Jumping on the Bandwagon? Attendance Response to Recent Victories in the NBA[*†]

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Abstract

This article studies whether a recent victory impacts attendance at sports events. We apply a regression discontinuity design to estimate the local average treatment effect of a win on the attendance of subsequent games in professional basketball. Using National Basketball Association data from seasons 1980-81 to 2017-18, we find that home team fan bases react to recent outcomes, with an increase in attendance of approximately 425 attendants (a 3% boost) following a close win relative to a close loss. The increment is approximately one-eighth of a recent estimate of the superstar effect. We do not find an attendance effect when the visiting team has a recent victory, which provides evidence against the existence of externalities. The positive fan base response to narrow home wins relative to narrow losses suggests that recent luck is rewarded in sporting attendance. We discuss possible mechanisms and document a gradual decline in the attendance response that coincides with the rise of alternative means for viewing games and secondary markets for tickets.

JEL-Codes: D12, L83, Z2.

Keywords: *Regression discontinuity design, Consumer behavior, Winner effect.*

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I Introduction

Attendance in sports events depends on several factors (see Feehan, 2006; Villar & Guerrero, 2009). Within the framework of demand theory, the literature explores the role of ticket prices, team quality, superstars, weather conditions, local market size, outcome uncertainty (Rottenberg, 1956), and novelty effects of new facilities, among others, typically using multivariate regression as the empirical strategy (see for example, Coates & Humphreys, 2005, 2012; Humphreys & Johnson, 2020). Winning games can be a consequence of some of these factors but also can be interpreted by fans as a signal of quality and likelihood of continued winning. This perception could be rational, as there is some evidence of performance momentum in professional sports (Arkes & Martinez, 2011; Munoz, Chen, & Thomas, 2019). Alternatively, it may be irrational, with fans being "fooled by randomness" (Gauriot & Page, 2019). Also, if winning has an independent effect on attendance, and winning is affected by (or correlated with) some of those explanatory variables of interest for attendance (notably team quality, superstars), it is important for those multivariate analyses of attendance to control for previous wins. But due to those confounding factors, it is empirically challenging to identify the causal effect of winning, as shown by the literature on between-game momentum in sports (see for example, Arkes & Martinez, 2011; Gauriot & Page, 2018; Kniffin & Mihalek, 2014; Vergin, 2000). Our paper tackles this empirical challenge and contributes to the previous literature by providing the first causal estimate of the effect of a narrow preceding victory on attendance in the National Basketball Association.

We use a sharp regression discontinuity design with point difference at the end of the previous game as the running variable. We aim to approximate an infeasible experiment (in which we randomly assign the winner of each game) using data from close games. Ideally, one would use play-by-play data to identify those games whose outcome was determined by the final play (e.g., the trailing team takes the last shot and can win if it scores). However, the inability to acquire such data from enough seasons for a sufficiently powered study motivate us to use an alternative that plausibly identifies games decided by a large random component.

We use final score difference to determine whether the outcome of a game is likely to have been decided by one possession. Our estimates are based on the comparison of subsequent attendance for teams that lost the previous game by one point and teams that won the previous game by one point. Our strategy falls short of the experimental ideal (which would yield an average treatment effect) in that we estimate a local average treatment effect. Our results are internally valid for close games, but not necessarily for all games.

We find an increase of approximately 425 attendants (about 2.69% of average attendance in those close games) following a narrow victory. The magnitude of this effect is one-quarter of the attendance premium for weekend games, and one-eighth of the superstar premium (games featuring Michael Jordan, Larry Bird, LeBron James, Tim Duncan, or Magic Johnson) documented by Humphreys and Johnson (2020). In contrast, we do not find an impact of a recent win on attendance at subsequent games as visitor, which provides evidence against the existence of externalities. As in many economic organizations (Gauriot & Page, 2019), recent luck is rewarded in determining attendance to sporting events. We also document a steady decrease in the effect on attendance over time, which we believe could be attributable at least in part to growth in non-attendance alternatives to viewing games and how price setting for NBA tickets has evolved over time (i.e., fixed supply of seats and fixed prices without secondary markets in the earliest seasons that we consider in our analysis).

The rest of paper is organized as follows. In Section II we describe the data. Section III explains the empirical strategy and Section IV presents the results. In Section V we conclude with a discussion of possible mechanisms.

