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Does Losing Lead to Winning? An Empirical Analysis for Four Sports

Bouke Klein Teeselink,[a,*] Martijn J. van den Assem,[b,c] Dennie van Dolder[d]

[a] Marketing Department, Yale School of Management, New Haven, Connecticut 06511; [b] School of Business and Economics, Vrije Universiteit Amsterdam, 1081 HV Amsterdam, Netherlands; [c] Tinbergen Institute, 1082 MS Amsterdam, Netherlands; [d] Department of Economics, University of Essex, Colchester CO4 3SQ, United Kingdom

*Corresponding author

Contact: b.kleinteeselink@yale.edu, https://orcid.org/0000-0001-8869-3435 (BKT); m.j.vanden.assem@vu.nl, https://orcid.org/0000-0001-5166-1288 (MJvdA); d.vandolder@essex.ac.uk, https://orcid.org/0000-0002-2498-8311 (DvD)

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Abstract. Berger and Pope (2011) show that being slightly behind increases the likelihood of winning in professional (National Basketball Association; NBA) and collegiate (National Collegiate Athletic Association; NCAA) basketball. We extend their analysis to large samples of Australian football, American football, and rugby matches, but find no evidence of such an effect for these three sports. When we revisit the phenomenon for basketball, we only find supportive evidence for NBA matches from the period analyzed in Berger and Pope (2011). There is no significant effect for NBA matches from outside this sample period, for NCAA matches, or for matches from the Women's National Basketball Association. High-powered meta-analyses across the different sports and competitions do not reject the null hypothesis of no effect of being slightly behind on winning. The confidence intervals suggest that the true effect, if existent at all, is likely relatively small.

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1. Introduction

In an influential paper, Berger and Pope (2011, henceforth BP) argue that lagging behind halfway through a competition does not necessarily imply a lower likelihood of winning, and that being slightly behind can actually increase the chance of coming out on top. In particular, they argue that because winning is the goal, the performance of the opponent will serve as a salient benchmark—or reference point—to which a competitor will compare their own performance during the competition. Research on goals as reference points shows that people who are slightly below their goal work harder than those who have reached or exceeded it, in a manner consistent with loss aversion (Heath et al. 1999, Pope and Simonsohn 2011, Corgnet et al. 2015, Allen et al. 2016). Analogously, BP argue that people who are slightly behind in a competition may be more motivated than people who are slightly ahead.

To test this hypothesis, BP analyze more than 60,000 professional and collegiate basketball matches. Their main analyses focus on the score difference at half-time because the relatively long break allows players to reflect on their position relative to their opponent. BP find that National Basketball Association (NBA) teams that are slightly behind are between 5.8 and 8.0 percentage points more likely to win the match than those that are slightly ahead.[1] For collegiate matches of the National Collegiate Athletic Association (NCAA), they similarly find a positive effect of being behind, but the size of the effect is smaller and not always statistically significant. BP is regarded as one of the first studies to show that loss aversion is not limited to inexperienced subjects in low-stakes settings, but also affects the behavior of experts in a high-stakes professional environment.

The present paper first extends the analysis of BP to large samples of Australian football, American football, and rugby matches, and then revisits the analysis of basketball. Our main analyses consider the effect of being slightly behind at half-time on the likelihood of winning the match. To estimate this effect, we use a regression discontinuity design (RDD; Thistlethwaite and Campbell 1960). Whenever possible, we also analyze whether marginally trailing at half-time improves the likelihood of winning the third or fourth quarter separately, as is also done in BP, and whether marginally trailing after the third quarter improves the odds of winning the match.

For Australian football, American football, and rugby, we find no support for the hypothesis that being slightly behind improves performance. For basketball, we replicate the finding that trailing at half-time in NBA matches from the period analyzed in BP improves the odds of winning. Our estimated effect size of 8.3 percentage points is even somewhat larger than the top of the effect size range reported in BP. However, we exclusively obtain null results for NBA matches from outside that period, for collegiate matches, and for matches from the Women's National Basketball Association (WNBA).

To synthesize our results, we conduct meta-analyses across sports and competitions. According to the most comprehensive meta-analysis, the effect of trailing at half-time on winning the match is 1.2 percentage points. Statistically, this estimate is not significant. If we exclusively consider matches that have not been analyzed previously, the estimated overall treatment effect is economically and statistically indistinguishable from zero. The confidence intervals suggest that the true effect, if existent at all, is likely relatively small. Similar conclusions follow from meta-analyses of the effect of trailing at half-time on winning the third or fourth quarter separately and from a meta-analysis of the effect of trailing after the third quarter on winning the match. The overall conclusion, therefore, is that the results of BP do not generalize.

The paper proceeds as follows. Section 2 explains our empirical strategy, Sections 3–6 show the results for each of the four sports, Section 7 presents the meta-analyses, and Section 8 discusses the findings and concludes.

2. Empirical Strategy

We employ an RDD to estimate the causal impact of being behind on performance. RDDs are used to estimate treatment effects in nonexperimental settings. The distinct feature is that the treatment is assigned based on whether an observed covariate, the so-called running variable, exceeds a specific cutoff value. Under the assumption that all other determinants of the outcome variable are continuous through this cutoff value, the variation in the treatment status is "as good as randomized by an experiment" (Lee 2008, p. 676), and a discontinuity in the outcome variable at the cutoff can be causally attributed to the treatment.

In our main analyses, the running variable is the score difference at half-time, and the cutoff value is zero. We estimate the following regression model:

$$Y_i = \alpha + \tau \times T_i + \beta_1 \times X_i + \beta_2 \times T_i \times X_i + \varepsilon_i, \qquad (1)$$

where Y_i is an indicator variable that takes the value of one if team i wins the match and X_i is the half-time score difference between team i and the opposing team. The treatment variable T_i takes the value of one if team i is behind at half-time. The coefficient τ represents the discontinuity in the winning probability at a zero score difference. This coefficient is positive under the hypothesis that being slightly behind improves performance. The interaction term $T_i \times X_i$ allows for different slopes above and below the cutoff. We systematically take the perspective of the home team to avoid using every match twice, and omit matches where teams were tied at half-time.[2]

If the assumption of a piecewise linear relationship between the winning probability and the half-time score difference is violated, then the regression model will generate a biased estimate of the treatment effect. Hahn et al. (2001) propose the use of local linear regression to solve this problem. Even if the true relationship is nonlinear, a linear specification can provide a close approximation within a limited bandwidth around the cutoff. A downside of this solution is that it reduces the effective number of observations, and, therefore, the precision of the estimate. To strike the appropriate balance between bias and precision, we use the local linear method proposed by Calonico et al. (2014). This method selects the bandwidth that minimizes the mean squared error, corrects the estimated treatment effect for any remaining nonlinearities within the bandwidth, and linearly downweights observations that are farther away from the cutoff.

Our RDD requires that the skill difference between home and away teams is continuous at the cutoff. To examine whether this assumption holds, we also estimate a modified version of Equation (1), where the outcome variable is the skill difference between the two teams. As a proxy for the skill difference, we use the difference between the proportion of home matches won by the home team and the proportion of away matches won by the away team during the calendar year in which the given match was played.[3] For this skill difference continuity test, we again employ the local linear method proposed by Calonico et al. (2014).

We examine four sports: Australian football, American football, rugby, and basketball.[4] In all these sports, teams generally score a large number of points. The validity of our RDD hinges on the assumption of a piecewise linear relationship between the full-time winning probability and the half-time score difference around the cutoff. In sports where teams typically score only a small number of points, even the smallest possible half-time disadvantage has a strong impact on the probability of losing the match, and the marginal effect of larger differences quickly converges to zero. Consequently, for low-scoring sports, the assumption of linearity is violated even within a small bandwidth around the cutoff. Also, and perhaps even more importantly, the hypothesized psychological effect is unlikely to occur in such sports: when being behind is relatively hard to overcome, trailing by one or a few points is more likely to discourage than to motivate (Fershtman and Gneezy 2011, Gill and Prowse 2012).

Matches have to satisfy a number of criteria for inclusion. First, the half-time score, the full-time score, and the year of play need to be available. Second, the match must not have been tied at the end of regulation time (including stoppage time, excluding overtime). Last, the match must not be the only home (away) match played by the home (away) team in the given year. The latter condition is necessary to test the assumption that the skill difference between home and away teams is continuous at the cutoff.

We present the results on a sport-by-sport basis. For each sport, we look at multiple competitions. We always start with graphs that show the proportion of matches won by home teams at given half-time score differences. We construct these graphs following the approach proposed by Calonico et al. (2015). Smooth curves on both sides of the cutoff give a visual impression of whether the relationship is approximately linear within the estimated bandwidth and provide a first indication of the existence of a discontinuity. Next, we present the results for the main RDD, which is the RDD where the outcome variable takes the value of one if the home team won the match (at the end of regulation time, including stoppage time and excluding overtime), and where the running variable is the score difference at half-time. To assess the robustness of the results, we examine the sensitivity of the estimated coefficients to a range of imposed alternative bandwidths. If matches of a sport consist of quarters and we have data on the score after the third quarter, we also analyze the effect of trailing at half-time on winning the third quarter and the fourth quarter separately, as well as the effect of trailing after the third quarter on winning the match. Last, for each RDD, we examine the assumption that the skill difference is continuous at the cutoff.

3. Australian Football

3.1. Description and Data

The first sport that we consider is Australian football. We use data from two competitions. One is the Australian Football League (AFL), which is widely considered to be the sport's most important competition. It is the only fully professional Australian football league and the fourth most popular sports competition in the world by average weekly attendance.[5] The other is the South Australian National Football League (SANFL), a semiprofessional regional football league played in South Australia.

Australian football is played by two teams of 18 players each on an oval-shaped pitch. At both ends of the field, there are four goal posts behind a goal line. The object of the game is to kick the ball between the posts. A team scores six points by kicking the ball between the middle two posts. Teams score one point (i) when they kick the ball between a middle post and one of the outer posts, (ii) when a player on the ground touches the ball before it goes between the middle posts, and (iii) when a defender is forced to carry the ball across its own goal line. Australian football matches consist of four 20-minute quarters. There is a 20-minute half-time break, and a 6-minute break after both the first and third quarters.

