Loss aversion and high stakes

Stephen Easton, Newcastle Business School, University of Newcastle, Australia, 2305,

steve.easton@newcastle.edu.au

Sean Pinder, Department of Finance, University of Melbourne, Australia, 3010,

spinder@unimelb.edu.au

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Abstract

Berger and Pope (2011), using an analysis of more than 18,000 United States professional National Basketball Association (NBA) games played between the 1993 / 1994 season and 2009, show that, for both home and away teams, being behind by one point at halftime leads to a discontinuous increase in winning percentage. A similar but weaker result is found using an analysis of more than 45,000 National Collegiate Athletic Association (NCAA) basketball games played between the 1999/2000 season and 2009. They attribute this result to loss aversion.

This paper extends that analysis be examining the importance of what is at stake. Studies have found across a range of domains that loss aversion increases as stake increases. We posit that, *a priori*, stakes will be higher for NBA teams than for NCAA teams, and higher for home teams than for away teams.

This paper provides an analysis of over 68,000 United States professional basketball games played from the initial NBA season in 1946 / 1947 to the 2018 / 2019 season, and over 69,000 NCAA games played from the 2007 / 2008 season to the 2018 / 2019 season. We model outcomes using a digital call option rather than using the regression discontinuity design (RDD) applied by Berger and Pope. This model allows for necessary non-linearity in the relation between halftime score and winning percentage. Unlike for the RDD, it also provides an analysis for which the result for away teams is not simply the converse of that for home teams. We find evidence of better than expected performance for NBA home teams that are behind by up to four points. We find no evidence of this effect with respect to NBA away teams, nor for NCAA teams – whether home or away. Our results suggest that loss aversion is apparent when stakes are high.

1. Introduction

Berger and Pope (2011), using an analysis of more than 18,000 United States professional basketball games played between the 1993 / 1994 season and 2009, show that, for both home and away teams, being behind by one point at halftime leads to a discontinuous increase in winning percentage. As their results showed that being just slightly behind at halftime actually resulted in teams being more likely to win than those teams that were slightly ahead at halftime, their results generated much discussion, including in the *Harvard Business Review*, the *New York Times*, and *Scientific American*.

They attributed their result to loss aversion and the increased motivation that is manifest when teams are slightly behind. This argument is based on the work of Heath, Larrick and Wu (1999), Kahneman and Tversky (1979), Kivetz, Urminsky and Zheng (2006), and Tversky and Kahneman (1992), amongst others. Heath, Larrick and Wu (1999) argue that goals or targets can act as reference points. Consequently, position relative to a goal can influence motivation in a manner consistent with the three key tenets of prospect theory (Kahneman and Tversky (1979 and Tversky and Kahneman (1992)). These tenets are: that people categorize outcomes as gains (success) or losses (failure) depending on where they fall relative to a particular standard; loss aversion, whereby losses are more painful than gains are pleasurable; and diminishing sensitivity, whereby outcomes have a smaller marginal impact as they move further from the reference point. Loss aversion suggests that compared to people who are above their goal by a similar amount, people who are below or behind their goal will work harder because they see their performance as a loss. Furthermore, because of diminishing sensitivity, people who are slightly below their goals should work harder than those for whom the goal is further away (Heath Larrick and Wu (1999) and Kivetz, Urminsky and Zheng (2006)).

Berger and Pope conclude that "encouraging people to see themselves as behind others, albeit slightly, should increase effort. Managers trying to encourage employees to work harder, for example, might provide feedback about how a person is doing relative to a slightly better performer. Strategically scheduling breaks when someone is slightly behind should also help focus people on the deficit and subsequently increase effort. This should lead to stronger performance, and ultimately, success" (p. 826).

This paper extends that analysis be examining the importance of what is at stake. While Levitt and List (2008) argue that high stakes may reduce decision biases, especially in real-world settings with experienced agents, many studies have found across a range of domains that biases increase as stake increases. For example, Haigh and List (2005) found that professional traders exhibited greater loss aversion than students in an experimental laboratory setting. Green and Daniels (2018) report that Major League Baseball umpires display *impact aversion*, which is an aversion to making decisions that more greatly change the expected outcome of the game. Anbarci, Arin, Kuhlenkasper and Zenker (2018) report loss aversion in professional tennis players. In the most detailed study of loss aversion in a high stakes setting, Pope and Schweitzer (2011) found this bias pertained in professional golfers' performance on the PGA Tour – a setting with intense competition, large stakes, and very experienced agents.

We posit that, *a priori*, stakes will be higher for NBA teams than for NCAA teams, and higher for home teams than for away teams. With respect to NBA and NCAA teams, only the elite college players are drafted into the NBA, and many college basketball players do not choose professional careers. For example, only 52 out of 4,181 (1.2%) of draft eligible NCAA participants were drafted in the 2018 NBA draft (NCAA 2019). Stakes are markedly higher for NBA players. With respect to home and away teams, across a range of sports, including basketball, home teams win of the order of 60% of games (Jamieson (2010). Given the impact of crowd support on this outcome (see for example Myers (2014)), it may be posited that players experience loss aversion more acutely in front of a home crowd.

