Journal of Applied Sport Management

Volume 14 | Issue 1 | Article 7

3-15-2022

The Point Spread as a Reference Point: Evidence from the National Basketball Association

George Diemer
Temple University, george.diemer@temple.edu

Michael Leeds
Temple University, mleeds@temple.edu

Recommended Citation

Diemer, George and Leeds, Michael (2022) "The Point Spread as a Reference Point: Evidence from the National Basketball Association," *Journal of Applied Sport Management*: Vol. 14 : Iss. 1.
https://doi.org/10.7290/jasm14cBdG
Available at: https://trace.tennessee.edu/jasm/vol14/iss1/7

Journal of Applied Sport Management
https://doi.org/10.7290/jasm14cBdG
Vol. 14, No. 1
https://trace.tennessee.edu/jasm/vol14/iss1/7

The Point Spread as a Reference Point: Evidence from the National Basketball Association

George Diemer

Michael A. Leeds

Temple University

Abstract

A contentious literature surrounds the claim that heavy favorites' failure to cover the point-spread in National Collegiate Athletic Association (NCAA) basketball could indicate point-shaving. This paper extends the literature by using a new methodology to show that favorites in the National Basketball Association (NBA) also frequently fail to cover the spread. However, the high salaries in the NBA make point-shaving by players unlikely. Moreover, heavy underdogs also fail to cover the point spread and lose by more than expected. These seemingly anomalous findings are consistent with underdogs' using the point-spread as a reference point.

Keywords: *point-shaving; basketball; kernel density; reference points*

Please send correspondence to Michael A. Leeds, mleeds@temple.edu

Introduction

A sizable and contentious literature has arisen following Wolfers' (2006) assertion that widespread corruption might exist in college basketball. Wolfers found that, while heavily favored college teams generally beat their overmatched opponents, they fail to cover the point spread – the expected margin of victory – more often than random chance would dictate. Wolfers stirred controversy when he noted that his finding is consistent with "point shaving." Point shaving occurs when a team intentionally wins by less (or loses by more) than the oddsmakers predict in exchange for payment by gamblers who have guaranteed themselves a winning bet.

If point-shaving is as widespread as Wolfers' paper suggests, affecting as many as one percent of all games, then college basketball faces a potentially existential threat. Corruption scandals call the integrity of game outcomes into question and can have dire consequences for college basketball and intercollegiate sport in general. It is therefore important to determine whether Wolfers' findings indicate that point-shaving exists or whether a more benign explanation can be found for his results.

This paper provides empirical and theoretical evidence that Wolfers' results do not result from criminal activity but instead stem from normal behavior by economic agents (players, coaches, etc.) that could influence the game outcomes. It does so by applying a unique statistical technique to a data-set many have analyzed. One can then control for many of the problems cited by Wolfers' detractors.

The present results build upon the existing literature, particularly Borghesi's (2008) analysis of data from professional sports, in two ways. First, a data set is used that includes the point spreads and game results for all NBA regular season games from 1993 to 2019. Second, rather than using point estimates of whether teams cover point spreads, the entire distribution of game outcomes is used to analyze team behavior. It will be shown that both heavy favorites and heavy underdogs NBA teams fail to cover point spreads more often than they should. This is consistent w with Borghesi's claim (2008) that corrupt behavior by professional basketball players is highly unlikely, as the high salaries paid by the NBA create prohibitively high disincentives to shave points.[1] If professional basketball players display the same behavior as their collegiate counterparts, one must look for a different explanation for the failure to cover.

While Borghesi is correct that corruption is not the likely cause of Wolfers' observation, it is unlikely that one can attribute the findings to irrational behavior by bettors. A more likely explanation comes from prospect theory first proposed by Kahnemann and Tversky (1979), specifically from the existence of reference points in intercollegiate basketball games. Prospect theory suggests economic agents may not always act rationally. This irrationality often comes in the form of differing loss-aversions by economic agents. Other studies show acts of irrationality (often by displaying overly risky behavior) in pursuit of set goals.

