

# Momentum Effect in the NBA: Exploiting the Fine Line between Winning and Losing\*

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Preliminary and incomplete.

## Abstract

Competition in the National Basketball Association takes on two formats in a single season. This provides a pair of fronts on which to test the existence of momentum effects, which have been analyzed extensively in finance and sports. We assess whether a team that wins a match has a higher probability of winning the next match. Since winning is endogenous, we identify the causal effect of winning a game using a regression discontinuity design with NBA data from 1950 to 2018. Like other recent studies, we find evidence of a positive momentum effect in the regular season. In contrast, we find a negative momentum effect for the playoffs. We argue that the tournament design of the playoffs theoretically provides a better set up to estimate the momentum effect because opponents match up consecutively and repeatedly (allowing us to better control for unobserved factors such as team strength, home-court advantage, and rest time), and that the two parts of the NBA season are not comparable because the incentives of teams and the league shift during the playoffs. Our finding highlights the importance of defining both the nature and domain of momentum, and that, even within a sports league, the existence of momentum depends on context.

**JEL-Codes:** Z2.

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

## I Introduction

Athletic competition provides several arenas for evaluating the conventional adage and behavioral hypothesis that success breeds success. There is a vast literature in sports economics on inter-temporal correlation of performance both across games (the momentum effect) and

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within games (the “hot-hand” effect). As previous studies recognize, high serial correlation in performance is not necessarily evidence of momentum, because a wide range of confounding factors (such as team strength) may underlie the observed relationship between past and current performance. We address that endogeneity issue using a quasi-experimental empirical strategy that, to the best of our knowledge, has not been applied to date. We use a regression discontinuity design to identify the causal effect on the probability of winning a game by using only narrow margin victories. While we find a positive momentum effect for regular season games, the finding is reversed for the playoffs, which provide a test of momentum that is less subject to confounding factors.

This paper is organized as follows. In Section II we give a brief summary of recent literature and in Section III we describe the data set. Section IV presents the empirical strategy used to identify the impact of winning a game on success in the next game. In Section V, we discuss our findings and Section VI concludes with final remarks.

## II Literature Review

In the context of social sciences, momentum refers to a phenomenon by which success has a causal effect on future success. Popular belief in this phenomenon is widespread, and notably represented by PGA Champion Rocco Mediate’s claim that “Momentum is the most unstoppable force in sports.” [Iso-ahola and Dotson \[2014\]](#) review possible psychological underpinnings for the phenomenon, whose empirical existence in financial markets and competition is a topic of debate. There is a vast literature in sports economics on the effect of momentum both within games (the hot-hand effect) and between games (which we refer to as momentum, and is the main focus of this paper).

The hot-hand debate has been investigated empirically for decades. [Kahneman and Tversky \[1972\]](#) claim that the hot hand is a fallacy reflecting a misconception of “local representativeness.” [Gilovich et al. \[1985\]](#) show that basketball players claimed to believe

in the hot-hand effect. However, they found negative serial correlation among field goal attempts, in seeming contradiction to a hot hand effect. Similar studies over following decades led [Bar-Eli et al. \[2006\]](#) to conclude in a systematic review that evidence for the hot-hand effect was very limited. More recent work shows the existence of a hot hand effect. [Arkes \[2010\]](#) uses 2005-06 NBA season free throw data to show positive serial correlation in making free throw attempts. [Green and Zwiebel \[2017\]](#) find strong evidence for the hot hand effect in baseball using panel data from Major League Baseball. [Miller and Sanjurjo \[2018\]](#) show that streak selection bias may explain why many past studies were unable to find a hot-hand effect.

Evidence on the momentum effect has evolved similarly. In an early study, [Vergin \[2000\]](#) uses data from the National Basketball Association (NBA) and Major League Baseball and compares the frequency and length of actual winning streaks with the expected winning streaks if games are truly independent. He does not find evidence of momentum. [Schilling \[2013\]](#) tests for momentum effect within collegiate volleyball games. Based on analysis similar in spirit to [Vergin \[2000\]](#), he finds that actual number of runs (scoring four or more points in a row) is similar to the number predicted by a switching Bernoulli trials model with no momentum, and concludes there is no evidence of a momentum effect.

In the past decade, empirical methods and data for analyzing momentum have become more sophisticated. More recent efforts control for unobserved factors that can bias the momentum effect estimate. For example, [Arkes and Martinez \[2011\]](#) find evidence of momentum (proxied by win percentage over the past five games adjusted for opponent difficulty) in the NBA by estimating a logit model that controls for factors like home-court advantage, difference in team strength, and rest time. [Leard and Doyle \[2011\]](#) find some evidence of a positive momentum effect using data from the National Hockey League. [Page and Coates \[2017\]](#) use a quasi-experimental approach similar in spirit to that of this paper, and find a positive momentum effect between tennis match sets which may have a biological basis.

Conversely, [Parsons and Rohde \[2015\]](#) estimates a logit model with fixed effects and

conclude that there is no momentum between games in the Soccer English Premier League. [Salaga and Brown \[2018\]](#) test for momentum effect between college football games. They use various definitions to identify momentum of the  $n^{th}$  degree: 1) winning streak of  $n$  games; 2) win percentage over last  $n$  games. A third measure they use is halted momentum (a loss in the most recent contest after a winning streak of  $n$  games). They control for team quality, schedule strength, and rest, and find no effect of momentum on game outcomes. [Gauriot and Page \[2018\]](#) search for evidence of momentum within professional soccer matches. Their identification strategy is based on similar shots (those that hit the cross-bar) that go in vs out. They compare second-half outcomes on the basis of first-half shots, and do not find evidence of a momentum effect. [Kniffin and Mihalek \[2014\]](#) analyzes repeated games between opponents (a feature in NBA competition that we also exploit), finding no evidence of positive momentum in college hockey.

With evidence to support both sides of the debate, the momentum in sports debate is far from closed. [Arkes \[2013\]](#) uses simulation to show that the lack of clear evidence of a momentum effect could simply be a statistical artefact resulting in low probability of detection, even when the momentum effect is large and frequent. This could explain the lack of consensus, and suggests that further investigation applying new techniques to new settings can help uncover scenarios in which the between game momentum effect is empirically evident. We contribute novel evidence on the question of momentum using a regression discontinuity design and data from the NBA regular season and playoffs.

### III Data

We use game-level data publicly available from [www.basketball-reference.com](http://www.basketball-reference.com), which are obtained by using R to web scrape the site. We collect information for 61,999 games (3,918 of them from the playoffs), including home team name, visitor team name, game date, attendance, number of overtimes, type of game (regular season or playoff), and number of

points scored by each team.

We analyze regular season games and playoff games separately, because of the differences in performance incentives between the two parts of the season. For any given regular season game, a franchise may be disincentivized to exert maximum effort to win a game for a number of reasons, especially later in the season. These reasons include desire to rest players, worsen record to improve odds of winning the NBA draft lottery (“tanking”), or achieve a favorable playoff match-up. In the playoffs, no such heterogeneity of incentives exists - every team is incentivized to win every game in the series (though perhaps to varying degrees, as we discuss in Section V).

Figure 1 displays the number of games by type per season in our data set. There is an increase over time in the total number of games for the regular season and playoffs.

