Momentum Effects 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 findings highlight 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.

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I Introduction

Athletic competition provides several arenas for evaluating the conventional adage and behavioral hypothesis that success breeds success. There is a vast literature on inter-temporal

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correlation of performance both across games (the momentum effect) and 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 cognitive fallacy reflecting a misconception of "local representativeness." Gilovich et al. [1985] find that basketball players claimed to believe in the hot-hand effect, but that the belief is contradicted by negative serial correlation in field goal shooting. 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 a 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 previous 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 under complete game independence. He does not find evidence of momentum. Schilling [2013] tests for momentum effect within collegiate volleyball games. Based on analysis similar to that of Vergin [2000], he finds that the 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] estimate 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 a 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; and 3) 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 past wins on game outcomes. Gauriot and Page [2018] search for evidence of momentum within professional soccer matches. Their identification strategy is based on similar shots that go in versus out (those that hit the cross-bar). 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, 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 for the playoffs, achieve a league standing that ensures a favorable playoff opponent, or worsen their record to improve odds of winning the NBA draft lottery ("tanking"). 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 has been an increase over time in the total number of games for the regular season and playoffs as the league has expanded and the playoff format has changed.

Figure 1: Games per season

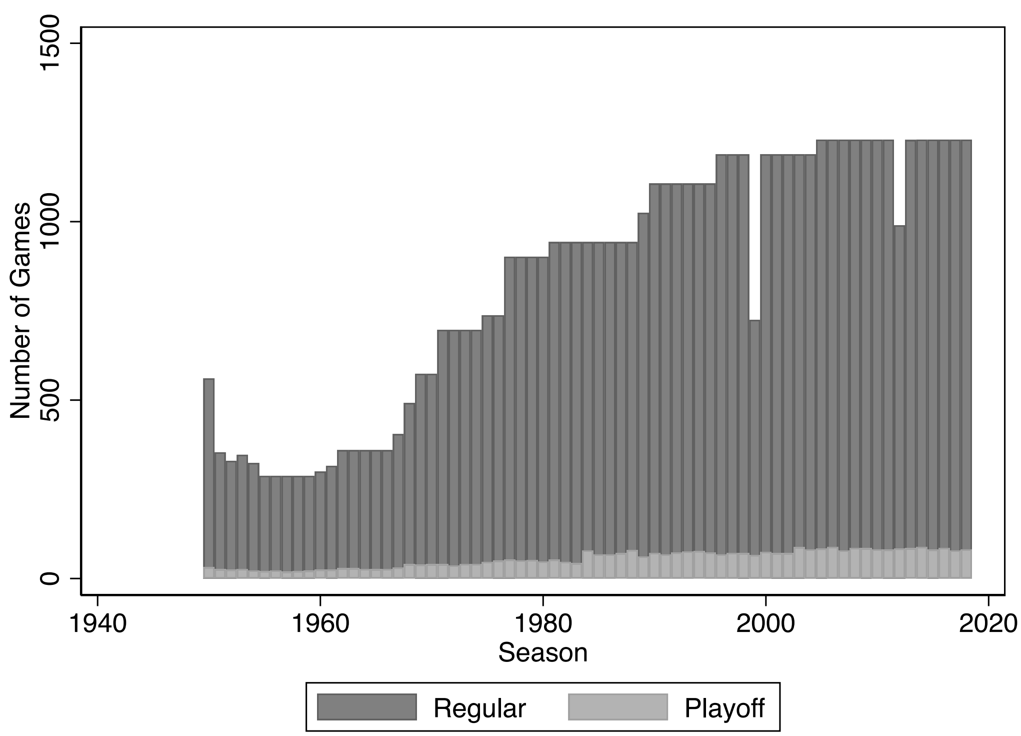


Figure 2 shows the distribution of the point difference between home team and visitor team at the end of the game by type (regular season and playoff), which will be a critical variable for our empirical strategy. The distribution shows a gap at zero because games cannot end in a tie games in basketball. 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