This paper provides an analysis of over 68,000 United States professional basketball games played from the initial NBA season in 1946 / 1947 to the 2018 / 2019 season, and over 69,000 NCAA games played from the 2007 / 2008 season to the 2018 / 2019 season. We model outcomes using a digital call option rather than using the regression discontinuity design (RDD) applied by Berger and Pope. Use of the digital call option allows for necessary non-linearity in the relation between halftime score and winning percentage. Unlike for the RDD, it also provides an analysis for which the result for away teams is not simply the converse of that for home teams.

We find evidence of better than expected performance for NBA home teams that are behind by up to four points. We find no evidence of this effect with respect to NBA away teams, nor for NCAA teams – whether home or away. Our results suggest that loss aversion is apparent when stakes are high.

This paper proceeds as follows. The expected relationship between halftime score and winning percentage is presented in Section 2. The empirical results of examining this relationship are presented in Section 3. A summary is provided in Section 4.

2. Expected relationship between halftime score and winning percentage

Any test for abnormality in winning percentage conditioned on halftime score difference must of course necessarily be a joint test of the expected or normal winning percentage. To model expected winning percentage, Berger and Pope use the regression discontinuity design introduced by Thistlethwaite and Campbell (1960), and developed by Imbeds and Lemieux (2008) and Lee and Lemieux (2009). To provide what they argue will be an expected linear relationship between halftime score difference and winning percentage (with a discontinuity at a halftime score difference of zero), they restrict their analysis to those games where the halftime score difference was less than or equal to 10 points and exclude any games that were tied at halftime. They also include a cubic function in their analysis – a robustness check that does not substantially alter their findings.

Their key finding is reproduced as Figure 1 below.

Figure 1

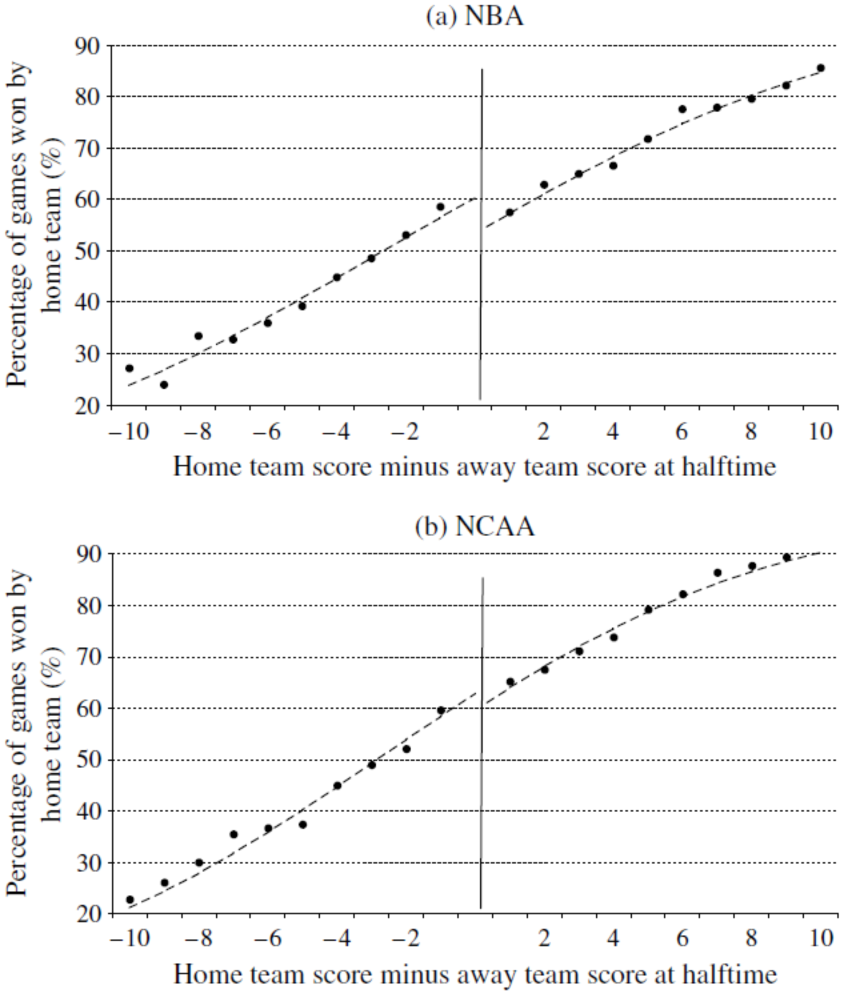

Figure 1: Reproduces Figure 1 from Berger and Pope (page 819). The raw data are presented with dots. The dashed lines represent the logistic linear fit of the score difference on winning, allowing for a discontinuity when a team is behind.

With respect to NBA games, they summarise this result by arguing, "this relationship is approximately linear over the range in our data. Every two points better a team is doing relative to its opponent at halftime is associated with a six to eight percentage point increase in the probability of winning" (page 819). They conclude that, "[t]here is a strong discontinuity, however, around zero. Rather than having a winning percentage that is six to eight percentage points less than teams ahead by a point (as the model would predict), home teams that are behind by one point are actually more likely than their opponents to win (triumphing in 58.2% relative to 57.1% of games)" (page 820).