II Data

We use NBA game-level data from www.basketball-reference.com. We collect information on 61,999 games (up to the 2017-2018 season), including home team, visiting team, date, attendance, number of overtimes, and number of points scored by each team. We only keep games from the regular season because those are less likely to have attendance equal to the maximum capacity (note that this is distinct from ticket sales). This reduces the number of games to 42,256 with available information about attendance.[1]

Figure 1 provides an overview of the number of games available in the data set. Figure 1a displays the number of games by season. There has been an increase over time in the total number of games per season as the league has expanded, with dips in the lockout-shortened seasons of 1998-1999 and 2011-2012. Figure 1a also shows the number of close games by season, which are defined as games with a point difference of three or fewer at the end of the game. That difference is small enough to allow the trailing team to tie the game in one possession. There is a total of 6,800 such games played in regular season over the period analyzed.[2] Figure 1b takes the sample of teams playing at home whose previous game was close (difference smaller than 4 points) and breaks them down by point difference (score of current home team in the previous game minus the score of its previous opponent regardless of who was playing as home team). In this case, we end up with 6,728 such games that are relatively balanced in terms of number of winners versus number of losers.[3] Moreover, 1,796 of these games ended with a difference of just one point (the smallest possible difference). These are arguably games for which the outcome was determined by randomness more so than games with larger final point differences.

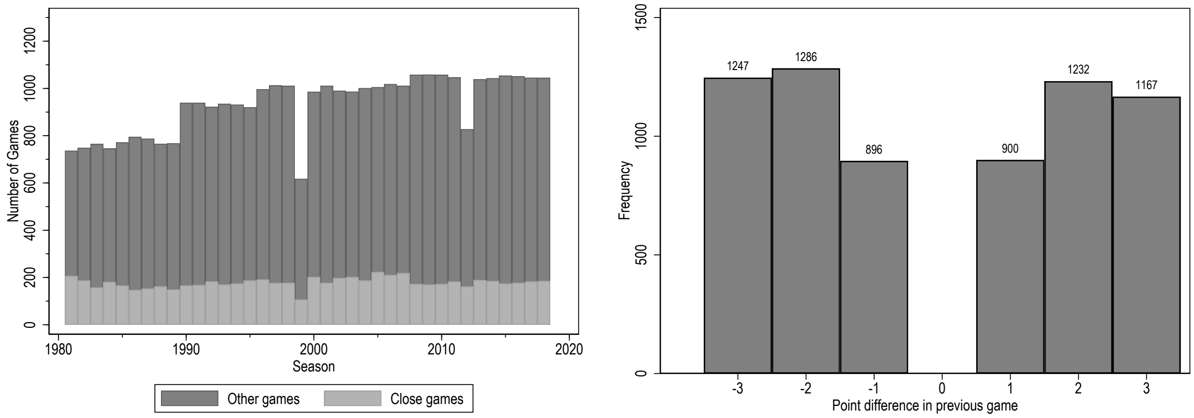
Figure 2 shows the distribution of game attendance in our sample, which is our main outcome variable. The distribution has a noticeable right tail of games with large attendance that includes one-off games in football stadiums and some home games in large facilities (see

[1]Games before 1981 do not have the information on attendance and there are 180 games with missing data after 1980.

[2]Table A1 in the Appendix provides some additional summary statistics by season.

[3]The difference between these 6,728 games and the original 6,800 is explained by a few factors. First, in some cases both teams from a close game play the next one as visitors, in which case a game identified as close in the 6,800 games does not translate into a game in the subset of games where the home team had a previous close game (i.e., the set of 6,728 games). Second, it can also happen that both teams playing a close game play the next game as the home team, in which case a game from the 6,800 maps into two games of the subset of games where the home team had a previous close game. Third, a close game played on the last day of a team season does not have a follow up, so it adds to the 6,800 but not to the second subset.

Figure 1: Regular season games



(a) Total number of games and total number of close games per season

(b) Frequency of close games by point difference

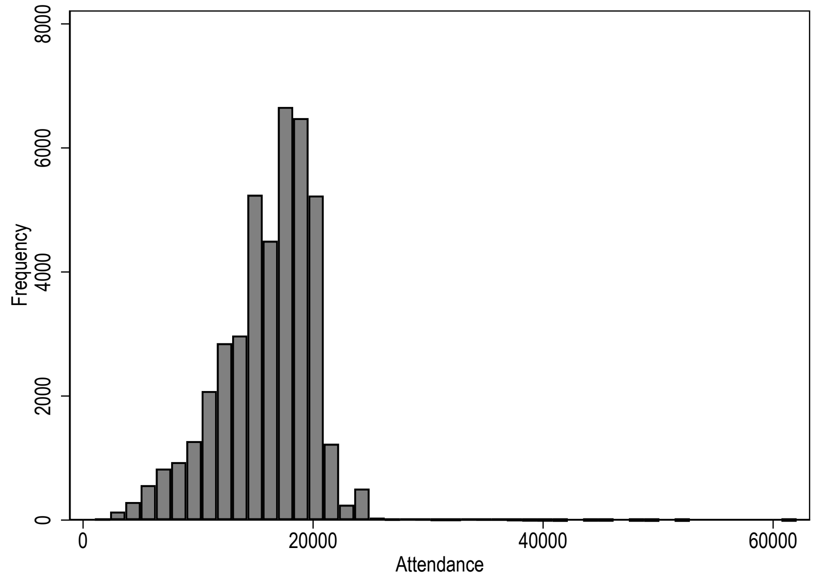
Notes: Close games are defined as games that end with a point difference smaller than 4 points and there is a total of 6,800 games that meet this restriction between 1980-81 and 2017-18. In the second figure, we consider the frequency in which teams playing as home team had close games in their previous game (these are 6,728 observations). Point difference in the previous game is computed as the score of the current home team minus the score of the previous opponent regardless of who was playing as home team.

