Journal of Sports Economics

http://jse.sagepub.com

NCAA ``Point Shaving'' as an Artifact of the Regression Effect and the Lack of Tie Games

Neal Johnson

Journal of Sports Economics 2009; 10; 59
DOI: 10.1177/1527002508327388

The online version of this article can be found at:
http://jse.sagepub.com/cgi/content/abstract/10/1/59

Published by:
SAGE
http://www.sagepublications.com

On behalf of:
The North American Association of Sports Economists

Journal of Sports Economics
Volume 10 Number 1
February 2009 59-67

10.1177/1527002508327388
http://jse.sagepub.com
hosted at
http://online.sagepub.com

NCAA "Point Shaving" as an Artifact of the Regression Effect and the Lack of Tie Games

Neal Johnson
Pacific Lutheran University

Wolfers concluded that point shaving may occur in 6% of NCAA Division I basketball games involving a team favored by more than 12 points. His analysis is flawed on two counts. First, a regression effect is introduced when the definition of a strong favorite is based on the betting market's estimate of the winning margin. Second, the effect that a lack of tie games has on the resulting distribution of game outcomes relative to the Vegas spread is mistaken as a shift in the distribution because of point shaving. When combined, the regression effect and the lack of ties generate the observed data patterns. Numerical analysis indicates that even if the betting market makes unbiased estimates of the winning margin, an error with a standard deviation of 1.35 points is sufficient to generate the observed data pattern.

Keywords: *basketball; point shaving; regression effect*

Point shaving in basketball occurs when a player or players on a favored team ease up in play with the intent of influencing whether their team covers the betting market's point spread. If successful, point shaving will result in a team winning the game but not covering the point spread. Incentive-based models of point shaving suggest point shaving is more likely when teams are favored by a large point spread, as these teams have greater latitude to not cover the spread yet still win the game. Wolfers (2006) examines this hypothesis using data on 44,120 NCAA Division I basketball games played between the 1989-1990 and the 2004-2005 seasons. After observing that only 48.37% of the teams favored to win by more than 12 points—what he terms "strong favorites"—covered the betting market's point spread, Wolfers concludes that some teams must be point shaving. By his estimation,

Author's Note: The author is grateful to session participants at the 2008 Western Economic Association International Conference in Honolulu, Hawaii; the article's discussant, Dennis Coates; and an anonymous referee, for their helpful comments and suggestions. Correspondence concerning this article should be addressed to Neal Johnson, Department of Economics, Pacific Lutheran University, Tacoma, WA 98447; e-mail: johnsons@plu.edu.

approximately 6% of games with strong favorites may have some degree of point shaving (Wolfers, 2006, p. 282).

Wolfers' research generated significant media coverage (see, e.g., Cannella, 2006; Fridson, 2006; Knightly, 2006; Leonhardt, 2006), motivated an undergraduate thesis paper on point shaving in the National Basketball Association (NBA; Gibbs, 2007), and generated at least one peer-reviewed article with an alternative explanation for the observed data pattern (Borghesi, 2008). Although the latter identifies the prevalence of the "point shaving pattern" in other sports and leagues, Borghesi (2008) attributes this to line shading by bookmakers. None of the studies mention or address the statistical phenomenon variously known as regression to the mean, regression to the median, the regression effect, or the regression fallacy. This is a bit ironic, given that several commonly used examples of the regression effect, such as the Sports Illustrated Cover Jinx, the Madden Curse, and the Sophomore Slump, involve sports. This oversight is perhaps because of the subtle nature of the regression effect in the present example. It need not arise from teams regressing toward some mean or median level of play. Kansas and Xavier do not need to start playing more like Penn and Harvard, or vice versa, for the regression effect to arise. Instead, a sufficient requirement is for the sports betting market to estimate teams' true abilities with an error, where the error is distributed with a zero mean and a nonzero variance.