**Figure 1:** Games per season

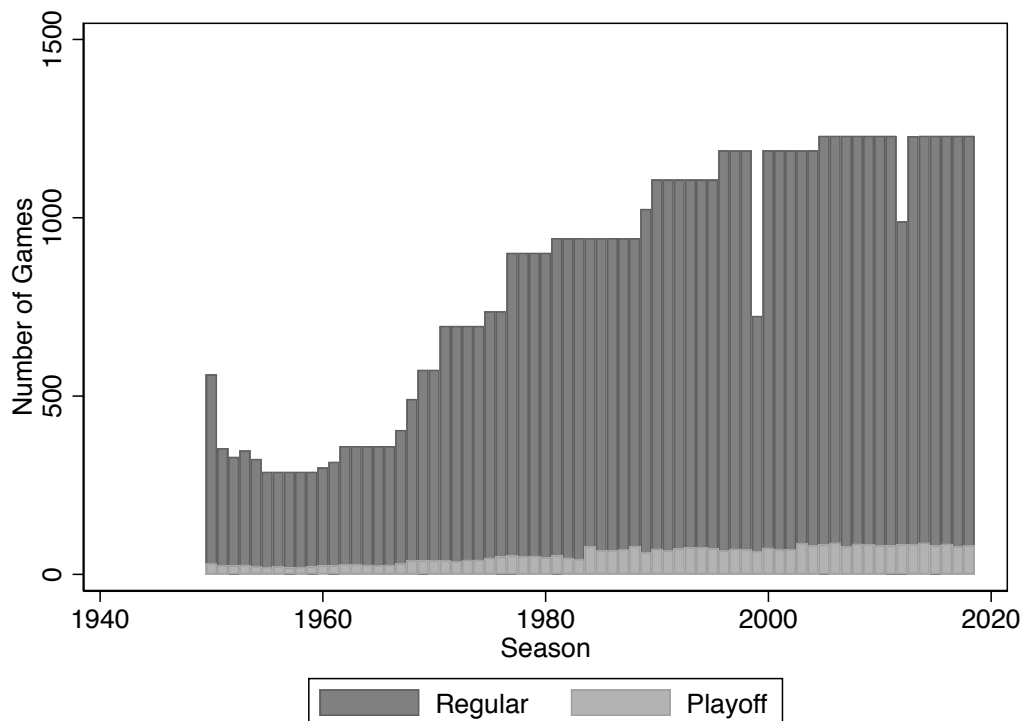


Figure 2 shows the distribution of the point difference between home team and visitor team at the end of the game by type (regular season and playoff), which is going to be useful

for constructing our running variable for the regression discontinuity design. The distribution shows a gap at zero because tied games are not allowed in basketball. In addition, the distribution is not centered around zero (with more mass above zero than below), reflecting home court advantage.

**Figure 2:** Margin of points at the end of the game

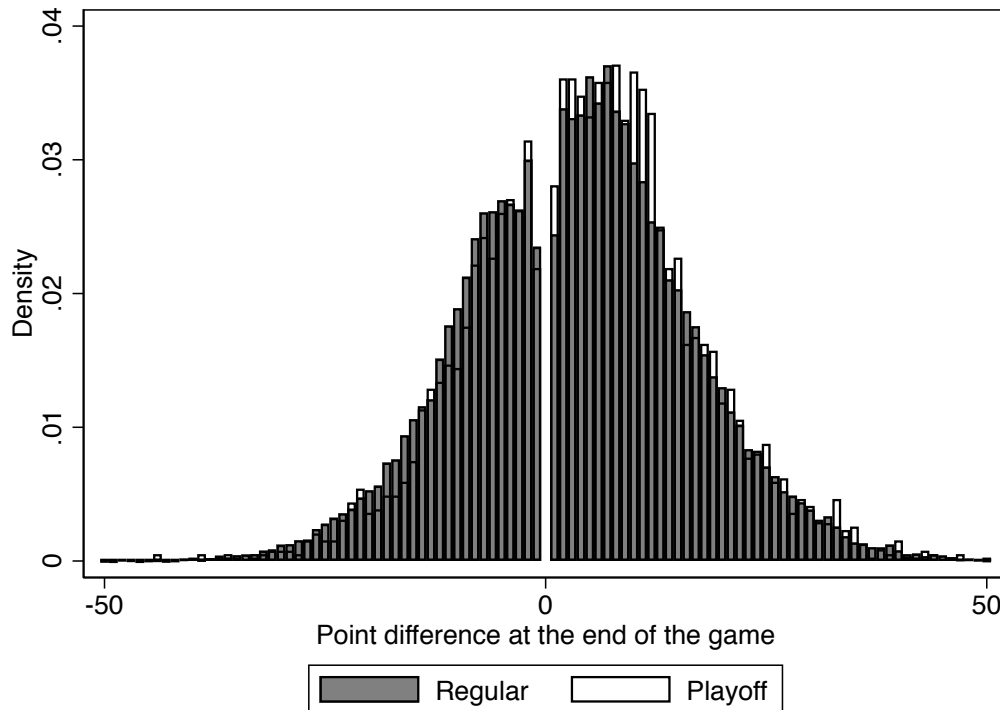


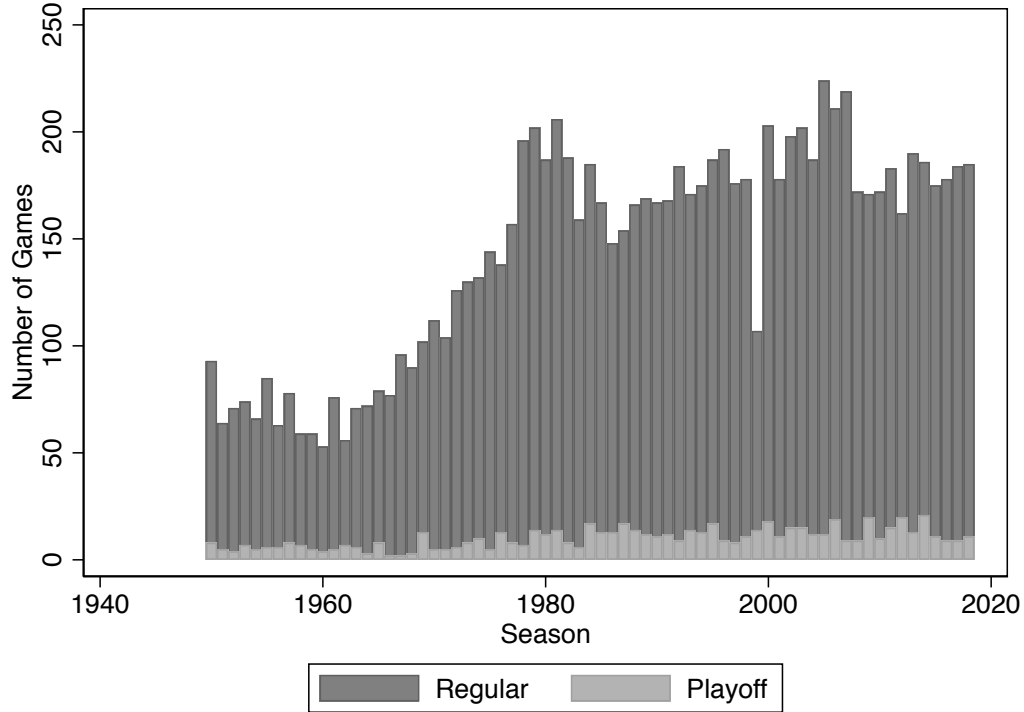
Figure 3 shows the number of close games by season, which are defined as games with a point difference less than four points at the end of the game. That difference is small enough to allow the trailing team to tie the game in one possession<sup>1</sup>. There is a total of 9,939 such games played in regular season and 698 in playoffs<sup>2</sup>. Table 1 breaks down the close games by point difference.

Using the available information, we construct measures of momentum, rest time, and

<sup>1</sup>This is not true before 1979 because the three-point field goal was not adopted yet.

<sup>2</sup>Figure 7 in the Appendix shows the share of close games by season.

**Figure 3:** Close games per season (point difference less than 4)



team strength that follow [Arkes and Martinez \[2011\]](#). Home team and away team strength are computed as their respective winning percentages for the season, excluding the current and previous three games. Similarly, we also construct total strength using both home and away games. Rest time is computed as the days since the previous game played by each team. Momentum measures are computed as the number of victories in the last 3 or 5 games.