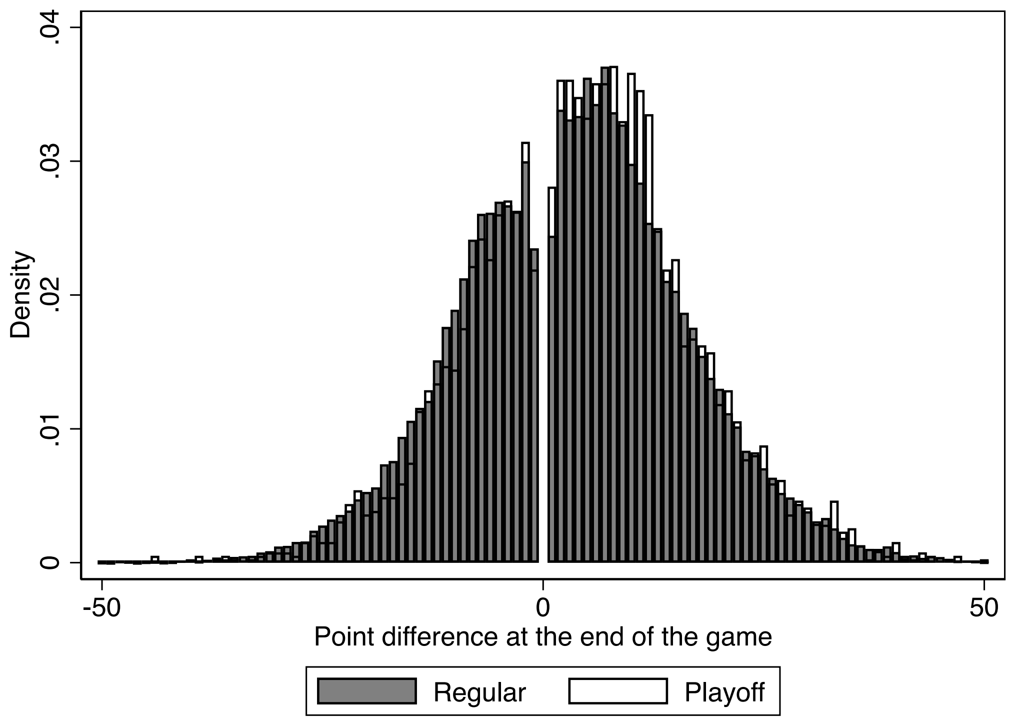
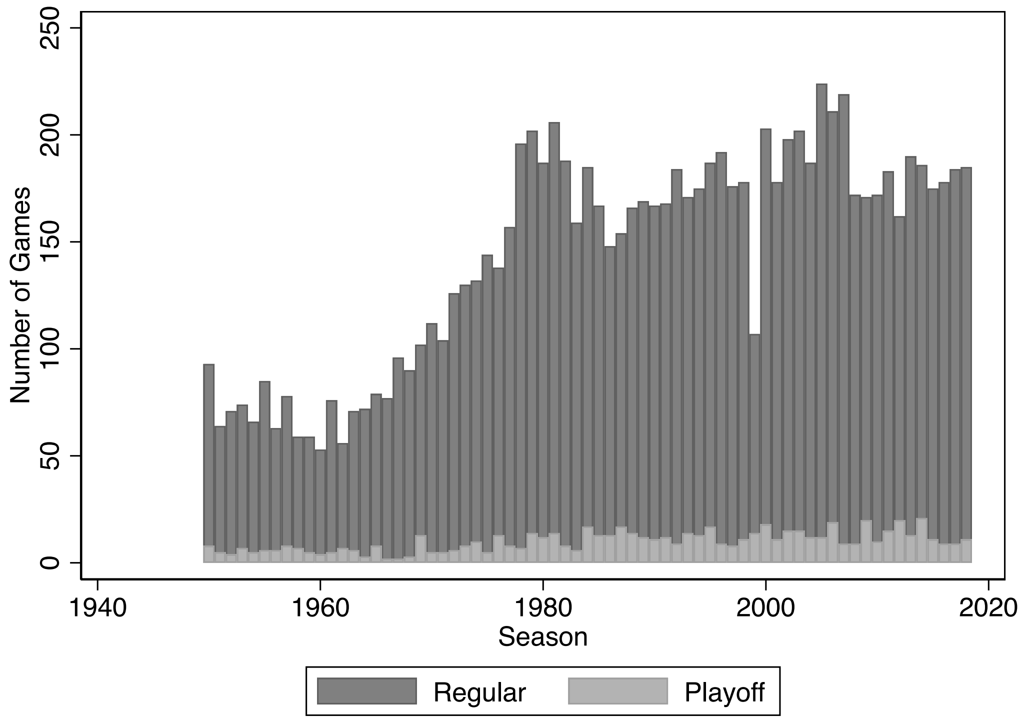