By categorizing teams as strong favorites based on the betting market's spread, Wolfers (2006) introduced the regression effect into his analysis. The 48.37% of strong favorites that failed to cover the point spread should not be compared to 50% but to some percentage less than 50. The intuition behind this assertion is straightforward. Given a betting market's unbiased estimate of a team's true ability relative to another team, the ensuing winning or losing margin is not drawn from a distribution centered on the betting market's point spread. Instead, it is drawn from a distribution centered on the unobserved population parameter, for which the point spread can be interpreted as an estimate. When a team's true ability against an opponent—in the sense of the mean margin if they played repeated games—is overestimated, the expected difference between the subsequent winning margin and the betting market's spread is negative. Teams that should not be categorized as strong favorites can be categorized as such because of the betting market's error. Similarly, a team that is rightfully labeled a strong favorite may be given too large a spread, while other true strong favorites might be omitted from such a grouping if the betting market sufficiently underestimates their true ability. As a group, strong favorites' true abilities are overstated and they should be expected to cover the spread less than half the time. If teams' true abilities were observable, or if the teams could be categorized based on some criteria uncorrelated with the betting market's spread, then the regression effect would not be an issue. Additionally, after omitting "pushes,"—games where the winning margin equals the spread—50% would be the correct percentage in the null hypothesis of a statistical test of point shaving.

1. Argument in Defense of the NCAA—Exhibit A

The presence of a regression effect does not preclude point shaving. After all, there are documented cases of point shaving by NCAA basketball players (McCarthy, 2007) and a recent example of gambling improprieties by an NBA referee (Beck & Schmidt, 2007). However, to bring some perspective to the impact of the regression effect on Wolfers' conclusions, an analysis of the magnitude of the betting market error required to generate the observed data is warranted. Attention is now turned toward this task.

Let $S^*_{i,j}$ be the unobserved true spread—in the sense of the expected mean margin in repeated match ups—between teams i and j. Let $S_{i,j}$ be the betting market's estimate of $S^*_{i,j}$:

$$S_{i,j} = S^*_{i,j} + \varepsilon \tag{1}$$

where ε is an error term with mean zero and standard deviation σ_ε. Let $M_{i,j}$ represent the realized point margin at the end of a game, with mean $S^*_{i,j}$ and standard deviation σ_M.

The conditional probability of a team covering the betting market's spread, given that the team is a strong favorite is given by

$$P(M_{i,j} - S_{i,j} > 0 | S_{i,j} > \mathrm{k}), \tag{2}$$

where k is a constant denoting the threshold for categorizing team i as a strong favorite. By substitution, equation (2) can be rewritten as

$$P(M_{i,j} - S^*_{i,j} - \varepsilon > 0 | S^*_{i,j} + \varepsilon > \mathrm{k}). \tag{3}$$

Under a null hypothesis of no-point shaving, assume that

[A1] $M - S^*$ is uncorrelated with S^*; and [A2] ε is uncorrelated with both M and S^*.

[A1] precludes point shaving and [A2] rules out a team's play regressing toward a mean level of performance. Although this may be occurring to some degree, allowing such regression is not necessary for the present argument. [A2] also rules out the line shading proposed by Borghesi (2008).

Wolfers notes that the sample standard deviation for $M - S$ in his data set is 10.9 points but does not report the sample statistics for either M or S. To fill in this missing information, sample statistics for the means and standard deviations for M and S were obtained from an 87,221 game data set provided by The Logical Approach of Las Vegas. These data include all NCAA Division I basketball games from the 1990-1991 through 2007-2008 seasons. For each game, the data include the date played, final scores, whether the game was a conference or nonconference game, whether the game had a home team or was played at a neutral site, and whether there were any overtime periods. For the 51,468 games that had betting, the opening and closing lines, as set by the Stardust Casino sports book, were also included. Of these games, 10,672 had a spread greater than 12 points, and of these, the favored team covered the spread in 47.34% of the games; failed to cover the spread in 50.29% of the games; and matched the spread in the remaining 2.37% of games. Omitting the 253 games that resulted in pushes, strong favorites covered the spread in 48.49% of the games. The mean spread, from the perspective of the favored team, was 7.92 points, with a standard deviation of 5.96 points. The winning margin, again from the perspective of the favored team, or the home team if the spread was zero, was 7.83 points, with a standard deviation of 12.50 points. The mean difference between M and S was -0.090 points, with a standard deviation of 10.9 points.