Of course, *a priori*, there is no basis for expecting the relation between halftime score difference and winning percentage to be linear. Indeed, the expected relationship must be non-linear. The winning percentage must approach an asymptote of zero for large negative halftime score differentials and an asymptote of one for large positive halftime score differentials.

A superior assumption to that of linearity may be that the relationship is sigmoidal, as presented in Figure 2.

In a two-team sporting contest, the probability of a team winning may be modelled as the value of a digital call option *C*. The terminal pay-off to this digital call option may be expressed as:

$$Payoff_T = \begin{cases} 1 \ \ if \ SD_T > \ 0 \\ 0 \ \ if \ SD_T < \ 0 \end{cases} \qquad (1)$$

where SD_T is the score differential, defined as the home team score less the away team score, at the completion of the game at time *T*. It follows that at any time t prior to the completion of the game, the value of the option may be expressed as a function of four parameters, namely the score differential at time t SD_t; the time remaining in the game $\tau = T - t$; the volatility σ of the underlying diffusion process of the score differential, and the drift in the score differential towards the home team *df*. Stern (1994) has shown that an arithmetic Brownian process with an expected mean of *df* and a standard deviation of σ may approximate the diffusion process of the score differential in basketball. Given that diffusion process, the value of the digital call option may be written as:

$$C = N(d) \text{ where } d = \frac{(SD_t + df.\tau)}{\sigma\sqrt{\tau}}, \qquad (2)$$

where *N (d)* is the cumulative distribution function of the standard normal distribution, and SD_t, *df*, σ and τ are as previously defined. The value of such a digital call option may be represented as a sigmoidal function as shown in Figure 2.

Figure 2

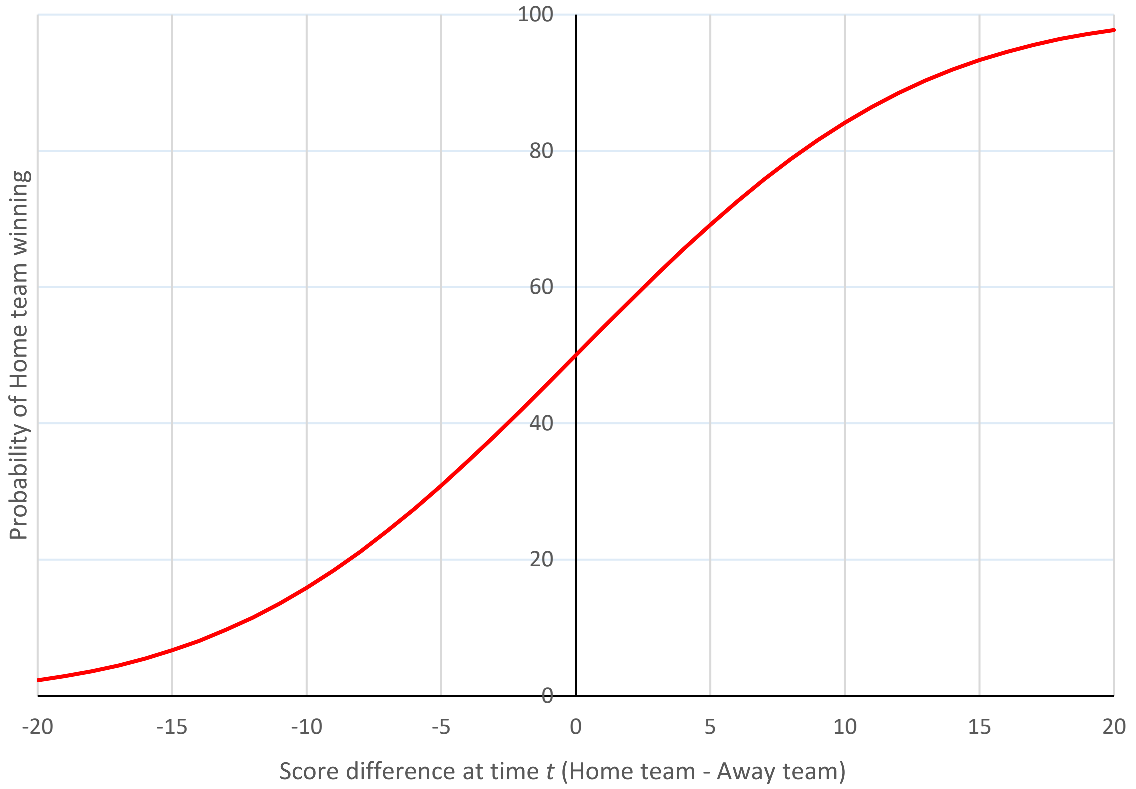

Figure 2: The expected relationship between score difference a time *t* and winning percentage modelled as a digital call option. This figure uses the model provided in Equation 2, with the assumption that there is no drift in the score differential towards the home team.

It may be noted that the real options framework used in this study dates back to the foundation analysis by Marschak (1949), and Arrow (1968), and was developed by, for example, Bernanke (1983), Brennan and Schwartz (1985), Pindyck (1991) and Dixit and Pindyck (1995).