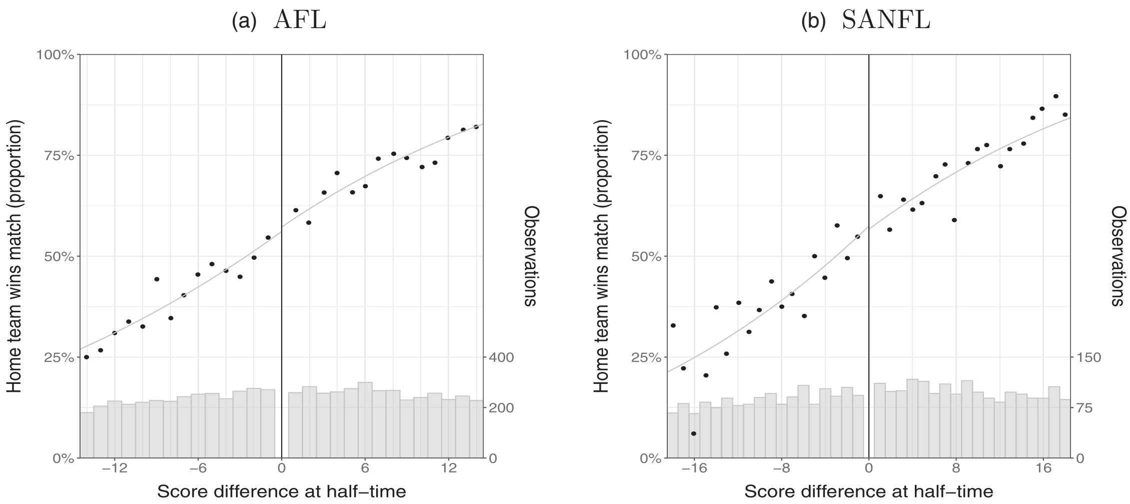
We obtained data for 15,209 AFL and 6,724 SANFL matches that satisfy the criteria stipulated in Section 2.[6] The exclusion of matches with a zero half-time score difference reduces these samples to 14,945 (AFL) and 6,622 (SANFL) matches. Table 1 summarizes the data. On average, the two teams combined scored 171 points in AFL matches and 185 points in SANFL matches. At half-time, these numbers were 84 and 90, respectively. In both samples, home teams on average led by four points at half-time and by nine points at full-time, and they won roughly 60% of the matches.

Table 1. Summary Statistics for Australian Football

	Mean	Standard deviation	Min	Quartile 1	Median	Quartile 3	Max
Panel A: AFL (1897–2018, N = 14,945)							
Total points at half-time	84.4	25.3	10	67	84	101	210
Total points at full-time	171.1	46.3	24	140	172	202	345
Score difference at half-time	4.4	24.2	−107	−11	5	20	120
Score difference at full-time	8.9	40.7	−164	−18	9	35	190
Home team wins match	0.60	0.49	0	0	1	1	1
Panel B: SANFL (1950–2018, N = 6,622)							
Total points at half-time	90.1	24.9	20	73	89	106	216
Total points at full-time	184.6	44.8	38	153	183	214	396
Score difference at half-time	4.3	27.4	−112	−14	5	22	108
Score difference at full-time	8.9	48.0	−178	−23	10	40	238
Home team wins match	0.58	0.49	0	0	1	1	1

Notes. The table displays the summary statistics for AFL and SANFL matches where the half-time score difference was nonzero. *Total points at half-time (full-time)* is the total number of points scored by the two teams combined at half-time (full-time). *Score difference at half-time (full-time)* is the half-time (full-time) score difference between the home and away team. *Home team wins match* is an indicator variable that takes the value of one if the home team won the match.

Figure 1. Regression Discontinuity Plots for Australian Football



Notes. The figure shows the regression discontinuity plots for (a) AFL and (b) SANFL matches with a half-time score difference that was within a limited bandwidth around the cutoff value of zero. The plots are constructed using the approach proposed by Calonico et al. (2015). Each dot represents the proportion of matches won by the home team at a given half-time score difference. The curves on both sides of the cutoff are fourth-order polynomials. The bandwidths correspond to the bandwidth estimates deriving from our main regression discontinuity design. Bars depict the number of observations.

3.2. Analysis and Results

We first visually explore the relationship between the half-time score difference and the full-time winning probability. Figure 1 shows that the relationship is approximately linear on both sides of the cutoff value of zero, both for AFL and for SANFL matches. The winning probability increases at a rate of roughly two percentage points per point. There is no clear evidence of a discontinuity at the cutoff.

Table 2, Panel A presents the results for the main RDD. There is no evidence of a positive performance effect of trailing. The point estimate for AFL teams even indicates that being slightly behind at half-time *decreases* the chances of winning by 3.4 percentage points, but this effect is statistically insignificant ($p = 0.253$). For the SANFL sample, the point estimate of the effect of being behind is virtually zero ($p = 1.000$). The wide 95% confidence intervals for the two estimates, however, indicate that a considerable range of positive and negative effect sizes cannot be ruled out. Figure S1 in the online appendix shows that the results are robust to a range of imposed alternative bandwidths.

A possible explanation for the absence of evidence of a performance-enhancing effect is that the effect is too ephemeral to materially affect the full-time match outcome. If being behind at half-time improves performance only temporarily, we are more likely to find an effect in a shorter period directly following the half-time break. We therefore also analyze the effect of being behind on performance in the third quarter separately. For completeness, we also look at the effect on the fourth quarter. In these alternative RDDs, the outcome variable takes the value of one if the home team scored more points than the away team in the given quarter. We again exclude matches where the half-time score difference was zero, and now also omit matches where both teams scored the same number of points in the quarter of interest. Figures S2 and S3 in the online appendix show the regression discontinuity plots, and Panels B and C in Table 2 report the estimated effects. Mirroring the picture emerging from the main RDD, there is no statistically significant evidence that trailing at half-time affects performance in the next (third) quarter (AFL: $\tau = -0.004, p = 0.889$; SANFL: $\tau = 0.027, p = 0.508$). Not surprisingly, the estimated treatment effects in the final (fourth) quarter are also nonsignificant (AFL: $\tau = -0.028$, $p = 0.318$; SANFL: $\tau = 0.004, p = 0.918$).

Being slightly behind is potentially more consequential in later stages of the match. We therefore also analyze whether being behind after the third quarter improves performance in the final quarter. In this alternative RDD, winning the match is the outcome variable, and the score difference after the third quarter is the running variable. We now include matches with a zero score difference at half-time and exclude those with a zero score difference after the third quarter. Figure S4 in the online appendix shows the regression discontinuity plots, and Table 2, Panel D reports the estimated treatment effects. The estimates for the AFL ($\tau = 0.016$, $p = 0.674$) and SANFL ($\tau = -0.020, p = 0.707$) samples are both nonsignificant.

Last, to investigate the validity of the RDDs, we examine the identifying assumption that the skill difference between the home and away teams is continuous at the cutoff value of a zero score difference. Figures S5 and S6 and Table S1 in the online appendix show that there is

Table 2. Results for Australian Football

	AFL	SANFL
Panel A: Score difference at half-time, winning match		
Behind at half-time	−0.034	0.000
	(−0.092, 0.024)	(−0.083, 0.082)
Bandwidth	14.73	18.47
Total observations	14,945	6,622
Included observations	6,902	3,348
Panel B: Score difference at half-time, winning third quarter		
Behind at half-time	−0.004	0.027
	(−0.053, 0.046)	(−0.054, 0.108)
Bandwidth	24.23	23.66
Total observations	14,599	6,471
Included observations	10,124	3,990
Panel C: Score difference at half-time, winning fourth quarter		
Behind at half-time	−0.028	0.004
	(−0.084, 0.027)	(−0.078, 0.087)
Bandwidth	19.61	23.04
Total observations	14,615	6,491
Included observations	8,577	3,997
Panel D: Score difference after third quarter, winning match		
Behind after third quarter	0.016	−0.020
	(−0.059, 0.091)	(−0.122, 0.083)
Bandwidth	12.04	16.55
Total observations	15,040	6,655
Included observations	4,447	2,230

Notes. The table reports the estimated effect of being slightly behind on the likelihood of winning for AFL and SANFL matches using a regression discontinuity design. Treatment effects are estimated with the local linear nonparametric estimator proposed by Calonico et al. (2014). The outcome variable is *Home team wins match* (Panels A and D), *Home team wins third quarter* (Panel B), or *Home team wins fourth quarter* (Panel C). The running variable is *Score difference at half-time* (Panels A–C) or *Score difference after third quarter* (Panel D). *Bandwidth* is the largest absolute score difference for matches included in the RDD. *Total observations* is the number of observations in the sample. *Included observations* is the number of observations within the bandwidth. Numbers in parentheses represent 95% confidence intervals. Asterisks denote significance at the 0.01 (***), 0.05 (**), and 0.1 (*) level.

no significant evidence for a discontinuity at half-time (AFL: $p = 0.216$; SANFL: $p = 0.633$) or at the end of the third quarter (AFL: $p = 0.879$; SANFL: $p = 0.623$).

Taken together, the results for Australian football do not support the hypothesis that being slightly behind increases the odds of winning. We cannot reject the null hypothesis of no effect, neither in the two main analyses nor in the additional analyses.

4. American Football

4.1. Description and Data

The second sport that we consider is American football. We analyze matches from the National Football League (NFL) and from the Division I Football Bowl Subdivision of the NCAA. The NFL is seen as the most important American football league, and it is the best attended professional sports league in the world.[7] The NCAA Division I Football Bowl Subdivision is the highest division of college football in the United States.