Humphreys & Johnson, 2020).

III Empirical Strategy

Identification strategy. Our approach to estimating the causal effect of a narrow victory on attendance in the next game is a sharp regression discontinuity design, with point difference at the end of the game as the running variable. The outcome of interest is denoted by $y_{i,j,t}$, which corresponds to attendance in a game between home team i against a visitor team j at game number $t \in [1, 82]$ within each season. The treatment variable is denoted by $d_{i,t} \in \{0, 1\}$, and takes value 1 if the team i playing against team k (usually different than team j) at game number *t-1* (within the same season) won and 0 if it did not. The

Figure 2: Game attendance distribution



treatment variable depends on the difference in points at the end of the game, such that:

$$d_{i,t} = 1[p^H_{i,k,t-1} > p^V_{i,k,t-1}] \tag{1}$$

where 1[.] is an indicator function and home team points in the last game is denoted by $p^H_{i,k,t-1}$ and visiting team points denoted by $p^V_{i,k,t-1}$. Note that for simplicity we denote team i as the home team in game *t-1*, however it could have been visitor, consequently the visiting team in *t-1* denotes the rival of team i regardless of where the game was played, and it is rarely equal to team j.

We estimate this local average treatment effect using a local randomization approach and perform inference using the general Fisherian inference framework as described by Cattaneo, Idrobo, and Titiunik (2018). To do this, we assume that there is a small window around the zero cutoff, such that for all the games whose scores fall in that window, the end result (win or lose) is assigned as if by a randomized experiment. We consider three different windows, from the smallest possible difference of one point to a three-point window (which would have allowed the losing team to tie or win the game in one possession). However, we base our conclusions on the smallest one, defined by games that end with a difference of only one point because these games were more likely to be decided by one high stakes play that can result in either of the teams winning (e.g., the trailing team with a close score having the last shot or the game being decided by free throws).

Validation analysis. Before presenting our results, we show a set of three standard validity checks for our regression discontinuity design. First, given the discrete nature of our running variable and that we are using a local randomization approach, we perform a binomial test on the three smallest feasible windows (final score difference of one, two, or three points). Table 1 reports the results, in which we fail to reject the null hypothesis that observations in these windows were generated by a binomial distribution with probability of success equal to 1/2. It is important to note that the nature of the data set helps to balance the number of observations on each side of the cutoff because for each close game we have a winner by a small margin and a loser by the same margin. However, this fact does not generate perfect balance because these teams need to play as home team in their next game to be included in our estimation (i.e., our estimation uses game attendance of teams whose result was close in the previous game).

Table 1: Binomial test

Window	**Binomial test p-value**	**Obs$<$c**	**Obs$\geq$c**
+/-1	0.944	896	900
+/-2	0.456	2182	2132
+/-3	0.116	3429	3299

Notes: Results of a test with the null hypothesis that the observations in a given small window (e.g., games that ended with the home team winning or losing by one point) were generated by a binomial distribution with probability of success equal to 1/2 (i.e., the final result looks as if it was generated randomly).

Second, we conduct a falsification test that assesses whether there are significant effects at fake or placebo cutoff values. We run our estimation using eight alternative cutoffs with windows of one point on each side of it (e.g., cutoff 4.5 means that we compare teams with a final point difference of 4 and 5 points). Table 2 reports the results. We reassuringly do not find evidence of jumps in attendance for the next game where there should be no effect. Additionally, this provides evidence that teams with close margins that do not differ in the end result (both are winners or both are losers) do not differ systematically in the level of attendance in the next game (i.e., if teams with close margins were still strongly sorted by quality and higher quality teams have greater attendance, then, for example, we would observe greater attendance in the next game for teams that win by 5 points relative to those that win by 4 points). Hence, the fact that we will only find an increase for those teams with close margin that differ in the end result of the game provides support for the validity of the research design and winning as the treatment.