Table 2 reports descriptive statistics of our main variables. Table 12 in the Appendix reports the correlation structure of these variables.

**Table 1:** Close games from home team perspective (point difference less than 4)

	Playoff	Regular	Total
-3	102	1524	1626
-2	122	1742	1864
-1	85	1364	1449
1	109	1419	1528
2	140	1966	2106
3	140	1924	2064
Total	698	9939	10637
$N$	10637		

**Table 2:** Descriptive statistics

	N	Mean	SD	Min	Max
Win		0.62	0.49	0.00	1.00
Point difference at the end of the game		10.82	7.98	1.00	68.00
Total winning percentage		50.86	15.17	9.23	90.12
Heat (victories in last 3 games) - home		1.50	0.92	0.00	3.00
Heat (victories in last 5 games) - home		2.51	1.27	0.00	5.00
Rest time (in days) - home		2.24	1.05	0.00	15.00
Home winning percentage		65.36	17.84	10.34	108.11
Heat (victories in last 3 games) - away		1.53	0.93	0.00	3.00
Heat (victories in last 5 games) - away		2.56	1.28	0.00	5.00
Rest time (in days) - away		1.95	0.99	0.00	12.00
Away winning percentage		40.84	16.63	0.00	91.89
Observations	61999				

## IV Empirical Strategy

### I Regression approach

As a benchmark for our regression discontinuity design, we first tackle the question using a regression approach as previous studies have done. We follow [Arkes and Martinez \[2011\]](#) and estimate the following empirical model:

$$Y_{it} = \alpha_h Q_{it}^h + \alpha_a Q_{it}^a + \beta'_h R_{it}^h + \beta'_a R_{it}^a + \gamma_h S_{it}^h + \gamma_a S_{it}^a + \epsilon_{it} \quad (1)$$



where the dependent variables  $Y_{it}$  is a dummy taking value 1 if home team won game  $i$  in season  $t$ ,  $Q^h$  and  $Q^a$  represent measures of the team strength for the home and away teams,  $R^h$  and  $R^a$  are measures of the amount of rest between games,  $S^h$  and  $S^a$  are measures of success over the past few games (momentum), and  $\epsilon$  represents an error term. Given that the dependent variable is binary, we use a logit estimator and a linear probability model.

## II Regression Discontinuity Design

Our second and preferred approach is a regression discontinuity design, with point difference as the running variable. The outcome of interest is denoted by  $y_{i,j,t}$ , which corresponds to a dummy variable equal to 1 if the home team  $i$  wins in a game at date  $t$  against a visitor team  $j$ , and 0 otherwise.

We denote our treatment by a dummy variable  $d_{i,j,t} \in \{0, 1\}$ , which is equal to 1 if the team  $i$  playing against team  $j$  at date  $t$  won the previous game and 0 if it did not. For regular season games, the previous game can be against any other team. However, due to the best-of-five or best-of-seven structure of playoff series, for playoff games the previous game must be against the same team  $j$ . For simplicity, we write the econometric specification as if the previous game is always against the same team.

With the previous definitions, we can write the following specification:

$$y_{i,j,t} = \alpha + \beta d_{i,j,t} + \gamma X + \epsilon_{i,j,t} \quad (2)$$

Where  $X$  corresponds to a vector of other exogenous determinants of the outcome variable  $y_{i,j,t}$ . The dummy variable  $d_{i,j,t}$  takes a value 1 when the points scored by the home team  $i$  in the previous game (denoted by  $p_{i,j,t-1}^H$ ) are greater than the points scored by the visiting team in that game (denoted by  $p_{i,j,t-1}^V$ ). Then we can denote the treatment as:

$$d_{i,j,t} = 1[p_{i,j,t-1}^H > p_{i,j,t-1}^V] \quad (3)$$

Where  $1[\cdot]$  is an indicator function. This generates a discontinuity that can be exploited for causal identification. As described in [Lee and Lemieux \[2010\]](#), consider the “potential” outcomes:  $y_{i,j,t}(1)$  for what would occur if home team  $i$  won and  $y_{i,j,t}(0)$  if home team  $i$  lost. The causal effect of the treatment is represented by the difference  $y_{i,j,t}(1) - y_{i,j,t}(0)$  which is not observed since the previous game was either won or lost. In the regression discontinuity design however, we use the average outcomes that could be denoted by  $E[y_{i,j,t}(1)|p_{i,j,t}^H - p_{i,j,t}^V]$  and  $E[y_{i,j,t}(0)|p_{i,j,t}^H - p_{i,j,t}^V]$ , where by design  $E[y_{i,j,t}(1)|p_{i,j,t}^H - p_{i,j,t}^V]$  is observed when  $p_{i,j,t}^H - p_{i,j,t}^V > 0$  and  $E[y_{i,j,t}(0)|p_{i,j,t}^H - p_{i,j,t}^V]$  is observed when  $p_{i,j,t}^H - p_{i,j,t}^V < 0$ . Hence, with these observable values we estimate:

$$\begin{aligned} & E[y_{i,j,t}(1) - y_{i,j,t}(0)|p_{i,j,t}^H - p_{i,j,t}^V = 0] = \\ & \lim_{\varepsilon \downarrow 0} E[y_{i,j,t}(1)|p_{i,j,t}^H - p_{i,j,t}^V = 0 + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[y_{i,j,t}(0)|p_{i,j,t}^H - p_{i,j,t}^V = 0 + \varepsilon] \end{aligned} \quad (4)$$

This is the “local average treatment effect” at the cutoff 0. We estimate it using local linear regression with optimal bandwidths using the following econometric specification:

$$\begin{aligned} y_{i,j,t} &= \alpha_+ + \beta_2 f_+(m_{i,j,t}) + \epsilon_{+,i,j,t} \quad \text{for } m_{i,j,t} > 0 \\ y_{i,j,t} &= \alpha_- + \beta_2 f_-(m_{i,j,t}) + \epsilon_{-,i,j,t} \quad \text{for } m_{i,j,t} < 0 \end{aligned} \quad (5)$$

where  $m_{i,j,t} = p_{i,j,t}^H - p_{i,j,t}^V$  corresponds to the running variable,  $f(\cdot)$  is a polynomial function, and  $\alpha_+ - \alpha_-$  is our parameter of interest.

Given that our running variable  $m_{i,j,t}$  is discrete and takes only a 118 different values, we transform it dividing  $m_{i,j,t}$  by the total number of points scored in the game ( $p_{i,j,t}^H + p_{i,j,t}^V$ ). This creates a transformed variable with 3,945 different values that is better suited for an estimation using the continuity-based approach.<sup>3</sup>

Alternatively, we keep our original discrete running variable, estimate a causal effect using local randomization approach and perform inference using the general Fisherian inference framework as described in [Cattaneo et al. \[2018\]](#). To do this, we assume that there is a