In the empirical analysis below, we first examine the capacity of the digital call option to model expected winning percentages conditional on halftime score difference. We then compare observed and expected winning percentages across halftime score differences.

3. Empirical results of examining the relationship between halftime score differential and winning percentage

Data for 68,380 NBA basketball games were obtained from the initial NBA season in 1946 / 1947 to the 2018 / 2019 season inclusive. These data were obtained from https://www.basketball-reference.com, www.espn.com, and www.nba.com.

These data included the date of each game, team identifiers, and indicator of the home team, and the scores at quarter time, halftime, three quarter time, and the final scores. NBA games are divided into 12-minute quarters, with a 15-minute break at halftime and overtime periods if the game ends in a tie. Data for 69,212 National Collegiate Athletic Association (NCAA) basketball games were also collected. These data were obtained from the 2007 / 2008 season to the 2018 / 2019 season from www.espn.com and www.sportsbookreviewsonline.com/scoresoddsarchives/ncaabasketball/ncaabasketballoddsarchives.htm. NCAA games are divided into 20-minute halves but like NBA have a 15-minute break at halftime.

Descriptive statistics for NBA games are provided in Table 1 and presented in Figure 3.

Table 1: NBA Descriptive Results

Score difference at halftime (home team less away team)	Number of games	Percentage of games won by home team	Average change in score differential in the second half	Median change in score differential in the second half	Standard deviation of the change in the score differential in the second half
-20	197	4.57	4.52	5	9.49
-19	286	8.39	3.50	4	11.20
-18	345	6.96	3.83	4	9.52
-17	412	7.52	3.50	3.5	9.41
-16	466	12.23	3.96	4	10.23
-15	566	12.90	3.53	4	10.32
-14	741	14.04	3.33	4	9.99
-13	802	18.08	3.78	4	10.20
-12	950	22.32	3.93	4	10.03
-11	1130	21.86	3.59	3	9.58
-10	1257	26.01	3.30	3	10.12
-9	1360	28.09	3.15	2	9.76
-8	1589	31.78	3.08	3	9.71
-7	1769	33.30	2.74	2	9.68
-6	1980	38.99	2.77	3	9.78
-5	2055	40.83	2.49	2	9.64
-4	2230	46.05	2.75	2	9.81
-3	2404	49.17	2.44	2	9.94
-2	2619	53.42	2.52	4	9.65
-1	2674	56.47	2.58	3	9.41
0	2872	55.92	1.75	2	9.80
1	2746	60.56	1.40	2	9.66
2	2858	64.21	1.40	2	9.42
3	2775	68.25	1.27	2	9.80
4	2777	69.93	0.95	2	9.75
5	2636	72.95	0.80	1	9.74
6	2659	77.02	0.88	1	9.69
7	2430	78.89	0.54	1	9.56
8	2236	81.22	-0.11	0	9.65
9	2207	83.60	0.17	0	9.66
10	2056	85.31	0.14	0	9.79
11	1913	87.98	0.02	0	9.80
12	1587	88.91	0.04	0	9.77
13	1542	90.60	-0.42	-1	9.72
14	1287	90.91	-0.66	-1	9.95
15	1217	93.10	-0.79	-1	10.07
16	954	92.98	-0.81	-1	10.38
17	887	95.72	-1.05	-1	9.78
18	772	95.47	-0.95	-1	10.04
19	621	96.30	-0.76	-1	10.30
20	517	96.52	-1.94	-2	10.14

Of the 68,380 games, 2999 games were excluded from those reported in Table 1 because the absolute score difference at halftime was greater than 20 points. These observations were excluded due to small sample sizes for individual halftime score differences in those ranges. For halftime score differences from -11 to +15 points, the percentage of games won by the home team increases monotonically, with the exception of the score difference changing from -1 to scores tied at halftime. Here the percentage of games won falls from 56.47% to 55.92%, a result that is consistent with the finding of Berger and Pope.

The range of the standard deviations of the second half score differential conditional on the halftime score difference is only from 9.41 to 10.38 points for halftime score differences from -18 to +20, and there is no obvious relation between score differences and these standard deviations. As documented by Goldman and Rao (2013) and others, teams have an incentive to increase (decrease) the riskiness or range of outcomes when they are behind (ahead). However, there is no evidence of risk-shifting with respect to teams' position at halftime.

There is a marked drift in the second half score differential towards the home team. This is evidenced by a mean (median) drift towards the home team of 1.75 (2) points where the scores are tied at halftime, with the home team winning 55.92% of these matches. The drift also varies across score differences at halftime, with a drift of the order of 3 to 4 points where the score difference is greater than -10 points at halftime, to between 2 and 3 points where the home team is trailing by less than 10 points at halftime. There is a drift away from the home team when the home team is leading by more than of the order of 13 points at halftime.

Figure 3 provides a representation of the relationship between the percentage of games won by the home team and the score differential at halftime.

