TI 2020-049/IV
Tinbergen Institute Discussion Paper

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

Bouke Klein Teeselink[1]
Martijn J. van den Assem[1]
Dennie van Dolder[1,2]

[1] Vrije Universiteit Amsterdam
[2] School of Business and Economics; Centre for Decision Research and Experimental Economics (CeDEx) - University of Nottingham

Does Losing Lead to Winning?

An Empirical Analysis for Four Different Sports

Bouke Klein Teeselink*[1], Martijn J. van den Assem[1,2] and Dennie van Dolder[1,2,3]

[1] *School of Business and Economics, Vrije Universiteit (VU) Amsterdam*
[2] *Tinbergen Institute*
[3] *Centre for Decision Research and Experimental Economics, University of Nottingham*

August 7, 2020

Abstract

Berger and Pope (2011) show that being slightly behind increases the likelihood of winning in professional and collegiate basketball. We extend their analysis to large samples of Australian football, American football and rugby matches, but find little to no evidence of such an effect for these three sports. When we revisit the phenomenon for basketball, we do find supportive evidence for National Basketball Association (NBA) matches from the period analyzed in Berger and Pope. However, we find no significant effect for NBA matches from outside this sample period, for collegiate matches, and for matches from the Women's NBA. 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.

Keywords: competition; motivation; performance; regression discontinuity design
JEL: D01; D91; Z20

*Corresponding author: b.kleinteeselink@vu.nl, De Boelelaan 1105, 1081 HV Amsterdam, the Netherlands. We thank Jonah Berger, Devin Pope, and Rogier Potter van Loon for their constructive and valuable comments. The paper has benefited from discussions with participants of FUR 2018 York, SABE/IAREP 2018 London, TIBER 2018 Tilburg, RBFC 2018 Amsterdam, and JDMx 2018 Konstanz. We gratefully acknowledge support from the Dutch Research Council.

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 to come out on top. In particular, they argue that because winning is the goal, the performance of an opponent will serve as a salient benchmark—or reference point—to which a competitor will compare his or her 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 (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 sixty thousand professional and collegiate basketball matches. Their main analyses focus on the score difference at half-time, because the relatively long break that occurs halfway through the match provides players with the time 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. For collegiate matches, they similarly find a positive effect of being behind, but the size of the effect is smaller.

The present paper extends the analysis of BP to large samples of Australian football, American football and rugby matches, and 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 in addition analyze whether marginally trailing at half-time improves the likelihood of winning the third or fourth quarter separately, as was also done by 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 little to no evidence that being slightly behind improves performance. For basketball we replicate the finding that half-time trailing 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 effect size reported in BP. For NBA matches from outside that period, for collegiate matches, and for matches from the Women's National Basketball Association (WNBA), however, we obtain null results.

To synthesize our results, we conduct a meta-analysis that estimates the overall effect of trailing at half-time on winning the match across all competitions and sports.

The estimated meta-analytic effect is close to zero and statistically insignificant. The narrow confidence interval for the overall effect size suggests that the true effect, if existent at all, is likely relatively small. Similar conclusions follow from meta-analyses of the effect of half-time trailing 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 paper proceeds as follows. Section 2 explains the methodology, Sections 3 to 6 show the results for each of the four sports, Section 7 presents the meta-analyses, and Section 8 discusses our findings and concludes.

2 Empirical Strategy

We employ a regression discontinuity design (RDD) to estimate the causal impact of being behind on performance. RDDs are used to estimate treatment effects in non-experimental 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 testable 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 1 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 1 if team i is behind at half-time. The coefficient τ represents the discontinuity in the winning probability at a zero score difference. Under the hypothesis that being slightly behind improves performance, this coefficient is positive. The interaction term $T_i \times X_i$ allows for different slopes above and below the cutoff. To not use every match twice, we systematically take the perspective of the home team. We omit matches where teams were tied at half-time.[1]

[1]If the score difference is negative, the home team is treated and the away time is not, whereas 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, in contrast, neither of the teams is treated. These matches

If the assumption of a piece-wise linear relation between the winning probability and the half-time score difference is violated, the regression model will generate a biased estimate of the treatment effect. As a solution to this problem, Hahn et al. (2001) propose the use of local-linear regression. Even if the true relation is non-linear, 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). Their method selects the bandwidth that minimizes the mean squared error, corrects the estimated treatment effect for any remaining non-linearities 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 through the cutoff. To examine whether this assumption holds, we in addition 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 proportions of home matches won by the home team and away matches won by the away team during the current calendar year.[2] We again employ the local-linear method proposed by Calonico et al. (2014).

We consider data from four different sports: Australian football, American football, rugby and basketball. In all these sports, teams generally score a large number of points. The validity of our RDD hinges on the assumption of a piece-wise linear relation between the full-time winning probability and the half-time score difference within a bandwidth 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 likely discourages rather than motivates (Fershtman and Gneezy, 2011; Gill and Prowse, 2012).

Matches have to satisfy a number of criteria for inclusion. First, the half-time

can therefore neither be used to estimate the linear relation below the cutoff value, nor to estimate the linear relation above it.

[2]The current 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.

score, the full-time score and the year of play need to be available. Second, the match must not have ended in a draw. 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 for our test of the assumption that the skill difference between home and away teams is continuous at the cutoff.

We present our 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). In each graph, smooth curves on both sides of the cutoff give a visual impression of whether the relation 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, where the outcome variable takes the value of 1 if the home team won the match, 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 in addition analyze the effect of trailing at half-time on winning the third quarter and on winning 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 through the cutoff.

3 Australian football

3.1 Description and Data

The first sport that we consider is Australian football. We use data from two different leagues. One is the Australian football League (AFL), which is widely considered to be the sport's most important league. It is the only fully professional Australian football division and the fourth most popular sports competition in the world by average weekly attendance.[3] The other is the South Australian National Football League (SANFL). The SANFL is a semi-professional 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

[3]The Guardian. 2014. Battle of the codes: Australia's four sports leagues compared. Available from https://www.theguardian.com/news/datablog/interactive/2014/apr/15/australia-football-interactive-statistics [Accessed: 7 July 2020].

Table 1: Summary statistics Australian football

Panel A: AFL (1897-2018, N=14,945)	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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)							
	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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

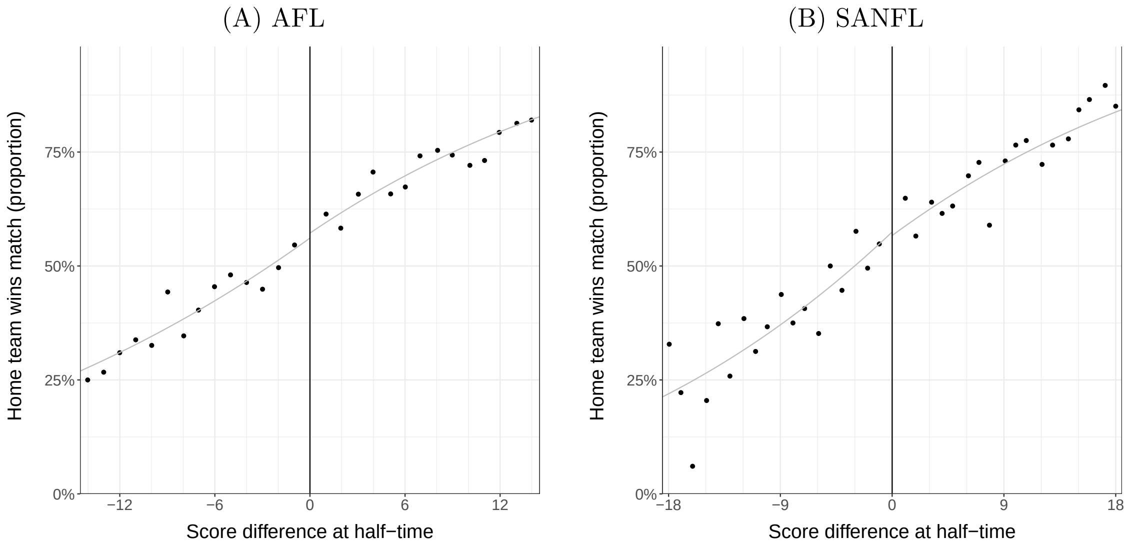
Notes: The table displays the summary statistics for AFL and SANFL matches where the half-time score difference was not zero. *Home team wins match* is an indicator variable that takes the value of 1 if the home team won the match. *Total points at half-time (full-time)* is the total number of points scored by the two teams together 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.