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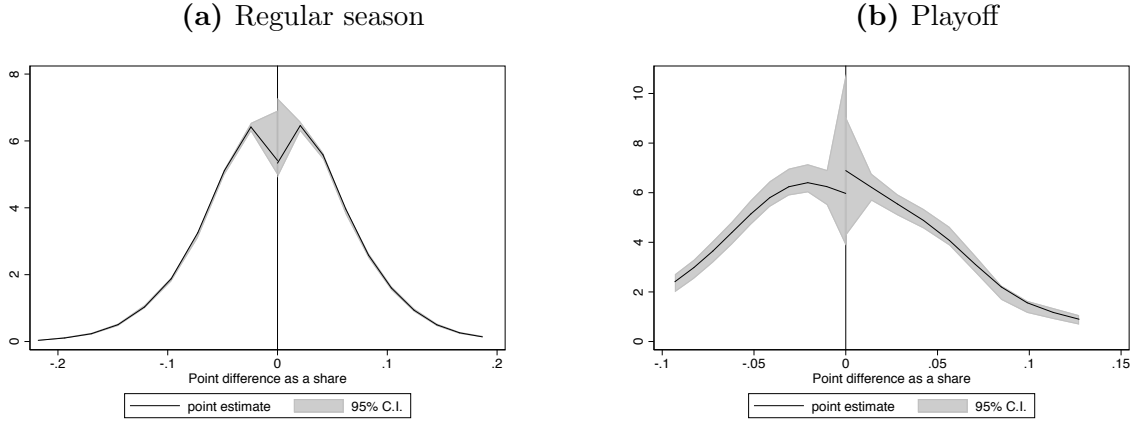
<sup>3</sup>See [Cattaneo et al. \[2018\]](#) for a complete discussion about RD design with discrete random variables.

small window around the zero cutoff, such that for all the games whose scores fall in that window their end result (win or lost) is assigned as in a randomized experiment. We consider three different windows, from the smallest possible difference of one point to a three point difference game that would have allowed the losing team to tie the game in one possession.

The way in which the playoffs are organized are particularly conducive for this regression discontinuity design. Opponents square off multiple times in the same location over a short span of time, allowing us to control for unobserved factors, such as home court advantage, team quality, rest time, and medium-term health, among others. For our playoff analysis, we do so by using only pairs of consecutive games that happen between the same teams and are played within one week of each other in the same location. Close games in the playoffs get us as close as conceivably possible to an experimental set-up in professional basketball, because teams are assigned to treatment - winning or losing a the previous game - despite similar ability and performance.

Before presenting our results for the regular season and playoffs, we present a set of three standard validity checks for our regression discontinuity design. First, we examine whether the density of the running variable, the margin of victory, is continuous at the cutoff. We run the manipulation testing using local-polynomial density estimation [McCrary, 2008] and find support for our empirical strategy (see Figure 4). We fail to reject the null hypothesis that there is no evidence of manipulation at the cutoff for both regular season games (p-value=.85) and playoff games (p-value=0.75). In addition, we take advantage of the discrete nature of our running variable and perform a binomial test on the smallest feasible window that consists of games with a difference of one point. Table 3 reports the results, in which we fail to reject the null at 5% that observations in the window appear as generated by a binomial distribution with probability 1/2.

Second, we run our estimation using alternative placebo cutoffs. Table 4 reports the results. In the case of regular season games, we do not find some evidence of jumps in

**Figure 4:** Density test**Table 3:** Binomial test over one-point difference games

	<b>Binomial test</b>	<b>Obs&lt; c</b>	<b>Obs<math>\geq</math> c</b>
Regular	0.697	1448.000	1470.000
Playoff	0.099	84.000	63.000

placebo cutoffs where there should be no effect (see panel (a) of Table 4a). Similarly, for playoff games our check fully supports the existence of a jump only in the cutoff equal to 0 (Table 4b).

Third, we inspect predetermined covariates and placebo outcomes at the cutoff. Table 5 report our results. We find that teams differ in terms of winning percentage (excluding the previous game, which corresponds to the game of the running variable we use) around the cutoff in regular season games. In contrast, we do not find evidence of any difference in the case of playoff games, which again supports our RD design for these games.

**Table 4:** Alternative cutoffs

(a) Regular season games						
	Continuity-based			Local randomization		
	1	2	3	4	5	6
<b>Coefficient</b>	-0.001	-0.003	-0.004	0.044	0.014	0.023
<b>Standard error</b>	0.015	0.014	0.013	.	.	.
<b>Probability</b>	0.954	0.656	0.795	0.022	0.339	0.144
<b>Cutoff</b>	0.000	0.050	-0.050	0.000	5.000	-5.000
(b) Playoff games						
	Continuity-based			Local randomization		
	1	2	3	4	5	6
<b>Coefficient</b>	-0.187	-0.031	0.083	-0.172	0.015	0.038
<b>Standard error</b>	0.061	0.065	0.051	.	.	.
<b>Probability</b>	0.015	0.402	0.207	0.000	0.745	0.310
<b>Cutoff</b>	0.000	0.050	-0.050	0.000	5.000	-5.000

## V Results

### I Regression results

#### I.1 Regular season

Using our data set, we estimate equation 1 and some variants of it. Table 6 reports the results using only regular season games, as [Arkes and Martinez \[2011\]](#) do. Our results are very similar to theirs, even after extending their sample to more seasons (see columns 4 and 5). Column 1 shows the naive estimate of the momentum effect, which is subject to no controls and suffers from omitted variable bias. The regression approach in essence attempts to eliminate the omitted variable bias by adding controls, and its validity depends on the unverifiable claim that the controls fully capture these omitted variables. Subsequent columns show that as we introduce more controls to , the estimate of the momentum effect shrinks to 2%.

**Table 5:** Placebo test**(a)** Regular season games

	Continuity-based			Local randomization	
	<b>Coef.</b>	<b>s.e.</b>	<b>Prob.</b>	<b>Coef.</b>	<b>Prob.</b>
Winning percentage (excluding same game)	0.91	0.42	0.09	1.98	0.00
Rest away team	-0.05	0.03	0.08	-0.05	0.17
Rest home team	-0.02	0.03	0.43	-0.04	0.29
Attendance (same game)	122.47	155.87	0.35	122.08	0.57

**(b)** Playoff games

	Continuity-based			Local randomization	
	<b>Coef.</b>	<b>s.e.</b>	<b>Prob.</b>	<b>Coef.</b>	<b>Prob.</b>
Winning percentage (excluding same game)	-1.38	1.09	0.31	-2.16	0.14
Rest away team	0.07	0.09	0.50	0.01	1.00
Rest home team	0.09	0.09	0.44	0.02	0.92
Attendance (same game)	116.85	559.84	0.87	-364.43	0.63

## I.2 Playoffs

We estimate the same models as in the previous section using only playoff data and winning percentage in regular season as a measure of strength. Table 7 reports these results. In contrast to the regular season (for which all specifications yielded a positive, significant momentum effect), we find a statistically significant effect of momentum only for certain combinations of control variables. This suggests that regular season games and playoff may have different dynamics.

This regression approach yields unbiased estimates of the momentum effect only under the strong assumption that our regressions control for all possible confounding factors. We proceed to our second estimation strategy, which is better-suited to identify the causal impact of momentum especially in the playoffs, for the reasons discussed in Section IV.

**Table 6:** Regression results (regular season)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	logit	logit	logit	logit	logit	LPM	LPM
Heat (victories in last 5 games) - home		0.069*** (0.002)	0.025*** (0.002)	0.025*** (0.002)	0.025*** (0.008)	0.022*** (0.002)	0.022*** (0.002)
Heat (victories in last 5 games) - away		-0.059*** (0.002)	-0.020*** (0.002)	-0.020*** (0.002)	-0.015* (0.008)	-0.017*** (0.002)	-0.017*** (0.002)
Home winning percentage			0.007*** (0.000)	0.007*** (0.000)	0.008*** (0.001)	0.007*** (0.000)	0.006*** (0.000)
Away winning percentage			-0.007*** (0.000)	-0.007*** (0.000)	-0.008*** (0.001)	-0.006*** (0.000)	-0.006*** (0.000)
Rest time (in days) - home				0.010*** (0.002)	0.012 (0.010)	0.009*** (0.002)	0.009*** (0.002)
Rest time (in days) - away				-0.017*** (0.002)	-0.002 (0.010)	-0.015*** (0.002)	-0.016*** (0.002)
Won game in t-1	0.088*** (0.004)						
Constant						0.444*** (0.010)	
Observations	57,327	54,172	54,172	54,172	3,452	54,172	54,172
R-squared						0.138	0.139
Team FE	No	No	No	No	No	No	Yes
r2_p	0.00611	0.0421	0.109	0.110	0.119	.	.