Table 2: Placebo cutoffs

	Dependent variable: Game attendance							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient	-306.692	179.714	-96.759	110.464	150.300	-279.545	251.314	11.564
P-value	0.066	0.282	0.579	0.533	0.403	0.084	0.145	0.938
Cutoff	-4.5	-3.5	-2.5	-1.5	1.5	2.5	3.5	4.5

Notes: The dependent variable in all the specifications is game attendance. The coefficient is the difference in average attendance of home teams that ended their previous game with a point difference just below the placebo cutoff and those that ended their previous game with a point difference just above the cutoff (e.g., when "Cutoff" is -3.5 (as in column (2)), we compute the difference in attendance of those that lost the previous game by 4 points and those that lost by 3 points). P-values are computed using randomization inference methods (see Cattaneo, Titiunik, & Vazquez-Bare, 2016).

Third, we run a key falsification exercise that assesses whether there are systematic differences between treated and control units. For this purpose, we run a regression discontinuity design using two pre-determined covariates as outcomes: stadium capacity (estimated as maximum attendance by team-season) and cumulative winning percentage (without taking into consideration current and previous game). Table 3 reports these results. We do not find statistically significant differences at the 5% level in either of the covariates. Furthermore, regardless of the statistical significance, the estimated differences are both very small in magnitude. This result provides further support for the validity of our research design for

Table 3: The effect of winning on pre-determined covariates (covariate balance)

	Dependent variable:	
	Stadium capacity	**Winning percentage**
Coefficient	241.65	1.79
P-value	0.29	0.09
N	1796	1725
N left	896	857
N right	900	868

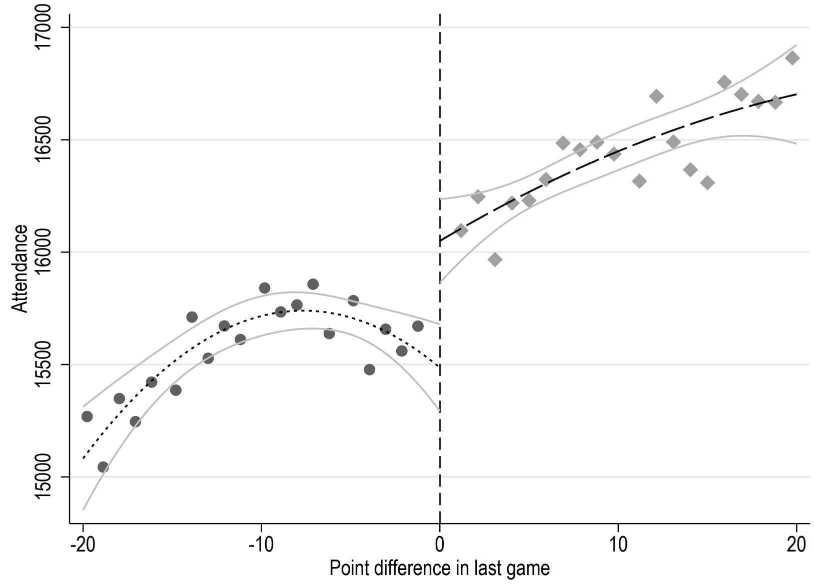
Notes: The dependent variables are stadium capacity computed as the maximum attendance by team-season, and cumulative winning percentage in the season excluding current and previous game. "Coefficient" is the difference in the average of the dependent variable between home teams that won their previous game by 1 point and those that lost their previous game by 1 point. "N" indicates the sample size, "N left" and "N right" respectively indicate the sample size for losers and winners. P-values are computed using randomization inference methods (see Cattaneo et al., 2016).

two reasons. First, we do not find important differences in the size of the stadium between teams that barely won and those that barely lost, which rules out the possibility that we are comparing teams with just different attendance capacity. Second, and more importantly, we do not find important differences in winning percentage (a proxy for team quality), which suggests that within this small window (winning by 1 point or losing by 1 point) teams are not systematically different in "quality" and the winner of the game is chosen as-if randomly assigned.

IV Results

Main results. Figure 3 displays visual evidence of the effect of winning a game on attendance in the next game by plotting conditional means of game attendance for different bins of point difference in the previous game. We find a clear discontinuity around the home team's win threshold, which suggests that a team that barely won its last game has on average higher attendance than a team that barely lost its last game.

