

# Jumping on the Bandwagon? Attendance Response to Recent Victories in the NBA \*

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## Abstract

In this paper we use a sharp regression discontinuity design to estimate the causal effect of a win on the attendance of the subsequent game in the National Basketball Association. The data cover games in 1981 to 2018. Our findings indicate that the fan base reacts to a recent victory, with an increase in attendance of approximately 425 tickets. This increase is approximately one-eighth of the superstar effect estimated by [Humphreys and Johnson \(2020\)](#). The positive response to narrow home wins relative to narrow losses suggests that sporting attendance is yet another example of luck being rewarded ([Gauriot and Page \(2019\)](#)). In contrast, we do not find changes in attendance for games when the visiting team has a recent victory, implying the absence of externalities.

**JEL-Codes:** D12, L83, Z2.

**Keywords:** *Regression discontinuity design, Attendance, Winner effect, Sports, Quasi experiments.*

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# I Introduction

There is a significant amount of research devoted to understanding the determinants of attendance at sports events (see [Feehan \(2006\)](#) and [Villar and Guerrero \(2009\)](#) for surveys). Within the theoretical framework of demand theory, the literature has explored the role of ticket prices, team quality, superstars, weather conditions, local market size, and outcome uncertainty ([Rottenberg \(1956\)](#)), among others, usually using multivariate regression as the empirical strategy. If winning has an independent effect on attendance and winning is affected by some of those explanatory variables of interest for attendance (notably team quality, superstars), it is important for those multivariate analyses to control for previous wins. But due to confounding factors, it is empirically challenging to identify the causal effect of winning, as shown by the literature on between-game momentum in sports ([Vergin \(2000\)](#), [Arkes and Martinez \(2011\)](#), [Kniffin and Mihalek \(2014\)](#), and [Gauriot and Page \(2018\)](#)).

This paper adds to this literature by providing a causal estimate of the effect of a 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 find an increase of approximately 425 tickets sold 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 \(2020\)](#). As in many economic organizations ([Gauriot and Page \(2019\)](#)), recent luck is rewarded in determining attendance to sporting events.

This paper is organized as follows. In Section II we describe the data set. Section III discusses the empirical strategy and Section IV presents the results. In Section V we conclude with final remarks.

## II Data

We use game-level data from [www.basketball-reference.com](http://www.basketball-reference.com). We collect information on 61,999 games, including home team name, visiting team name, game date, attendance, number of overtimes, and number of points scored by each team. We only keep games from the regular season since 1981 because they have information on attendance. That reduces the number of games to 42,256.<sup>1</sup>

Figure 1 displays the number of games by season in our data set. There has been an increase over time in the total number of games, with dips in the lockout-shortened seasons of 1998-1999 and 2011-2012. Figure 1 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 6,728 such games played in regular season over the period analyzed. Figure 2 breaks down our sample of close games by point difference.