Reference points are one such goal. Researchers have provided evidence of the pursuit of reference points in such areas as academic assessment (Pope & Simonsohn, 2011), performance in sports or game shows (Bartling et al., 2015; Pope & Simonsohn, 2011; Stone & Arkes, 2016; Jetter & Walker), and even with scorekeepers recording NBA game outcomes (Diemer et al., 2020).

In the present context, reference points anchor a team's expectations. Performing better or worse than the reference point increases or reduces the team's well-being. If heavy underdogs have reference-dependent preferences, then the point spread could serve as a target by which they could achieve a "moral victory" even when victory is out of reach. The conflict in the preceding literature may be the result of attempting to analyze three sorts of victory – winning the game, beating the point spread, and achieving a moral victory – by appealing to only the first two types of victory. Reference points thus introduce a new explanation to the literature, one that does not rely on irrational behavior and is less sinister than point-shaving.

[1]Wyshynski and Purdum (2021) write about a disturbing case to the contrary.

The Impact of Point Spreads on Game Outcomes

Point spreads enable bookmakers to generate interest among gamblers in games whose outcome is not in doubt. No one would bet that Swarthmore College, a small liberal arts college, could beat UCLA, a perennial basketball powerhouse, no matter what the promised payoff of such a bet is. While everyone agrees that UCLA would win such a game, there is sure to be disagreement over UCLA's margin of victory. Some might believe UCLA would win by 35 points, while others say that a 50-point margin is more realistic. Point spreads exploit this disagreement. By setting a point spread of 40.5 points, a bookmaker can generate bets by those who think UCLA will win by at least 41 points and those who think that it will win by 40 or less.

Point spreads create powerful incentives for unscrupulous gamblers to rig the outcome of a game. They can approach a player, coach, or even a referee and offer him money to make plays, player substitutions, or foul calls that will keep the game closer than the official point spread.[2] The gambler can then place large bets on a specific outcome, sure that the bet will pay off. Despite anecdotal evidence of periodic point shaving scandals, most recently a 2010 case involving players from the University of San Diego (Assael, 2014), there had been no systematic study of point shaving in the economics literature until Wolfers (2006).

In his study, Wolfers (2006) used data from the 1989-1990 through 2004-2005 NCAA basketball seasons (44,120 games) to show, first, that point spreads accurately predict game outcomes. He did so by regressing the winning margin of a game on the point spread and finding a constant that was close to zero and a slope coefficient that was close to one. Thus, a game with a point spread of zero (two evenly matched teams) typically has a close outcome, and the difference in scores rises roughly 1:1 with the point spread.

Wolfers (2006) hypothesized that gamblers do not want to risk detection by inducing a favored team to lose, so he next studied the outcomes of games with point spreads of at least 12 points so that players could safely (?) lose "against the spread" without losing the game. If gambling markets are efficient and game outcomes are normally distributed, a key assumption by Wolfers and most subsequent studies, the distribution of winning margins should be symmetric and reach its maximum at the point spread.

Under the above assumptions, a test of the null hypothesis of no point shaving rests on whether the distribution of game outcomes is symmetric:

$$p(0 < \text{Winning margin} < \text{Spread}) = p(\text{Spread} < \text{Winning margin} < 2 * \text{Spread}) \quad (1)$$

Wolfers (2006) found that teams favored by at least 12 points typically won, but they too frequently failed to cover the point spread. As a result, the expression on the left side of Equation (1) is larger than that on the right. He concluded that "point shaving led roughly 3% of heavy favorites who would have covered the spread not to cover (but still win)" (Wolfers, p. 282).

Borghesi (2008) argued that Wolfers misinterpreted his own results. Borghesi found that heavy favorites in professional basketball or football games failed to cover the point spread about as often as college teams do. He then argued, correctly, that point shaving by professional basketball or football players is unlikely because the high salaries they earn make the cost of being caught prohibitively high. There must, therefore, be a more innocent explanation for the observed behavior. Borghesi attributed the findings to the irrational behavior of fans who bet on popular favorites "even if the spread is too large" (Borghesi). Bookmakers respond rationally by setting a spread that is greater than the margin they expect.