Figure 3

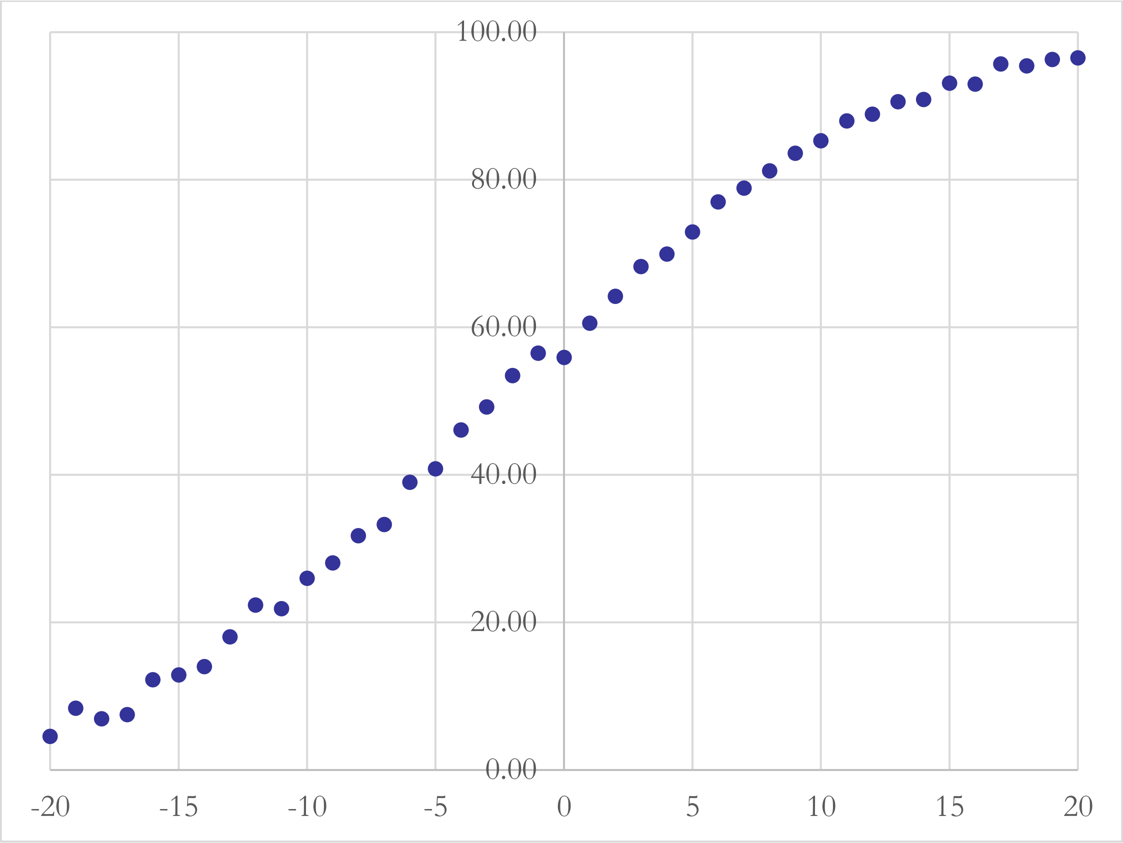

Figure 3: The observed relationship between halftime score difference and percentage of games won by the home team.

The apparent similarity between Figures 2 and 3 suggests that at a descriptive level a sigmoidal function as represented by a digital call option may usefully represent the expected relationship.

To estimate the value of the digital call option and therefore the *expected* winning percentage for each halftime score difference across the range from the home team being 20 points behind to 20 points ahead, it is necessary to estimate the *expected* standard deviation of the second half score differential ($\sigma.\sqrt{\tau}$ where $\tau = 0.5$), and the *expected* drift in the second half score differential towards the home team for each of those score differences ($df.\tau$, where $\tau = 0.5$).

The expected standard deviation of the second half score differential, for each halftime score, was calculated as the average of the observed standard deviations of the second half score differentials for those games where the halftime score was between plus or minus 10 points of the halftime score of those games for which the estimate was being obtained. The games for which the expected standard deviation of the second half time score were being calculated were omitted. For example, the expected standard deviation of the second half score differential for games tied at halftime was calculated as the average of the standard deviations of those games where the halftime score differential was between minus 10 and plus 10 points, with the standard deviation of the second half score differential for games tied at halftime omitted.

The expected drift in the second half score differential towards the home team for each score difference was calculated using the same approach.

The results are provided in Table 2 and Figure 4.