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 outside posts, (ii) when a player on the ground touched 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 there are two 6-minute breaks after the first and third quarter.

We obtained data for 15,209 AFL and 6,728 SANFL matches that satisfy the criteria stipulated in Section 2.[4] 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 together scored 171 points in AFL matches and 185 in SANFL matches. At half-time, these numbers were 84 and 90, respectively. In both samples, home teams on average led by 4 points at half-time and by 9 points at full-time, and won roughly 60 percent of the times.

[4]We scraped the AFL matches from www.afltables.com on 3 September 2018 and the SANFL matches from www.australianfootball.com on 2 October 2018. The data on both websites are collected and edited by fans.

Figure 1: Regression discontinuity plots for Australian football



Notes: The figure shows the regression discontinuity plots for AFL (Panel A) and SANFL (Panel B) 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.

3.2 Analysis and Results

We first visually explore the relation between the half-time score difference and the full-time winning probability. Figure 1 shows that the relation 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 discontinuous change at the cutoff.

Table 2, Panel A presents the results for the main RDD. There is no evidence of a positive performance effect from trailing. In fact, the point estimate for AFL teams indicates that being slightly behind at half-time *decreases* the winning chances 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 percent confidence intervals for the two estimates, however, indicate that a considerable range of positive and negative effect sizes cannot be ruled out. Figure A1 in the 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 could be 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

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)	(−0.082, 0.082)
Bandwidth	14.73	18.53
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 behind on the likelihood of winning for AFL and SANFL matches using a regression discontinuity design. Treatment effects are estimated with the local-linear non-parametric 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, B and 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 analyzed sample. *Included observations* is the number of observations within the bandwidth. Numbers in parentheses represent 95 percent confidence intervals. Asterisks denote significance at the 0.01 (***), 0.05 (**) and 0.1 (*) level.

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 1 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. Panels B and C show the results. 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 effect in the final (fourth) quarter is also insignificant (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 these alternative RDDs, winning the match is the outcome variable and the score difference after the third quarter is the running variable. For this analysis we include matches with a zero score difference at half-time and exclude matches with a zero score difference after the third quarter. Panel D shows the results. The estimates for the AFL ($\tau = 0.016, p = 0.674$) and SANFL ($\tau = -0.020, p = 0.707$) samples are both insignificant.

Last, to investigate the validity of the RDDs, we examine the identifying assumption that the skill difference between the home and away team is continuous at the cutoff value of a zero score difference. There is no significant evidence for a discontinuity, neither at half-time (AFL: $p = 0.217$; SANFL: $p = 0.633$) nor at the end of the third quarter (AFL: $p = 0.650$; SANFL: $p = 0.177$).

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 National Collegiate Athletic Association (NCAA). The NFL is seen as the most important American football league and is the best attended professional sports league in the world.[5] The NCAA is an

[5] Business Insider. 2015. The NFL and Major League Baseball are the most attended sports leagues in the world. Available from: https://www.businessinsider.com/attendance-sports-leagues-world-2015-5 [Accessed: 7 July 2020].

Table 3: Summary statistics American football

Panel A: NFL (1945-2017, N=10,590)							
	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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)							
	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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 not zero. All definitions are as in Table 1.

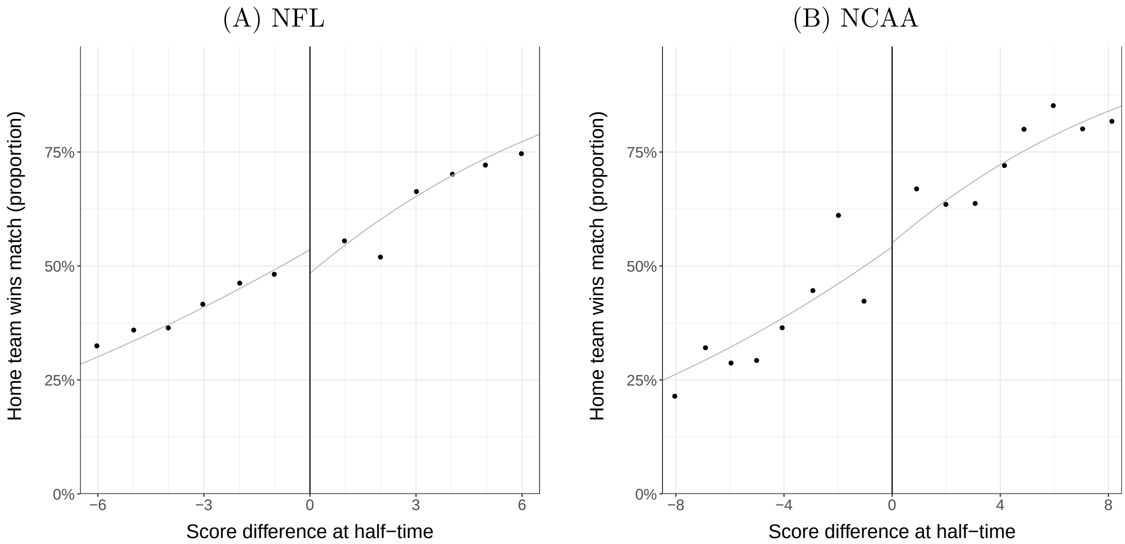
American intercollegiate competition, and is often regarded as the second-highest level of competition in American football.

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 within 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 either 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 two (NFL) or three (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 gains two points when they tackle a member of the opposing team who holds the ball in the opposing team's end zone. Matches consist of four 15-minute quarters. There is a 12-minute half-time break and there are two 2-minute breaks after the first and third quarter.

We obtained data for 12,279 NFL and 7,936 NCAA matches that satisfy the data requirements outlined in Section 2.[6] The exclusion of 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,

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

Figure 2: Regression discontinuity plots for American football



Notes: The figure shows the regression discontinuity plots for NFL (Panel A) and NCAA (Panel B) matches. Definitions are as in Figure 1.

respectively. Home teams led by an average of 2 (NFL) and 4 (NCAA) points at half-time, and 3 (NFL) and 7 (NCAA) points at full-time. Home teams won roughly 60 percent of the matches.

4.2 Analysis and Results

Figure 2 shows that the proportion of home teams winning the match increases approximately linearly with the half-time score difference, at a rate of roughly four percentage points per point for both NFL and NCAA matches. There appears to be a small negative discontinuity at zero for NFL teams, suggesting that marginally trailing at half-time enhances teams' performance. In NCAA matches, there is no indication of such an effect.

Table 4, Panel A presents the results for the main RDD. Statistically there is no significant evidence that half-time trailing affects the full-time winning probability, neither for NFL ($p = 0.431$) nor for NCAA ($p = 0.425$) matches. The estimated effect sizes of 4.8 (NFL) and −4.6 (NCAA) percentage points are economically substantial, but the 95 percent confidence intervals are wide. Figure A2 in the 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 half-time trailing on performance in the third (and fourth) quarter separately. The outcome variable now takes the value of 1 if the team

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	0.134**	0.072
	(0.023, 0.245)	(−0.040, 0.185)
Bandwidth	6.27	8.83
Total observations	10,107	6,712
Included observations	3,557	2,592
Panel C: Score difference at half-time, winning fourth		
Behind at half-time	-0.000	−0.106
	(−0.125, 0.124)	(−0.252, 0.041)
Bandwidth	5.59	7.00
Total observations	10,187	6,827
Included observations	3,040	1,695
Panel D: Score difference after third quarter, winning match		
Behind after Q3	−0.052	−0.018
	(−0.207, 0.102)	(−0.208, 0.173)
Bandwidth	6.31	5.41
Total observations	8,956	6,235
Included observations	3,678	1,845

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

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. Panels B and C show the results. In contrast to the results for the main RDD, being slightly behind at half-time in the NFL does significantly improve performance in the first quarter after the break: half-time trailing increases the odds of winning the third quarter by a sizable 13.4 percentage points ($p = 0.018$). There is no statistically significant evidence for such an effect in the third quarter for NCAA matches, but the point estimate is economically large ($\tau = 0.072, p = 0.206$). The effect of half-time trailing on the odds of winning the fourth quarter is insignificant in both samples (NFL: $\tau = -0.000, p = 0.997$; NCAA: $\tau = -0.106, p = 0.158$).

To further examine whether the effect exists within a single quarter, we examine 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.