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## II Regression discontinuity design results

### II.1 Regular season

Figure 5 reports visual evidence of the effect of winning a game on the probability of winning the next game in regular season. We do not find a clear discontinuity in the probability of winning around the threshold.

Table 8 reports the point estimates using data-driven optimal bandwidths. The graphical result is confirmed and we do not find evidence of a discontinuity.

Table 9 reports the results of the estimation using local randomization approach with games ending with one, two or three point difference. We find a statistically significant 4% increase in the probability of winning the next game when we use the smallest possible window. The first three columns report the unconditional result, while column 4 is conditional on winning the previous game and column 5 on previously winning two consecutive games.

**Table 7:** Regression results (Playoffs)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logit	logit	logit	logit	LPM	LPM
Heat (victories in last 5 games) - home		0.039*** (0.008)	0.008 (0.008)	0.003 (0.009)	0.003 (0.008)	0.001 (0.008)
Heat (victories in last 5 games) - away		-0.027*** (0.008)	-0.030*** (0.008)	-0.035*** (0.008)	-0.034*** (0.008)	-0.033*** (0.008)
Home winning percentage in regular season			0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)
Away winning percentage in regular season			0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Rest time (in days) - home				0.015** (0.007)	0.013** (0.006)	0.012* (0.006)
Rest time (in days) - away				0.012 (0.009)	0.012 (0.008)	0.014* (0.008)
Won game in t-1	-0.010 (0.015)					
Constant					0.095 (0.065)	
Observations	3,883	3,883	3,883	3,883	3,883	3,879
R-squared					0.043	0.056
Team FE	No	No	No	No	No	Yes
r2_p	8.20e-05	0.0105	0.0317	0.0344	.	.

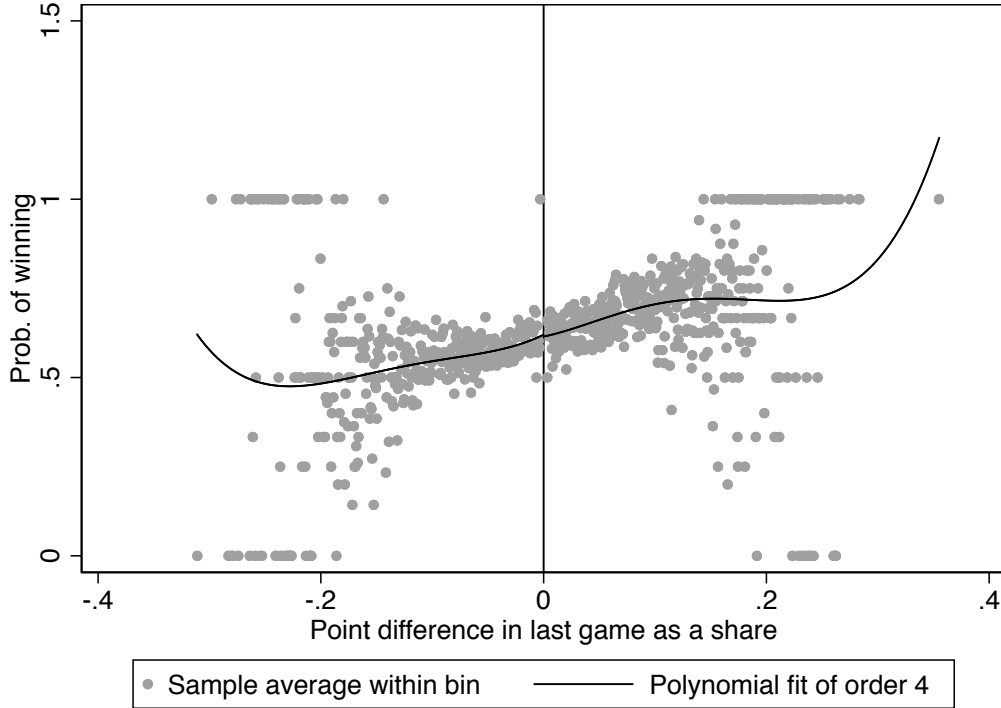
Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 8:** The effect of winning on the probability of winning the next game

	(1)	(2)	(3)	(4)	(5)
<b>Coef.</b>	-.00101	.00114	.0342	.00622	.0182
<b>S.E.</b>	.0175	.018	.0231	.0209	.0256
<b>Prob.</b>	.954	.95	.138	.767	.478
<b>N left</b>	28725	28725	28725	28725	28725
<b>N right</b>	28602	28602	28602	28602	28602
<b>p</b>	1	1	1	2	3
<b>h left</b>	.0427	.0413	.0247	.0656	.0873
<b>h right</b>	.0427	.0398	.0247	.0656	.0873



**Figure 5:** The effect of winning on the next game result in regular season



These last two columns aim to capture the marginal effect of a win over a small winning streak.

**Table 9:** The effect of winning on the probability of winning the next game

	(1)	(2)	(3)	(4)	(5)
<b>Coef.</b>	0.04	0.02	0.01	0.03	0.02
<b>Prob.</b>	0.02	0.16	0.31	0.35	0.66
<b>N</b>	2744.00	6418.00	9819.00	1378.00	739.00
<b>N left</b>	1357.00	3206.00	4947.00	668.00	342.00
<b>N right</b>	1387.00	3212.00	4872.00	710.00	397.00
<b>Window</b>	1.00	2.00	3.00	1.00	1.00

## II.2 Playoffs

Figure 11 reports visual evidence of the effect of winning a game on the probability of winning the next game in repeated match-ups during playoffs. We find a clear discontinuity

that suggests a negative impact of a previous win on the probability of victory.

**Figure 6:** The effect of winning on the next playoff game

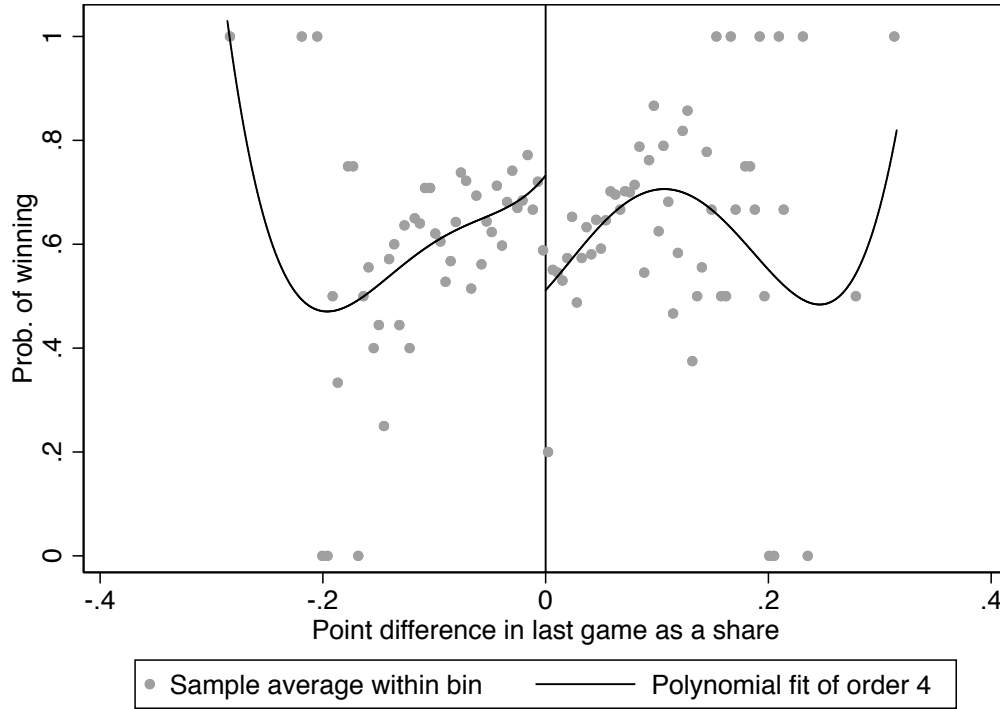


Table 10 reports point estimates that confirm the negative effect: a statistically significant 18% decrease in the probability of winning.