Figure 3: The effect of winning on next game attendance



Notes: Visual evidence to assess the existence of a potential discontinuity on game attendance by plotting conditional means of game attendance for different bins of point difference in last game (computed as the score in the previous game of the current home team minus the score of the previous opponent, regardless of who was playing at home). It also plots an estimated quadratic polynomial on each side of the cutoff at 0, and its associated 95% confidence interval.

Next we estimate the causal effect of winning on attendance using the local randomization approach described in the previous section, which is based on the comparison of the outcomes for winners and losers of close games. Table 4 reports the results of the estimation using games ending in a one-, two-, or three-point difference. We find a statistically significant increase of approximately 425 tickets sold for the next game when we use the smallest possible window. To put this effect in perspective, the increase in attendance is equivalent to 25% of the attendance increase generated by holding a game on the weekend, and 10% of the attendance increase generated by Michael Jordan (Humphreys & Johnson, 2020). Furthermore, this effect may be an underestimation of the impact of winning on attendance because some games are sold out in advance, which prevents a winning effect on sales.[4]

[4]Given the long right tail observed in Figure 2, we also compute the main regressions excluding games with attendance outside the percentiles 1 and 99 (see Table A2 of the Appendix). We find qualitatively similar results although smaller effects.

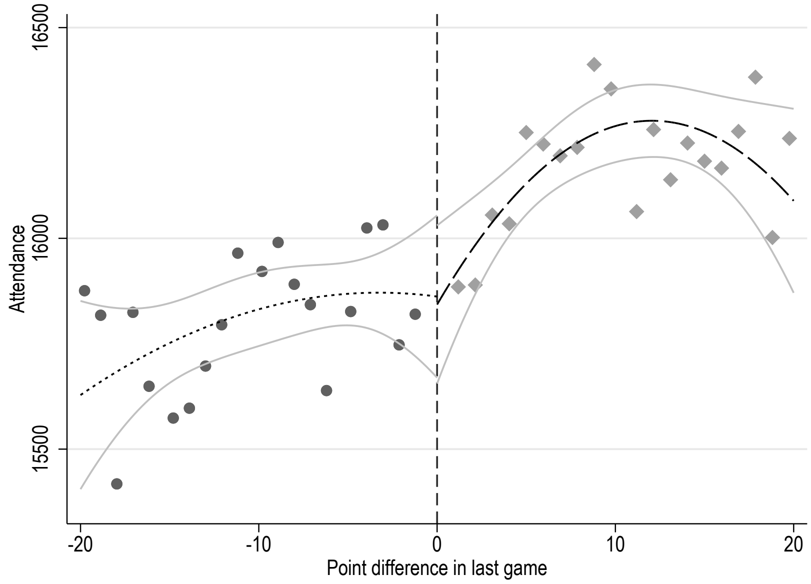
Table 4: The effect of winning on attendance in the next game

Dependent variable: Game attendance			
	(1)	(2)	(3)
Coefficient	425.31	577.26	482.13
P-value	0.03	0.00	0.00
N	1796	4314	6728
N left	896	2182	3429
N right	900	2132	3299
Window	1	2	3

Notes: The dependent variable in all the specifications is game attendance. Coefficient is the difference in attendance between home teams that won their previous game and those that lost their previous game by a small number of points (the greatest margin of points considered is indicated in the last row named "Window"). "N" indicates the sample size, "N left" and "N right" respectively indicate the number of teams that lost and won their previous game. P-values are computed using randomization inference methods (see Cattaneo et al., 2016).

Externalities. The previous estimate considers only the impact of winning the previous game on attendance at the winners' home games and as a consequence affects only their own revenue derived from ticket sales. However, it may be the case that fans also pay attention to recent performance of their rivals and therefore current performance of a team may affect attendance in games as visitor too. We test this hypothesis by estimating the same regression discontinuity design for the case of games as the visiting team and do not find any effect (see Figure 4), which implies that there are no externalities from winning (i.e. the last win of a team does not increase or decrease attendance when they play the next game as visitors). This contrasts with the case of superstar externalities, which increase game attendance when the visiting team has certain popular, high-performing players (see Berri & Schmidt, 2006; Hausman & Leonard, 1997; Humphreys & Johnson, 2020). This suggests that fans do take into account the overall quality of the visiting team (which includes whether or not they have a superstar) when deciding whether to attend a game, but are not responsive to very recent performance of the visiting team.[5]

Figure 4: The effect of winning on next game attendance in visitor games (Estimate=64 with p-value=0.737)



Notes: The figure provides visual evidence to assess the existence of a potential discontinuity on game attendance in visitor games by plotting conditional means of game attendance in these games for different bins of point difference in last game. It also plots an estimated quadratic polynomial on each side of the cutoff at 0, and its associated 95% confidence interval. The point estimate reported in the subtitle of the figure was estimated using a local randomization approach to regression discontinuity design including only games that ended with a difference of 1 point (winners by 1 versus losers by 1). The associated p-value is computed using randomization inference methods (see Cattaneo et al., 2016).