Panel D shows the results. The two estimates are statistically insignificant (NFL: $\tau = -0.052, p = 0.507$; NCAA: $\tau = -0.018, p = 0.855$), which suggests that trailing after the third quarter does not materially affect the chance of winning the match.

Last, we examine whether the identifying assumption that the skill difference between home and away teams is continuous through the cutoff holds. There is no significant evidence of a discontinuity, neither at half-time (NFL: $p = 0.604$; NCAA: $p = 0.218$) nor after the third quarter (NFL: $p = 0.311$; NCAA: $p = 0.649$).

Overall, our analyses of American football provide little evidence that being behind improves performance. The only exception is that being behind at half-time in the NFL has a significantly positive effect on the chances of winning the third quarter. The other analyses for the NFL and the analyses for the NCAA do not provide supportive evidence for the hypothesis that trailing enhances performance.

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 League and the Rugby World Cup. For rugby league, we consider two different match categories: international matches from prominent tournaments such as the Super League and the Rugby League World Cup, and domestic matches played by British club teams.

Rugby league (union) is played between two teams of 13 (15) players. The rectangular playing field contains 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 posts with a crossbar. In rugby league (union), teams score four (five) 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 two (three) points if they kick a penalty between the posts, and one (three) by kicking the ball through the posts during game play. Matches consist of two

Table 5: Summary statistics rugby

Panel A: Rugby union (1990-2018, N=2,338)							
	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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: International Rugby League (1957-2017, N=2,057)							
	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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: Domestic Rugby League (2006-2018, N=8,690)							
	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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

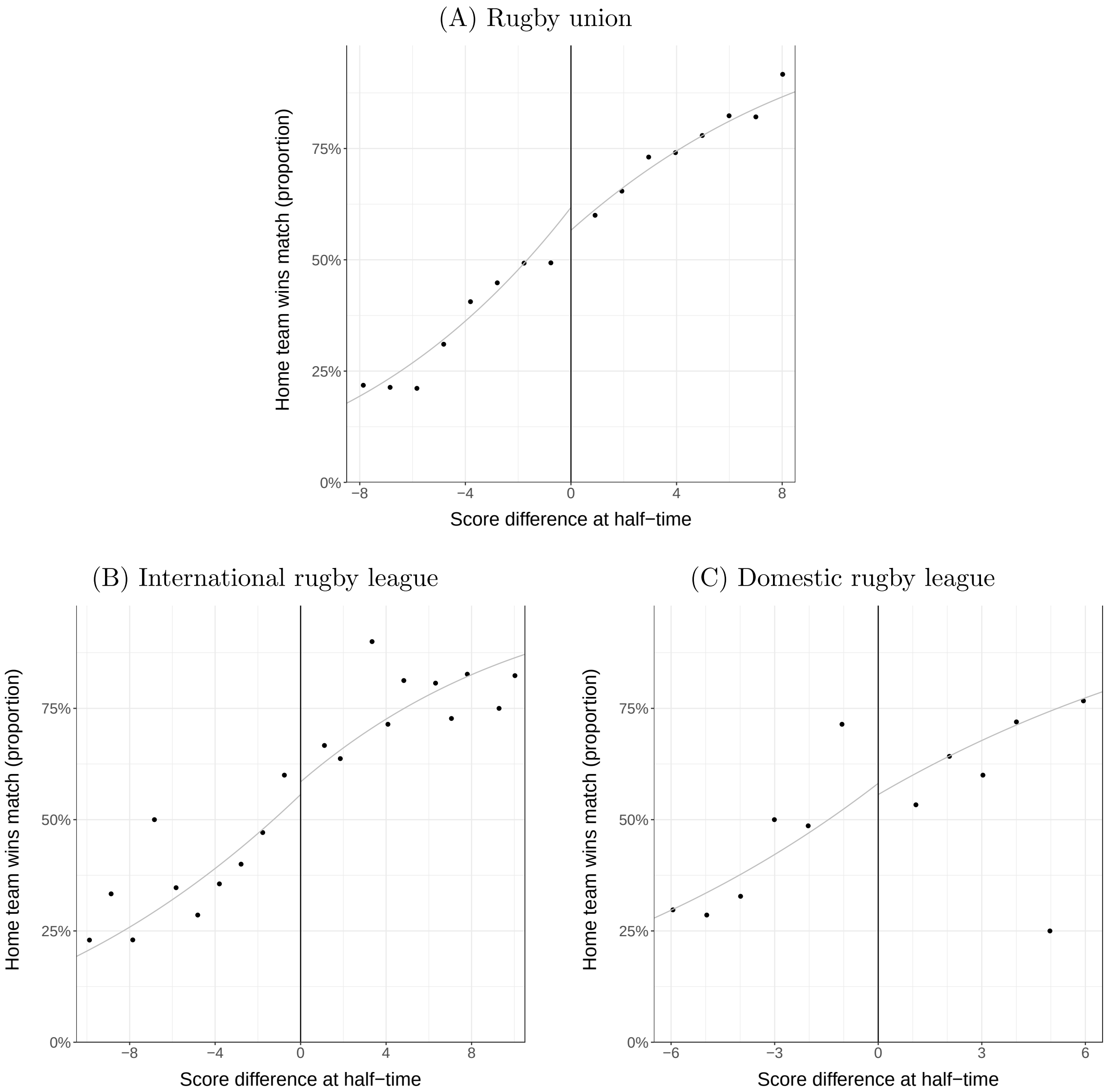
Notes: The table displays the summary statistics for rugby union, international rugby league and domestic rugby league matches where the half-time score difference was not zero. All definitions are as in Table 1.

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.[7] The exclusion of matches with a zero half-time score difference reduces the samples to 2,338, 2,057 and 8,690 matches, respectively. 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 1 point (union) or 3 points (international league and domestic league). At full-time, the average score difference is 2 (union) or 6 (international league and domestic league). Home teams won approximately 60 percent of the matches.

[7] We scraped the data for rugby union matches from stats.espnscrum.com on 11 September 2018, for international rugby league matches from www.rugbyleagueproject.org on 7 November 2018, and for domestic rugby league matches from www.rugby-league.com on 5 October 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.

Figure 3: Regression discontinuity plots for rugby



Notes: The figure shows the regression discontinuity plots for rugby union (Panel A), international rugby league (Panel B) and domestic rugby league (Panel C) matches. Definitions are as in Figure 1.

5.2 Analysis and Results

Figure 3 shows that there is an approximately linear relation between the winning probability and the half-time score difference in rugby. In each sample, the winning probability increases at a rate of roughly four percentage points per point. All three samples exhibit some indication of a discontinuity in the winning probability at the half-time score difference of zero, but the sign of the visual discontinuity differs. For rugby union and domestic rugby league matches, the discontinuity suggests that trailing increases the chance of winning the match, whereas for international rugby

Table 6: Results for rugby

	Rugby union	International rugby league	Domestic rugby league
Behind at half-time	0.033	−0.029	0.065
	(−0.112, 0.179)	(−0.194, 0.135)	(−0.044, 0.175)
Bandwidth	8.70	10.31	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 behind on the likelihood of winning for rugby union, international rugby league and domestic rugby league matches matches using a regression discontinuity design. Definitions are as in Table 2.

league matches it suggests the opposite.[8]

Table 6 shows the results for the main RDD. We find no convincing evidence that half-time trailing 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 A3 in the 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 effect for domestic rugby league matches increases considerably when we impose more restrictive bandwidths, 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 through the cutoff. The results point out that there is no reason to doubt the validity of the RDDs: the discontinuity estimates are insignificant for all three samples (all $p > 0.157$).

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

[8] As a consequence of the scoring system, odd score differences are relatively rare in rugby league matches. This explains why some dots in Panel B and Panel C deviate sharply from the smooth curve. For example, the domestic rugby league sample includes only four matches where the half-time score difference between the home and away team was five, whereas there are 460 (609) matches where the difference was four (six).

6 Basketball

6.1 Description and Data

Thus far, we found little to no evidence that being behind improves the odds of winning in Australian football, American football and rugby. We now turn to basketball—the sport that is central in the study of BP—and consider four different samples. The first contains independently collected data for National Basketball Association (NBA) matches that took place in the same period as the NBA matches analyzed in BP. The second contains older and more recent NBA matches. The NBA is widely considered to be the premier basketball competition in the world, and pays the highest average salary of all the world's sports competitions.[9] Following BP, we also examine basketball matches of the National Collegiate Athletic Association (NCAA), the association that organizes the main intercollegiate competition in the US. Our fourth sample contains matches of the Women's National Basketball Association (WNBA), the women's counterpart to the NBA.