## III Empirical Strategy

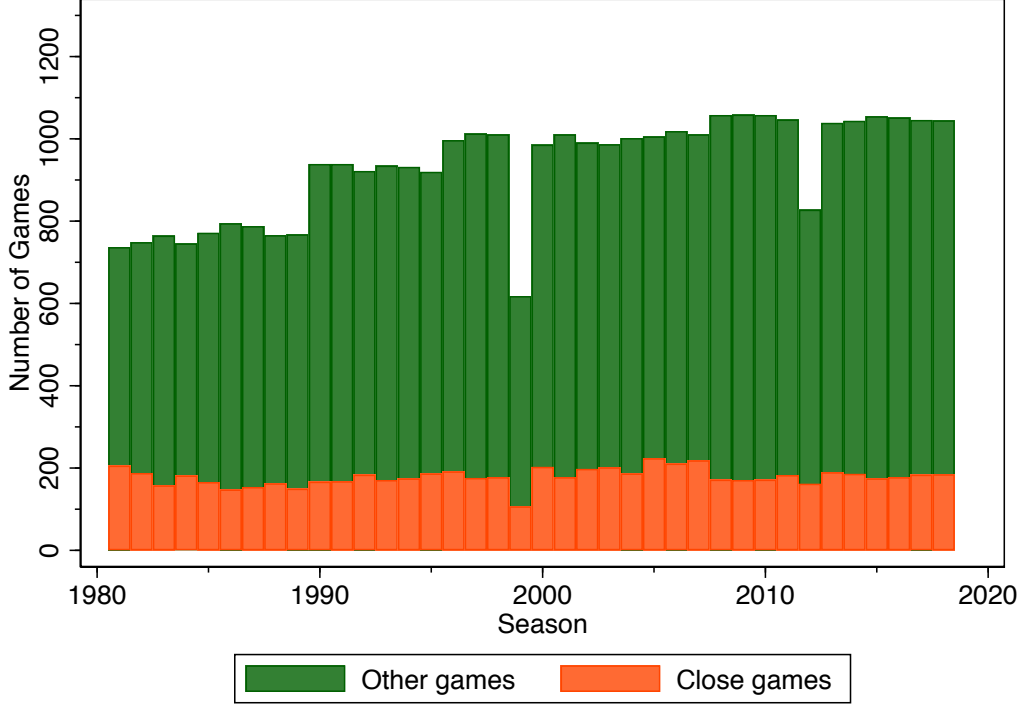
Our approach to estimating the causal effect of winning a game on attendance in the next game is a sharp regression discontinuity design, with point difference at the end of the game as the running variable. The outcome of interest is denoted by  $y_{i,j,t}$ , which corresponds to attendance in a game between home team  $i$  against a visitor team  $j$  at game number  $t$ . The treatment variable is denoted by  $d_{i,t} \in \{0, 1\}$ , and takes value 1 if the team  $i$  playing against team  $k$  at game number  $t-1$  won and 0 if it did not. The treatment variable depends on the difference in points at the end of the game, such that:

$$d_{i,t} = 1[p_{i,k,t-1}^H > p_{i,k,t-1}^V] \quad (1)$$

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<sup>1</sup>Games before 1981 do not have the information on attendance and there are 180 games with missing data after 1980.

**Figure 1:** Games per season  
Close games defined as games with point difference less than 4

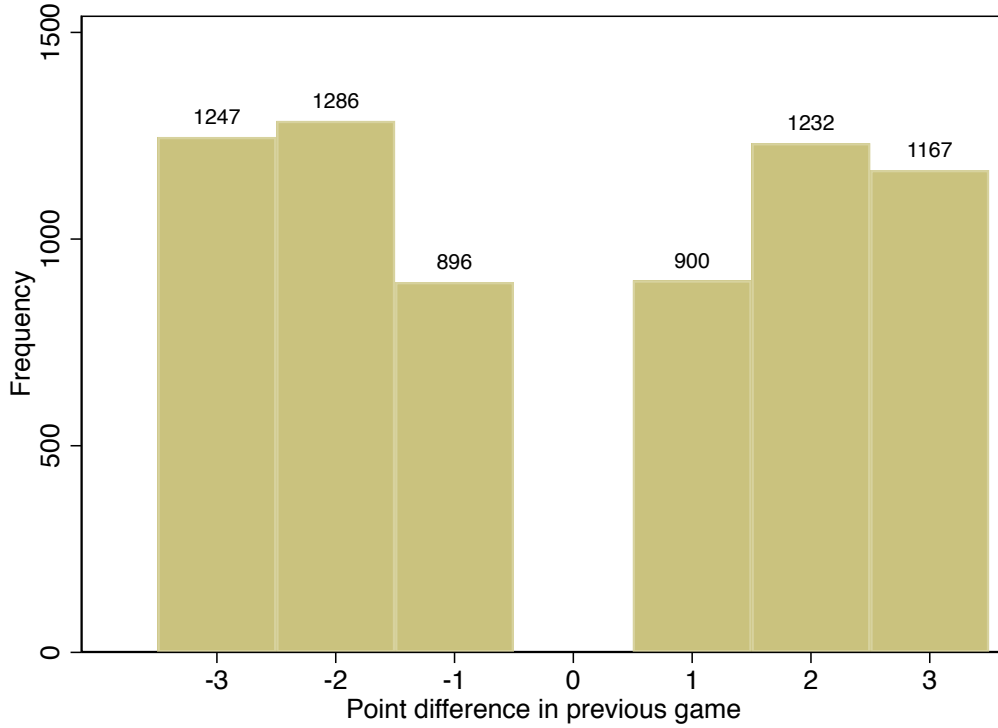


where  $1[\cdot]$  is an indicator function and home team points in the last game is denoted by  $p_{i,k,t-1}^H$  and visiting team points denoted by  $p_{i,k,t-1}^V$ . Note that the visiting team in game number  $t - 1$  and  $t$  are not necessarily the same.