Interpretation and evolution over time. The estimated effect can be interpreted as a demand increase if the supply does not respond in terms of quantity (which is likely because of the short-term capacity constraints of stadiums) or price to the same event. This would be plausible if ticket prices are set at the beginning of the season and there is no secondary market. However, teams in the NBA have been using dynamic ticket pricing since early 2010s, in part due to the increasing importance of the secondary market for tickets that

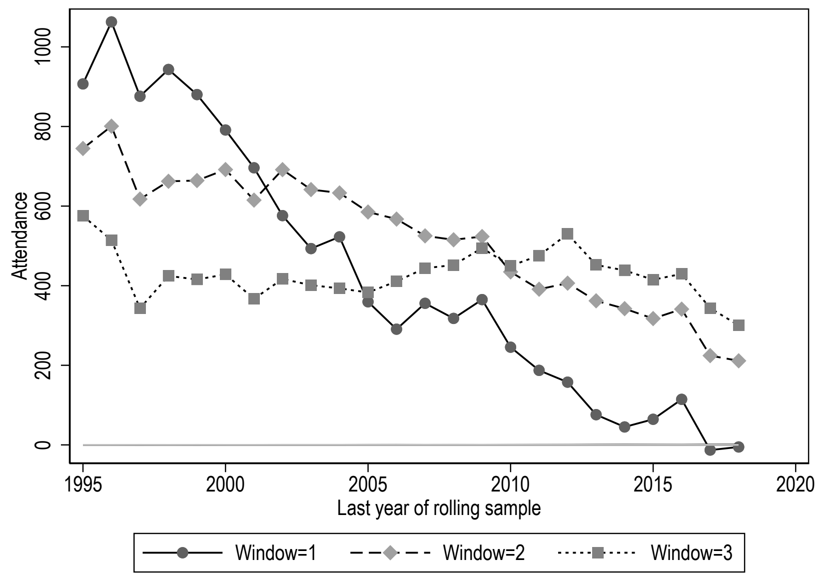
[5]In contrast to our results, Berri and Schmidt (2006) find that each regular season win is associated with a 1,011-person increase in team's seasonal road attendance. However, they use a linear regression approach with team-season-level data (for three seasons with a total of 108 observations) rather than game-level data, without the aim of estimating a causal effect.

began even before this decade. We explore whether the estimated effect varies over time by running our regression discontinuity design using a 15-year rolling window, where the supply is arguably unresponsive in early windows and potentially more responsive in latter windows. We find a clear downward trend (see Figure 5), which (using the smallest possible window for the regression discontinuity design - games ending with a one point difference) approaches zero at the end of our sample. The magnitude at the beginning of the sample (when dynamic pricing was not in place and secondary markets were not available) suggests that our estimate captures a demand increase. In addition, the downward trend in magnitude is consistent with a supply response to recent victories attenuating the attendance response by fans. However, we are not able to rule out that this decrease is due to an increasing share of games reaching maximum capacity, which would bias our estimates downward. Figure 6 shows how the average game attendance by season has evolved in our sample period, showing a pronounced increase in the 1980s and a stabilization over the last two decades.

Nonetheless, an inspection of the percentage of games sold out by season (defined as games with attendance equal to the maximum by team-season) does not indicate a clear increasing trend for all the games or for the sample of close games used in our estimation (see Figure 7), which suggests that the falling response is not because of a downward bias due to sell-outs being more important over time.

The evidence presented is suggestive about the role of dynamic pricing and secondary markets in explaining the downward trend, but far from conclusive. In addition to the previous potential explanations, the large growth in television broadcasting and live streaming as substitutes for attendance could also be a factor that attenuates the effect of a recent victory on attendance.

Figure 5: The effect of winning on next game attendance over time
(15-year rolling period)



Notes: The figure shows the evolution over time of the estimated effect of winning on next game attendance (y-axis). We use a 15-year rolling period. The effect is estimated as the difference in attendance between home teams that won their previous game by a small number of points and those that lost their previous game by a small number of points. We consider three windows: games that end with at most a difference of 1 point, 2 points, and 3 points.

V Discussion and Final Remarks

In this paper, we use a sharp regression discontinuity design to estimate the local average treatment effect of a win on the attendance of a subsequent game in the National Basketball Association with data spanning 18 seasons from 1980-2018. Our findings indicate that the fan base reacts to the most recent game outcome, with an increase in attendance after close wins of approximately 425 additional attendants (approximately 2.69% of the average attendance in regular season close games). This result is one-eighth of the superstar effect and one-quarter of the weekend effect reported by Humphreys and Johnson (2020), and provides evidence of the potential influence of recent team performance on revenue through ticket sales. In contrast, fans do not react to a recent victory of the visiting team, which is evidence against the existence of externalities.