Although neither Wolfers, the rules of basketball, nor statistical theory suggest any of the unconditional variates should follow a normal distribution, an assumption of normality is adopted for illustrative purposes. Let $S^* \sim N\left(7.92, \sqrt{5.96^2 - \sigma_\varepsilon^2}\right)$ reflect the assumption that the true mean spread across all games follows a continuous distribution. M and S, however, follow discrete distributions. Ignoring this complication for now, let $(M - S) \sim N(0, 10.90)$. Finally, let $\varepsilon \sim N(0, \sigma_\varepsilon)$.

Numerical analysis was used to evaluate the distribution of $M - S$, conditioned on $S > 12$ points. The discrete nature of the game was reintroduced using 0.50 point discrete intervals for S^* and $M - S$, and 0.25 intervals for ε in the numerical analysis. Games ending in ties were left as ties, although see the next section for the relevance of tie games. Pushes were also ignored. The standard deviation of ε was varied until

$$P(M - S^* - \varepsilon > 0 | S^* + \varepsilon > 12; M - S \neq 0) \approx 0.4849 \tag{4}$$

The resulting solution was $\sigma_\varepsilon = 1.35$ points.

The regression effect, in the presence of a betting market error with a mean of 0 and a standard deviation of 1.35 points, is sufficient to explain the observed data without a need to assert the presence of point shaving, strategic play, or line shading. Proponents of the view that point shaving is widespread in the NCAA will need to show that a standard deviation of 1.35 points is significantly greater than the true standard deviation of the betting market's error.

The 1990-1991 through 2007-2008 data set provides some evidence of the source of the betting market's error. When the data are partitioned[1] into four subsets, defined by conference/nonconference and neutral court/nonneutral court, only the conference games on nonneutral courts have strong favorites covering significantly less than half the time. Of the 32,002 games in this subset, 5,606 had strong favorites. Excluding the 146 games that were pushes, 47.4% of the games with strong favorites covered the spread. A test of the null hypothesis that the true proportion is 0.50 yields a two-tailed p value of .000127. The other three data subsets have corresponding p values greater than .59. These results are suggestive that the regression effect may be attributable to errors in estimating home court advantages.

2. Argument in Defense of the NCAA—Exhibit B

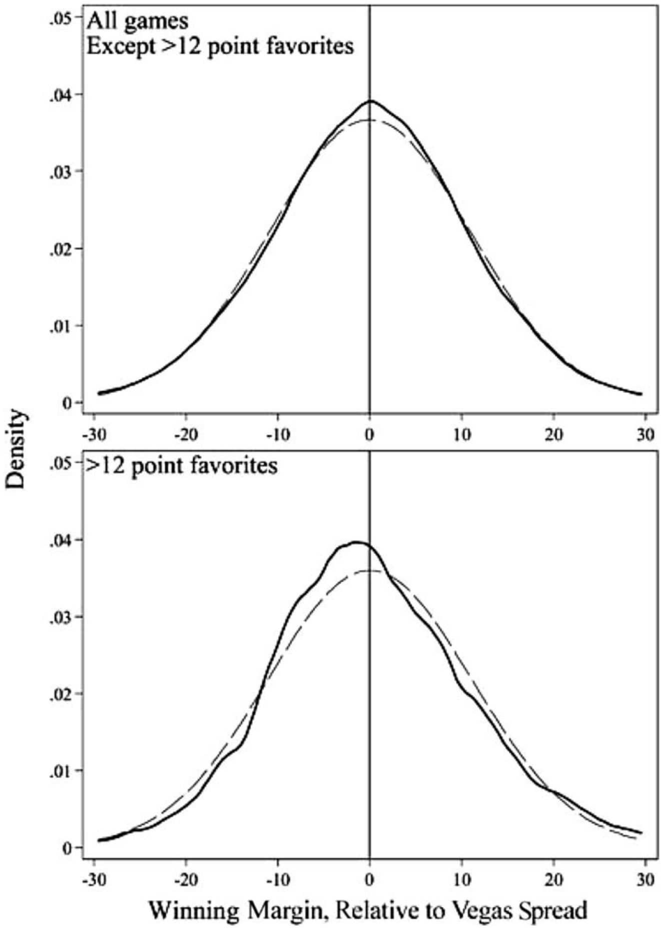
In addition to falling prey to the regression fallacy, Wolfers (2006) is led astray by the shape of the distribution of game outcomes relative to the spread, reproduced here as Figure 1. Wolfers notes "[c]ompared to the normal distribution, this figure suggests that "too few" strong favorites beat the spread and that this missing probability mass is largely displaced to outcomes in which the team wins, but fails to cover" (Wolfers, 2006, pp. 280-281). The "too few" is because of the regression effect that acts to shift the distribution to the left. The extra probability mass on the left, however, is not a shift from the right side of the distribution. Its peculiar shape is because of a lack of games ending as ties. Note that games that are tied at the end of regulation play must originally fall below −12 in the distribution. With play continuing beyond regulation, these games are redistributed. Because strong favorites should still be favored to win, the majority of these games should result in a win for the favored team, shifting the probability mass to the right relative to where ties would lie. When combined with the regression effect, the lack of tie games confers the appearance of a leftward leaning distribution. The empirical evidence supports this supposition.