Other studies have included criticism of Wolfers' approach rather than his interpretation. For example, Johnson (2009) pointed out that Wolfers tendency to focus on heavy favorites biased his results. Like Borghesi (2008), Johnson believes that bettors drive the point spread too high for heavy favorites. If there is significant regression to the mean, heavy underdogs will cover the point spread disproportionately often.

[2] Alternatively, they can approach the underdog and offer incentives to lose by more than the specified amount.

Johnson also pointed to a bias that comes from the fact that basketball games must have a winner and a loser. Because of this binary result, it is arithmetically impossible for a team that is favored by two points to fail to cover by exactly two points. This could lead to Type I error: rejecting the null hypothesis of no point shaving even though point shaving does not take place.

Borghesi and Dare (2009) calculated the expected scores of favorites and underdogs in college basketball games and found that the mean scores of heavy favorites were not significantly less than expected and that heavy favorites held their opponents to slightly fewer points than expected. They speculated that coaches of heavy favorites pursued conservative strategies toward the end of games they are winning, while coaches of heavy underdogs pursued riskier strategies. There are two problems with this conclusion. First, rational bettors will likely incorporate predictable coaching behavior into point spreads. Second, the conclusion never addresses a less-discussed finding from Wolfers that heavy favorites are involved in too many blowouts.

Bernhardt and Heston (2010) compared the outcomes of games that bookmakers list with those of games they do not list and found no difference in the likelihood that favorites cover the spread. They also claimed that the distributions of outcomes of the two sets of games differ from the normal distribution, though they provided no formal test. While the distributions differ from the normal distribution, Bernhardt and Heston claimed that they do not differ from each other, which suggests that point shaving is not involved.

Like Borghesi and Dare, Bernhardt and Heston speculated that teams that are far ahead may substitute freely and play conservatively at the end of games, while heavy underdogs pursue high-risk strategies (e.g., pressure defense and three-point shots) to try to catch up. If the strategy succeeds, the game will be closer than predicted. If it fails, the underdog will fall even farther behind. As noted above, however, if teams with big leads regularly let down at the end of games, point spreads should fall as a result.

The above models share one common flaw. They focus solely on the favorite team's failure to cover the spread. Diemer and Leeds (2013) avoided this problem by comparing the distributions of game outcomes. They began by computing "Net Favored Points" (NFP):

$$\text{NFP} = \text{favored team's score} - \text{underdog team's score} + \text{point spread} \quad (2)$$

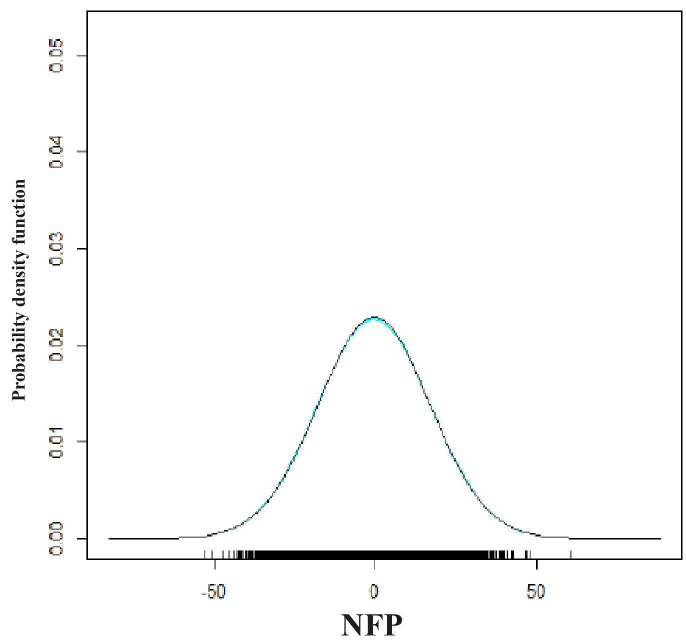
Using Equation (2), if the favored team covers the point spread, NFP > 0. If it fails to cover the spread, NFP < 0. Diemer and Leeds (2013) then compared the distribution of NFP for games with more than a given point spread against the distribution of NFP for game with less than that point spread. They found that the distributions differed for many large point spreads, which is consistent with point shaving.