American football matches are played between two teams of 11 players. The playing field is rectangular and contains an end zone on each side. In each end zone, there are two posts with a crossbar. Teams score a touchdown, worth six points, when a player either catches the ball in the opposing team's end zone or advances into the end zone while holding the ball. After a touchdown, the offensive team gets the opportunity to score one point by kicking the ball through the posts from a distance of 15 yards from the end zone or two points by taking the ball into the end zone from a distance of 2 (NFL) or 3 (NCAA) yards from the end zone. A team scores a field goal, worth three points, by kicking the ball through the posts during normal play. The defensive team earns two points when they tackle a member of the opposing team who holds the ball in the opposing team's end zone. Matches are divided into four 15-minute quarters. There is a 12-minute half-time break and a 2-minute break after both the first and third quarters.

Table 3. Summary Statistics for American Football

	Mean	Standard deviation	Min	Quartile 1	Median	Quartile 3	Max
Panel A: NFL (1945–2017, N = 10,590)							
Total points at half-time	20.7	8.7	2	14	20	27	62
Total points at full-time	40.6	12.1	8	32	41	49	113
Score difference at half-time	2.0	11.5	–35	–7	3	10	42
Score difference at full-time	2.9	15.5	–55	–7	3	14	59
Home team wins match	0.58	0.49	0	0	1	1	1
Panel B: NCAA (2003–2018, N = 7,024)							
Total points at half-time	29.0	11.8	2	21	28	37	94
Total points at full-time	55.0	17.6	5	43	54	66	137
Score difference at half-time	4.3	15.2	–49	–7	5	14	56
Score difference at full-time	7.1	21.5	–73	–7	7	22	78
Home team wins match	0.63	0.48	0	0	1	1	1

Notes. The table displays the summary statistics for NFL and NCAA matches where the half-time score difference was nonzero. Definitions are as in Table 1.

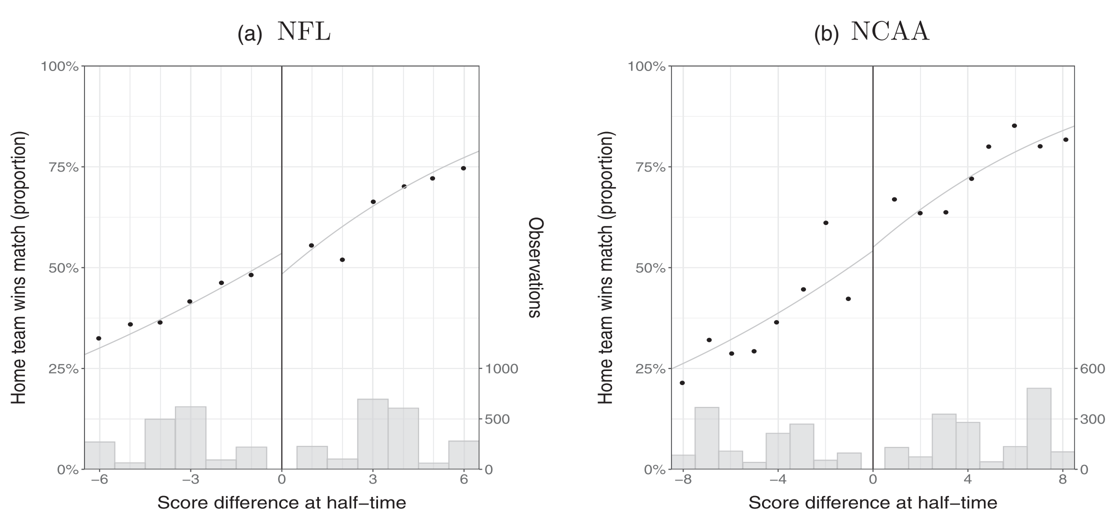
We obtained data for 11,622 NFL and 7,536 NCAA matches that satisfy the data requirements outlined in Section 2.[8] Excluding matches with a zero half-time score difference reduces the samples to 10,590 (NFL) and 7,024 (NCAA) matches. Table 3 shows summary statistics. Together, teams scored on average 41 (NFL) and 55 (NCAA) points per match. At half-time, these numbers were 21 and 29, respectively. Home teams led by an average of two (NFL) and four (NCAA) points at half-time and by three (NFL) and seven (NCAA) points at full-time. Home teams won roughly 60% of the matches.

4.2. Analysis and Results

In American football, some score differences are more common than others because of the scoring system. Figure 2 shows that differences of two or five are relatively rare, whereas differences of three or four occur relatively often. Nevertheless, the proportion of home teams winning the match increases approximately linearly with the half-time score difference, and the rate of roughly four percentage points per point for both NFL and NCAA matches means that small score differences do not have a major impact on the probability of winning. The regression discontinuity plot for NFL matches suggests that there is a small negative discontinuity at a zero half-time score difference, which would mean that being slightly behind enhances performance. For NCAA matches, there is no indication that marginally trailing affects teams' performance.

Table 4, Panel A presents the results for the main RDD. The estimated effect sizes of 4.8 (NFL) and –4.6 (NCAA) percentage points are large, but the 95% confidence intervals are wide. Statistically, there is no significant evidence that trailing at half-time affects the

Figure 2. Regression Discontinuity Plots for American Football



Notes. The figure shows the regression discontinuity plots for (a) NFL and (b) NCAA matches. Definitions are as in Figure 1.

Table 4. Results for American Football

	NFL	NCAA
Panel A: Score difference at half-time, winning match		
Behind at half-time	0.048	−0.046
	(−0.072, 0.168)	(−0.160, 0.067)
Bandwidth	6.06	8.70
Total observations	10,590	7,024
Included observations	3,736	2,812
Panel B: Score difference at half-time, winning third quarter		
Behind at half-time	0.054	0.034
	(−0.043, 0.152)	(−0.100, 0.168)
Bandwidth	8.72	8.79
Total observations	8,150	5,804
Included observations	4,344	2,303
Panel C: Score difference at half-time, winning fourth quarter		
Behind at half-time	0.083	0.000
	(−0.023, 0.189)	(−0.106, 0.106)
Bandwidth	7.42	12.30
Total observations	8,606	5,786
Included observations	4,449	3,325
Panel D: Score difference after third quarter, winning match		
Behind at half-time	−0.056	−0.002
	(−0.157, 0.045)	(−0.144, 0.139)
Bandwidth	7.18	7.18
Total observations	10,986	7,219
Included observations	4,635	2,154

Notes. The table reports the estimated effect of being slightly behind on the likelihood of winning for NFL and NCAA matches using a regression discontinuity design. Definitions are as in Table 2.

full-time winning probability, neither for NFL (p = 0.431) nor for NCAA (p = 0.425) matches. Figure S7 in the online appendix shows that the results are robust to alternative bandwidth choices.

The effect of trailing at half-time may be relatively short-lived. We therefore also analyze the effect of trailing at half-time on performance in the third (and fourth) quarter separately. The outcome variable now takes the value of one if the team scored more points than the opposing team in the quarter of interest. In addition to excluding matches where the half-time score difference was zero, we now also exclude matches where the two teams scored the same number of points in the quarter of interest. Figures S8 and S9 in the online appendix show the regression discontinuity plots, and Table 4, Panels B and C report the estimated discontinuities. Even though the two effect sizes are positive and considerable, there is no statistically significant evidence that trailing at half-time improves performance in the quarter after the break (NFL: $\tau = 0.054$, p = 0.277; NCAA: $\tau = 0.034$, p = 0.621). For the fourth quarter, the effect of trailing at half-time is also nonsignificant in the two samples (NFL: $\tau = 0.083$, $p = 0.125$; NCAA: $\tau = 0.000$, $p = 0.998$).

To further examine whether the effect exists within a single quarter, we also consider the effect of trailing after the third quarter on the likelihood of winning the match. We now include matches with a zero score difference at half-time and exclude matches with a zero score difference after the third quarter. Figure S10 in the online appendix shows the regression discontinuity plots, and Table 4, Panel D shows the discontinuity estimates. The two coefficients are negative and statistically insignificant (NFL: $\tau = -0.056, p = 0.278$; NCAA: $\tau = -0.002$, $p = 0.976$), which suggests that marginally trailing after the third quarter does not improve the chance of winning the match.

Last, we examine whether the identifying assumption that the skill difference between home and away teams is continuous at the cutoff holds. As shown in Figures S11 and S12 and Table S2 in the online appendix , there is no significant evidence of a discontinuity at half-time (NFL: p = 0.604; NCAA: p = 0.218) or after the third quarter (NFL: p = 0.722; NCAA: $p = 0.864$).

Overall, our analyses of American football do not provide convincing evidence of a performance-enhancing effect of being slightly behind.

5. Rugby

5.1. Description and Data

The third sport that we analyze is rugby. There are two similar yet distinct forms, namely rugby union and rugby league. For rugby union, our analysis covers international matches, including matches from famous tournaments such as the Six Nations Championship and the Rugby World Cup. For rugby league, we consider two different match categories: international matches from prominent leagues and tournaments such as the Super League and the Rugby League World Cup, and domestic matches played by British club teams.

Rugby union (league) is played between two teams of 15 (13) players. The rectangular playing field has two try lines across the width of the field, one on each side. These lines demarcate the in-goal areas. On the line, there are two goalposts with a crossbar. In rugby union (league), teams score five (four) points with a try, which happens when a team grounds the ball in the opposing team's in-goal area. Following a successful try, a team gets a conversion attempt, yielding two points if the team kicks the ball through the posts and over the crossbar from a chosen distance on the line perpendicular to the location where the try was scored. Teams score three (two) points if they kick a penalty between the posts and three (one) by kicking the ball through the posts during game play. Matches consist of two 40-minute periods, separated by a 10-minute half-time break.

We obtained data for 2,475 rugby union, 2,306 international rugby league, and 11,340 domestic rugby league matches that satisfy the data requirements outlined in Section 2.[9] Excluding matches with a zero half-time score difference reduces the samples to 2,338, 2,057, and 8,690 matches, respectively.[10] Table 5 gives summary statistics. On average, the two teams together scored approximately 25 points in the first half and 50 points in the whole match. At half-time, home teams on average led by one point (union) or three points (league). At full-time, the average score difference was two (union) or six (league). Home teams won approximately 60% of the matches.