Table 11 reports the results of the estimation using local randomization approach with games ending with one, two or three points difference. We find a decrease of 14% in the probability of winning the next game for the smallest window, which is not statistically significant. However, when we consider greater windows we find a statistically significant negative effect of 16-17% (see column 2 and 3 in Table 11), which is similar in magnitude to our previous estimation. The first three columns report the unconditional result, while column 4 is conditional on winning the previous game and column 5 on previously winning two consecutive games. These last two columns aims to capture the marginal effect of a win over a small winning streak. The fact that our estimates are only statistically significant at

**Table 10:** The effect of winning on the probability of winning the next game during playoff

	(1)	(2)	(3)	(4)	(5)
<b>Coef.</b>	-.179	-.183	-.174	-.155	-.138
<b>S.E.</b>	.0733	.0714	.0876	.11	.128
<b>Prob.</b>	.0145	.0106	.0477	.16	.281
<b>N left</b>	1664	1664	1664	1664	1664
<b>N right</b>	1438	1438	1438	1438	1438
<b>p</b>	1	1	1	2	3
<b>h left</b>	.0482	.0553	.0323	.0574	.0818
<b>h right</b>	.0482	.0467	.0323	.0574	.0818

5% when we consider a games of at least two point difference is likely due to limited power to detect the effect (because of the reduced number of games using the smallest window possible), as the last row in the Table 11 shows.

**Table 11:** The effect of winning on the probability of winning the next game

	(1)	(2)	(3)	(4)	(5)
<b>Coef.</b>	-0.14	-0.16	-0.17	-0.09	-0.07
<b>Prob.</b>	0.13	0.00	0.00	0.13	0.43
<b>N</b>	147.00	358.00	551.00	255.00	132.00
<b>N left</b>	84.00	182.00	276.00	146.00	74.00
<b>N right</b>	63.00	176.00	275.00	109.00	58.00
<b>Window</b>	1.00	2.00	3.00	3.00	3.00
<b>Power vs. d=.15</b>	0.45	0.84	0.96	0.71	0.43

In addition, we restrict the games to repeated match-ups played in the same location and estimate the effect using the same methods. Figure 11 in the Appendix shows the standard RD design plot that shows a discontinuity similar to Figure 6. Table 13 and 14 in the Appendix reports the point estimates. We find a negative effect ranging between 11% and 17% that is statistically significant in only one specification (see column 3 in Table 14). This is consistent with the limited power of our restricted sample to detect the effect, as our analysis of power corroborates<sup>4</sup>. It also suggests that controlling for location does not

<sup>4</sup>See the power function for regular, repeated match-ups and repeated match-up/location in Figure 8, 9, and 10 in the Appendix)

dramatically change our estimates.

## VI Discussion

In summary, we find some evidence of a modest positive momentum effect (2-4%) for the regular season, using both empirical strategies. For the playoffs, we find weak evidence of positive momentum emulating the Arkes and Martinez (2011) regression specification, and strong evidence of negative momentum effect using the regression discontinuity approach. We interpret these results below.

### I Definition of momentum

As is discussed in [Iso-ahola and Dotson \[2014\]](#), there are many different dimensions of momentum including intensity, duration, and frequency. It could be argued that by estimating the effect of momentum based only on narrow victories, our RDD approach is unduly limited, and does not represent what is generally meant by momentum in statistical analyses of sports. Our identification strategy is based on the exclusion of moderate and blowout victories, both of which could contribute to a team’s momentum.

On the other hand, it could be equally said that this offers the cleanest possible estimate of the psychological effect of momentum on team performance, since around the cut-off, on average the only difference between two teams on either side is that they won a previous game, rather than lost it. Since momentum has many nuanced interpretations, our RDD approach makes a valuable contribution by evaluating the effect of momentum interpreted in its strictest, most narrow sense.

### II Validity of the RD design in regular season

Some of our validity checks reject the use of RD design in the case of regular season games, which cast some doubt on any conclusion derived from regular season games. However,

we note that the ordinary regression and regression discontinuity design approaches are in agreement that there is a modest, positive effect of past winning.

### III Negative momentum

Our RDD result for the playoffs contradicts previous findings in the NBA, as well as in other sports. A full exploration of the mechanisms required further analysis and is left to future research. However, we discuss two non-mutually exclusive hypotheses about the causes of this apparent disadvantage.

The first possibility is that teams simply exert more effort (players play with more focus, coaches make more strategic adjustments) after losing the previous game in a playoff series, because they are closer to facing elimination.<sup>5</sup> While such motivation to make up for a loss also exists in the regular season, it is much more diluted over the larger number of games compared with the playoffs, especially since teams rarely play the same opponent back-to-back in the regular season. Equivalently, teams that just won a close game may relax and exert less effort (a house money effect).<sup>6</sup> Future research could estimate the effect of winning the previous game conditional on the playoff series tally. This is not feasible in our RD design because of few observations.

A more invidious explanation comes from the incentives of agents that are not directly engaged in the competition, which are a result of the “best-of-n” structure of the NBA playoffs. Since each playoff game is a huge source of revenue, the league has preference for longer series, all else equal. According to ESPN reporter Darren Rovell, a NBA finals game can generate as much as \$13.5 million in ticket revenue. Referees may implicitly factor in the value of longer series to their employer, and favor the team who is trailing in the series. That team is likely to be the one who lost the previous game, generating the negative

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<sup>5</sup>Our explanation is related but different from [Kniffin and Mihalek \[2014\]](#) in the context of two-game college hockey series. They offer loss aversion as the explanation to the negative momentum effect. [Pope and Schweitzer \[2011\]](#) provides similar argument among professional golfers

<sup>6</sup>We also notice that in the contest theory literature, we should expect a positive winning effect from our RDD analysis in the playoff games. See [Klumpp and Polborn \[2006\]](#) for sequential election and [Malueg and Yates \[2010\]](#) for best-of-three tennis games

momentum effect we observe. While this speculation cannot be tested with our data, it would be consistent with research by [Price et al. \[2012\]](#) on referee bias favoring the extension of playoff series (i.e. in support of the trailing team). To test this hypothesis, one interesting future research direction would be performing RDD for non-discretionary turnovers and discretionary turnovers conditional on points differential of last game in playoff series.

## VII Final Remarks

In this paper we examine the existence of momentum effect in the NBA. We use a regression discontinuity design to estimate the causal effect of a win on the probability of winning the subsequent game. The data comprises 61,999 NBA games from seasons 1950 to 2018, with 3918 of them from the playoffs. We find evidence of positive momentum effect during regular season, consistent with [Arkes and Martinez \[2011\]](#), although some of the standard validity checks do not fully support the validity our RD design.

We then focus on a restricted sample of repeated, same location playoff match-ups, which allow us to better control for team strength and home-court advantage. Our RDD estimate of the momentum effect in the playoffs, which is validated by the standard checks and we believe better controls for unobserved factors, identifies a statistically significant negative effect of approximately 18%. Our study illustrates how the existence of the momentum effect is context dependent, even within the same sports league, and suggests that future research could investigate mechanisms behind the strong negative momentum effect observed in the playoffs, such as trailing team effort and referee bias in support of trailing teams.

