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

Ercio Muñoz Jiadi Chen Milan Thomas

August 11, 2020

Abstract

Previous studies show that bettors and competitors alike believe that momentum carries over positively between contests in major league sports. This article applies a regression discontinuity design to estimate the causal effect of a win on the attendance of subsequent games in professional basketball. Using National Basketball Association data from 1981 to 2018, we find that home team fan bases react to a recent victory, with an increase in attendance of approximately 425 tickets. 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. The positive fan base response to narrow home wins relative to narrow losses suggests that like bettors, fans believe in momentum, and that recent luck is rewarded in sporting attendance. We document a gradual decline in the attendance effect that coincides with the rise of secondary markets and dynamic ticket pricing.

JEL-Codes: D12, L83, Z2.

Keywords: *Regression discontinuity design, Momentum, Winner effect.*

*Ercio Munoz; CUNY Graduate Center; Email: emunozsaavedra@gc.cuny.edu. Jiadi Chen; Georgetown University; Email: jc2450@georgetown.edu. Milan Thomas; Georgetown University; mt839@georgetown.edu.

I Introduction

Research on the determinants of sporting event attendance is surveyed in Feehan (2006) and Villar and Guerrero (2009). Within the theoretical 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 and Humphreys (2005), Coates and Humphreys (2012), and Humphreys and Johnson (2020)). 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 the 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.

The rest of 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. We collect information on 61,999 games, 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 have information on attendance. That reduces the number of games to 42,256.[1]

Figure 2 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 2 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 3 breaks down our sample of close games by point difference.

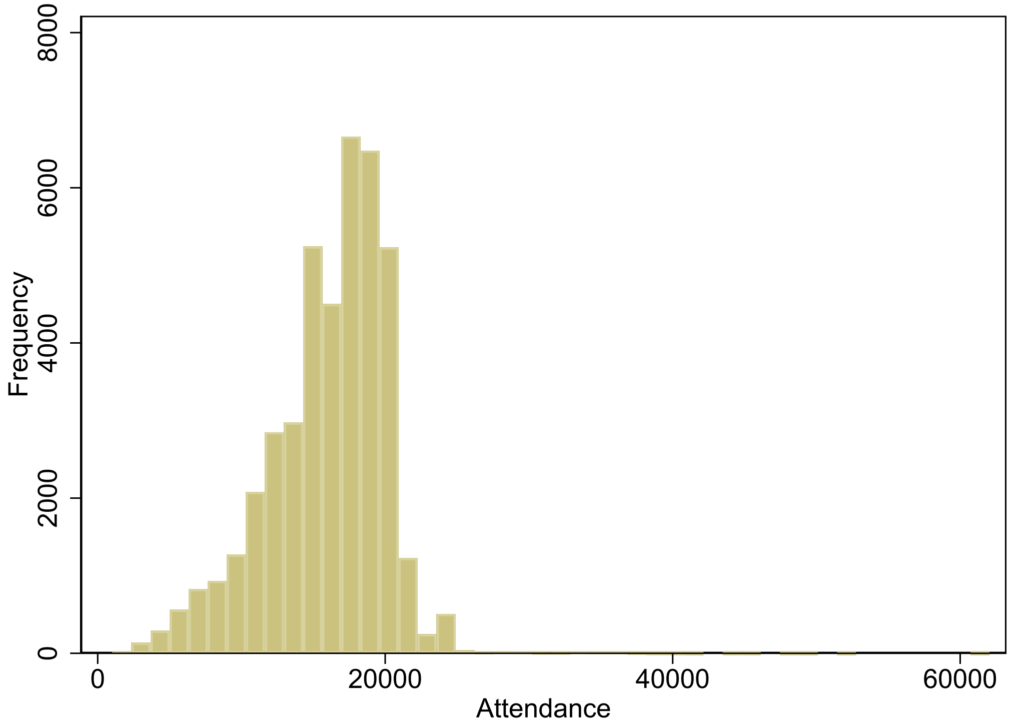
Figure 1 shows the distribution of game attendance in our sample, which is our main outcome variable. The distribution has a noticeable right tail of games with large attendance that includes one-off games in football stadiums and some home games in large facilities (see Humphreys and Johnson (2020)).

