14.15
Realized margin - spread	14785	0.35	11.53
Probability of beating the spread	14785	0.51	0.50
Black starters	17179	3.90	1.05
Difference in black starters	17178	0.01	1.41
Black players on the roster	17179	7.60	1.63
Difference in black players on the roster	17178	-0.01	2.12
Black minutes	17022	0.78	0.16
Difference in black minutes	16982	0.001	0.21

Notes: Point spread is the quoted spread on a game as of the closing time for bets, expressed from the home team's perspective. Realized margin is the actual difference between the home team score and the visiting team score at the end of the game. Probability of beating the spread is a dummy that is 1 if a bet on the home team wins. Black starters is the number of black players in the starting line-up. Black players on the roster is the number of black players on the team roster. Black minutes is the proportion of minutes played by black players to the total minutes in the game, calculated over the past five games the team has played. These measures of blackness of a team refer to the home team. Difference in black starters is calculated as the number of black players in the starting line-up (number of black players on the roster, proportion of black minutes) of the home team minus the number of black players in the starting line-up (number of black players on the roster, proportion of black minutes) of the visiting team.

Table 2. Winning the Game

	Realized margin		
Difference in black starters	0.290***		
	[0.105]		
Diff. in black players on the roster		0.091	
		[0.066]	
Difference in black minutes			-4.356***
			[0.675]
Team fixed effects	yes	yes	yes
Season fixed effects	yes	yes	yes
Team-season interactions	yes	yes	yes
Observations	17178	17178	16982
R-squared	0.14	0.14	0.14
	Probability of winning		
Difference in black starters	-0.023***		
	[0.009]		
Diff. in black players on the roster		-0.029***	
		[0.006]	
Difference in black minutes			-0.399***
			[0.065]
Team fixed effects	yes	yes	yes
Season fixed effects	yes	yes	yes
Team-season interactions	yes	yes	yes
Observations	17178	17178	16982

Notes: The dependent variable in the upper panel is the realized margin in the game, computed as the home team score minus the visiting team score. The dependent variable in the lower panel is the probability of winning, which is a dummy that is 1 if the home team won the game. The regressions are estimated using ordinary least squares for the realized margin, and using probit for the probability of winning. Difference in black starters is calculated as the number of black players in the starting line-up (number of black players on the roster, proportion of black minutes over the past five games) of the home team minus the number of black players in the starting line-up (number of black players on the roster, proportion of black minutes over the past five games) of the visiting team. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3. Beating the Spread

	Point spread		
Difference in black starters	0.364***		
	[0.032]		
Diff. in black players on the roster		0.143***	
		[0.021]	
Difference in black minutes			3.161***
			[0.224]
Team fixed effects	yes	yes	yes
Season fixed effects	yes	yes	yes
Team-season interactions	yes	yes	yes
Observations	14784	14784	14631
R-squared	0.33	0.32	0.33
	Realized margin - spread		
Difference in black starters	-0.239***		
	[0.083]		
Diff. in black players on the roster		-0.275***	
		[0.053]	
Difference in black minutes			-1.427**
			[0.596]
Team fixed effects	yes	yes	yes
Season fixed effects	yes	yes	yes
Team-season interactions	yes	yes	yes
Observations	14784	14784	14631
R-squared	0.06	0.06	0.06
	Probability of beating the spread		
Difference in black starters	-0.021**		
	[0.009]		
Diff. in black players on the roster		-0.033***	
		[0.006]	
Difference in black minutes			-0.116*
			[0.066]
Team fixed effects	yes	yes	yes
Season fixed effects	yes	yes	yes
Team-season interactions	yes	yes	yes
Observations	14784	14784	14631

Notes: The dependent variable in the upper panel is the point spread quoted on the game, expressed from the home team's perspective. The dependent variable in the middle panel is the difference between the realized margin (the final score of the home team minus the final score of the visiting team) and the point spread. The dependent variable in the lower panel is the probability of beating the spread, which is a dummy that is 1 if a bet on the home team wins. The regressions are estimated using ordinary least squares for the point spread and the difference between the realized margin and the spread, and using probit for the probability of beating the spread. Difference in black starters is calculated as the number of black players in the starting line-up (number of black players on the roster, proportion of black minutes over the past five games) of the home team minus the number of black players in the starting line-up (number of black players on the roster, proportion of black minutes over the past five games) of the visiting team. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4a. Robustness: Referees

	Probability of beating the spread	
	At least one black referee	At least one white referee
Difference in black starters	-0.015*	-0.022***
	[0.011]	[0.009]
Team fixed effects	yes	yes
Season fixed effects	yes	yes
Team-season interactions	yes	yes
Observations	11244	14460
	All-black crew	All-white crew
Difference in black starters	-0.098	-0.044**
	[0.128]	[0.021]
Team fixed effects	yes	yes
Season fixed effects	yes	yes
Team-season interactions	yes	yes
Observations	126	3464
	Neither all-black nor all-white crew	Referee race as additional control
Difference in black starters	-0.017*	-0.019**
	[0.011]	[0.009]
Proportion of white referees		-0.150***
		[0.046]
Team fixed effects	yes	yes
Season fixed effects	yes	yes
Team-season interactions	yes	yes
Observations	10911	14694