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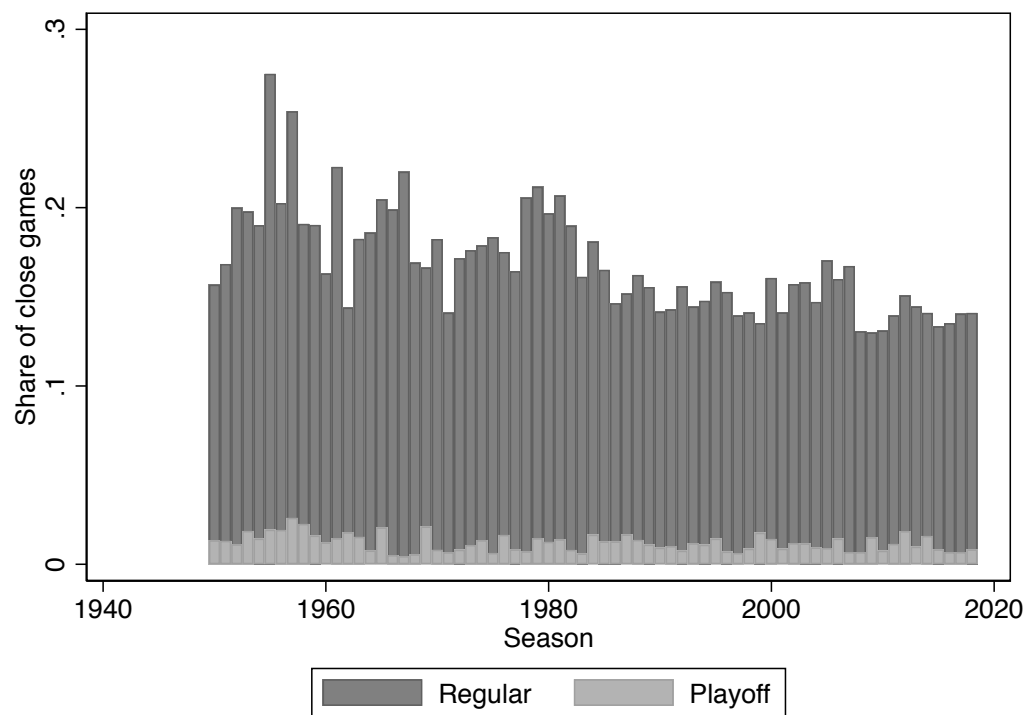
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# Appendix

**Figure 7:** Share of close games per season



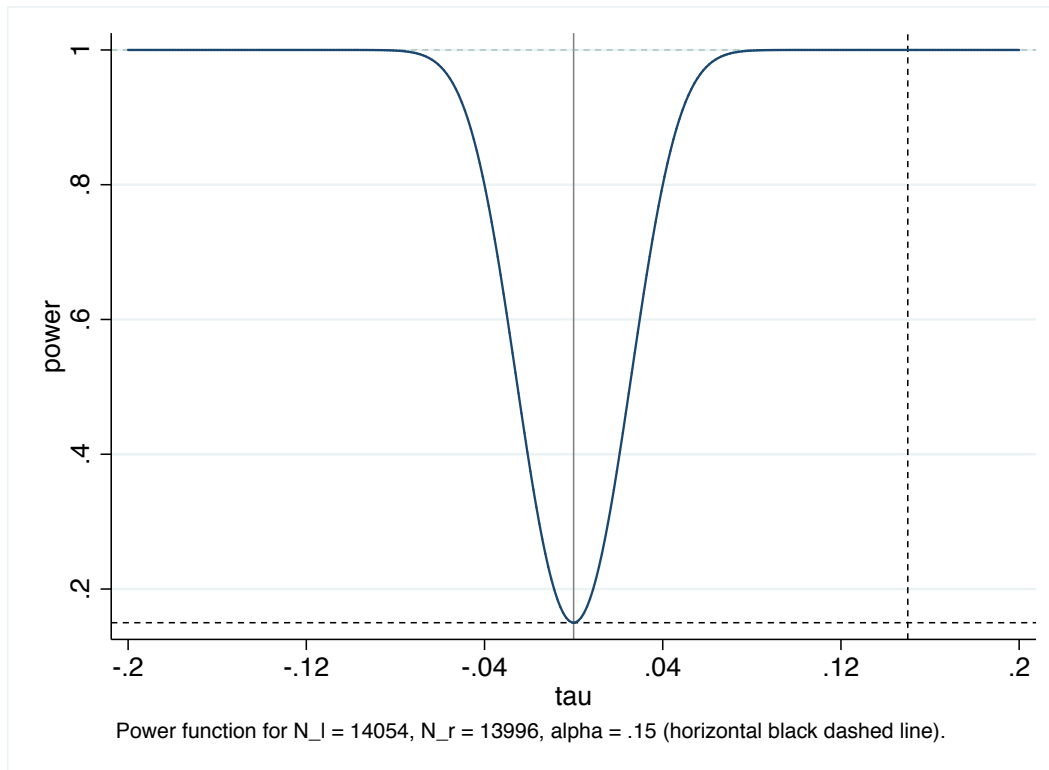
**Table 12:** Correlation matrix

	win	dif	total_strenght	heat_3_h	heat_5_h	rest_h	home_strenght	heat_3_a	heat_5_a	rest_a	away_strenght
win	1.00										
dif	0.79***	1.00									
total_strenght_regular	0.31***	0.34***	1.00								
heat_3_h	0.15***	0.16***	0.47***	1.00							
heat_5_h	0.18***	0.19***	0.58***	0.82***	1.00						
rest_h	0.02***	0.02***	0.04***	0.03***	0.03***	1.00					
home_strenght	0.27***	0.30***	0.92***	0.37***	0.49***	0.03***	1.00				
heat_3_a	-0.12***	-0.13***	-0.00	-0.05***	-0.04***	0.02***	0.01***	1.00			
heat_5_a	-0.15***	-0.17***	0.01	-0.03***	-0.03***	0.02***	0.02***	0.82***	1.00		
rest_a	-0.01***	-0.03***	0.05***	0.02***	0.02***	0.31***	0.05***	0.02***	0.02***	1.00	
away_strenght	-0.23***	-0.26***	0.02***	-0.00	0.01	0.02***	0.00	0.40***	0.50***	0.03***	1.00
<i>N</i>	61999										

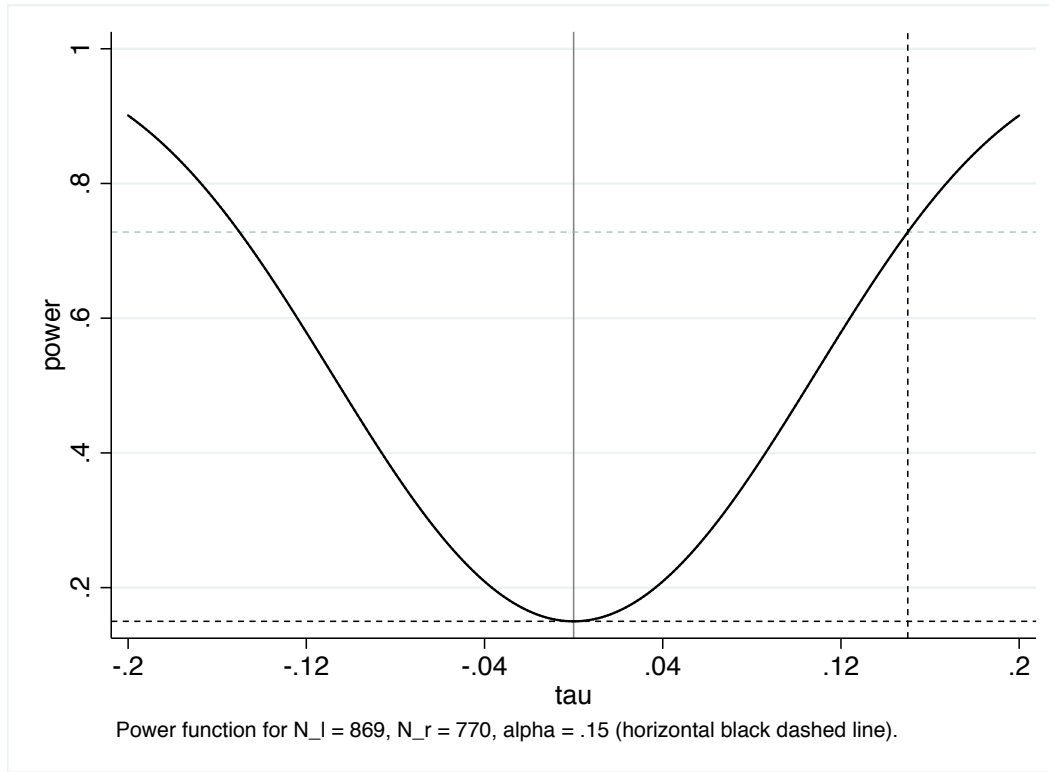
*t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