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

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

Figure 1: Game Attendance Distribution



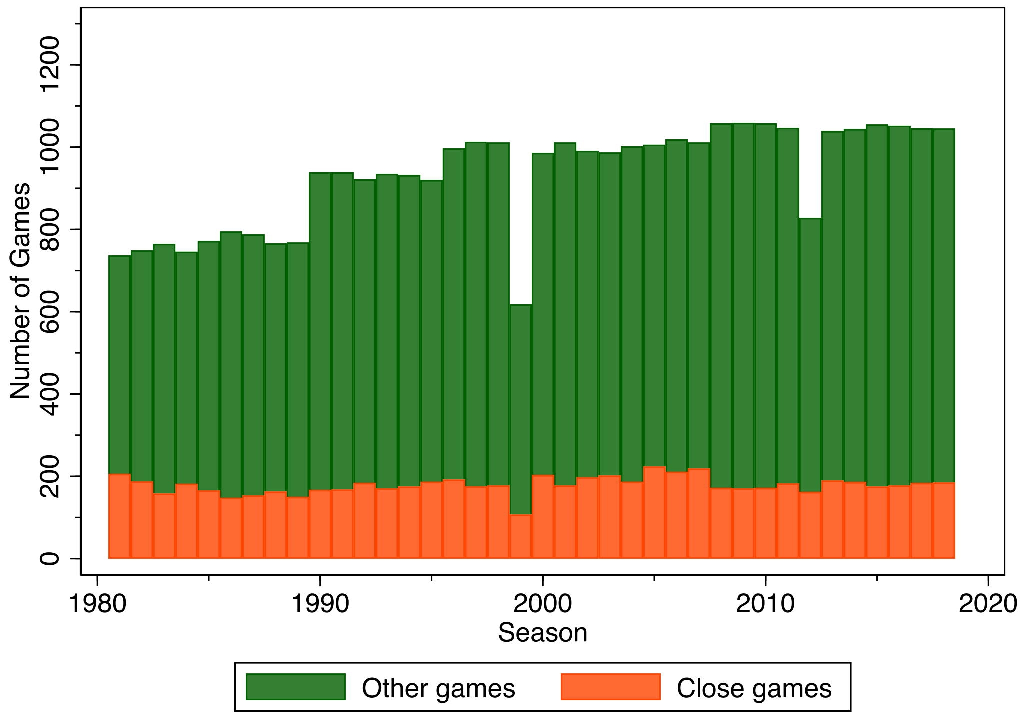
team k (commonly different than team j) at game number t-1 won and 0 if it did not. The treatment variable depends on the difference in points at the end of the game, such that:

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

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

Figure 2: Games per season
Close games defined as games with point difference less than 4



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).

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 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.

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 attendance of

Figure 3: Number of close games
Total of 6,728 games with point difference less than 4 points