Empirical Model and Data

If betting markets are competitive, the efficient market hypothesis says that the point spread should be the best predictor of the outcome on average (Sauer, 1998; Vaughan Williams, 2005). This is supported in Figure 1, which is the kernel density of the NFP for all NBA regular season games in the present sample. The confidence band around the smooth curve represents a 95 percent confidence interval around a normal distribution. Because the kernel density lies within the band, one cannot reject the hypothesis that the distribution is normal. Thus, the distribution of game outcomes relative to the point spreads (the NFP) appears to be normal with the peak of the distribution occurring where NFP = 0 in the aggregate.

Figure 1

Complete Regular Season NFP PDF: Confidence Band Tests for a Normal Distribution



N = 19,303

Consistent with the literature (e.g., Wolfers, 2006; Borghesi and Dare, 2009; and Diemer, 2009), the distribution is split into two subsets, heavy and slight favorites. One can then vary the truncated threshold to analyze how changing the point spread affects the NFP, the game outcome relative to the spreads and conduct non-parametric tests of each kernel PDF using normal optimal smoothing parameters. Absent a world where the size of the spread impacts the game outcome relative to the spread, the two densities should equal each other. One can now perform a global test of equality for the two distributions of heavy favorites (f(NFP)) and slight favorites (g(NFP)):

H_o: f(NFP) = g(NFP), for all NFP

H_1: f(NFP) ≠ g(NFP), for some NFP

This test uses a bootstrap method and is illustrated by a confidence band that is two standard errors wide at any NFP.

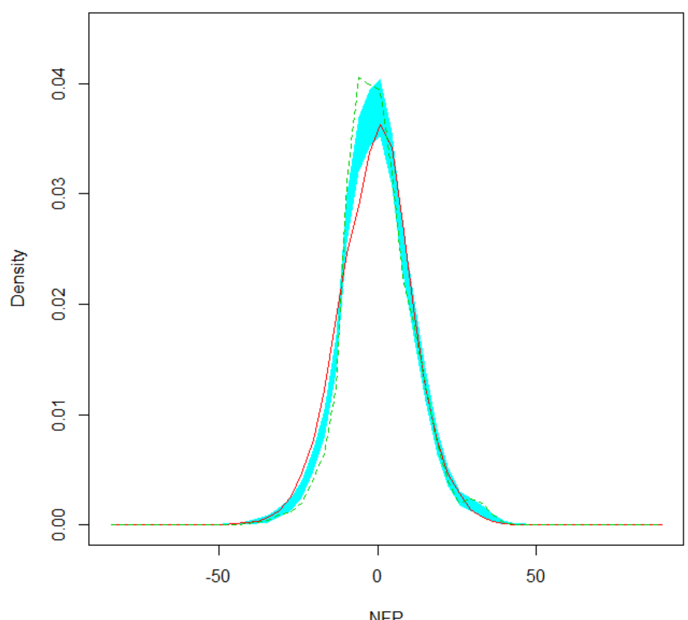
This approach has three advantages. First, one can analyze the behavior of both favorites and underdogs. Previous work focuses almost strictly on whether favorites cover the spread. Looking at the entire distribution shows how likely favorites are to win by "too little" (or lose), the left tail of the distribution, and how likely underdogs are to lose by "too much," the right tail of the distribution. Second, comparing the location and peaks of the distributions provides deeper insights into the nature of the failure to cover. Finally, comparing the distributions for different point spreads enables one to draw a causal relationship between the point spread and the game outcome, which previous studies cannot do.