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 in 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).

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, we perform a binomial test on the three smallest feasible windows (final score difference of

**Figure 2:** Number of close games  
Total of 6,728 games with point difference less than 4 points



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  $1/2$ .

**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

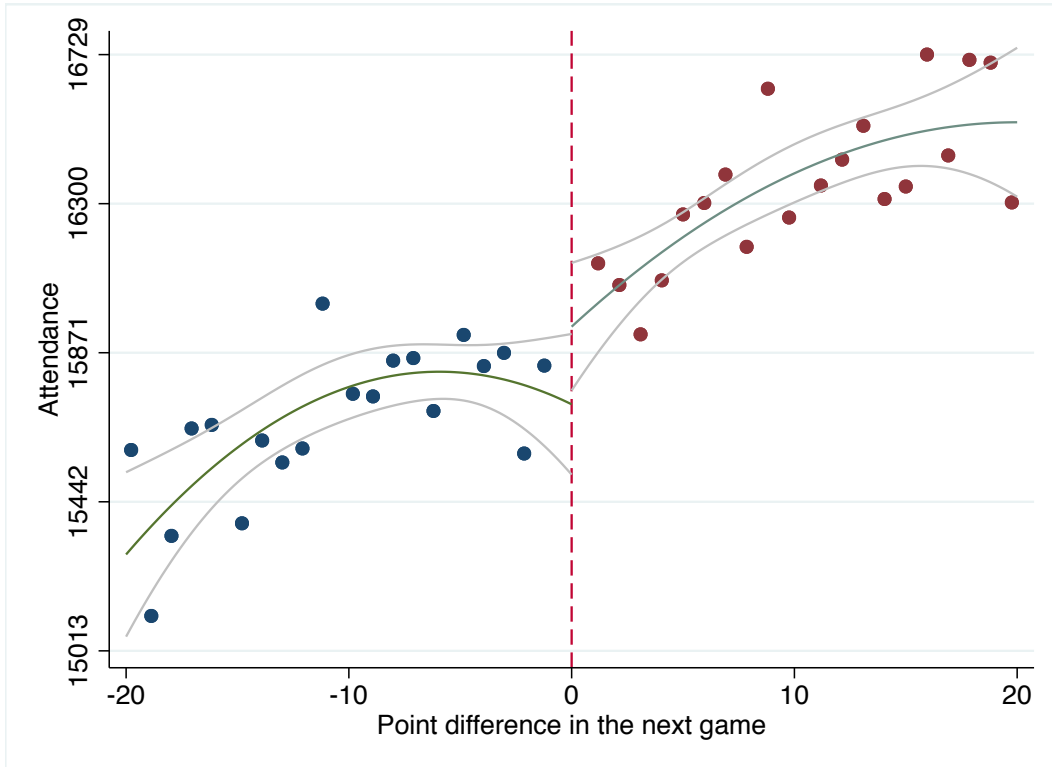
Second, we run our estimation using eight alternative cutoffs with windows of one point on each side (e.g., cutoff 4 means a final point difference between three and five points). Table 2 reports the results. We reassuringly do not find evidence of jumps in probability of winning the next game where there should be no effect.

**Table 2:** Alternative cutoffs

	1	2	3	4	5	6	7	8
<b>Coefficient</b>	-2.608	-216.799	130.590	-51.398	14.314	-149.624	257.392	56.157
<b>Probability</b>	0.990	0.130	0.395	0.716	0.925	0.308	0.070	0.681
<b>Cutoff</b>	-5	-4	-3	-2	2	3	4	5

Third, we inspect a placebo outcome at the cutoff. To rule out the possibility of sorting by team quality, we run our regression discontinuity design with the point difference in the current game as the running variable and attendance in the previous game as the outcome variable. Figure 3 shows the result. We do not find a clear discontinuity, and our estimation confirms this result with a p-value equal to 0.338.