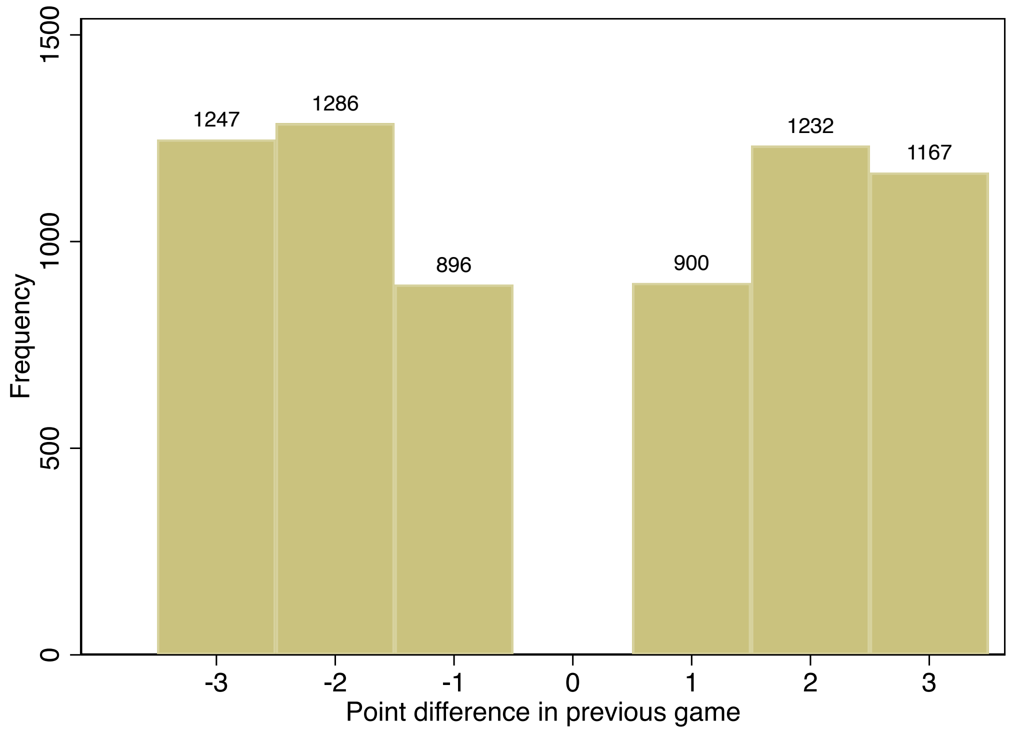


Table 1: Binomial test

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

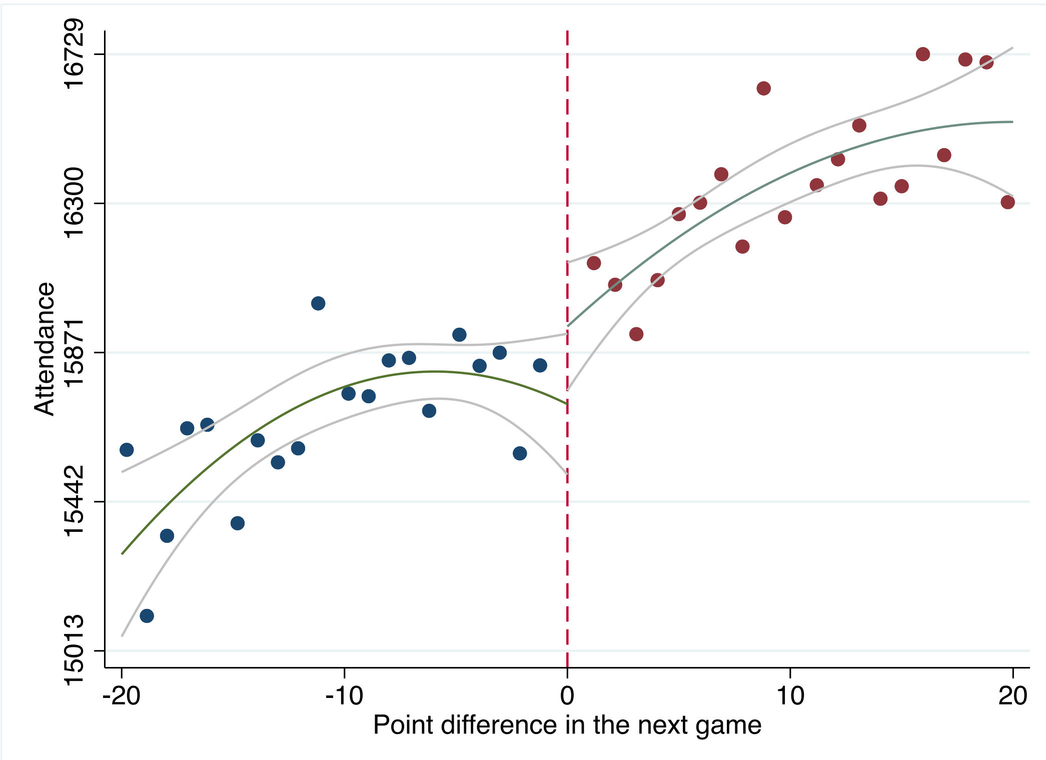
the next game where there should be no effect.

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 4 shows the result. We do not find a clear discontinuity, and our estimation confirms this result with a p-value of 0.338.