5.2. Analysis and Results

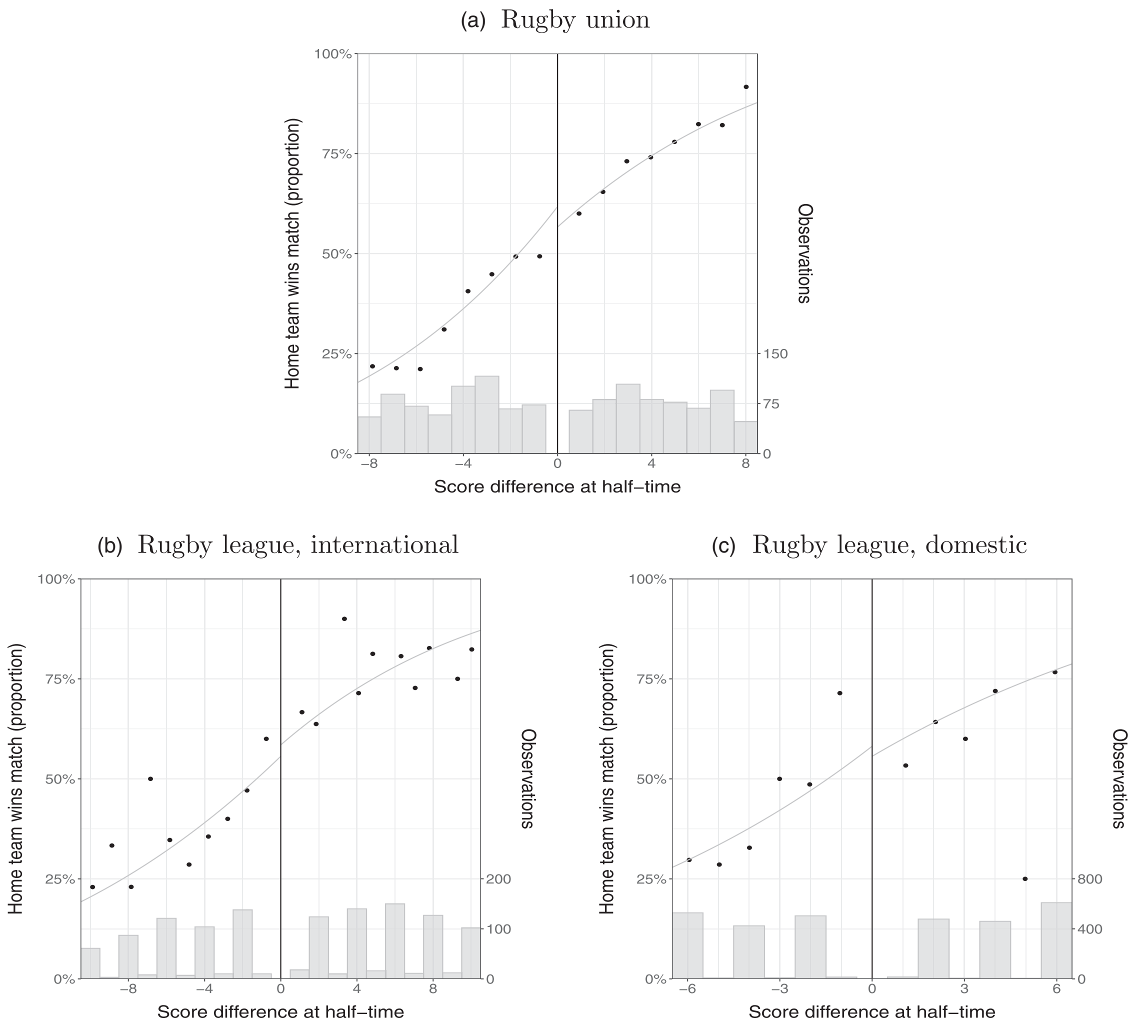
Figure 3 shows that virtually all score differences in rugby league are multiples of two. For example, the domestic rugby league sample includes only four matches with a half-time score difference of five, whereas there are 460 (609) matches with a half-time score difference of four (six). The distribution of score differences in rugby union is much more uniform. In each sample, there is an approximately linear relationship between the winning probability and the half-time score difference. The slope of roughly four percentage points per point implies that the impact of a small score difference on the probability of winning is only modest. All three samples exhibit some indication of a discontinuity in the winning probability at the half-time score difference of zero, but the signs are different. For rugby union and domestic rugby league matches, the regression discontinuity plot suggests that trailing increases the chance of winning the match, whereas for international rugby league matches, it suggests the opposite.

Table 5. Summary Statistics for Rugby

	Mean	Standard deviation	Min	Quartile 1	Median	Quartile 3	Max
Panel A: Rugby union (1990–2018, N = 2,338)							
Total points at half-time	23.6	9.5	7	16	22	29	87
Total points at full-time	47.0	17.5	9	35	45	57	162
Score difference at half-time	0.5	12.3	−68	−7	1	8	81
Score difference at full-time	1.7	24.1	−152	−11	2	14	128
Home team wins match	0.55	0.50	0	0	1	1	1
Panel B: Rugby league, international (1957–2017, N = 2,057)							
Total points at half-time	21.6	9.3	1	15	20	28	58
Total points at full-time	45.0	15.4	4	34	44	56	114
Score difference at half-time	3.1	12.9	−38	−6	4	12	52
Score difference at full-time	5.6	21.5	−74	−8	6	19	106
Home team wins match	0.61	0.49	0	0	1	1	1
Panel C: Rugby league, domestic (2006–2018, N = 8,690)							
Total points at half-time	24.8	9.7	2	18	24	30	84
Total points at full-time	51.5	16.1	6	40	50	62	144
Score difference at half-time	3.0	15.3	−68	−8	4	12	82
Score difference at full-time	5.9	27.0	−130	−12	6	22	144
Home team wins match	0.59	0.49	0	0	1	1	1

Notes. The table displays the summary statistics for rugby union, international rugby league, and domestic rugby league matches where the half-time score difference was nonzero. Definitions are as in Table 1.

Figure 3. Regression Discontinuity Plots for Rugby



Notes. The figure shows the regression discontinuity plots for (a) rugby union, (b) international rugby league, and (c) domestic rugby league matches. Definitions are as in Figure 1.

Table 6 shows the results for the main RDD. We find no convincing evidence that trailing at half-time discontinuously affects the chance of ultimately winning the match. The estimated effect of trailing ranges from a 2.9-percentage point decrease (international rugby league) to a 6.5-percentage point increase (domestic rugby league). Notwithstanding these considerable effect sizes, all are statistically insignificant (all $p > 0.242$). Figure S13 in the online appendix shows the estimated treatment effects for a range of imposed alternative bandwidths. The rugby union and international rugby league results are not very sensitive. The estimated treatment

Table 6. Results for Rugby

	Rugby union	Rugby league, international	Rugby league, domestic
Behind at half-time	0.034	−0.029	0.065
	(−0.114, 0.182)	(−0.194, 0.137)	(−0.044, 0.175)
Bandwidth	8.55	10.27	6.97
Total observations	2,338	2,057	8,690
Included observations	1,249	1,259	3,056

Notes. The table reports the estimated effect of being slightly behind on the likelihood of winning for rugby union, international rugby league, and domestic rugby league matches using a regression discontinuity design. Definitions are as in Table 2.

effect for domestic rugby league matches increases considerably when we impose a more restrictive bandwidth but remains statistically insignificant at the five-percent level. We cannot analyze the effect of being behind on a quarter by quarter basis because rugby matches do not consist of quarters.

Last, we examine whether the skill difference between home and away teams is continuous at the cutoff. Figure S14 and Table S3 in the online appendix show that there is no reason to doubt the validity of the RDDs; the discontinuity estimates are nonsignificant for all three samples (all $p > 0.164$).

In conclusion and consistent with the findings for Australian football and American football, rugby offers no compelling evidence that trailing at half-time improves the odds of winning.

6. Basketball

6.1. Description and Data

Thus far, we found no statistical support for the hypothesis that being behind improves the odds of winning in Australian football, American football, or rugby. We now turn to basketball—the sport that is central in BP—and consider five samples. The first two contain independently collected data for NBA matches. The NBA is widely considered to be the premier basketball competition in the world and pays the highest average salaries of all sports competitions.[11] We distinguish between NBA matches that took place in the period analyzed in BP and NBA matches from outside that period. Our third and fourth samples cover matches of the NCAA, the association that organizes the main intercollegiate basketball competition in the United States. One of these corresponds to the NCAA sample analyzed in BP and was provided to us by the authors. The other consists of independently collected data for more recent NCAA matches. Our fifth sample contains matches of the WNBA, the women's counterpart to the NBA.

Basketball is played by two teams of five players each. It is played on a rectangular court, with baskets at each end. Teams obtain two points by successfully throwing the ball through the opposing team's hoop from the area inside the three-point arc, a semicircle around the hoop, and three points by throwing the ball through the hoop from beyond the arc. After a foul, a team gets awarded one or more free throws, which are worth one point each. NBA (WNBA) matches are played in four quarters of 12 (10) minutes separated by a 10-minute half-time break and 2-minute breaks after the first and third quarters. NCAA matches are played in two 20-minute halves and have a 15-minute half-time break.

We obtained data for a total of 35,921 NBA, 97,639 NCAA, and 4,666 WNBA matches that satisfy the criteria outlined in Section 2.[12] Approximately half of the NBA matches were played between November 5, 1993 and March 1, 2009, the period that was analyzed in BP. This subset, henceforth the "NBA BP" sample, comprises 18,230 matches.[13] The sample of remaining NBA matches, henceforth the "NBA non-BP" sample, includes 17,691 matches played either between June 14, 1987 and June 20, 1993 or between March 2, 2009 and June 8, 2018. The NCAA data comprise the subset of 41,801 matches played between November 11, 1999 and March 22, 2009 that was analyzed in BP, henceforth the "NCAA BP" sample, and a subset of 55,838 matches played between March 23, 2009 and March 11, 2020, henceforth the "NCAA non-BP" sample. The exclusion of matches with a zero half-time score difference reduces the samples to 17,535 (NBA BP), 17,001 (NBA non-BP), 40,216 (NCAA BP), 53,751 (NCAA non-BP), and 4,499 (WNBA) matches.