Basketball is played by two teams of five players each. The aim of the game is to score points by shooting a ball through the opposing team's hoop. Teams obtain two points by successfully throwing the ball through the hoop from the area inside the three-point arc, a semi-circle 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 and WNBA matches are played in four quarters of 12 and 10 minutes, separated by a 10-minute half-time break and two 2-minute breaks after the first and third quarter. NCAA matches are played in two 20-minute halves and have a 15-minute half-time break.

We obtained data for 35,921 NBA, 70,484 NCAA, and 4,666 WNBA matches that satisfy the criteria outlined in Section 2.[10] Approximately half of the NBA matches are from the period of 5 November 1993 to 1 March 2009 that was analyzed in BP. This subset, henceforth the "NBA BP" sample, contains 18,230 matches (BP's sample contains 18,060 matches). The sample of remaining NBA matches, henceforth the "NBA non-BP" sample, contains 17,691 matches played between 14 June 1987 and 20 June 1993 or between 2 March 2009 and 8 June 2018. The NCAA data cover the years 2006-2020. To have a clean out-of-sample test for the NCAA, we

[9]Business Insider. 2015. The NBA is the highest-paying sports league in the world. Available from https://www.businessinsider.com/sports-leagues-top-salaries-2015-5 [Accessed: 7 July 2020].

[10]We scraped the NBA data from www.basketball-reference.com, a fan-edited basketball website, on 14 September 2018. We scraped the NCAA data from www.cbssports.com, the sports channel of the American TV network CBS, on 18 July 2020. We received the WNBA data from Michael Beuoy of www.inpredictable.com, a fan-edited prediction website, on 16 October 2018.

Table 7: Summary statistics Basketball

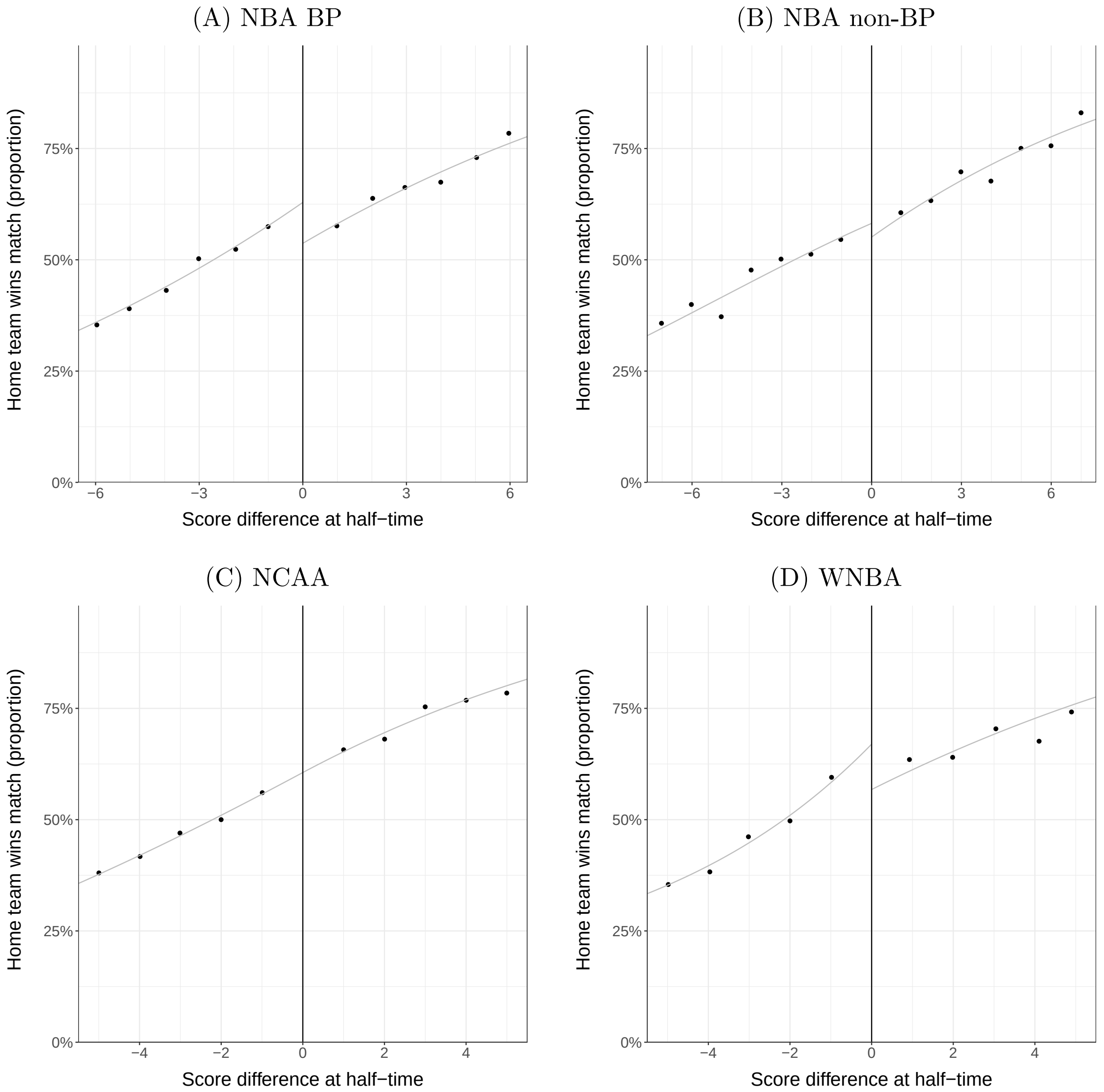
Panel A: NBA BP (1993-2009, N=17,535)	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Total points at half-time	97.1	12.4	55	89	97	105	152
Total points at full-time	193.0	20.0	121	179	193	206	286
Score difference at half-time	2.3	10.2	−39	−5	3	9	39
Score difference at full-time	3.6	13.3	−52	−6	5	12	65
Home team wins match	0.61	0.49	0	0	1	1	1
Panel B: NBA non-BP (1987-1993, 2009-2018, N=17,001)	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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 (2009-2020, N=53,770)	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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	3.9	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 D: WNBA (1997-2018, N=4,499)	Mean	St. Dev.	Min	Q1	Median	Q3	Max
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 and WNBA matches where the half-time score difference was not zero. Definitions are as in Table 1.

exclude matches that were played before 23 March 2009. This leaves 55,857 NCAA matches. The exclusion of matches with a zero half-time score difference reduces the four different samples to 17,535 (NBA BP), 17,001 (NBA non-BP), 53,770 (NCAA) and 4,499 (WNBA) matches.

Table 7 summarizes the data. On average, the two teams together scored around 200 (NBA) or 140 (NCAA and WNBA) points per match. At half-time, these averages were approximately 100 and 70. The average score differences at half-time and full-time were around 2 and 4 (NBA and WNBA), or 4 and 7 (NCAA) points, respectively. Home teams won approximately 61 percent (NBA and WNBA) or 67 percent (NCAA) of the matches.

Figure 4: Regression discontinuity plots for basketball



Notes: The figure shows the regression discontinuity plots for NBA BP (Panel A), NBA non-BP (Panel B), NCAA (Panel C) and WNBA (Panel D) matches. Definitions are as in Figure 1.

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 roughly four percentage points per point in all four samples. In line with the findings in BP we visually observe a negative discontinuity at a zero half-time score difference for the NBA BP sample, 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 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 ($p = 0.015$). For the same sample period, BP report an increase of 5.8 to 8.0 percentage points. Hence, our point estimate of the positive effect of trailing is even slightly higher.[11]

For the NBA non-BP, NCAA and WNBA samples, however, the effects of being behind are all statistically insignificant. The point estimates are 0.9 ($p = 0.788$), -0.1 ($p = 0.950$) and 6.0 percentage points ($p = 0.417$), respectively.[12,13] Figure A4 in the Appendix shows that these results are robust to imposing alternative bandwidths.

BP show that the effect of half-time trailing in NBA matches is stronger in the third quarter than in the fourth quarter. Because NCAA matches do not consist of quarters and because we do not have quarter-by-quarter scoring data for the WNBA, we can only conduct such an analysis for the two NBA samples. We exclude matches in which the competing teams scored the same number of points in the quarter of interest. Panels B and C show the results. Being behind at half-time increases the chance of winning the third quarter by 2.9 percentage points for NBA BP matches, but, in contrast to the results in BP, this effect is statistically insignificant ($p = 0.408$). In the NBA non-BP sample, the estimated treatment effect for the third quarter is negative and not significantly different from zero ($\tau = -0.027, p = 0.516$). The effect on winning the fourth quarter is statistically insignificant in both samples (NBA BP: $\tau = 0.018, p = 0.605$; NBA non-BP: $\tau = 0.027, p = 0.469$).