Table 2: Alternative cutoffs

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

Figure 4: The effect of winning next game on current game attendance (Estimate=291 with p-value=0.338)

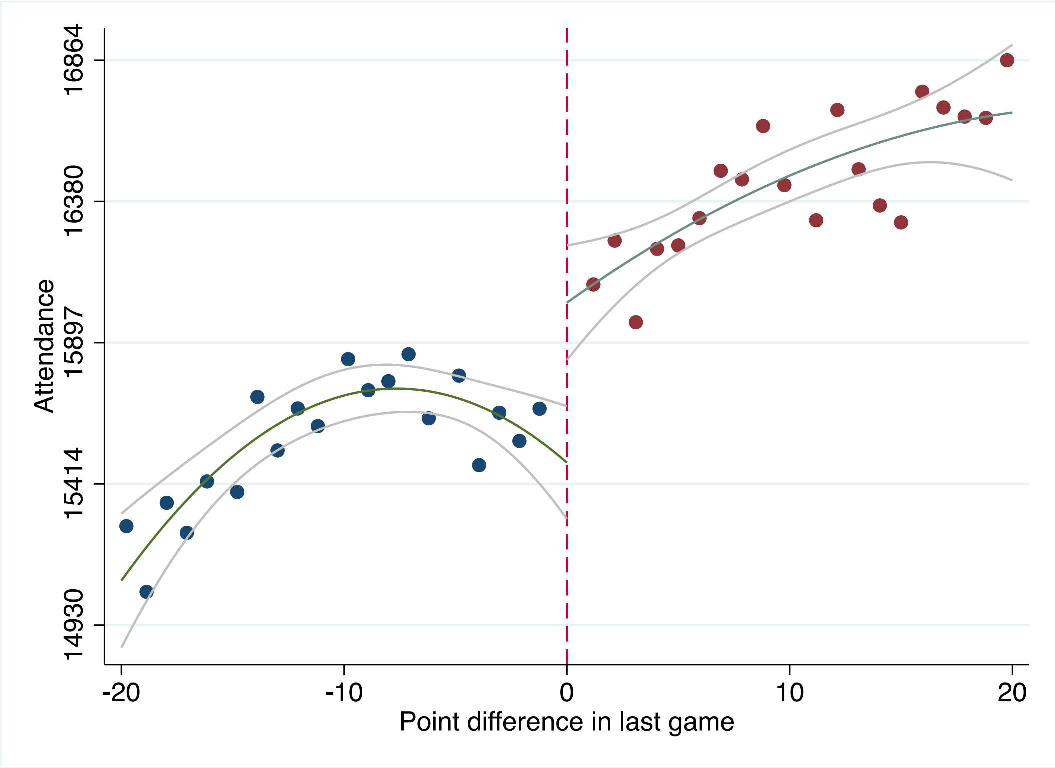


IV Results

Figure 5 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, 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.

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

Figure 5: The effect of winning on next game attendance



increase of approximately 425 tickets sold for the next game when we use the smallest possible window.[2] 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 and Johnson (2020)).