Our findings may represent an under estimation of the true local average treatment effect

Figure 6: Average game attendance by season

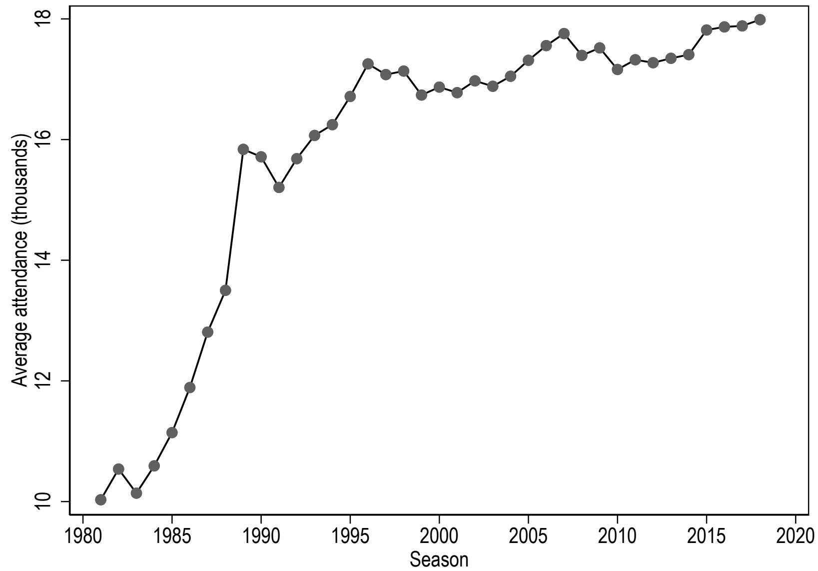
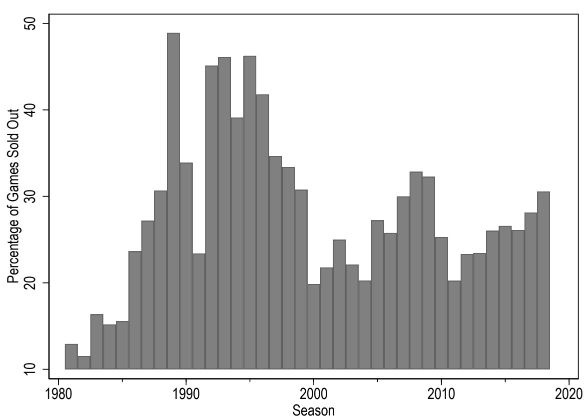
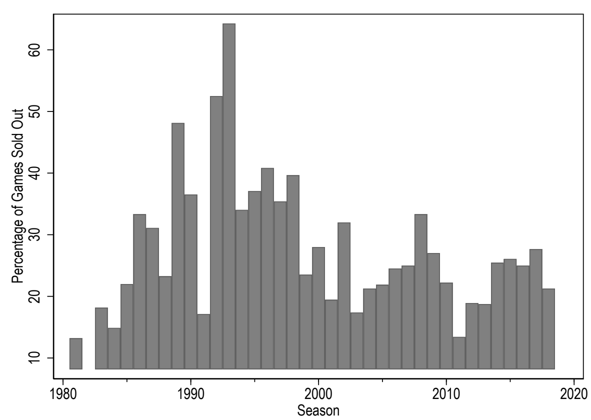


Figure 7: Percentage of sold out games by season



(a) All regular season games



(b) Home team had a previous close game

Notes: Percentage of games sold out by season (defined as games with attendance equal to the maximum attendance by team-season). The figure on the left considers all regular games while the figure on the right only considers those games where the home team had a previous close game (defined as games that end with a team winning by one point).

of a win on attendance because of at least two factors. First, stadium capacity limits the attendance response to recent victories, which implies that our outcome variable is censored at different values depending on where the team plays (i.e., attendance cannot increase over the maximum stadium capacity). Second, supply responses through price increases after recent victories may attenuate the observed responses (i.e., ticket sellers may increase the price of each ticket in response to an increase in demand). Unfortunately, we do not have game-level data on the evolution of ticket prices over time to check this conjecture. Moreover, platforms that allow individuals to re-sell their tickets make this task even more difficult.