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 half-time score difference was zero, and excludes those in which the score difference after the third quarter was zero. Panel D shows that the treatment effect is insignificant in both the NBA BP ($\tau = 0.003, p = 0.935$) and the NBA non-BP sample ($\tau = -0.018, p = 0.574$), suggesting that trailing after the third quarter does not lead to better performance.

[11] The difference can be considered relatively small in the light of the somewhat different methodological approaches and the independently collected data. 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 ten points around the cutoff value of zero. If we conduct all analyses in the present paper with their method, our conclusions remain unchanged.

[12] For the combination of the NBA BP and NBA non-BP data, the estimated effect is 5.0 percentage points ($p = 0.023$)

[13] For NCAA matches older than those in our sample (1999-2009), BP find that trailing at half-time increases the chance of winning, albeit by a smaller magnitude than for their NBA matches. If we do not exclude matches that were played before 23 March 2009—accepting that our sample period overlaps with that of BP—the estimated effect is 0.4 percentage points ($p = 0.821$).

Table 8: Results for Basketball

	NBA BP	NBA non-BP	NCAA	WNBA
Panel A: Score difference at half-time, winning match				
Behind at half-time	0.083**	0.009	−0.001	0.060
	(0.016, 0.150)	(−0.056, 0.074)	(−0.043, 0.040)	(−0.084, 0.204)
Bandwidth	6.06	7.32	5.25	5.67
Total observations	17,535	17,001	53,770	4,499
Included observations	7,938	8,513	19,183	1,792
Panel B: Score difference at half-time, winning third quarter				
Behind at half-time	0.029	−0.027		
	(−0.040, 0.098)	(−0.108, 0.054)		
Bandwidth	5.52	4.76		
Total observations	17,020	16,516		
Included observations	6,387	4,896		
Panel C: Score difference at half-time, winning fourth quarter				
Behind at half-time	0.018	0.027		
	(−0.050, 0.086)	(−0.046, 0.099)		
Bandwidth	5.67	5.76		
Total observations	17,032	16,499		
Included observations	6,418	6,014		
Panel D: Score difference third quarter, winning match				
Behind after third quarter	0.003	−0.018		
	(−0.063, 0.069)	(−0.081, 0.045)		
Bandwidth	5.66	6.20		
Total observations	17,274	16,780		
Included observations	8,615	9,543		

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

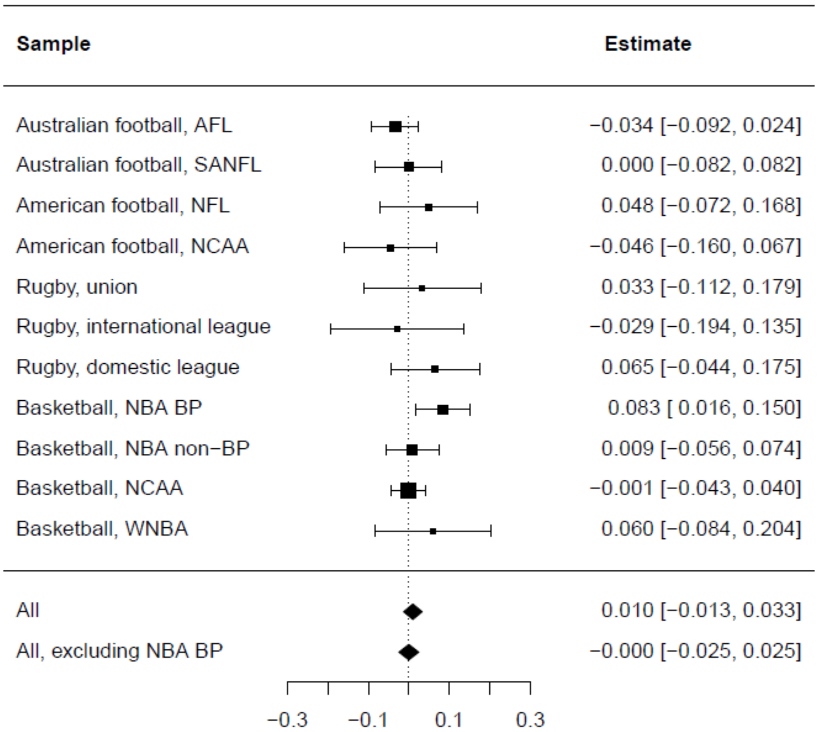
The validity of our RDDs is not rejected by evidence against the continuity assumption: there is no significant discontinuity in the skill difference between home and away teams at the cutoff value of zero, neither at half-time nor after the third quarter (all $p > 0.225$).

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. There is, however, no evidence of such an effect for NBA matches outside of this sample period, and neither for NCAA matches nor for WNBA matches.

7 Meta-analysis

Figure 5 summarizes the results of the previous sections for the main RDD. Trailing at half-time significantly improves the odds of winning in NBA matches from the period analyzed in BP, but there is no evidence of such an effect in any of the

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 corresponding meta-analytic treatment effect estimates. The meta-analytic effects are estimated with the Paule-Mandel estimator (Paule and Mandel, 1989). The size of the squares represent the weights given to each sample. The lines (diamonds) represent the 95 percent confidence intervals for the individual analyses (meta-analyses). *Estimate* is the estimated effect of trailing at half-time on the chance of winning the match. Numbers in brackets represent 95 percent confidence intervals.

other basketball samples or 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 have sufficient power if it has an 80 percent probability of obtaining an estimate that is statistically significant at the five percent level.

To calculate the statistical power of each individual analysis, we use the approach proposed by Cattaneo et al. (2019), who developed a method to calculate the statistical power for the local-linear method proposed by Calonico et al. (2014). For the hypothetical true effect, we adopt the NBA estimates of BP, who find that half-time trailing improves the likelihood of winning by 5.8 to 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: Power calculations

	Matches	Power
Australian football		
AFL	14,945	0.501
SANFL	6,622	0.284
American football		
NFL	10,590	0.158
NCAA	7,024	0.170
Rugby		
Rugby union	2,733	0.119
International rugby league	2,057	0.106
Domestic rugby league	8,690	0.180
Basketball		
NBA BP	17,535	0.400
NBA non-BP	17,001	0.420
NCAA	53,770	0.787
WNBA	4,499	0.124
Meta-analysis		
All	145,071	0.998
All, excluding NBA BP	127,536	0.996

Notes: This table presents the power calculations for both the main individual analyses and the meta-analyses. *Matches* is the number of matches in which the half-time score difference is not zero. *Power* is the probability of finding an estimate that is significant at the five percent level if the true effect is 0.058. The power of the individual samples is calculated with the approach proposed by Cattaneo et al. (2019), and the power of the meta-analysis is calculated with the analogical approach given in Jackson and Turner (2017).

Table 9 shows the results of the power calculations. None of the individual analyses meets the 80 percent power benchmark. This is problematic if analyses are considered in isolation. Combined, however, these power statistics imply that the probability of finding insignificant estimates in all new samples—assuming a true effect of 0.058—is only 1.7 percent.

To synthesize the different results, we perform a meta-analysis. Because the true effect may differ across the different samples, we employ a random-effects meta-analytic model (Hedges and Vevea, 1998). The overall effect is the weighted average of the estimated treatment effects, 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). The total number of matches underlying the meta-analysis is 145,071, or 59,788 if we only consider observations that are within the different bandwidths around the cutoff. Based on the analytical power calculation for meta-analyses as described in Jackson and Turner (2017), there is a 99.8 percent probability that our meta-analysis will detect a significant effect if the average true effect is 0.058. If we exclude the NBA BP sample, the power is 99.6 percent.