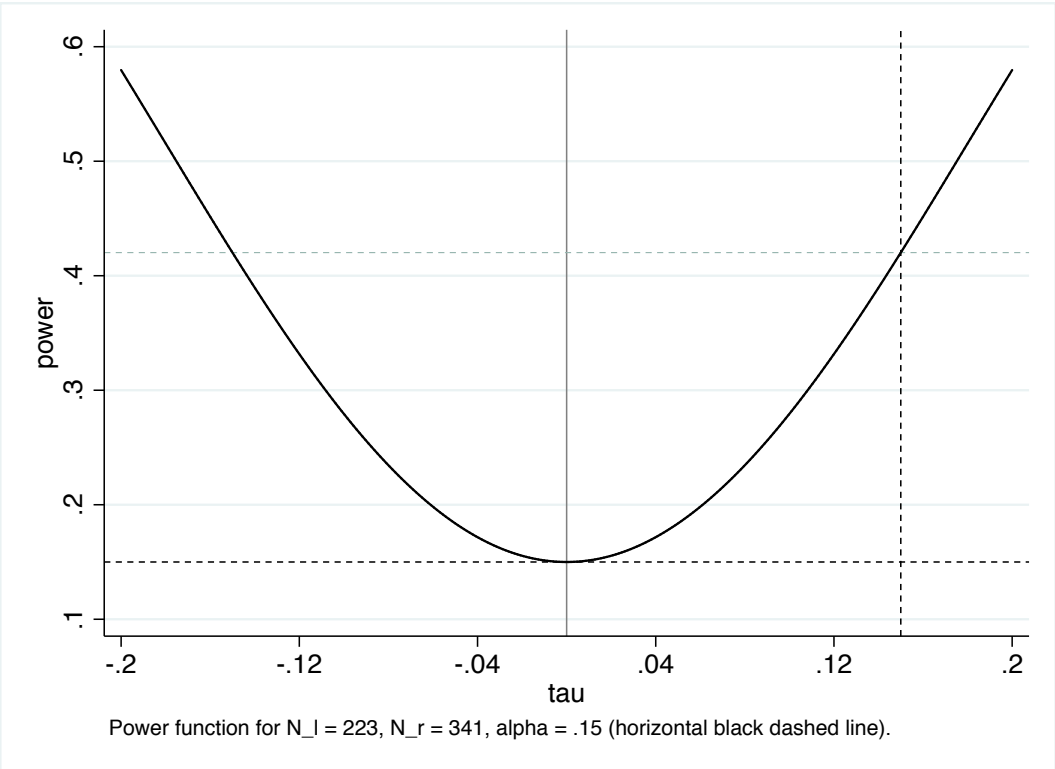
**Figure 8:** Power function for regular season games



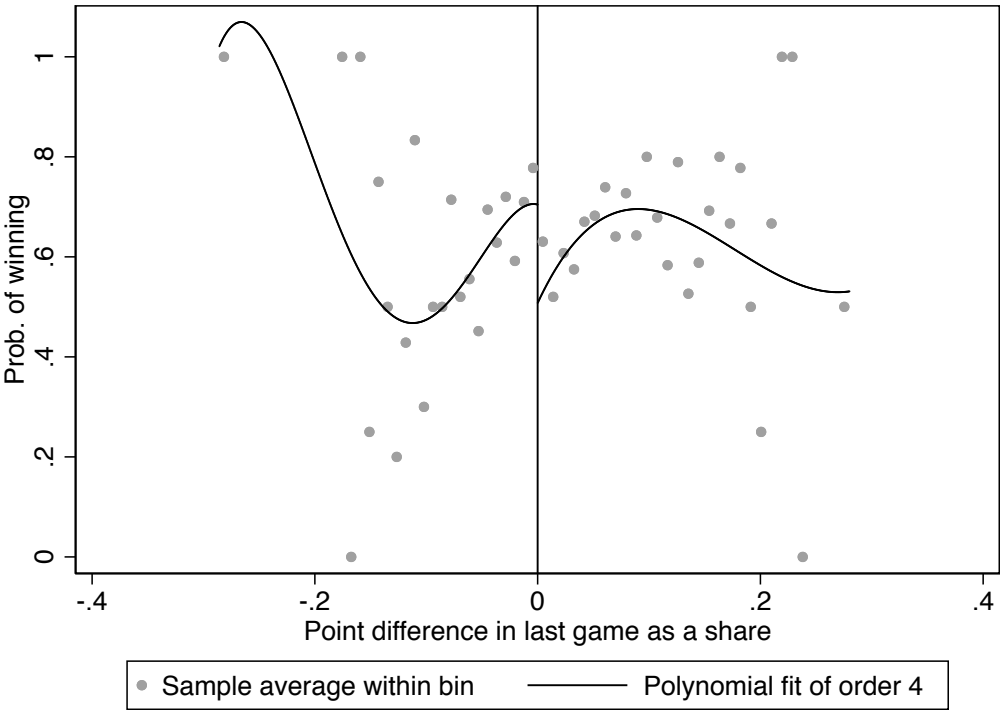
**Figure 9:** Power function for repeated match-ups in playoff games



**Figure 10:** Power function for repeated match-ups/location in playoff games



**Figure 11:** The effect of winning on the next game result in playoff



**Table 13:** The effect of winning on the probability of winning the next game during  
payoff

	(1)	(2)	(3)	(4)	(5)
<b>Coef.</b>	-.132	-.172	-.169	-.0974	-.149
<b>S.E.</b>	.122	.114	.143	.169	.236
<b>Prob.</b>	.28	.131	.237	.566	.526
<b>N left</b>	414	414	414	414	414
<b>N right</b>	878	878	878	878	878
<b>p</b>	1	1	1	2	3
<b>h left</b>	.0407	.041	.0285	.0539	.0644
<b>h right</b>	.0407	.0521	.0285	.0539	.0644

**Table 14:** The effect of winning on the probability of winning the next game

	(1)	(2)	(3)	(4)	(5)
<b>Coef.</b>	-0.11	-0.14	-0.15	-0.16	-0.24
<b>Prob.</b>	0.42	0.10	0.02	0.07	0.07
<b>N</b>	56.00	147.00	231.00	125.00	59.00
<b>N left</b>	25.00	61.00	91.00	54.00	22.00
<b>N right</b>	31.00	86.00	140.00	71.00	37.00
<b>Window</b>	1.00	2.00	3.00	3.00	3.00
<b>Power vs. d=.15</b>	0.23	0.48	0.66	0.45	0.28