Figure 3 shows the number of close games by season, which are defined as games with a point difference less than four points at the end of the game. That difference is small enough to allow the trailing team to tie the game in one possession[1]. There is a total of 9,939 such games played in regular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

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

[1]This is not true before 1979 because the three-point field goal was not adopted yet.
[2]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 game and previous three games. Similarly, we 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 three or five 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	1,524	1,626
-2	122	1,742	1,864
-1	85	1,364	1,449
1	109	1,419	1,528
2	140	1,966	2,106
3	140	1,924	2,064
Total	698	9,939	10,637
N	10,637		

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	61,999				

IV Empirical Strategy

I Regression approach

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

$$Y_{it} = \alpha_h Q_{it}^h + \alpha_a Q_{it}^a + \beta_h' R_{it}^h + \beta_a' R_{it}^a + \gamma_h S_{it}^h + \gamma_a S_{it}^a + \epsilon_{it} \tag{1}$$

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 ϵ represents an error term. Since 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:

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

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 $p^H_{i,j,t-1}$) are greater than the points scored by the visiting team in that game (denoted by $p^V_{i,j,t-1}$). Then we can denote the treatment as:

$$d_{i,j,t} = 1[p^H_{i,j,t-1} > p^V_{i,j,t-1}] \tag{3}$$

where 1[.] 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 $E[y_{i,j,t}(1)|p^H_{i,j,t} - p^V_{i,j,t}]$ and $E[y_{i,j,t}(0)|p^H_{i,j,t} - p^V_{i,j,t}]$, where by design $E[y_{i,j,t}(1)|p^H_{i,j,t} - p^V_{i,j,t}]$ is observed when $p^H_{i,j,t} - p^V_{i,j,t} > 0$ and $E[y_{i,j,t}(1)|p^H_{i,j,t} - p^V_{i,j,t}]$ is observed when $p^H_{i,j,t} - p^V_{i,j,t} < 0$. Hence, with these observable values, we estimate:

$$\begin{aligned} E[y_{i,j,t}(1) - y_{i,j,t}(0)|p^H_{i,j,t} - p^V_{i,j,t} = 0] = \\ lim_{\varepsilon \downarrow 0} E[y_{i,j,t}(1)|p^H_{i,j,t} - p^V_{i,j,t} = 0 + \varepsilon] - lim_{\varepsilon \uparrow 0} E[y_{i,t}(0)|p^H_{i,j,t} - p^V_{i,j,t} = 0 + \varepsilon] \end{aligned} \tag{4}$$

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:

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

where $m_{i,j,t} = p^H_{i,j,t} - p^V_{i,j,t}$ corresponds to the running variable, $f(.)$ 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 118 different values, we transform it dividing $m_{i,j,t}$ by the total number of points scored in the game $(p^H_{i,j,t} + p^V_{i,j,t})$. This creates a transformed variable with 3,945 different values that is better suited for an estimation using the continuity-based approach.[3]

Alternatively, we keep our original discrete running variable, estimate a causal effect using local randomization approach and perform inference using the general Fisherian inference

[3]See Cattaneo et al. [2018] for a complete discussion about regression discontinuity design with discrete random variables.

framework as described in Cattaneo et al. [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 difference game that would have allowed the losing team to tie or win the game in one possession.