Notes: The regressions are estimated using probit. Difference in black starters is calculated as the number of black starters on the home team minus the number of black starters on the visiting team. The race composition of referees are taken into account by splitting the sample by the proportion of black referees in the 3-person crew. Alternatively, the proportion of white referees is included as a control variable. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4b. Robustness: History of Teams

	Probability of beating the spread				
Difference in black starters	-0.019**	-0.023**	-0.023**	-0.026***	-0.033***
	[0.009]	[0.009]	[0.010]	[0.010]	[0.012]
Difference in records	0.033***				
	[0.007]				
Difference in recent performance		0.041			
		[0.033]			
Margin on the teams' last match			0.002**		
			[0.001]		
Spread on the teams' last match				0.0001	
				[0.003]	
Team fixed effects	yes	yes	yes	yes	yes
Season fixed effects	yes	yes	yes	yes	yes
Team-season interactions	yes	yes	yes	yes	yes
Match fixed effects	no	no	no	no	yes
Observations	14781	14631	14041	13437	13324

Notes: The regressions are estimated using probit. Difference in black starters is calculated as the number of black starters on the home team minus the number of black starters on the visiting team. Difference in records is calculated as the difference between the number of wins the home team had in a particular season prior to the game under consideration and the corresponding number for the visiting team. Difference in recent performance is calculated as the difference between the number of wins the home team had in a particular season over the five previous games before the game under consideration and the corresponding number for the visiting team. Margin on the teams' last match is computed as the difference between home team's score and the visiting team's score obtained the last time the two teams played against each other (irrespective of the location and expressed from the home team's perspective). Spread on the teams' last match is the point spread quoted on the last game the two teams faced each other (irrespective of the location and expressed from the home team's perspective). Note that the margin/spread is equal to the margin/spread from the last match-up in the previous season when the game under consideration is the first time the two teams face each other in a given season. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4c. Robustness: Alternate explanations

	Probability of beating the spread			
Difference in black starters	-0.022**	-0.022**	-0.020**	-0.028***
	[0.009]	[0.009]	[0.009]	[0.006]
Difference in popularity: televised games	0.052***			
	[0.017]			
Difference in popularity: attendance		0.002***		
		[0.001]		
Difference in all-star players			0.191***	
			[0.015]	
Difference in foreign players				0.011
				[0.010]
Team fixed effects	yes	yes	yes	yes
Season fixed effects	yes	yes	yes	yes
Team-season interactions	yes	yes	yes	yes
Observations	14781	14781	14781	14781

Notes: The regressions are estimated using probit. Difference in black starters is calculated as the number of black starters on the home team minus the number of black starters on the visiting team. Difference in popularity: televised games is calculated as the difference between the number of nationally televised games of the home team during the season and the corresponding value for the visiting team. Difference in popularity: attendance is the average home attendance of the home team during the season minus the corresponding value for the visiting team. Difference in all-star players is calculated as the difference between the number players selected for the all-star team in the season for the home team and the corresponding value for the visiting team. Difference in foreign players is calculated as the difference between the number of foreign players on the roster of the home team and the corresponding value for the visiting team. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5a. Moving the Point Spread

	Closing spread - Opening spread			
Difference in black starters	0.014**	0.008	0.008	0.006
	[0.007]	[0.008]	[0.008]	[0.009]
Team fixed effects	no	yes	yes	yes
Season fixed effects	no	no	yes	yes
Team-season interactions	no	no	no	yes
Observations	7977	7977	7977	7977
R-squared	0.00	0.01	0.01	0.05

Notes: The dependent variable is the difference between the closing and opening values of the spread on the game, showing how much the point spread moves from the start of betting until all bets close. The regressions are estimated using ordinary least squares. Difference in black starters is calculated as the number of black starters on the home team minus the number of black starters on the visiting team. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5b. Bias in Bets

	Money bet on home team			
Difference in black starters	0.285*	0.408*	0.412*	0.411*
	[0.158]	[0.227]	[0.228]	[0.228]
Difference in recent performance		-0.922***		
		[0.224]		
Difference in popularity: televised games			0.054	
			[0.035]	
Difference in all-star players				-0.012
				[0.020]
Team fixed effects	yes	yes	yes	yes
Season fixed effects	yes	yes	yes	yes
Team-season interactions	yes	yes	yes	yes
Observations	8011	8011	8011	8011
R-squared	0.01	0.01	0.01	0.01