Of the 10,672 games in the 1990-1991 through 2007-2008 data set with strong favorites, 220 games ended regulation play in a tie. Of these games, 173 (78.6%) were won by the favored team. Of these games, none of the favored teams tied or beat the spread. Figure 2 shows the kernel density estimate of the distribution of the winning margins relative to the spreads, along with the distribution of the margins relative to the spreads at the end of regulation play. The end-of-regulation-play distribution is visibly more symmetrical than the end-of-game distribution. As further proof, Figure 3 shows the net shift in the discrete frequency distribution from the end of regulation play to the end of the game, showing a clear shift from below −12.0 to outcomes between −12.0 and −1.5. Any remaining asymmetry in Figure 2 might be attributable to the skewness of the conditional distribution.

3. Discussion

If the betting market makes unbiased, but imprecise, estimates of teams' true abilities, then this needs to be incorporated into any use of "forensic economics" to determine the presence or absence of point shaving. In the case of NCAA Division I basketball games—and NBA games, too—assertions of measurable levels of point shaving by strong favorites are based on faulty analyses. This does not imply that point shaving does not exist. Actual cases of point shaving clearly demonstrate its existence. But the strongest evidence for widespread point shaving is tainted by faulty statistics.

Figure 1
Probability Distribution: Game Outcomes Relative to the Spread



Source: Wolfers (2006).

The regression effect is subtle and has confounded researchers in the past. As in previous instances, failure to recognize the regression effect can lead to incorrect policy prescriptions. Such is the case here. Wolfers' (2006) call to change the structure of the NCAA basketball betting markets from one using point spreads, to one based on winning margins alone, is premature.

Figure 2
Probability Distribution: Margin Relative to the Spread at the End of the Game and at the End of Regulation Play

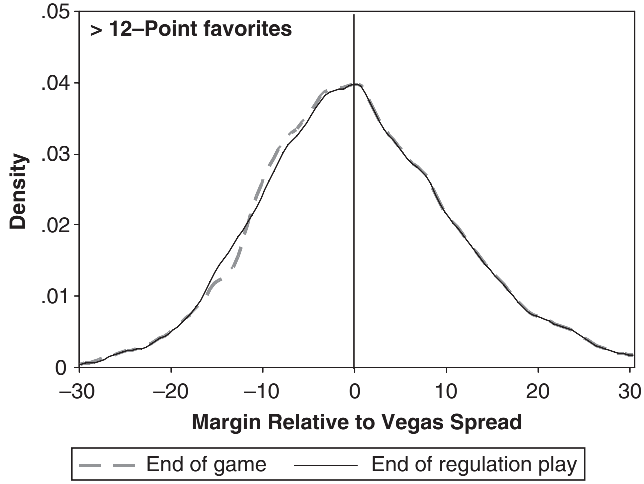
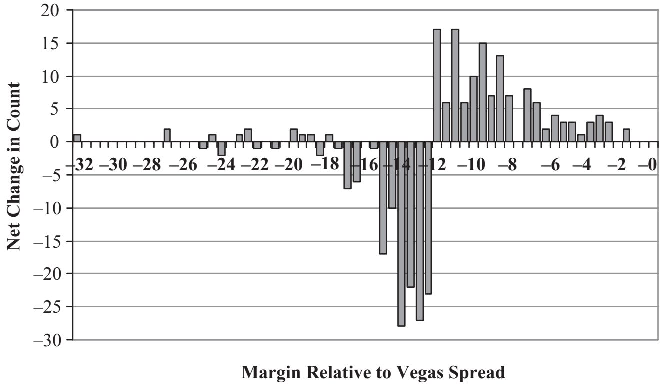