As shown in Figure 5, across all analyses the overall effect of being behind at half-time on the probability of winning the match is 1.0 percentage point, and statistically insignificant ($p = 0.398$).[14] If we leave out the analysis of the NBA BP sample and thus exclusively consider sports matches that have not been analyzed previously, the estimated overall effect size is economically and statistically indistinguishable from zero ($p = 0.996$). In both cases, the confidence intervals are relatively narrow.[15]

If performance improves only temporarily, an effect is more likely to emerge in the period directly following the half-time break. Figures A5 and A6 in the Appendix show the results of meta-analyses for the effect of half-time trailing on winning the third quarter and for the effect on winning the fourth quarter. The estimated overall effect of half-time trailing on winning the third quarter is 2.6 percentage points. This value is economically non-negligible, but statistically insignificant ($p = 0.208$). If we omit the corresponding analysis of the NBA BP sample, the coefficient is slightly higher but remains statistically insignificant ($\tau = 0.028, p = 0.283$). The meta-analytic estimates for the effect on winning the fourth quarter are negative and statistically insignificant: -0.5 percentage points ($p = 0.781$) for all analyses combined and -1.1 percentage points ($p = 0.557$) without the analysis of the NBA BP sample. In addition, Figure A7 shows that there is no meta-analytic evidence that trailing after the third quarter significantly affects the chance of winning the match, neither when the analysis of the NBA BP sample is included ($\tau = -0.007, p = 0.702$) nor when it is excluded ($\tau = -0.011, p = 0.615$).

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 Berger and Pope's (2011) analysis of whether marginally trailing improves the odds of winning in basketball to Australian football, American football and rugby. We find no clear evidence for these three sports: the estimated effects are sometimes positive and sometimes negative, and statistically almost always insignificant. We also revisit the phenomenon for basketball. For NBA matches from

[14] The estimated overall effect is 1.1 percentage points ($p = 0.321$) if we do not exclude NCAA basketball matches that were played before 23 March 2009.

[15] If we conduct meta-analyses for each sport separately, all four estimates are statistically insignificant (all $p > 0.199$).

the period analyzed in BP we replicate the finding that half-time trailing improves the odds of winning, but for NBA matches from outside this period and for matches from the NCAA and WNBA we again obtain null results. 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 data sets (Abadie, 2020).

Australian football, American football and rugby are attractive sports for the analysis of interest, because of the large numbers of points that are generally scored. For reliably identifying a discontinuous effect of trailing on performance, it is important that the relation 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 different regression discontinuity plots. Also, 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 slightly behind still have a reasonable chance of winning. Otherwise, trailing by one or a few points likely discourages rather than motivates (Fershtman and Gneezy, 2011; Gill and Prowse, 2012). For Australian football, American football, and rugby, the relationship between the half-time score difference and the winning probability resembles the relationship for basketball, implying that the psychological effect of trailing in these sports should be similar to that in basketball.

Our null results do not mean that being slightly behind in a competition does not or cannot have any systematic positive motivating effects. There is a robust literature that demonstrates that people who are slightly below their goal work harder than those who already reached it (see, for example, Heath et al., 1999; Pope and Simonsohn, 2011; Corgnet et al., 2015; Allen et al., 2016). In addition to the findings for basketball, BP present results from two laboratory experiments that show that this motivational effect also occurs during a competition. In a two-period button-pressing contest, subjects who were told after the first period that they are slightly behind worked harder in the second period than subjects who were told that they are far behind, tied, or slightly ahead. An important difference between sports matches and BP's laboratory task, however, is in the feedback that participants received. 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 after a moment of reflection. 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 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 a leading team or subject realizes that their opponent will exert additional effort, they should anticipate this and adjust their own effort accordingly. Subjects in the laboratory may not realize that their trailing opponent will exert more effort, but 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, for example, 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.

References

Abadie, A. (2020), 'Statistical non-significance in empirical economics', *American Economic Review: Insights* **2**(2), 193–208.

Allen, E. J., Dechow, P. M., Pope, D. G. and Wu, G. (2016), 'Reference-dependent preferences: Evidence from marathon runners', *Management Science* **63**(6), 1657–1672.

Berger, J. and Pope, D. G. (2011), 'Can losing lead to winning?', *Management Science* **57**(5), 817–827.

Calonico, S., Cattaneo, M. D. and Titiunik, R. (2014), 'Robust nonparametric confidence intervals for regression-discontinuity designs', *Econometrica* **82**(6), 2295–2326.

Calonico, S., Cattaneo, M. D. and Titiunik, R. (2015), 'Optimal data-driven regression discontinuity plots', *Journal of the American Statistical Association* **110**(512), 1753–1769.

Cattaneo, M. D., Titiunik, R. and Vazquez-Bare, G. (2019), 'Power calculations for regression-discontinuity designs', *Stata Journal* **19**(1), 210–245.

Corgnet, B., Gómez-Miñambres, J. and Hernán-González, R. (2015), 'Goal setting and monetary incentives: When large stakes are not enough', *Management Science* **61**(12), 2926–2944.

Dechenaux, E., Kovenock, D. and Sheremeta, R. (2015), 'A survey of experimental research on contests, all-pay auctions and tournaments', *Experimental Economics* **18**(14), 609–669.

Fershtman, C. and Gneezy, U. (2011), 'The tradeoff between performance and quitting in high power tournaments', *Journal of the European Economic Association* **9**(2), 318–336.

Gauriot, R. and Page, L. (2019), 'Does success breed success? A quasi-experiment on strategic momentum in dynamic contests', *Economic Journal* **129**(624), 3107–3136.

Gill, D. and Prowse, V. (2012), 'A structural analysis of disappointment aversion in a real effort competition', *American Economic Review* **102**(1), 469–503.

Hahn, J., Todd, P. and Van der Klaauw, W. (2001), 'Identification and estimation of treatment effects with a regression-discontinuity design', *Econometrica* **69**(1), 201–209.

Harris, C. and Vickers, J. (1987), 'Racing with uncertainty', *Review of Economic Studies* **54**(1), 1–21.

Heath, C., Larrick, R. P. and Wu, G. (1999), 'Goals as reference points', *Cognitive Psychology* **38**(1), 79–109.

Hedges, L. V. and Vevea, J. L. (1998), 'Fixed- and random-effects models in meta-analysis', *Psychological Methods* **3**(4), 486–504.

Jackson, D. and Turner, R. (2017), 'Power analysis for random-effects meta-analysis', *Research Synthesis Methods* **8**(3), 290–302.

Klumpp, T. and Polborn, M. K. (2006), 'Primaries and the New Hampshire effect', *Journal of Public Economics* **90**(6-7), 1073–1114.

Lee, D. S. (2008), 'Randomized experiments from non-random selection in U.S. House elections', *Journal of Econometrics* **142**(2), 675–697.

Malueg, D. A. and Yates, A. J. (2010), 'Testing contest theory: Evidence from best-of-three tennis matches', *Review of Economics and Statistics* **92**(3), 689–692.

Page, L. and Coates, J. (2017), 'Winner and loser effects in human competitions. Evidence from equally matched tennis players', *Evolution and Human Behavior* **38**, 530–535.

Panityakul, T., Bumrungsup, C. and Knapp, G. (2013), 'On estimating residual heterogeneity in random-effects meta-regression: A comparative study', *Journal of Statistical Theory and Applications* **12**(3), 253–265.

Paule, R. C. and Mandel, J. (1989), 'Consensus values, regressions, and weighting factors', *Journal of Research of the National Institute of Standards and Technology* **94**(3), 197–203.

Pope, D. G. and Simonsohn, U. (2011), 'Round numbers as goals: Evidence from baseball, SAT takers and the lab', *Psychological Science* **22**(1), 71–79.

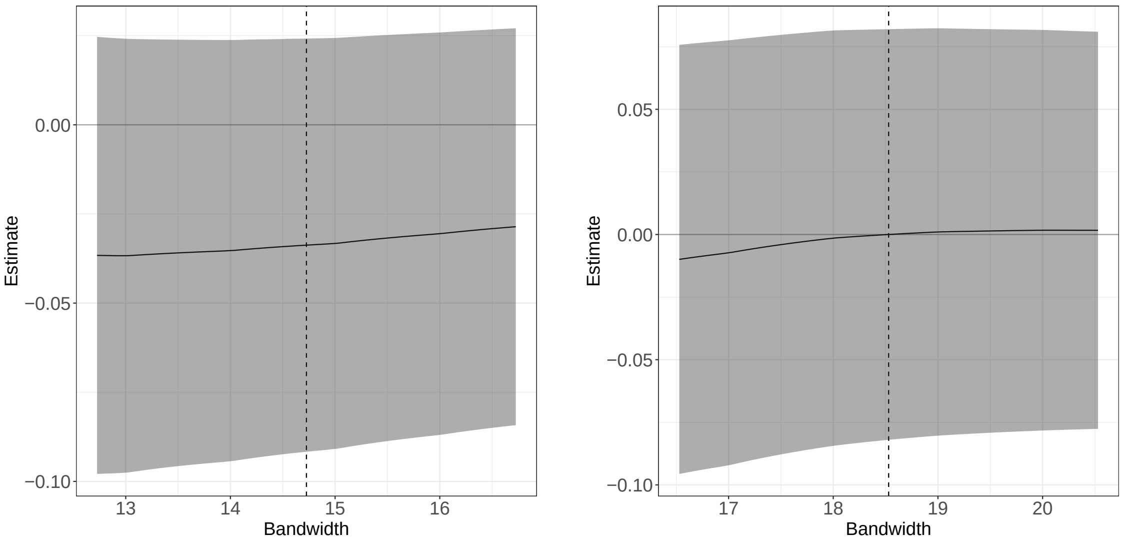
Thistlethwaite, D. L. and Campbell, D. T. (1960), 'Regression-discontinuity analysis: An alternative to the ex post facto experiment', *Journal of Educational Psychology* **51**(6), 309–317.