Notes: The dependent variable is the money bet on the home team, expressed as a percentage of the total bets placed on the game. The regressions are estimated using ordinary least squares. Difference in black starters is calculated as the number of black starters on the home team minus the number of black starters on the visiting team. Difference in recent performance is calculated as the difference between the number of wins the home team had in a particular season over the prevous five games before the game under consideration and the number of corresponding wins for the visiting team. Difference in popularity: televised games is calculated as the difference between the number of nationally televised games of the home team during the season minus the corresponding value for the visiting team. Difference in all-star players is calculated as the difference between the number players selected for the all-star team in the season for the home team minus the corresponding value for the visiting team. Robust standard errors are in square brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6. Chances of Winning with Simple Strategies

Strategy 1	Bet on the team that has X more black starters ...											
	1			2			3			4		
	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %
Average	6518	49.2	-6.0	2670	46.9	-10.4	783	46.8	-10.6	254	44.9	-14.3
Average for all	10225	48.3	-7.7									
Strategy 2	Bet on the team that has X more white starters ...											
	1			2			3			4		
	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %
Average	6518	50.8	-3.1	2670	53.1***	1.3***	783	53.3***	1.8***	254	55.8***	6.6***
Average for all	10225	51.7	-1.3									
Strategy 3	Bet on the home team only when it has X more white starters than the visiting ...											
	1			2			3			4		
	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %
Average	3224	51.5	-1.8	1331	56.0***	7.0***	399	57.9***	10.5***	118	55.9***	6.8***
Average for all	5072	53.3***	3.6***									

Notes: The table shows the outcome of bets placed on a team when it has X (taking on values of 1, 2, 3, or 4) more white/black starters than the opposing team, as defined by the strategy. Bets show the number of games that satisfy the condition and the strategy would require an $11 bet being placed on the team. Win % is the proportion of bets that the betted-on team would beat the spread and the bettor would receive $21. Return % denotes the return on the betting strategy, computed as the total money earned on the bets as a proportion of the money spent on placing the bets. Bets are expressed in units; win % and return % are in percent terms. The first row reports the total number of bets and the simple average for the wins and returns over all the seasons in the sample. The last row reports the total number of bets and the simple average for the wins and returns for the strategy considered as a whole. *** indicates that the win % (return %) is significantly higher than 52.4% (0.0%), i.e., the win percentage required to break even, according to a one sample t-test at the 1% level.

Table 7. Chances of Winning with a Simple Strategy: Season by Season

	Bet on the home team only when it has X more white starters than the visiting ...											
	1			2			3			4		
	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %	Bets	Win %	Return %
2007-08	243	56.4	7.6	141	57.4	9.7	41	58.5	11.8	8	75.0	43.2
2006-07	270	48.5	-7.4	110	53.6	2.4	40	52.5	0.2	10	70.0	33.6
2005-06	244	54.9	4.8	126	54.0	3.0	50	56.0	6.9	8	50.0	-4.5
2004-05	214	50.9	-2.8	123	57.7	10.2	38	52.6	0.5	20	35.0	-33.2
2003-04	209	51.2	-2.3	80	63.8	21.7	47	63.8	21.9	27	55.6	6.1
2002-03	217	49.3	-5.9	101	59.4	13.4	38	60.5	15.6	11	63.6	21.5
2001-02	192	54.2	3.4	99	59.6	13.8	28	53.6	2.3	11	63.6	21.5
2000-01	202	51.5	-1.7	122	54.1	3.3	29	51.7	-1.3	13	46.2	-11.9
1999-00	227	53.7	2.6	101	59.4	13.4	18	61.1	16.7	1	100.0	90.9
1998-99	141	53.2	1.5	57	43.9	-16.3	21	61.9	18.2	4	50.0	-4.5
1997-98	201	55.2	5.4	73	58.9	12.5	12	58.3	11.4	4	75.0	43.2
1996-97	227	45.4	-13.4	52	65.4	24.8	16	81.3	55.1			
1995-96	235	49.8	-5.0	42	45.2	-13.6	2	50.0	-4.5			
1994-95	199	49.7	-5.0	60	41.7	-20.5	7	71.4	36.4			
1993-94	203	48.8	-6.9	44	56.8	8.5	12	41.7	-20.5	1	100.0	90.9
Average	3224	51.5	-1.8	1331	56.0***	7.0***	399	57.9***	10.5***	118	55.9***	6.8***
Average for all	5072	53.3***	3.6***									

Notes: The table shows the outcome of bets placed on the home team only when the home team has X (taking on values of 1, 2, 3, or 4) more white starters than the visiting team. Bets show the number of games that satisfy the condition in a given season and the strategy would require an $11 bet being placed on the home team. Win % is the proportion of bets that the home team would beat the spread and the bettor would receive $21. Return % denotes the return on the betting strategy, computed as the total money earned on the bets as a proportion of the money spent on placing the bets. Bets are expressed in units; win % and return % are in percent terms. The row before last reports the total number of bets and the simple average for the wins and returns over all the seasons in the sample. The last row reports the total number of bets and the simple average for the wins and returns if one bets anytime the home team has more white starters than the visiting team. *** indicates that the win % (return %) is significantly higher than 52.4% (0.0%) i.e., the win percentage required to break even, according to a one sample t-test at the 1% level.