Table 2: NBA Results

Score difference at halftime (home team less away team)	Percentage of games won by home team	Average change in score differential in the second half	Standard deviation of the change in the score differential in the second half	Expected percentage of games won by home team
-20	4.57	4.52	9.49	5.84
-19	8.39	3.50	11.20	6.82
-18	6.96	3.83	9.52	8.18
-17	7.52	3.50	9.41	9.34
-16	12.23	3.96	10.23	10.76
-15	12.90	3.53	10.32	12.46
-14	14.04	3.33	9.99	14.45
-13	18.08	3.78	10.20	16.39
-12	22.32	3.93	10.03	18.73**
-11	21.86	3.59	9.58	21.61
-10	26.01	3.30	10.12	24.48
-9	28.09	3.15	9.76	27.32
-8	31.78	3.08	9.71	30.27
-7	33.30	2.74	9.68	33.53
-6	38.99	2.77	9.78	36.83*
-5	40.83	2.49	9.64	40.15
-4	46.05	2.75	9.81	43.52**
-3	49.17	2.44	9.94	47.06*
-2	53.42	2.52	9.65	50.34**
-1	56.47	2.58	9.41	53.66**
0	55.92	1.75	9.80	57.20
1	60.56	1.40	9.66	60.63
2	64.21	1.40	9.42	63.91
3	68.25	1.27	9.80	67.10
4	69.93	0.95	9.75	70.16
5	72.95	0.80	9.74	73.02
6	77.02	0.88	9.69	75.68
7	78.89	0.54	9.56	78.24
8	81.22	-0.11	9.65	80.75
9	83.60	0.17	9.66	82.88
10	85.31	0.14	9.79	84.75
11	87.98	0.02	9.80	86.81
12	88.91	0.04	9.77	88.49
13	90.60	-0.42	9.72	90.09
14	90.91	-0.66	9.95	91.47
15	93.10	-0.79	10.07	92.63
16	92.98	-0.81	10.38	93.80
17	95.72	-1.05	9.78	94.75
18	95.47	-0.95	10.04	95.56
19	96.30	-0.76	10.30	96.31
20	96.52	-1.94	10.14	96.90

Table 2: Table 2 provides the observed percentage of games won by the home team and the expected percentage of games won estimated using the digital option pricing model described in Equation 2. ** (*) denotes that the observed percentage of games won by the home team was significantly greater than expected at the 0.01 (0.05) level using the two-tailed binomial test.

Figure 4

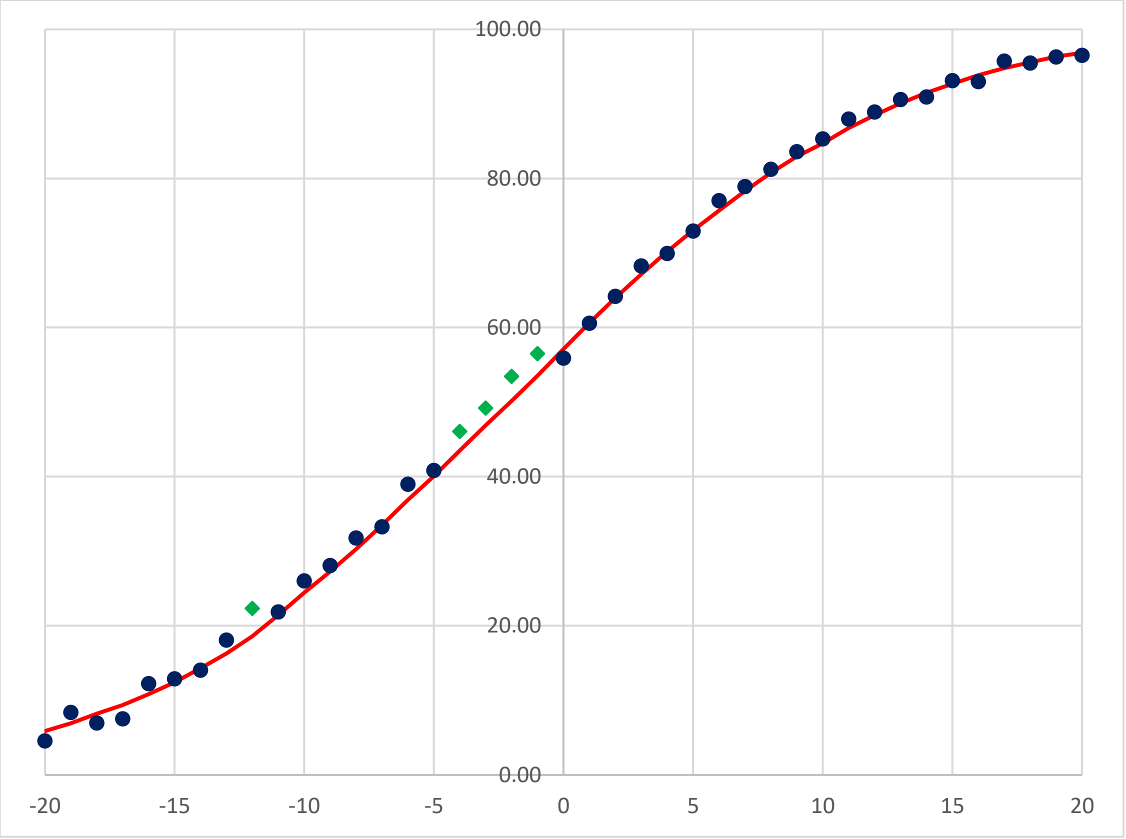

Figure 4: The observed and expected relationship between halftime score difference and percentage of games won by the home team. The raw observed data are presented with dots and diamonds. For those observed data presented as diamonds, the observed percentage of games won by the home team was significantly greater than expected at the 0.05 level under the two-tailed binomial test. The line represents the expected percentages of games won as estimated using the digital option pricing model described in Equation 2.

In contrast to Berger and Pope who find that home teams win significantly more games than expected when behind by 1 point at halftime, Table 2 and Figure 4 show that these teams win significantly more games than expected when behind by between 4 points and 1 point. The finding is stronger for score differences of -2 and -1 points.