Veroniki, A. A., Jackson, D., Viechtbauer, W., Bender, R., Bowden, J., Knapp, G., Kuss, O., Higgins, J. P. T., Langan, D. and Salanti, G. (2015), 'Methods to estimate the between-study variance and its uncertainty in meta-analysis', *Research Synthesis Methods* **7**(1), 55–79.

Appendix

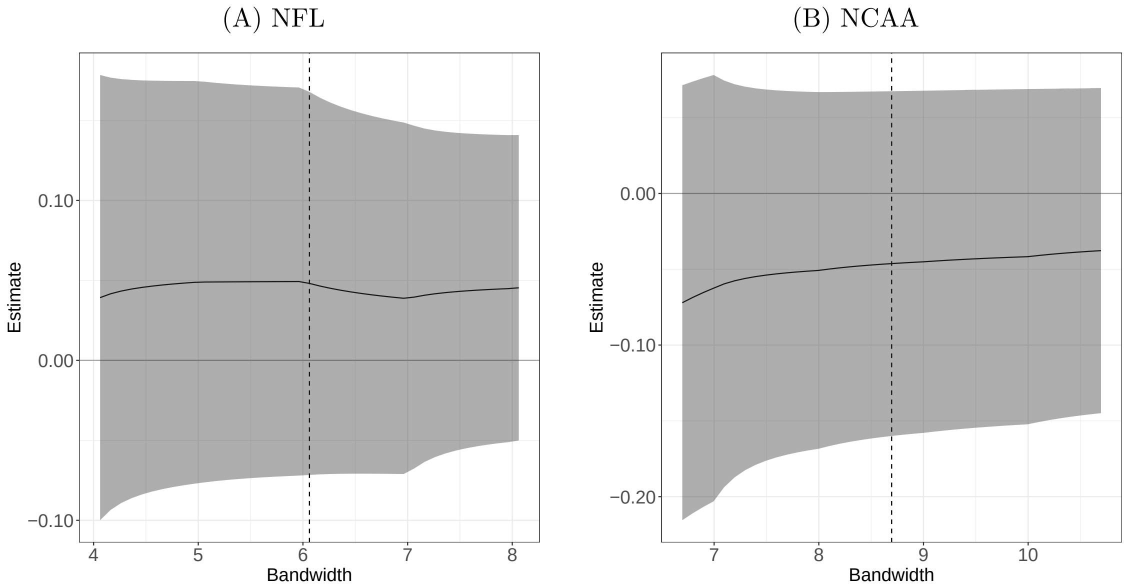
Figure A1: Bandwidth sensitivity Australian football

(A) AFL (B) SANFL



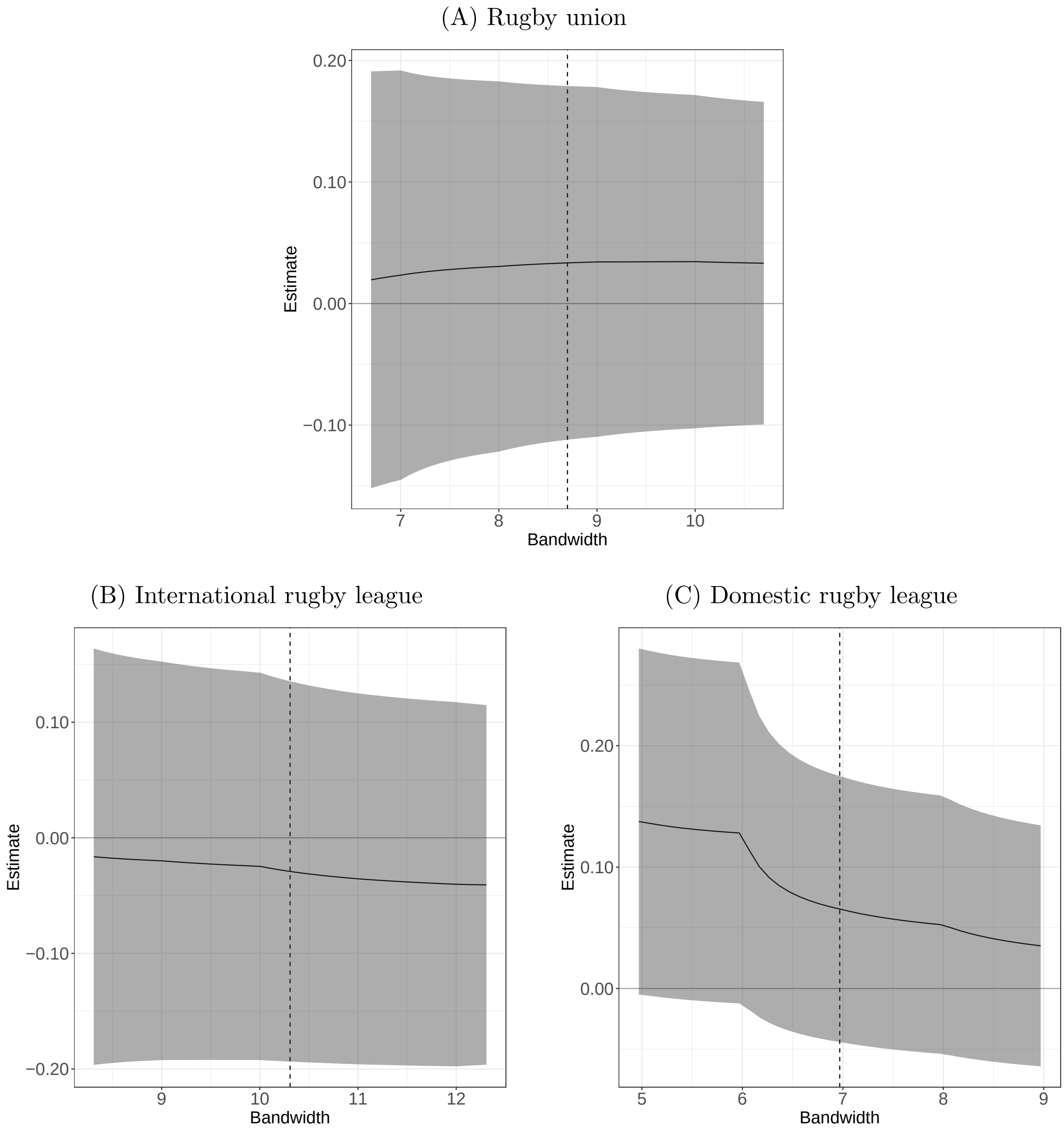
Notes: The figure shows the sensitivity of the main analyses for Australian football to a range of imposed alternative bandwidths. Compared to the bandwidth reported in Table 2, the smallest bandwidth is two points narrower and the largest is two points wider. The curves show the point estimates, the grey regions represent the 95 percent confidence intervals, and the dotted line shows the bandwidth of that minimizes the mean squared error.