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

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

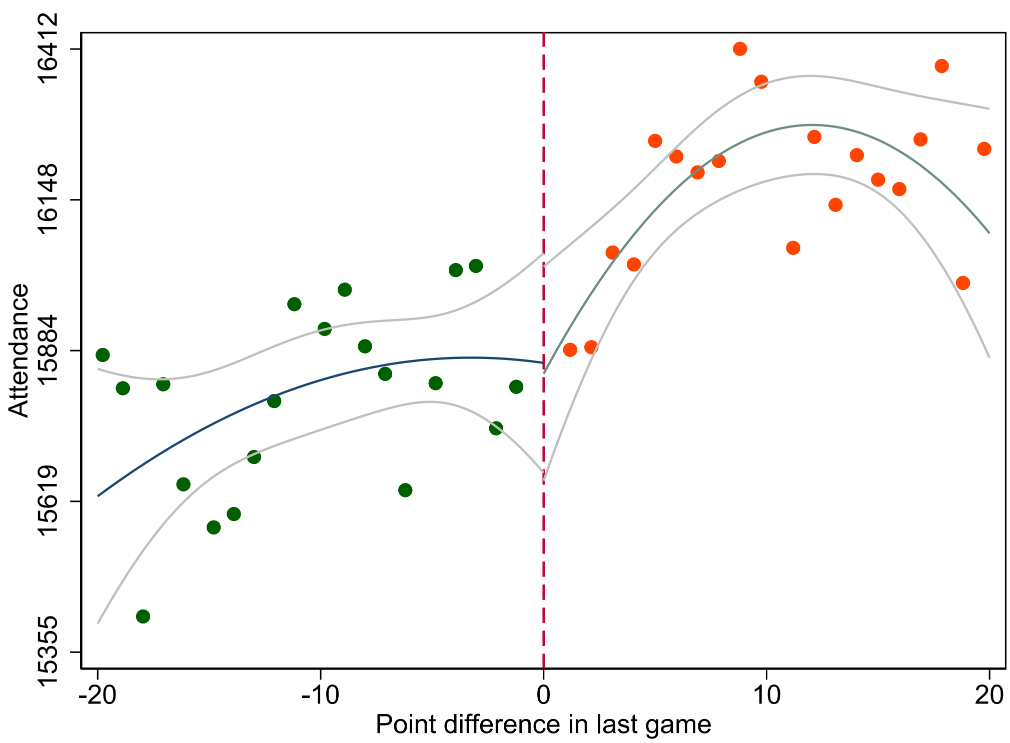
This effect represents a lower bound of the impact of winning on attendance because

[2] 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.

some games are sold out in advance, which prevents a winning effect on sales.

The previous estimate considers only the impact of winning last game on attendance at the winners' home games. In the case of games as the visiting team, we do not find any effect (see Figure 6), which implies that there are no externalities from winning (i.e. the last win of a team does not increase 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 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.

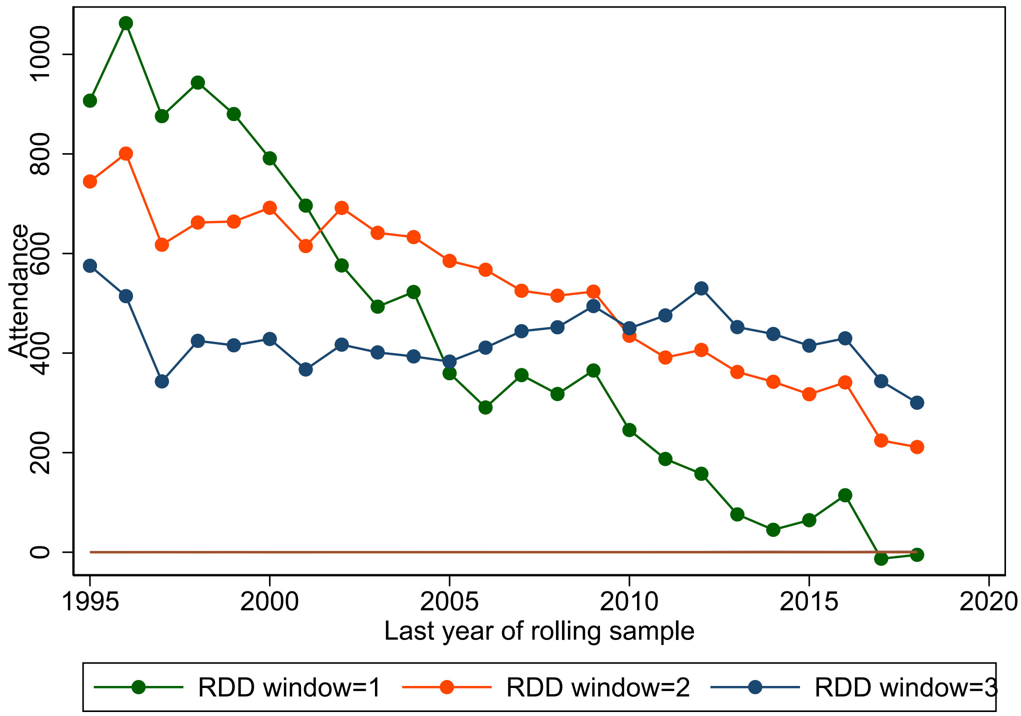
Figure 6: The effect of winning on next game attendance in visitor games (Estimate=64 with p-value=0.737)



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 began even before this decade. We explore whether the estimated effect varies over time 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 7), which using the smallest possible window for the regression discontinuity design with games ending with a one point difference approaches zero at the end of our sample. This suggests that our estimate is a demand increase due to its magnitude at the beginning of the sample where dynamic pricing was not in place and secondary markets were not available. In addition, the downward trend is consistent with a supply response to recent victories that can attenuate 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 8 shows how the average game attendance by season has evolved in our sample period, showing a pronounced increase in the 80s and a stabilization in the last two decades.