A starker difference in our results to those of Berger and Pope is that as they recognise, their results pertain equally to home and away teams. Given the implementation of the regression discontinuity design, had they chosen to analyse away teams, they would have found simply a mirror image of the results they presented. For example, they found that away teams behind by a point were more likely to win than their opponents (42.9% versus 41.8%), (see page 820). While our results are also presented in terms of the home teams, as home teams do not lose more games than expected when ahead at halftime, necessarily away teams do not win more games than expected when behind at halftime. This finding suggests that loss aversion is apparent when teams are playing in front of a home crowd.

Sensitivity analysis was performed by estimating the expected winning percentage using the option pricing model described in Equation 2 using games where the halftime score was between plus or minus, from 3 to 10 points, of the halftime score of those games for which the estimate was being obtained. Further, sensitivity analysis was performed where those games with score differentials closest to the halftime score of those games for which the estimate was being obtained were also omitted. These sensitivity analyses had virtually no impact on the results.

Table 3 presents an analysis of those games played for the period examined by Berger and Pope, namely from the 1993 / 1994 season to March 1, 2009.

Table 3: 1993 / 1994 Season to March 1, 2009

Score difference at halftime (home team less away team)	Number of games	Percentage of games won by home team	Average change in score differential in the second half	Standard deviation of the change in the score differential in the second half	Expected percentage of games won by the home team
-20	65	6.15	4.49	9.67	5.27
-19	93	7.53	3.04	11.09	6.31
-18	111	9.01	3.77	9.80	7.67
-17	107	8.41	4.43	8.40	8.80
-16	125	7.20	2.56	8.39	10.72
-15	172	12.79	3.45	10.19	12.05
-14	218	16.06	3.27	10.41	13.32
-13	230	17.39	3.67	10.57	15.68
-12	262	28.24	4.85	10.74	17.51**
-11	347	20.17	3.21	9.74	20.92
-10	391	26.85	3.39	10.06	23.78
-9	402	23.63	2.47	9.47	26.68
-8	471	32.27	3.22	9.54	29.57
-7	556	32.01	2.50	9.57	32.80
-6	557	35.91	2.33	9.42	35.90
-5	610	39.02	2.08	9.27	39.60
-4	636	43.87	2.31	9.79	43.01
-3	660	48.48	2.21	9.97	46.48
-2	720	53.61	2.71	9.64	49.61*
-1	757	57.73	2.46	9.41	52.72**
0	767	56.06	1.90	9.83	56.36
1	796	56.41	0.99	9.57	59.76
2	780	61.92	1.47	9.41	63.22
3	769	65.67	0.78	9.81	66.49
4	820	65.61	-0.01	9.89	69.79##
5	719	71.35	0.91	9.85	72.63
6	743	77.79	1.08	9.65	75.25
7	680	77.65	0.47	9.42	78.02
8	584	77.57	-0.50	9.92	80.59
9	585	82.39	-0.35	9.55	82.89
10	581	85.03	0.41	9.87	84.71
11	518	85.14	-0.72	9.94	87.05
12	432	90.97	0.53	9.47	88.68
13	422	91.00	-0.66	9.48	90.38
14	362	92.82	-0.73	9.05	91.52
15	338	93.79	-0.23	10.18	92.89
16	261	90.80	-1.25	10.40	94.02
17	264	95.83	-0.66	9.63	94.96
18	231	93.94	-1.16	10.60	95.93
19	183	98.36	0.75	10.29	96.80
20	149	97.32	-2.05	9.88	97.01

Table 3: Table 3 provides the observed and expected percentage of games won by the home team for the period from the 1993 / 1994 season to March 1, 2009. ** (*) denotes that the observed percentage of games won by the home team was significantly greater than expected at the 0.01 (0.05) level using the two-tailed binomial test. ## denotes that the observed percentage of games won by the home team was significantly less than expected at the 0.01 level using the two-tailed binomial test.

Over this period, our sample comprised 19,281 games while the Berger and Pope sample comprised 18,060 games. Of the 19,281 games, 807 games were excluded because the absolute score difference at halftime was greater than 20 points. The percentage of games won by the home team reported in the second column are virtually identical to those provide in Figure 1, page 819 of Berger and Pope. Like Berger and Pope, we find that home teams win more games than expected when one point behind, but we also find that this result pertains to situations where the home team is two points behind. Further, while the observed percentage of away (home) teams winning when they are one point behind (ahead) appears to be similar to the figure reported in Figure 1 of Berger and Pope, this percentage is not abnormal when assessed using the digital call option framework. Again, in our analysis it is only home teams that appear to display superior performance when behind at halftime.

As noted, we also collected quarter time and three quarter time scores for all NBA games. We repeated the analysis using quarter time and three quarter time score. The winning percentages again appeared to follow those predicted using a digital call option framework, but no abnormalities in terms of observed and expected winning percentages conditional on quarter or three quarter time scores were found.

In order to examine whether any abnormalities in performance related only to NBA games or whether they also pertained to NCAA games, we repeated the analysis using the 69,212 NCAA games played from the 2007 / 2008 season to the 2018 / 2019 season. The results are reported in Table 4.