This result is consistent with fans having a preference for victories (and distaste for losses) and revising the probability of winning upward due to winner effects. Although the evidence remains mixed, several quasi-experimental studies over the past decade confirm the existence of positive performance momentum in professional sports (see for example, Arkes, 2011; Arkes & Martinez, 2011; Leard & Doyle, 2011; Munoz et al., 2019; Page & Coates, 2017). In addition, Arkes (2011) finds that gamblers incorporate momentum into predictions. An alternative explanation is that close wins are given more media coverage (for a study on the relationship between team performance and TV viewership, see Mondello, Mills, & Tainsky, 2017), which increases short term demand for attending games. Regardless of the underlying mechanism, the finding suggests yet another setting in which lucky successes are rewarded, an apparent violation of the informativeness principle (Gauriot & Page, 2019).

Finally, we also document that the attendance response to recent victories has declined over time, which is consistent with three non-mutually exclusive hypotheses. First, it could be that the attendance response was attenuated by the rise of secondary markets and dynamic ticket pricing by NBA teams in the early 2010s (Jessop, 2012). Second, the attendance response may have declined as the percentage of sell-out games increased, capping the attendance effect on sales. However, our evidence suggests that the latter explanation is not supported by the data. Third, the large growth in television broadcasting and live streaming since the mid-nineties could have provided a viewing alternative that attenuated the attendance response to recent game outcomes.

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Appendices

In this Appendix we provide some additional tables and graphs.

Table A1: Summary by season

Season	Home points	Visitor points	Difference	Games	Close games	Close games (%)
1981	110.03	106.18	10.22	943	206	21.85
1982	110.40	106.69	9.78	937	188	20.06
1983	110.22	106.57	10.44	923	158	17.12
1984	112.55	107.76	9.91	928	182	19.61
1985	112.68	109.02	10.49	938	166	17.70
1986	112.49	107.95	10.79	943	148	15.69
1987	112.53	107.34	11.30	942	154	16.35
1988	111.05	105.17	11.09	929	163	17.55
1989	111.95	106.22	11.92	918	150	16.34
1990	109.50	104.49	11.23	1106	167	15.10
1991	108.67	103.95	11.45	1107	168	15.18
1992	107.56	103.09	11.15	1106	184	16.64
1993	107.29	103.25	11.37	1106	171	15.46
1994	103.52	99.50	11.45	1107	175	15.81
1995	102.99	99.82	11.07	1107	187	16.89
1996	101.12	97.89	10.93	1189	192	16.15
1997	98.18	95.62	10.98	1189	176	14.80
1998	97.04	94.10	11.11	1189	178	14.97
1999	93.30	89.86	10.48	725	107	14.76
2000	99.24	95.70	10.89	1189	203	17.07
2001	96.27	93.35	10.60	1189	178	14.97
2002	97.18	93.78	10.83	1189	198	16.65
2003	97.02	93.14	10.71	1189	202	16.99
2004	95.20	91.60	10.35	1189	187	15.73
2005	98.76	95.64	10.32	1230	224	18.21
2006	98.69	95.32	10.37	1230	211	17.15
2007	100.23	97.25	10.62	1230	219	17.80
2008	101.63	98.22	11.50	1230	172	13.98
2009	101.58	98.33	10.94	1230	171	13.90
2010	101.81	99.08	11.07	1230	172	13.98
2011	101.13	97.97	10.59	1230	183	14.88
2012	97.67	94.85	11.13	990	162	16.36
2013	99.75	96.52	10.99	1229	190	15.46
2014	102.31	99.71	10.93	1230	186	15.12
2015	101.22	98.81	11.11	1230	175	14.23
2016	104.01	101.33	11.09	1230	178	14.47
2017	107.17	104.02	11.32	1230	184	14.96
2018	107.39	105.28	11.13	1230	185	15.04

First three columns report the average home team points, average visitor team points, average point difference (absolute value) for regular season games from 1981-2018. Next columns report total number of regular season games and number of close games (point difference less than 4). Last column reports the percentage of close games per season.

Table A2: The effect of winning on attendance in the next game

Dependent variable: Game attendance			
	(1)	(2)	(3)
Coefficient	352.38	418.96	383.83
P-value	0.048	0.000	0.000
N	1758	4218	6583
N left	882	2131	3355
N right	876	2087	3228
Window	1	2	3

The dependent variable in all the specifications is game attendance. The coefficient is the difference in attendance between home teams that won their previous game and those that lost their previous game by a small number of points (the greatest margin of points considered is indicated in the last row named "Window"). "N" indicates the sample size, "N left" and "N right" respectively indicate the sample size at each side of the running variable defined as home team points minus opponent points in the previous game (i.e., previous losers and winners). P-values are computed using randomization inference methods (see Cattaneo et al., 2016).