These tests were performed with data on game outcomes and point spreads for the 1993-1994 through 2018-2019 NBA seasons. The data came from the website *NBA Odds and Scores* on Kaggle. Several games every season are marked by an unusually large degree of uncertainty regarding game outcome (e.g., when it is unclear whether a star player will be able to play). When this happens, bookmakers do not post a point spread. These games were omitted from the present sample. The resulting dataset consisted of 26,739 regular season games.[3]

Results

Figure 2 splits the regular season distributions into heavy favorites (at least 14 points), the dotted line, and lesser favorites (13.5 points or less)., the solid line. The p-value is close to zero, so one can reject the null hypothesis that the two distributions are equal. Three ranges are particularly worth noting. In range #1 in the left tail of the kernel density, that heavy favorites are shown to be significantly less likely to cover (the peak of the dashed distribution) than slight favorites (the peak of the solid distribution). In addition, the peak of the dashed distribution falls outside of the confidence band. This provides a likely reason for rejecting the null hypothesis that the two distributions in Figure 2 are equal. In other words, the outcomes for games with heavy favorite outcomes show that the heavy favorites almost always win, but they fail to cover the point spread at a statistically significant level. In range #2, in the right tail, underdogs are unable to cover the point spread at the low end, losing by more than predicted at an unexpectedly high rate.

Figure 2
Regular Season



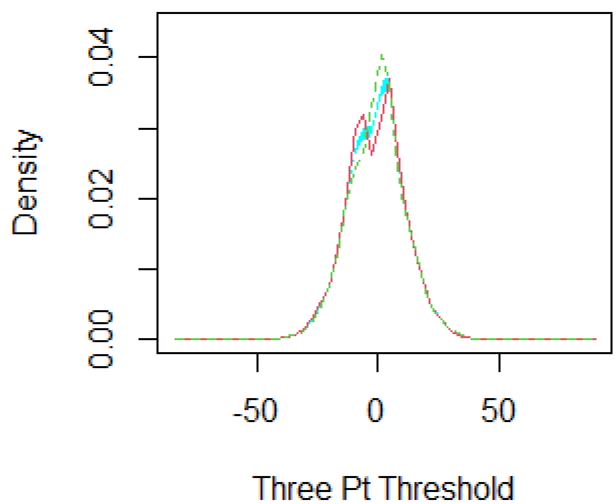
Lower bound: 14 and over n=984
Upper bound: 13.5 and under n=25,755
Test of equal densities: p-value = 0
Dashed line- heavy favorites
Solid line- slight favorites

[3] Only games with a favored team were included in this dataset. Games with a point spread of zero were omitted.

Note that, as one moves from left to right in Figure 2, the kernel density for heavy favorites initially tracks the density for slight favorites but then rises much more steeply. It peaks at NFP<0, while the density for slight favorites peaks at about NFP=0. This indicates that heavy favorites are more likely than lesser favorites to fail to cover the point-spread.

Finally, consider Johnson's (2009) observation that the nature of basketball prevents tie games. This tie game constraint could, in theory, impact game outcomes, which would lead to a type I error. Constructing nonparametric PDFs allows the data to flow more freely. One can then see how the tie game constraint impacts game outcomes relative to the point spread. This can clearly be shown in Figure 4. The dashed distribution encompasses the majority of the data, thus becomes more 'normal' while the solid distribution is suppressed around the tie game constraint. Clearly when the point spread threshold increases the tie game constraint does not affect the results (as seen in Figures 2 and 3).