Table 4: NCAA Results

Score difference at halftime (home team less away team)	Number of games	Percentage of games won by home team	Average change in score differential in the second half	Standard deviation of the change in the score differential in the second half	Expected percentage of games won by the home team
-20	184	4.89	1.60	11.54	3.06
-19	226	5.75	1.14	9.99	3.87
-18	276	3.62	1.31	9.88	4.50
-17	325	5.85	1.34	10.30	5.55
-16	420	6.67	1.16	9.39	7.04
-15	455	10.33	2.74	9.34	8.78
-14	588	11.39	2.06	9.93	10.57
-13	664	15.36	3.28	9.35	12.84
-12	781	18.95	2.99	9.94	15.34**
-11	955	16.02	2.00	9.36	18.29
-10	1086	21.64	2.50	9.63	21.02
-9	1258	25.83	2.72	9.66	23.99
-8	1476	29.47	2.78	9.31	27.51
-7	1606	33.06	2.70	9.48	31.34
-6	1736	37.44	2.78	9.29	35.26
-5	1875	38.56	2.37	9.18	39.54
-4	2160	44.54	2.44	9.17	43.57
-3	2118	49.06	2.38	9.46	47.86
-2	2371	52.00	2.45	9.44	51.97
-1	2528	55.85	2.21	9.18	56.20
0	2636	61.46	2.42	9.31	60.51
1	2715	64.90	2.42	9.41	64.59
2	2618	65.66	2.12	9.42	68.56##
3	2679	73.76	2.70	9.36	72.10
4	2697	74.05	2.15	9.40	75.68
5	2628	77.28	2.00	9.60	78.91#
6	2563	81.27	2.35	9.55	81.77
7	2530	84.86	2.50	9.46	84.41
8	2309	87.74	2.80	9.60	86.80
9	2302	89.75	2.91	9.83	88.99
10	2130	91.46	3.18	9.81	90.76
11	1920	93.13	2.88	9.73	92.35
12	1756	93.85	3.29	10.08	93.73
13	1634	94.92	3.20	10.00	94.83
14	1565	96.29	3.78	10.49	95.89
15	1423	97.96	3.69	10.13	96.71**
16	1296	97.76	3.77	10.49	97.48
17	1150	99.05	4.41	10.60	98.05**
18	929	98.71	4.81	10.95	98.52
19	876	99.54	5.51	10.94	98.85**
20	748	99.47	5.33	11.50	99.11

Table 4: Table 4 provides the observed and expected percentage of games won by the home team for NCAA games. ** denotes that the observed percentage of games won by the home team was significantly greater than expected at the 0.01 level using the two-tailed binomial test. ## (#) denotes that the observed percentage of games won by the home team was significantly less than expected at the 0.01 (0.05) level using the two-tailed binomial test.

Of the 69,212 games, 5005 games were excluded from those reported in Table 4 because the absolute score difference at halftime was greater than 20 points. For halftime score differences from -11 to +15 points, the percentage of games won by the home team increases monotonically.

The range of the standard deviations of the second half score differential conditional on the halftime score difference is only from 9.17 to 10.08 points for halftime score differences from -16 to +13, and there is no obvious relation between score differences and these standard deviations. There is again no evidence of risk shifting.

As for the NBA games, there is a marked drift in NCAA games in the second half score differential towards the home team. This is evidenced by a mean drift towards the home team of 2.42 points where the scores are tied at halftime, with the home team winning 61.46% of these matches. The drift also varies across score differences at halftime, although unlike for NBA games the drift appears to *increase* as the relative position of the home team as halftime improves. The drift is less than 2 points where the score difference is greater than -15 points at halftime, between 2 and 3 points where the halftime score difference is between -15 and 9 points, and more than 3 points where the home team is leading by more than 12 points at halftime.

As to the key finding from Table 4, while for some halftime score differentials the observed percentage of games won by the home team was significantly greater than expected, for other halftime score differentials the observed percentage of games won by the home team was less than expected. There is no apparent underlying relationship suggested by these results.

Taken in aggregate, our result suggest that professional basketball teams, namely those in the NBA rather than the NCAA, may win more games than expected when they are behind at halftime by of the order of 1 to 4 points. The argument of Berger and Pope may be used to suggest that, consistent with the work of Heath, Larrick and Wu (1999), Kahneman and Tversky (1979), Kivetz, Urminsky and Zheng (2006), and Tversky and Kahneman (1992), teams in this position may try harder and that their efforts are rewarded. However, our result suggests that it is only for home teams that this effort is rewarded; the result does not pertain to away teams.

4. Summary

Berger and Pope (2011) show that for both home and away US professional basketball teams, being behind by one point at halftime leads to a discontinuous increase in winning percentage. They attribute this result to loss aversion. Using a sample that is more than three times the size of that used by Berger and Pope, we find evidence of better than expected performance for NBA home teams that are behind by up to four points. We find no evidence of this effect with respect to NBA away teams that are behind, nor for NCAA teams – whether home or away. Our results suggest that loss aversion is apparent when stakes are high.

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