**Figure 3:** The effect of winning next game on current game attendance  
(Estimate=291 with p-value=0.338)



## IV Results

Figure 4 displays visual evidence of the effect of winning a game on attendance in the next game. We find a clear discontinuity around the home team’s win threshold.

**Figure 4:** The effect of winning on next game attendance

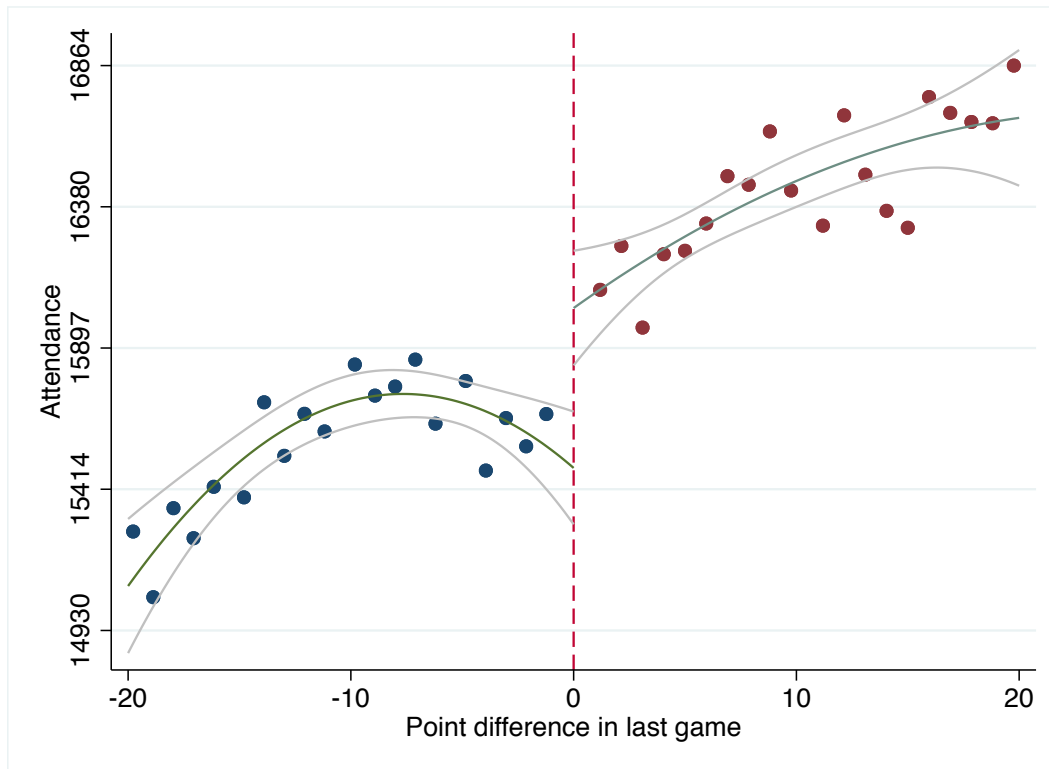


Table 3 reports the results of the estimation using the local randomization approach with games ending in a one-, two-, or three-point difference. We find a statistically significant increase of approximately 425 tickets sold for the next game when we use the smallest possible window.<sup>2</sup> To 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 superstar attendance increase generated by Michael Jordan (Humphreys and Johnson (2020)).

<sup>2</sup>Berri and Schmidt (2006) using a sample of 108 games estimates that the number of wins in regular season increases road attendance by 1,010.

**Table 3:** The effect of winning on attendance in the next game

	(1)	(2)	(3)
<b>Coef.</b>	425.31	577.26	482.13
<b>Prob.</b>	0.03	0.00	0.00
<b>N</b>	1796	4314	6728
<b>N left</b>	896	2182	3429
<b>N right</b>	900	2132	3299
<b>Window</b>	1	2	3

This effect represents a lower bound of the impact of winning on attendance because some games are sold out in advance, which prevents a winning effect on sales.