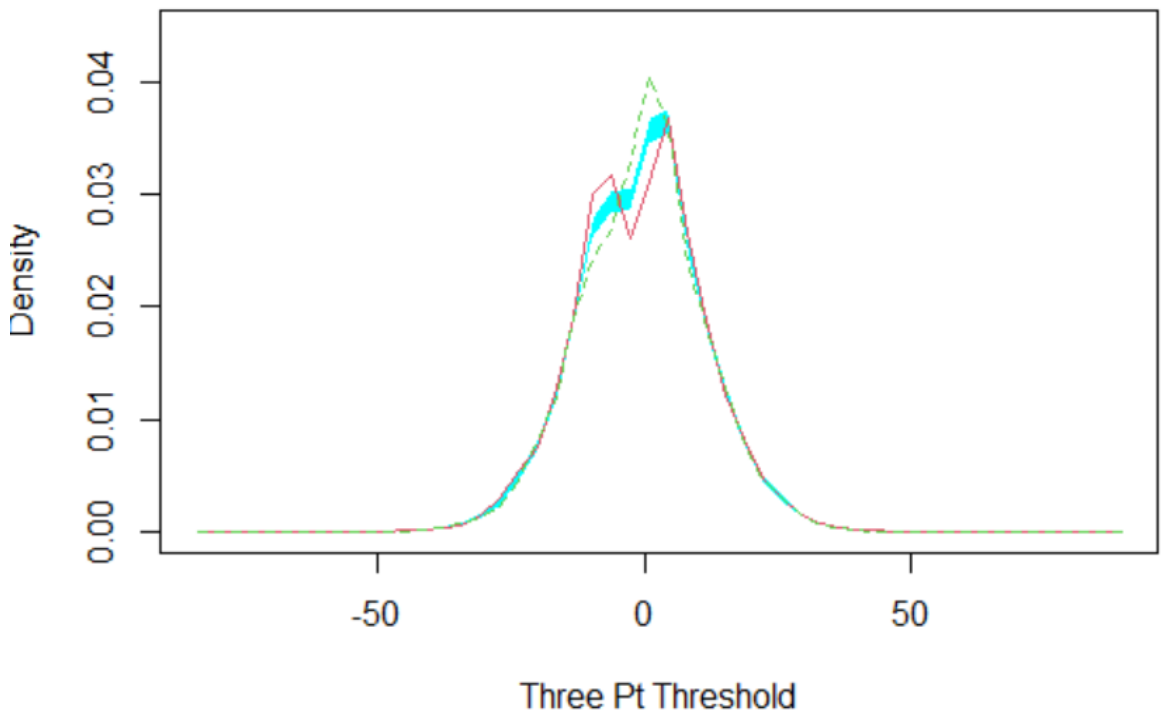
Figure 4
Regular Season



Lower bound: 3 and over n=21,787
Upper bound: 2.5 and under n=4,952
Test of equal densities: p-value = 0
Dashed line- heavy favorites
Solid line- slight favorites

Figure 3 shows a similar pattern for games in which a team is favored by 10 or more points. Again, the kernel densities show that heavy favorites are less likely to cover the point-spread and more likely to win by huge margins. As before, the kernel density for heavy favorites peaks at NFP<0 while the kernel density for lesser favorites peaks at NFP=0. The only significant difference from Figure 2 is that the kernel density for heavy favorites is now unimodal.

Figure 3
Regular Season



Lower
Upper bound: 2.5 and under n=4,952
Test of equal densities: p-value = 0
Dashed line- heavy favorites
Solid line- slight favorites

As noted above, there are several possible explanations for these findings, ranging from good sportsmanship in which heavy favorites ease up at the end of games against outmatched opponents to irrational behavior by bettors, many of whom are biased toward heavy favorites. Unfortunately, these explanations focus solely on one tail of the distribution, the failure of heavy favorites to cover the point spread as much as they should. They do not account for the fact that heavy underdogs also fail to cover more often than expected.

One explanation that accounts for both sides of the distribution stems from the behavioral economics concept of reference points. Clearly the most common reference point is the other team's score. That is, the goal of any team is to score the most points and win the game.

When a win is out of reach, however, the point spread may become a secondary reference point. In effect, if a team cannot gain a literal victory, it might strive for a "moral victory" by making the score closer than expected. This could induce the underdog to undertake risky strategies late in the game. If the strategies are successful, the underdog will lose by less than expected. If they are unsuccessful, the underdog could lose by more than expected. Whether this occurs in fact is the subject for further research. This explanation has the advantage of relying on rational behavior. It also cannot be offset by bettor behavior, as the reference point is conditional on the point spread.

Conclusion

Data from NBA contests shows that outcomes in professional basketball closely resemble those for college basketball. This paper applies these data to kernel densities to reject the null hypothesis that the distribution of NFP is the same for heavy favorites and slight favorites.