Figure 3
Net Change in Frequency Distribution Because of the Resolution of Games Tied at the End of Regulation Play



The nonlinear payoff structure from point shaving, whereby a team can fail to cover the betting market's spread yet still win the game, provides an incentive for point shaving. A risk-neutral player considering participating in point shaving would compare this benefit to the expected penalty. If either the probability of detection or the penalty if caught were sufficiently high, players would opt to play honestly. Although penalties for point shaving can be inferred by looking at penalties from prior point shaving scandals, the probability of detection is largely unknown, as the true prevalence of point shaving is in question. The NCAA would prefer a low incidence of point shaving, as this would reinforce the perception that the probability of detection is high. The danger in Wolfers' analysis, via his failure to properly use "forensic statistics," is that players may believe his results, which have been widely disseminated, and incorrectly infer that the probability of being caught is small. This could subsequently increase the reported and unreported incidents of point shaving.

In closing, several suggested refinements to this study bear mentioning. First, if strong favorites cover the spread less than 50% of the time, one would expect some bettors to specialize in betting solely on games with strong favorites. This should cause a downward bias in large Vegas spreads, partially masking the evidence of a regression effect. Related to this issue is whether the regression effect is strong enough for such a betting strategy to prove profitable. Finally, the betting market's error in forecasting spreads might diminish over a season, leading to a reduction in the observed regression effect. Finding this to be true would lend further support to the regression effect as the underlying cause of a majority of strong favorites failing to cover the point spread. Failure to find this pattern, on the other hand, would be inconclusive, as it may indicate that the source of the betting market's error is tied to estimating the strength of a team against a specific opponent in a specific game, rather than in estimating a team's general strength.

Note

1. See Raymond Sauer (1998, pp. 2050-2054) for the general importance of partitioning data sets when analyzing point spread betting markets.

References

Beck, H., & Schmidt, M. S. (2007, August 16). Former N.B.A. Referee pleads guilty. *The New York Times (Late Edition (East Coast))*, D.1.

Borghesi, R. (2008). Widespread corruption in sports gambling: fact or fiction? *Southern Economic Journal*, *74*, 1063-1069.

Cannella, S. (2006, March 27). Shaving lather. *Sports Illustrated*, *104*, 26.

Fridson, M. (2006, March 27). Nab crooks, not shavers. *Barron's*, *86*, 48.

Gibbs, J. (2007). Point shaving in the NBA: An economic analysis of the National Basketball Association's point spread betting market. *Undergraduate Honor's Thesis,* Stanford University.

Knightly, A. M. (2006, March 27). NCAA casting wary eye on betting. *Las Vegas Business Press* 23, 1, 10.

Leonhardt, D. (2006, March 8). Sad suspicions about scores in basketball. *The New York Times (Late Edition (East Coast))*, C.1.

McCarthy, M. (2007, May 9). Point-shaving remains a concern in college athletics. *USA Today (Sports Section)*, 01c.

Sauer, R. D. (1998). The economics of Wagering markets. *Journal of Economic Literature*, *36*, 2021-2064.

Wolfers, J. (2006). Point shaving: Corruption in NCAA Basketball. *American Economic Review*, *96*, 279-283.

Neal Johnson is a visiting assistant professor in the Department of Economics at Pacific Lutheran University.