Nonetheless, an inspection of the share 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 9), which suggests that the falling response is not due to a downward bias due to sell-outs being more important over time.

Figure 7: The effect of winning on next game attendance over time (15-year rolling period)



V Discussion and 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.

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 . By finding evidence of a win 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.

Figure 8: Average game attendance by season

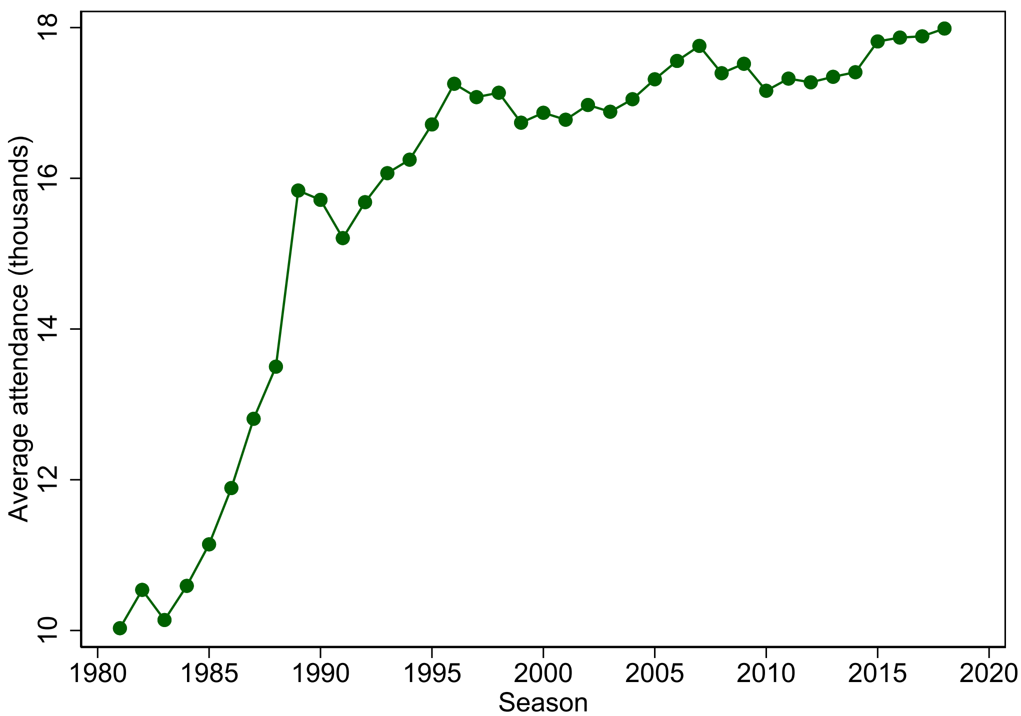
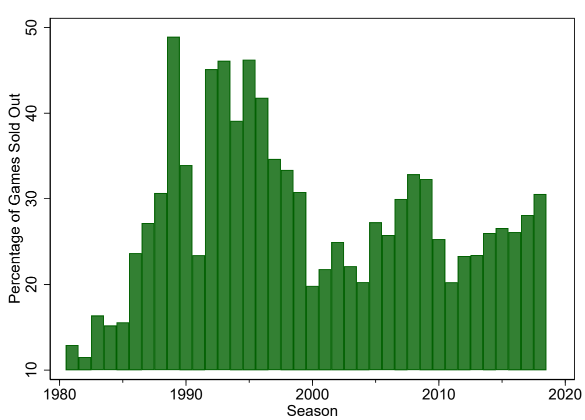
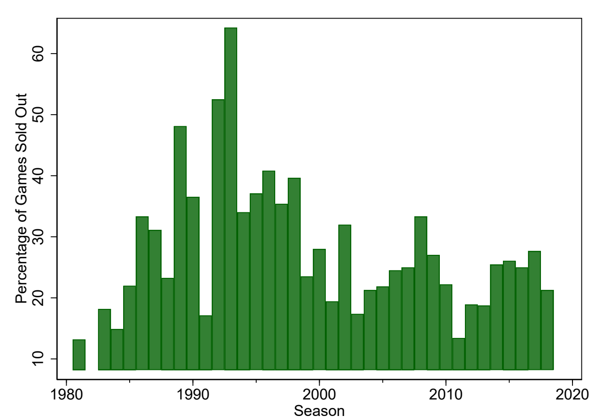