Figure A2: Bandwidth sensitivity American football



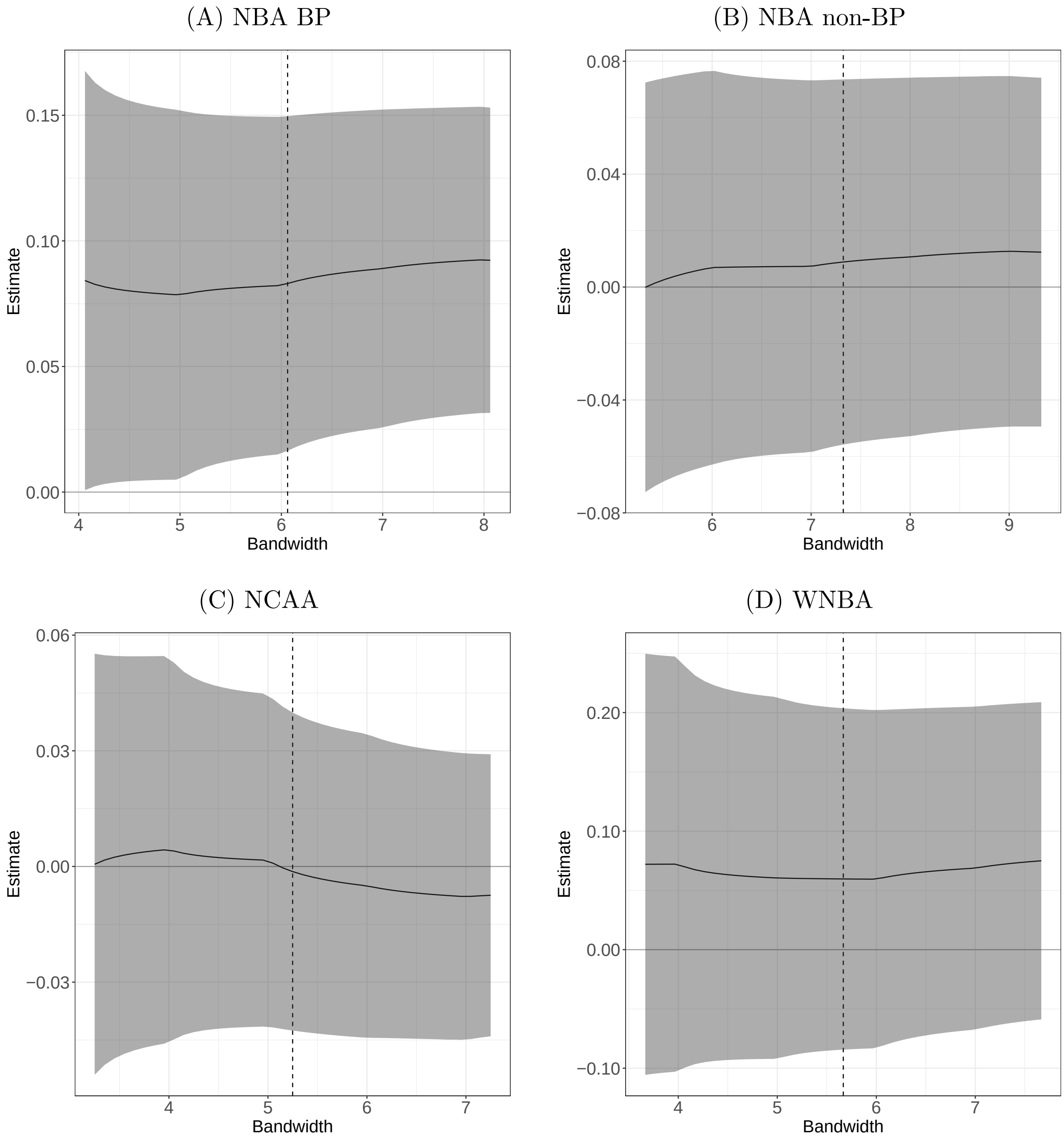
Notes: The figure shows the sensitivity of the main analyses for American football to a range of imposed alternative bandwidths. Definitions are as in Figure A1.

Figure A3: Bandwidth sensitivity rugby



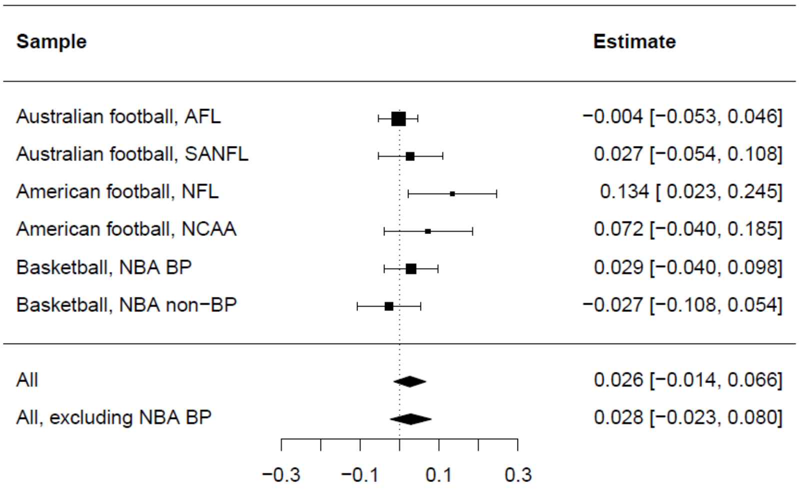
Notes: The figure shows the sensitivity of the analyses for rugby to a range of imposed alternative bandwidths. Definitions are as in Figure A1.

Figure A4: Bandwidth sensitivity basketball



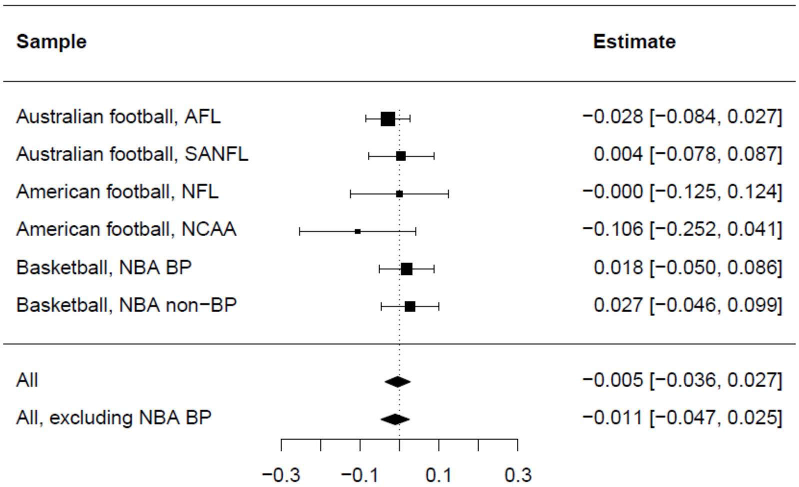
Notes: The figure shows the sensitivity of the main analyses for basketball to a range of imposed alternative bandwidths. Definitions are as in Figure A1.

Figure A5: Meta-analysis for the effect of trailing at half-time on winning the third quarter



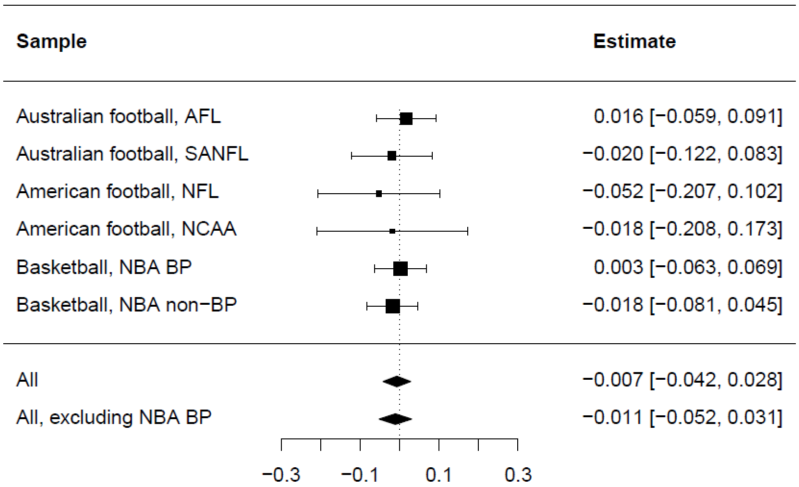
Notes: The figure summarizes the results of the analyses of the effect of trailing at half-time on winning the third quarter, both for the individual samples and for the meta-analyses. *Estimate* is the estimated effect of trailing at half-time on the chance of winning the third quarter. All definitions are as in Figure 5.

Figure A6: 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, both for the individual samples and for the meta-analyses. *Estimate* is the estimated effect of trailing at half-time on the chance of winning the fourth quarter. All definitions are as in Figure 5.

Figure A7: 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, both for the individual samples and for the meta-analyses. *Estimate* is the estimated effect of trailing after the third quarter on the chance of winning the match. All definitions are as in Figure 5.