Table 7 summarizes the data. On average, the two teams combined scored around 200 (NBA) or 140 (NCAA and WNBA) points per match. At half-time, these averages were approximately 100 and 70, respectively. The average score differences at half-time and full-time were around two and four (NBA and WNBA) or four and seven (NCAA) points, respectively. Home teams won approximately 61% (NBA and WNBA) or 67% (NCAA) of the matches.

6.2. Analysis and Results

Figure 4 shows that the winning probability increases roughly linearly with the half-time score difference at a rate of approximately four percentage points per point in all five samples. In line with the findings in BP, there appears to be a negative discontinuity at a zero half-time score difference for the NBA BP and NCAA BP samples, suggesting that marginally trailing at half-time increases the likelihood of winning the match. Visual discontinuities for the NBA non-BP sample and for the WNBA sample similarly suggest that there is a performance-enhancing effect of being behind. There is no indication of such an effect for NCAA non-BP matches.

Table 8, Panel A shows the results for the main RDD. For the NBA BP sample, we find that trailing improves the odds of winning by 8.3 percentage points ($p = 0.015$). BP report an increase of 5.8–8.0 percentage points for the same sample period. Hence, our point estimate of the positive effect of trailing is even slightly higher. For the NCAA BP sample, our estimate of the discontinuity is 2.1 percentage points. This effect is not statistically significant. BP report effect sizes in the range of 2.1–2.5 percentage points for this sample, with the estimate based on their most flexible model specification similarly being nonsignificant. The differences between our results and those in BP for these two samples can be considered relatively

Table 7. Summary Statistics for Basketball

	Mean	Standard deviation	Min	Quartile 1	Median	Quartile 3	Max
Panel A: NBA BP (1993–2009, N = 17,535)							
Total points at half-time	97.1	12.4	55	89	97	105	152
Total points at full-time	193.0	20.0	121	179	193	206	286
Score difference at half-time	2.3	10.2	−39	−5	3	9	39
Score difference at full-time	3.6	13.3	−52	−6	5	12	65
Home team wins match	0.61	0.49	0	0	1	1	1
Panel B: NBA non-BP (1987–1993, 2009–2018, N = 17,001)							
Total points at half-time	103.1	12.8	58	95	103	111	174
Total points at full-time	205.0	20.8	133	191	204	219	320
Score difference at half-time	2.4	10.6	−41	−5	3	10	47
Score difference at full-time	3.9	13.7	−58	−6	5	13	68
Home team wins match	0.62	0.49	0	0	1	1	1
Panel C: NCAA BP (1999–2009, N = 40,216)							
Total points at half-time	64.8	11.7	25	57	64	72	125
Total points at full-time	138.2	19.6	62	125	138	151	253
Score difference at half-time	3.7	10.5	−43	−4	4	11	61
Score difference at full-time	6.4	14.9	−60	−4	7	15	93
Home team wins match	0.67	0.47	0	0	1	1	1
Panel D: NCAA non-BP (2009–2020, N = 53,751)							
Total points at half-time	65.5	11.5	22	57	65	73	146
Total points at full-time	139.3	19.4	65	126	139	152	241
Score difference at half-time	4.0	10.9	−40	−4	4	11	62
Score difference at full-time	6.9	15.7	−59	−4	7	16	104
Home team wins match	0.67	0.47	0	0	1	1	1
Panel E: WNBA (1997–2018, N = 4,499)							
Total points at half-time	71.9	12.8	26	63	72	80	119
Total points at full-time	146.8	20.1	78	133	146	160	217
Score difference at half-time	1.9	9.8	−32	−5	2	9	45
Score difference at full-time	3.5	13.0	−45	−7	5	12	59
Home team wins match	0.61	0.49	0	0	1	1	1

Notes. The table displays the summary statistics for NBA BP, NBA non-BP, NCAA BP, NCAA non-BP, and WNBA matches where the half-time score difference was nonzero. Definitions are as in Table 1.

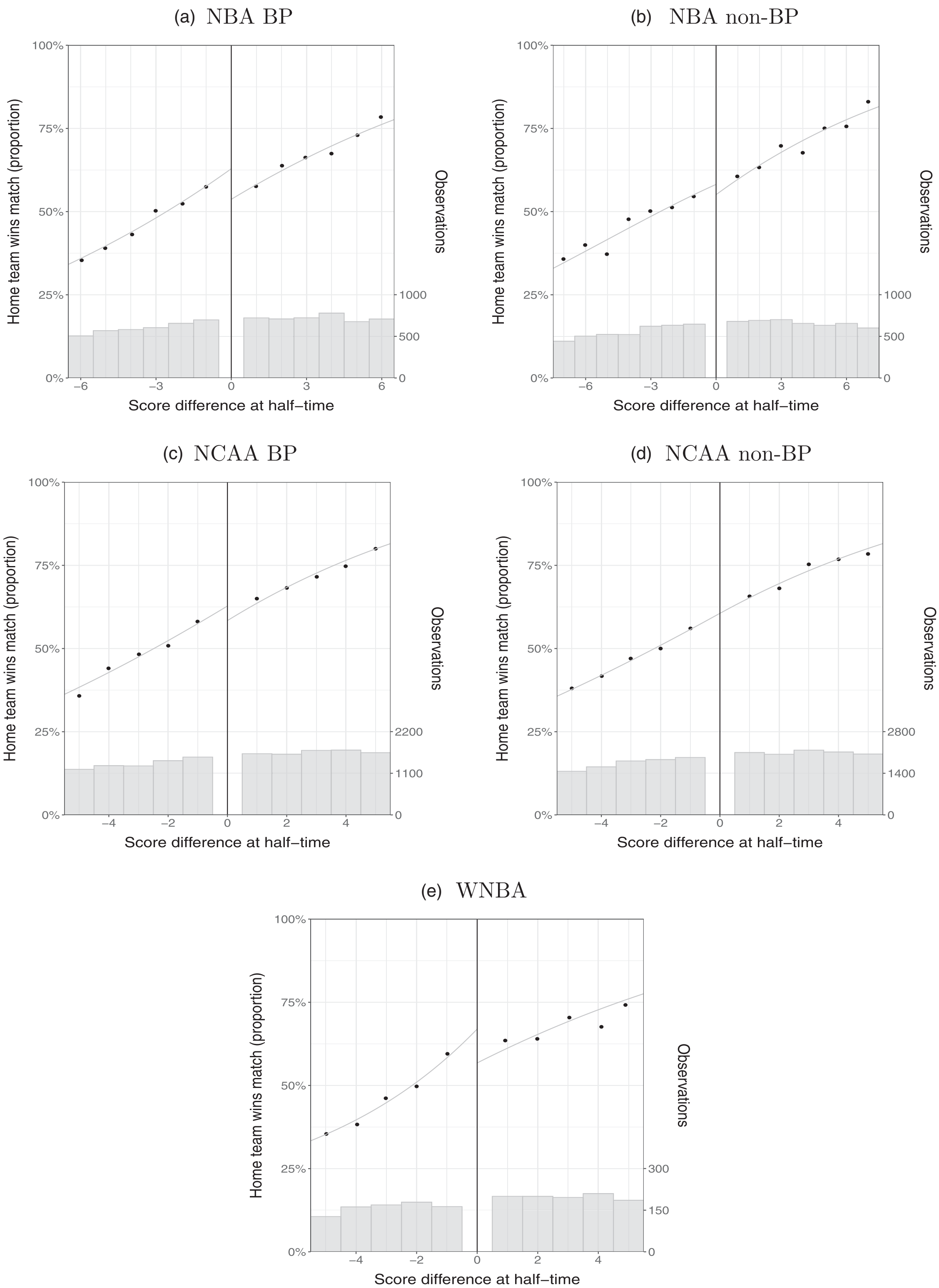
small in the light of the somewhat different methodological approaches and the independently collected NBA data.[14]

For the basketball samples that do not overlap with those analyzed in BP, the effects of being behind are all statistically insignificant. The three point estimates are 0.9 (NBA non-BP; $p = 0.788$), −0.1 (NCAA non-BP; $p = 0.945$), and 6.0 percentage points (WNBA; $p = 0.417$).[15] If we estimate the discontinuity for the two NBA samples combined, we obtain a statistically significant effect size of 5.0 percentage points ($p = 0.023$). For the combined NCAA data, the estimated effect size is relatively close to zero and statistically insignificant ($\tau = 0.008, p = 0.643$). Figure S15 in the online appendix shows that the results for the five individual samples are robust to imposing alternative bandwidths.

Next, we analyze the effect of being behind for the third and fourth quarters separately. BP find some evidence that the effect of trailing at half-time is stronger in the third than in the fourth quarter. We conduct these analyses for the NBA samples only, because NCAA matches do not consist of quarters and because we do not have quarter by quarter scoring data for the WNBA. We exclude matches in which the two teams scored the same number of points in the quarter of interest. Figures S16 and S17 in the online appendix show the regression discontinuity plots, and Table 8, Panels B and C report the estimated effects. Being behind at half-time increases the chance of winning the third quarter by 2.4 percentage points for NBA BP matches. In contrast to the results in BP, this effect is statistically insignificant ($p = 0.396$). In the NBA non-BP sample, the estimated treatment effect for the third quarter is negative and statistically not significantly different from zero ($\tau = -0.026, p = 0.436$). For the two NBA samples combined, the estimated effect is close to zero and nonsignificant ($\tau = 0.002, p = 0.922$). The effect of trailing at half-time on winning the fourth quarter is nonsignificant throughout (NBA BP: $\tau = 0.017, p = 0.633$; NBA non-BP: $\tau = 0.029, p = 0.379$; NBA all: $\tau = 0.026, p = 0.237$).

For the NBA, we also examine the effect of trailing after the third quarter on the probability of winning the match. This analysis includes matches in which the

Figure 4. Regression Discontinuity Plots for Basketball



Notes. The figure shows the regression discontinuity plots for (a) NBA BP, (b) NBA non-BP, (c) NCAA BP, (d) NCAA non-BP, and (e) WNBA matches. Definitions are as in Figure 1.