Figure 9: Percentage of sold out games by season

(a) All regular season games



(b) Games where home team had a previous close game (one point difference)



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)).

It is unclear whether this recent victory effect is accounted for in the dynamic pricing strategies that have been widely applied in sports tickets market in recent years (Jessop (2012)), but Figure 7 shows suggestive evidence that it is. We document that the attendance response to recent victories has declined over time, which is consistent with two 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 share of sell-out games increased, capping the attendance effect on sales. However, Figure 9 shows that the latter explanation is not supported by our data.

References

Arkes, J., & Martinez, J. (2011). Finally, Evidence for a Momentum Effect in the NBA. *Journal of Quantitative Analysis in Sports*, *7*(3).

Berri, D. J., & Schmidt, M. B. (2006). On the Road With the National Basketball Association's Superstar Externality. *Journal of Sports Economics*, *7*(4), 347–358.

Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2018). A Practical Introduction to Regression Discontinuity Designs: Volume II. *Cambridge Elements: Quantitative and Computational Methods for Social Science*, *II*, 113.

Coates, D., & Humphreys, B. R. (2005). Novelty Effects of New Facilities on Attendance at Professional Sporting Events. *Contemporary Economic Policy*, *23*(3), 436–455.

Coates, D., & Humphreys, B. R. (2012). Game Attendance and Outcome Uncertainty in the National Hockey League. *Journal of Sports Economics*, *13*(4), 364–377.

Feehan, P. (2006). Attendance at Sports Events. In W. Andreff & S. Szymanski (Eds.), *Handbook on the economics of sport* (pp. 90–99). Cheltenham, UK: Edward Elgar Publishing Limited.

Gauriot, R., & Page, L. (2018). Psychological Momentum in Contests: The Case of Scoring before Half-time in Football. *Journal of Economic Behavior and Organization*, *149*, 137–168.

Gauriot, R., & Page, L. (2019). Fooled by Performance Randomness: Overrewarding Luck. *The Review of Economics and Statistics*, *101*, 658–666.

Hausman, J. A., & Leonard, G. K. (1997). Superstars in the National Basketball Association: Economic value and policy. *Journal of Labor Economics*, *15*(4), 586–624.

Humphreys, B. R., & Johnson, C. (2020). The Effect of Superstars on Game Attendance: Evidence From the NBA. *Journal of Sports Economics*, *21*(2), 152–175.

Jessop, A. (2012). The NBA and Ticketmaster announce a partnership creating a new ticketing method. *Forbes Sportsmoney*. Retrieved from https://www.forbes.com/sites/aliciajessop/2012/08/20/the-nba-and-ticketmaster-announce-a-partnership-creating-a-new-ticketing-method/#43bc688e4f7a

Kniffin, K. M., & Mihalek, V. (2014). Within-series Momentum in Hockey: No Returns for Running up the Score. *Economics Letters*, *122*(3), 400–402.

Rottenberg, S. (1956). The Baseball Players' Labor Market. *The Journal of Political Economy*, *64*(3), 242–258.

Vergin, R. C. (2000). Winning Streaks in Sports and the Misperception of Momentum. *Journal of Sport Behavior*, *23*(2), 181–197.

Villar, J. G., & Guerrero, P. R. (2009). Sports Attendance: a Survey of the Literature 1973-2007. *Rivista di Diritto ed Economia dello Sport*, *5*(2), 2009.