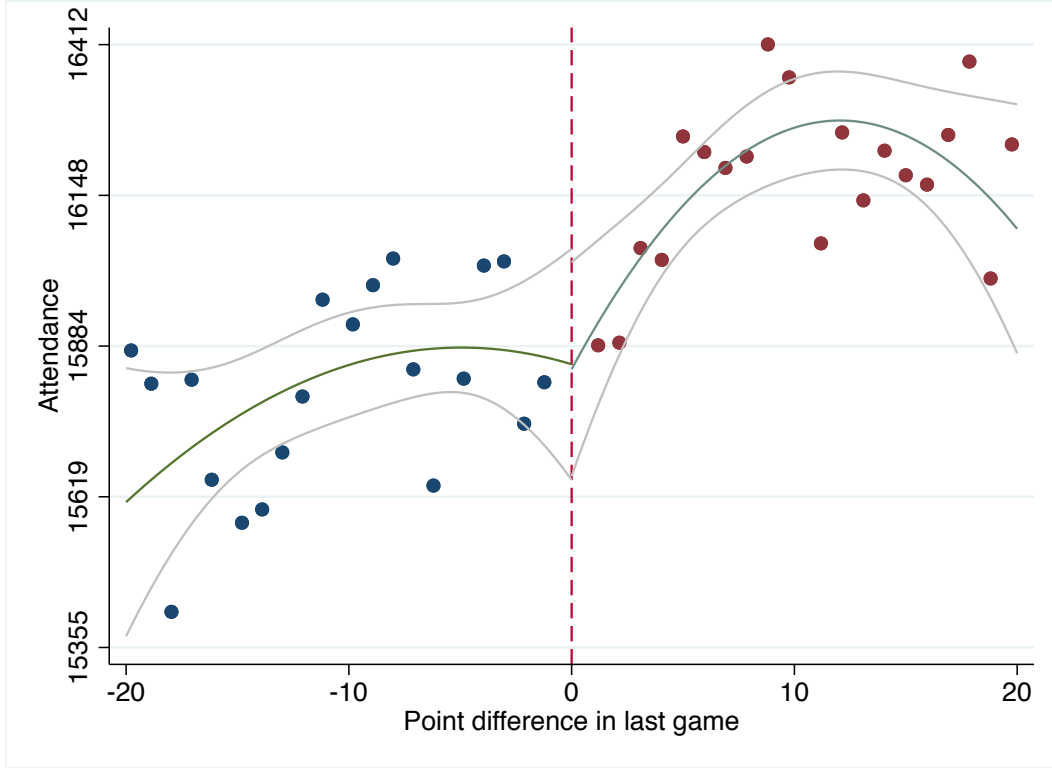
The previous estimate considers only the impact of winning on attendance at the winners' home games. In the case of games as the visiting team, we do not find any effect (see Figure 5), which implies that there are no externalities from winning. This contrasts with the case of superstar externalities, which increase game attendance when the visiting team has certain popular, high-performing players (see Hausman and Leonard (1997), Berri and Schmidt (2006), and Humphreys and 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.

## V Final Remarks

In this paper we use a sharp regression discontinuity design to estimate the causal effect of a win on the attendance of a subsequent game in the National Basketball Association. The data cover games from 1981 to 2018. Our findings indicate that the fan base reacts positively to a recent victory with an increase in attendance of approximately 425 additional tickets. In contrast, fans do not react to a recent victory of the visiting team, implying the absence of externalities.



**Figure 5:** The effect of winning on next game attendance in visitor games  
(Estimate=64 with p-value=0.737)



This result is one-eighth of the superstar effect and one-quarter of the weekend effect reported by [Humphreys and Johnson \(2020\)](#), and provides clean evidence of the influence of recent team performance on revenue generation. By finding evidence of a winning effect on attendance that is unconfounded by other factors (team quality, superstars, etc.), it also suggests that it is important for analyses estimating the causal effect of those other factors to control for recent wins.

This result is consistent with fans having a preference for victories and revising the probability of winning upward due to momentum or winner effects (see [Arkes and Martinez \(2011\)](#)). It also suggests yet another setting in which lucky successes are overly rewarded, an apparent violation of the informativeness principle ([Gauriot and Page \(2019\)](#)). In addition, it carries implications for dynamic ticket pricing in the NBA as well as the optimal revenue maximization strategy pursued by teams.

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