Table 8. Results for Basketball

	NBA BP	NBA non-BP	NBA all	NCAA BP	NCAA non-BP	NCAA all	WNBA
Panel A: Score difference at half-time, winning match							
Behind at half-time	0.083**	0.009	0.050**	0.021	−0.001	0.008	0.060
	(0.016, 0.150)	(−0.056, 0.074)	(0.007, 0.094)	(−0.024, 0.067)	(−0.043, 0.040)	(−0.025, 0.041)	(−0.084, 0.204)
Bandwidth	6.06	7.32	6.30	5.48	5.25	4.73	5.67
Total observations	17,535	17,001	34,536	40,216	53,751	93,967	4,499
Included observations	7,938	8,513	15,408	15,051	19,179	27,864	1,792
Panel B: Score difference at half-time, winning third quarter							
Behind at half-time	0.024	−0.026	0.002				
	(−0.031, 0.078)	(−0.090, 0.039)	(−0.036, 0.040)				
Bandwidth	9.47	7.26	9.88				
Total observations	16,617	16,133	32,750				
Included observations	10,468	8,062	20,386				
Panel C: Score difference at half-time, winning fourth quarter							
Behind at half-time	0.017	0.029	0.026				
	(−0.053, 0.088)	(−0.036, 0.095)	(−0.017, 0.070)				
Bandwidth	6.63	7.43	7.86				
Total observations	16,560	16,091	32,651				
Included observations	7,482	8,065	16,643				
Panel D: Score difference after third quarter, winning match							
Behind at half-time	−0.009	0.017	0.001				
	(−0.077, 0.060)	(−0.058, 0.092)	(−0.053, 0.055)				
Bandwidth	6.13	5.87	5.33				
Total observations	17,630	17,126	34,756				
Included observations	6,640	5,267	10,895				

Notes. The table reports the estimated effect of being slightly behind on the likelihood of winning for NBA (BP, non-BP, all), NCAA (BP, non-BP, all), and WNBA matches using a regression discontinuity design. Definitions are as in Table 2.

half-time score difference was zero and excludes those in which the score difference after the third quarter was zero. Figure S18 in the online appendix displays the regression discontinuity plots. Table 8, Panel D shows that the treatment effect is nonsignificant in the two individual samples and in the two samples combined (NBA BP: $\tau = -0.009, p = 0.803$; NBA non-BP: $\tau = 0.017, p = 0.663$; NBA all: $\tau = 0.001, p = 0.976$), suggesting that marginally trailing after the third quarter does not lead to better performance.

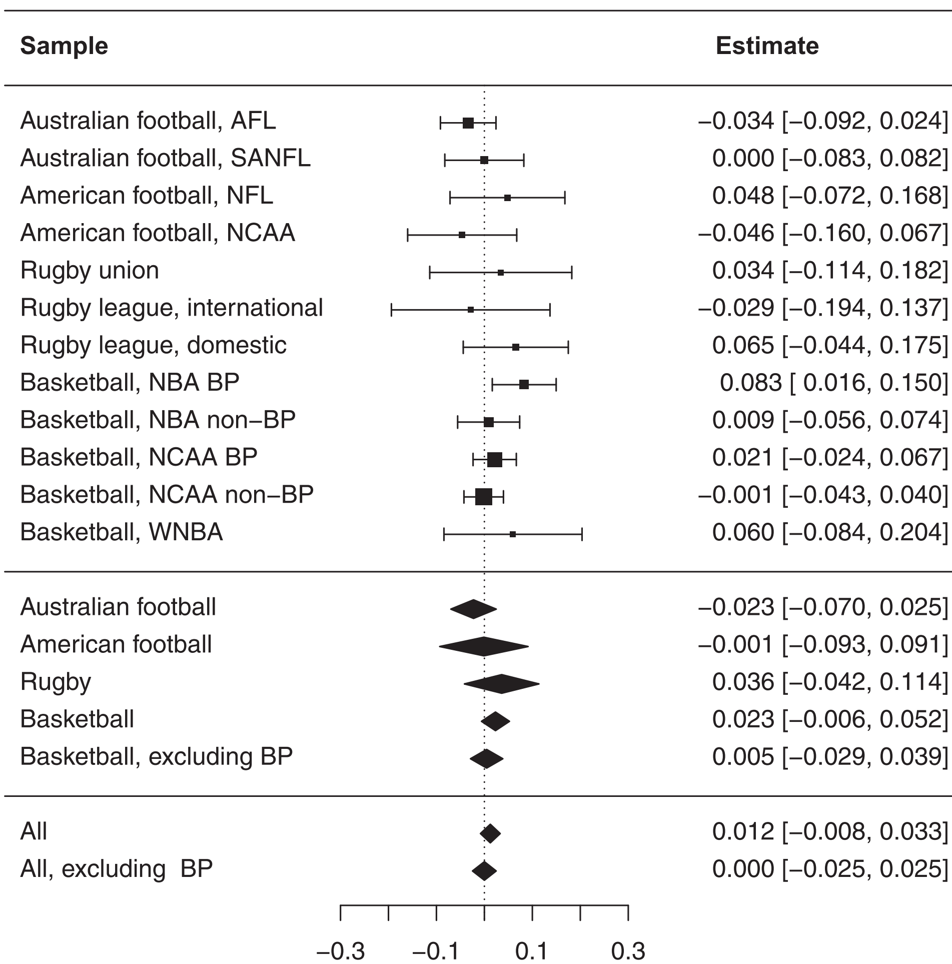
The validity of our RDDs is not rejected by evidence against the continuity assumption; Figures S19 and S20 and Table S4 in the online appendix show that all estimated discontinuities in the skill difference between home and away teams at the cutoff value of a zero score difference are statistically insignificant, both at half-time and after the third quarter (all $p > 0.174$).

In summary, we replicate the finding that trailing at half-time improves the odds of winning for NBA matches from the period analyzed in BP. However, we find no compelling evidence of such an effect for NBA matches from outside this sample period, for NCAA matches, or for WNBA matches.

7. Meta-Analysis

Figure 5 summarizes the main results of the previous sections. Trailing at half-time improves the odds of winning only in the NBA sample covering the period

Figure 5. Meta-Analysis for the Effect of Trailing at Half-Time on Winning the Match



Notes. The figure summarizes the main results for the individual samples and shows the meta-analytic estimates per sport and for all sports combined. *Estimate* is the estimated effect of trailing at half-time on the chance of winning the match; numbers in brackets represent 95% confidence intervals. Meta-analytic effects are estimated with the Paule–Mandel estimator (Paule and Mandel 1989). The sizes of the squares represent the weights of individual samples in the meta-analysis that covers all samples. The lines (diamonds) represent the 95% confidence intervals for the individual (meta-analytic) estimates.

analyzed in BP. There is no statistically significant evidence of such an effect in any of the other basketball samples or in any of the samples for the other sports that we have analyzed.

To assess the informativeness of these null results, it is important to consider the statistical power of the underlying analyses. Statistical power refers to the likelihood of obtaining a significant estimate under the assumption of a given true effect size. An analysis is generally considered to be sufficiently powered if there is at least an 80% probability of obtaining an estimate that is statistically significant at the five-percent level. We determine the power of each analysis with the approach that Cattaneo et al. (2019) developed for the regression discontinuity method of Calonico et al. (2014). For the hypothetical true effect, we consider the NBA estimates of BP, who report that trailing at half-time improves the likelihood of winning by 5.8–8.0 percentage points. To be conservative, we assume that the true effect size is 0.058, the lower end of this range.

Table 9 shows the results of the power calculations. None of the individual analyses meet the 80% power threshold, and the lack of power is especially pronounced for American football and rugby. This is problematic if analyses are considered in isolation. Combined, however, the power statistics imply that if the true effect size is 0.058, the probability of finding nonsignificant estimates in all new samples is only 1.7%.

To synthesize the results, we turn to meta-analyses. We employ a random-effects meta-analytic model (Hedges and Vevea 1998) because the true effect may differ across samples. The estimated overall treatment effect is the weighted average of the individual estimates, where the weights are the inverse of the sum of the estimate's squared standard error and the estimated between-analysis variance. As recommended by Panityakul et al. (2013) and Veroniki et al. (2015), we estimate the between-analysis variance with the Paule–Mandel estimator (Paule and Mandel 1989). We calculate the power of the meta-analyses with the analytical approach described in Jackson and Turner (2017).

The total number of matches in all samples combined is 185,268, or 74,835 if we only consider observations that are within the bandwidths around the cutoff. The power of the meta-analysis for all sports and competitions combined approaches 100%, which means that it is as good as certain that we will detect a significant effect if the average true effect is 0.058 (Table 9). As shown in Figure 5, the estimated overall effect of being behind at half-time on the probability of winning the match is 1.2 percentage points.

Table 9. Statistical Power

	Total observations	Included observations	Statistical power
Australian football			
AFL	14,945	6,902	0.501
SANFL	6,622	3,348	0.281
American football			
NFL	10,590	3,736	0.158
NCAA	7,024	2,812	0.170
Rugby			
Rugby union	2,338	1,249	0.120
Rugby league, international	2,057	1,259	0.106
Rugby league, domestic	8,690	3,056	0.180
Basketball			
NBA BP	17,535	7,938	0.400
NBA non-BP	17,001	8,513	0.420
NCAA BP	40,216	15,051	0.712
NCAA non-BP	53,751	19,179	0.788
WNBA	4,499	1,792	0.124
Meta-analyses			
Australian football	21,567	10,250	0.670
American football	17,614	6,548	0.234
Rugby	13,085	5,564	0.310
Basketball	133,002	52,473	0.973
Basketball, excluding BP	75,251	29,484	0.920
All	185,268	74,835	1.000
All, excluding BP	127,517	51,846	0.996

Notes. The table presents the estimates of statistical power for all analyses where the outcome variable is *Home team wins match* and the running variable is *Score difference at half-time*. *Total observations* is the number of observations in the analyzed sample(s), and *Included observations* is the number of observations within the bandwidth(s). *Statistical power* is the probability of finding an estimate that is significant at the five percent level if the true effect size is 0.058. The power for the individual samples is calculated with the approach proposed by Cattaneo et al. (2019), and the power of the meta-analyses is calculated with the analytical approach described in Jackson and Turner (2017).