While this result could indicate that players, coaches, or referees engage in point shaving, such a conclusion would require that even marginal players risk huge sums of money in the form of lost salary if they are caught. This risk distinguishes NBA players from college players, most of whom have little chance of an NBA career.

This result builds on Borghesi's (2008) in several ways. Perhaps most importantly, it is not only the favorites who fail to cover. Underdogs also fail by participating in blowouts in which they lose by more than the spread predicts. An alternative explanation in the form of reference points is also provided. Heavy underdogs may set beating the point spread as a secondary goal to winning the game. Slight underdogs, who are more likely to be involved in a close match, in which they have a good chance of winning until very late in the game, do not face this incentive.

The present results should come as some relief to college coaches, athletic directors, and college administrators. By providing an innocent explanation of Wolfers' (2006) findings, one can avoid a nightmare scenario for intercollegiate athletics. Widespread point-shaving would have required a massive increase in the policing of college athletes. Such worry appears to be unnecessary.

References

Allen, E., Dechow, P., Pope, D., & Wu, G. (2016). Reference-Dependent Preferences: : Evidence from Marathon Runners. *Management Science*, 1657-1672.

Bartling, B., Brandes, L., & Schunk, D. (2015). Expectations as Reference Points: Field Evidene from Professional Soccer. *Management Science*, 2646-2661.

Bernhardt, D., & Heston, S. (2010). Point Shaving in College Basketball: A Cautionary Tale for Forensic Economics. *Economic Inquiry*, 14-25.

Borghesi, R. (2008). Widespread Corruption in Sports Gambling: Fact or Fiction? *Southern Economic Journal*, 1063-1069.

Borghesi, R. (2015). A case study in sports law analytics: The debate on widespread point shaving. *Journal of Sports Analytics*, 87-89.

Borghesi, R., & Dare, W. (2009). A Test of the Widespread Point-Shaving Theory. *Finance Research Letters*, 115-121.

Bowman, A., & Azzalini, A. (1997). *Applied Smoothing Techniques for Data Analysis: The Kernel Approach with S-Plus Illustrations.* London: Oxford University Press.

Diemer, G. (2009). Point Shaving in the NFL Gambling Market: A Bootstrap Investigation. *Journal of Prediction Markets*, 13-31.

Diemer, G. (2012). Comment on "Investigating Allegations of Point-shaving in NCAA Basketball Using Actual Sportsbook Betting Percentages. *Journal of Sports Economics*, 207-210.

Diemer, G., & Leeds, M. A. (2013). Failing to Cover: Point Shaving or Statistical Abnormality? *International Journal of Sport Finance*, 175-191.

Diemer, G., Kim, J. W., & Kneavel, M. (2020). Statistical Anomalies Associated with NBA Scorekeepers: A Bootstrap Investigation. *The Journal of Prediction Markets, 14*(1), 49-68.

Johnson, N. (2009). NCAA Point Shaving as an Artifact of the Regression Effect and the Lack of Tie Games. *Journal of Sports Economics*, 59-67.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica*, 263-291.

Larrick, R., & Wu, G. (1999). Goals as Referene Points. *Cognitive Psychology*, 79-109.

Leeds, M., & von Allmen, P. (2010). *The Economics of Sports.* Boston: Pearson.

Paul, R., & Weinbach, A. (2011). Investigating Allegations of Pointshaving in NCAA Basketball Using Actual Sportsbook Betting Percentage. *Journal of Sports Economics*, 432-447.

Pope, D., & Simonsohn, U. (2011). Round Numbers as Goals: Evidence from Baseball, SAT Takers, and the Lab. *Psychological Science*, 71-79.

Sauer, R. (1998). The Economics of Wagering Markets. *Journal of Economic Literature*, 2021-2064.

Stone, D., & Arkes, J. (2016). Reference points, prespect theory, and momentum on the PGA Tour. *Journal of Sports Economics*, 453-482.

Wolfers, J. (2006). Point shaving: Corruption in NCAA basketball. *American Econoimc Review*, 279-283.