Statistically, this estimate is not significantly different from zero ($p = 0.239$).

If we exclude the NBA BP and NCAA BP samples—and thus, exclusively consider sports matches that have not been analyzed previously—the total number of matches (within the bandwidths) is 127,517 (51,846). The power of the meta-analysis for this combination of samples is 99.6%. The estimated overall treatment effect for matches that are unique to our study is economically and statistically indistinguishable from zero ($\tau = 0.000$, $p = 0.993$).

Figure 5 also shows the results of meta-analyses per sport. All estimated effects of trailing at half-time are nonsignificant (all $p > 0.121$) and range between a negative 2.3 percentage points for Australian football and a positive 3.6 percentage points for rugby. For American football and rugby, however, the statistical power is low. For basketball matches that were not analyzed in BP, the meta-analytic estimate is close to zero ($\tau = 0.005$, $p = 0.783$). This null result can be considered informative in the light of the high statistical power of this analysis (92%; Table 9).

If performance improves only temporarily, then the effect is more likely to emerge in the period directly following the half-time break. Figures A.1 and A.2 in the appendix show the results of meta-analyses for the effect of trailing at half-time on winning the third quarter and on winning the fourth quarter. The estimated overall effect on winning the third quarter is 0.9 percentage points. Statistically, this value is not significantly different from zero ($p = 0.511$). Without the results for the NBA BP and NCAA BP samples, the effect is 0.4 percentage points and again nonsignificant ($p = 0.793$). The meta-analytic estimates for the effect of trailing at half-time on winning the fourth quarter are also nonsignificant: 0.9 percentage points ($p = 0.583$) for all analyses combined, and 0.7 percentage points ($p = 0.703$) without the analyses of the BP samples. Furthermore, Figure A.3 in the appendix shows that there is no meta-analytic evidence that trailing after the third quarter affects the chance of winning the match, regardless of whether the results for the BP samples are included ($\tau = -0.004, p = 0.810$) or excluded ($\tau = -0.003$, $p = 0.895$).

Each individual RDD in this paper requires that the skill difference between the home and away team is continuous at the cutoff value of a zero score difference. Figures S21 and S22 in the online appendix give an overview of the estimated skill difference discontinuities for the individual samples, both for the half-time score difference and for the score difference after the third quarter (if applicable). As discussed previously, all are statistically not significantly different from zero. Analogous to the meta-analyses for the RDDs that are central to this paper, we also perform meta-analyses for the skill difference continuity tests per sport and for all sports combined. As shown in Figures S21 and S22 in the online appendix, all meta-analytic estimates are nonsignificant, lending support to the validity of the approach that we employed throughout this paper.

In summary, our meta-analyses cannot reject the null hypothesis of no effect of marginally trailing on winning, and the confidence intervals suggest that the true effect, if existent at all, is likely relatively small.

8. Discussion and Conclusion

We extend the analysis of Berger and Pope (2011) of whether marginally trailing improves the odds of winning in basketball to Australian football, American football, and rugby. We find no supportive evidence for these three sports; the estimated effects are sometimes positive and sometimes negative, and statistically they are always insignificant. We then also revisit the phenomenon for basketball. We replicate the finding that half-time trailing improves the chances of winning in NBA matches from the period analyzed in BP but consistently find null results for NBA matches from outside this period, for the sample of NCAA matches analyzed in BP, for more recent NCAA matches, and for WNBA matches. Moreover, our high-powered meta-analyses across the different sports and competitions cannot reject the hypothesis of no effect of marginally trailing on winning, and the confidence intervals suggest that the true effect, if existent at all, is likely relatively small. This absence of supportive evidence is particularly informative in the light of BP's prior finding of a large positive effect and our sizable datasets (Abadie 2020).

Australian football, American football, and rugby are attractive sports for extending the analysis of the effect of trailing on the probability of winning. First, for reliably identifying a discontinuous effect of trailing on performance, it is important that the relationship between the half-time score difference and the winning probability is approximately linear within a reasonable bandwidth around the cutoff value of a zero score difference. Australian football, American football, and rugby satisfy this criterion as demonstrated by the regression discontinuity plots. Second, for the hypothesized psychological phenomenon to arise, it is important that the negative impact of trailing on the winning probability is limited, such that teams that are only one or a few points behind still have a reasonable chance of winning. Otherwise, trailing by even the smallest possible margin is more likely to discourage rather than motivate (Fershtman and Gneezy 2011, Gill and Prowse 2012). For American football and rugby, the relationship between the half-time score difference and the winning probability resembles the relationship for basketball, and it is somewhat weaker for Australian football. This suggests that the psychological effect of marginally trailing should be similar across the four sports.

In terms of statistical power, some of our analyses are more informative than others. The statistical power is especially low in the cases of American football and rugby. Compared with Australian football and basketball, our tests for these sports rely on fewer observations, and as a consequence of the scoring systems, there is a lower density of observations around the cutoff. At the same time, every individual analysis—including those for American football and rugby—contributes to the overall picture of the effect of marginally trailing on winning. Even though none of the individual analyses meet the 80% power threshold, the probability of wrongly failing to reject the null hypothesis for the combination of sports and competitions is low; the meta-analysis that covers all new samples reaches a statistical power that is close to 100%.

Our null results do not mean that trailing in a competition does not or cannot have a systematic positive motivating effect. Several studies have demonstrated that people who are slightly behind on their goal work harder than those who already reached it (Heath et al. 1999, Pope and Simonsohn 2011, Corgnet et al. 2015, Allen et al. 2016). In addition to their findings for basketball, BP present results from two laboratory experiments that show that such a motivational effect also occurs in a competition. In a two-period button-pressing contest, subjects who were told after the first period that they were slightly behind worked harder in the second period than subjects who were told that they were far behind, tied, or slightly ahead. An important difference between sports matches and BP's laboratory task is in the feedback that participants receive. In the experiments, there was only one feedback moment, which precluded participants from responding to developments in the score difference after that. In sports matches, by contrast, players do get continuous feedback on the score difference. A disadvantage can turn into an advantage within mere seconds. Even if trailing is performance enhancing and driving a turnaround in the short run, the effect may get lost in the chain of subsequent events and the two opposing players' or teams' responses to these events.

Another potentially relevant difference is that professional athletes are highly experienced, whereas BP's laboratory subjects engaged in the button-pressing contest only once. If leading teams or subjects realize that their trailing opponent will exert additional effort, they should anticipate this and adjust their own effort accordingly. Subjects in the laboratory may not realize that a trailing opponent will exert more effort, but they can be expected to learn this if the game is repeated often enough. Therefore, the performance-enhancing effect of trailing may disappear with experience.

In the light of contest theory, our null results are not surprising. Contest theory considers situations in which agents have the opportunity to expend scarce resources to win prizes. A common prediction is that trailing by a considerable margin leads to further losing because of the relatively weak incentive to exert effort (Harris and Vickers 1987). Such a demotivating effect of trailing has been empirically confirmed in experiments (Dechenaux et al. 2015), tennis (Malueg and Yates 2010, Page and Coates 2017, Gauriot and Page 2019), and political campaigns (Klumpp and Polborn 2006). For infinitesimal score differences, however, contest theory predicts no material effect on effort and final outcomes.

It remains an open question why marginally trailing did have a strong and statistically significant effect on winning in NBA matches between 1993 and 2009. This is the main finding in BP, and the present paper replicates it using independently collected data and a more sophisticated methodological approach. Possibly, the anomaly is related to irregularities in refereeing. The period of 1993–2009 encompasses an episode in the history of the NBA during which a referee was betting on NBA games—including games that he officiated—and accepting payments from professional gamblers in exchange for betting recommendations.[16] Price et al. (2012) describe how this referee later claimed that "NBA refs have several biases" and that "the league sometimes knowingly turns a blind eye to these biases, and sometimes even subtly encourages them" (Price et al. 2012, p. 275). Analyzing play-by-play NBA data from 2002 to 2008, Price et al. (2012) indeed find evidence for several kinds of refereeing bias, including a tendency to favor teams that are behind. Even though such irregularities may have an impact on the relationship between score difference (at any time) and winning probability, it is not clear whether and how they would specifically lead to a discontinuous effect of trailing at half-time on the chance of winning. In our view, the performance-enhancing effect documented in BP is most likely a chance occurrence.

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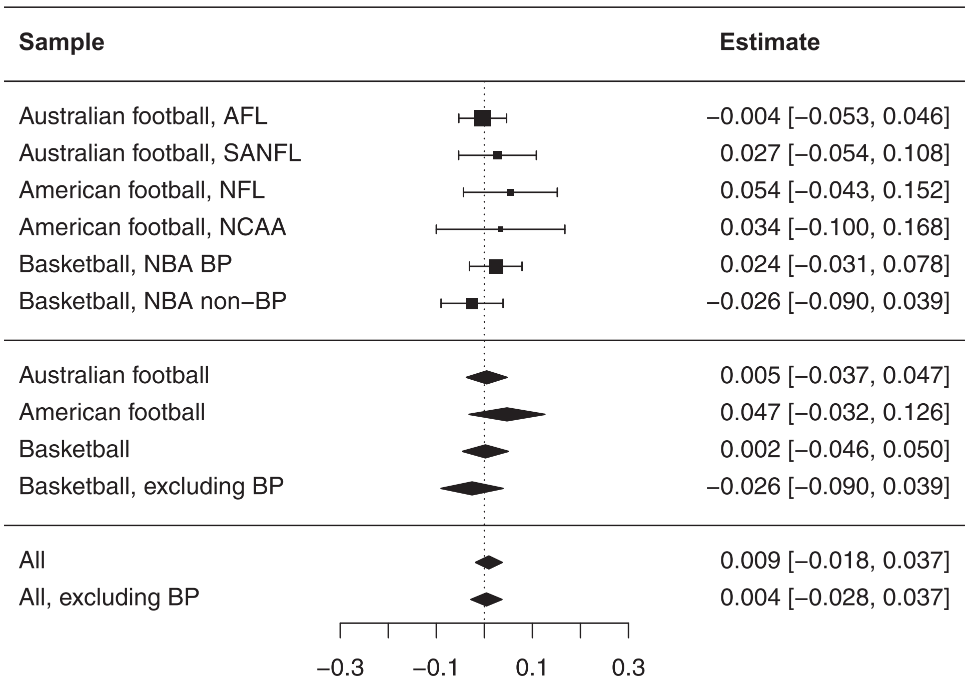
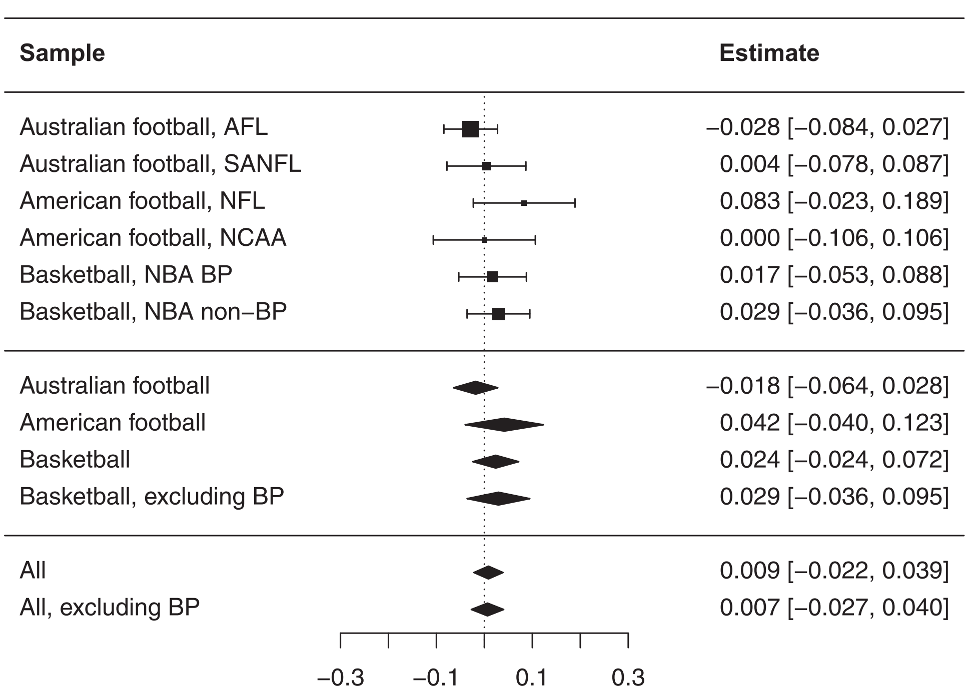
Appendix

Figure A.1. Meta-Analysis for the Effect of Trailing at Half-Time on Winning the Third Quarter



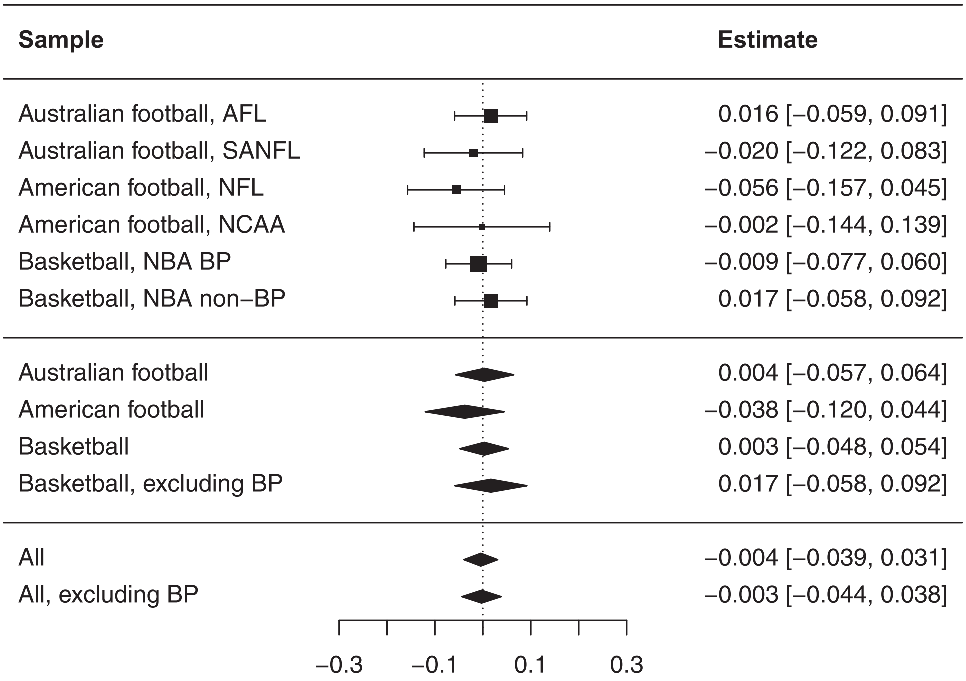
Notes. The figure summarizes the results of the analyses of the effect of trailing at half-time on winning the third quarter for the individual samples and shows the meta-analytic estimates per sport and for all sports combined. Definitions are as in Figure 5.

Figure A.2. Meta-Analysis for the Effect of Trailing at Half-Time on Winning the Fourth Quarter



Notes. The figure summarizes the results of the analyses of the effect of trailing at half-time on winning the fourth quarter for the individual samples and shows the meta-analytic estimates per sport and for all sports combined. Definitions are as in Figure 5.

Figure A.3. Meta-Analysis for the Effect of Trailing After the Third Quarter on Winning the Match



Notes. The figure summarizes the results of the analyses of the effect of trailing after the third quarter on winning the match for the individual samples and shows the meta-analytic estimates per sport and for all sports combined. Definitions are as in Figure 5.

Endnotes

[1] For the sake of readability, we use the terms "marginally" and "slightly" (behind) as substitutes for an infinitely small difference.

[2] If the score difference is negative, the home team is treated and the away team is not. If the score difference is positive, the away team is treated and the home team is not. In matches with a zero half-time score difference, neither of the teams is treated. These matches can therefore neither be used to estimate the linear relationship below the cutoff value, nor to estimate the linear relationship above it.

[3] The given match itself is excluded from these calculations. We exclusively use home (away) matches for the home (away) team to take account of the home advantage and possible imbalances in the numbers of home and away matches. We calculate the proportion for the home (away) team prior to the exclusion of matches that were against a team for which we originally had obtained no other away (home) match from the same calendar year.

[4] We also considered including handball and test cricket. For handball, the relationship between the half-time score difference and winning is highly nonlinear, which makes it impossible to apply the regression discontinuity method. For test cricket, there are not enough matches with close scores halfway through the match to reliably estimate the discontinuity.

[5] See "Battle of the codes: Australia's four sports leagues compared" from *The Guardian* (https://www.theguardian.com/news/datablog/interactive/2014/apr/15/australia-football-interactive-statistics; accessed July 7, 2020).

[6] We scraped the AFL matches from https://afltables.com on September 3, 2018 and the SANFL matches from https://www.australianfootball.com on October 2, 2018. The data on the two websites are collected and edited by fans.

[7] See "The NFL and Major League Baseball are the most attended sports leagues in the world" from *Business Insider* (https://www.businessinsider.com/attendance-sports-leagues-world-2015-5; accessed July 7, 2020).

[8] We scraped the NFL data from https://www.pro-football-reference.com on September 8, 2018 and the NCAA data from https://www.sports-reference.com on October 2, 2018. Both websites report official NFL and NCAA statistics.

[9] We scraped the data for rugby union matches from https://www.espn.com/rugby on September 11, 2018; for international rugby league matches from http://www.rugbyleagueproject.org on November 7, 2018; and for domestic rugby league matches from http://www.rugby-league.com on October 5, 2018. ESPN is primarily known as a sports TV channel, and their website offers extensive rugby union statistics. The Rugby League Project is a volunteer-run rugby statistics website, and rugby-league.com is the official website of the Rugby Football League.

[10] The relatively large fraction of omitted matches for domestic rugby league can be explained by the incorrect use of "0–0" for missing half-time scores in our source for this sample.

[11] See "The NBA is the highest-paying sports league in the world" from *Business Insider* (https://www.businessinsider.com/sports-leagues-top-salaries-2015-5; accessed July 7, 2020).

[12] We scraped the NBA data from https://www.basketball-reference.com, a fan-edited basketball website, on September 14, 2018. Jonah Berger and Devin Pope provided the data for the NCAA matches analyzed in BP. For the more recent NCAA matches, we scraped the data from https://www.cbssports.com, the website of the sports channel of the American TV network CBS, on July 18, 2020. We received the WNBA data from Michael Beuoy of https://www.inpredictable.com, a fan-edited prediction website, on October 16, 2018.

[13] BP's sample comprises 18,060 matches. The two samples were collected independently from each other. The difference in sample size could be related to the different sources and to possible differences in inclusion criteria.

[14] BP estimate the treatment effect with a standard logit model for matches with a half-time score difference that falls within an ad hoc fixed bandwidth of 10 points around the cutoff value of zero. For each sample, they report the results for four specifications (linear or nonlinear, controlling or not controlling for skill). If we conduct all analyses with their method and four specifications, our conclusion that the findings of BP do not generalize remains unchanged.

[15] For the subset of 6,186 NBA non-BP matches played before the start of the BP sample period, the point estimate is −2.0 percentage points ($p = 0.698$); for the subset of 10,815 NBA non-BP matches from after the BP sample period, it is 3.6 percentage points ($p = 0.350$).

[16] See "N.B.A. referee pleads guilty to gambling charges" from *The New York Times* (https://www.nytimes.com/2007/08/16/sports/basketball/16nba.html; accessed May 3, 2021) and "Disgraced referee's book describes gambling on N.B.A. games" from *The New York Times* (https://www.nytimes.com/2009/12/03/sports/basketball/03donaghy.html; accessed May 3, 2021).

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