The way in which the playoffs are organized are particularly conducive for this regression discontinuity design. The NBA playoffs are a tournament in which opponents square off multiple times in the same locations over a short span of time (with the winner advancing to the next round after the best-of-seven series), 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 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=0.85) 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 hypothesis that observations in the window appear as if generated

Figure 4: Density test

(a) Regular season **(b)** Playoff

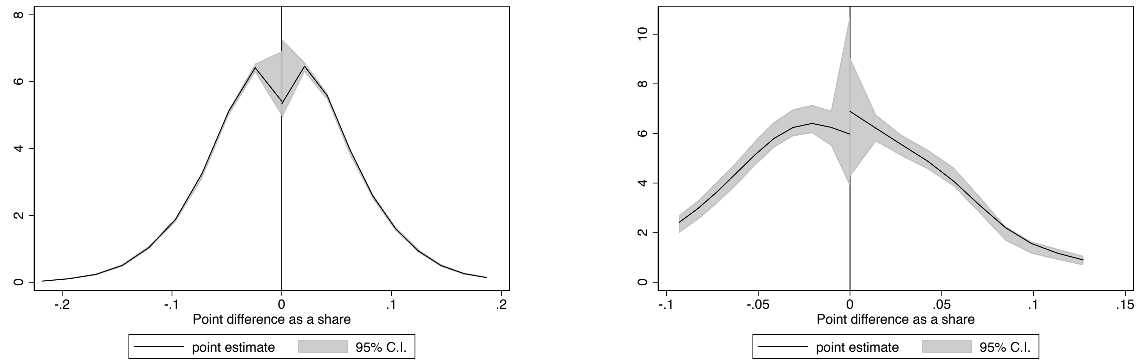


Table 3: Binomial test over one-point difference games

	Binomial test	**Obs<c**	**Obs≥c**
Regular	0.697	1448.000	1470.000
Playoff	0.099	84.000	63.000

by a binomial distribution with probability of success equal to 1/2.

Second, we run our estimation using alternative placebo cutoffs. Table 4 reports the results. In the case of regular season games, we reassuringly do not find evidence of jumps in 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 at the cutoff equal to 0 (Table 4b).

Third, we inspect predetermined covariates and placebo outcomes at the cutoff. Table 5 reports our results. We find that teams differ in terms of winning percentage (excluding the previous game, which corresponds to the running variable's game) 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 regression discontinuity design for these games.

Table 4: Alternative cutoffs

(a) Regular season games

	Continuity-based			Local randomization		
	1	2	3	4	5	6
Coefficient	-0.001	-0.003	-0.004	0.044	0.014	0.023
Standard error	0.015	0.014	0.013	.	.	.
Probability	0.954	0.656	0.795	0.022	0.339	0.144
Cutoff	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
Coefficient	-0.187	-0.031	0.083	-0.172	0.015	0.038
Standard error	0.061	0.065	0.051	.	.	.
Probability	0.015	0.402	0.207	0.000	0.745	0.310
Cutoff	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 regression, the estimate of the momentum effect shrinks from 9% to 2%.

Table 5: Placebo test

(a) Regular season games

	Continuity-based			Local randomization	
	Coef.	**s.e.**	**Prob.**	**Coef.**	**Prob.**
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	
	Coef.	**s.e.**	**Prob.**	**Coef.**	**Prob.**
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 have different competitive 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***	0.025***	0.025***	0.025***	0.022***	0.022***
		(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)
Heat (victories in last 5 games) - away		-0.059***	-0.020***	-0.020***	-0.015*	-0.017***	-0.017***
		(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)
Home winning percentage			0.007***	0.007***	0.008***	0.007***	0.006***
			(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Away winning percentage			-0.007***	-0.007***	-0.008***	-0.006***	-0.006***
			(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Rest time (in days) - home				0.010***	0.012	0.009***	0.009***
				(0.002)	(0.010)	(0.002)	(0.002)
Rest time (in days) - away				-0.017***	-0.002	-0.015***	-0.016***
				(0.002)	(0.010)	(0.002)	(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 displays 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 of the momentum effect using three different data-driven optimal bandwidths: column 1 uses the symmetric mean squared error optimal bandwidth, column 2 uses the asymmetric mean squared error optimal bandwidth, and column 3 uses the coverage error rate optimal bandwidth. The graphical result is confirmed: we do not find evidence of a momentum effect using the continuity-based approach.

Table 9 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

Table 7: Regression results (Playoffs)

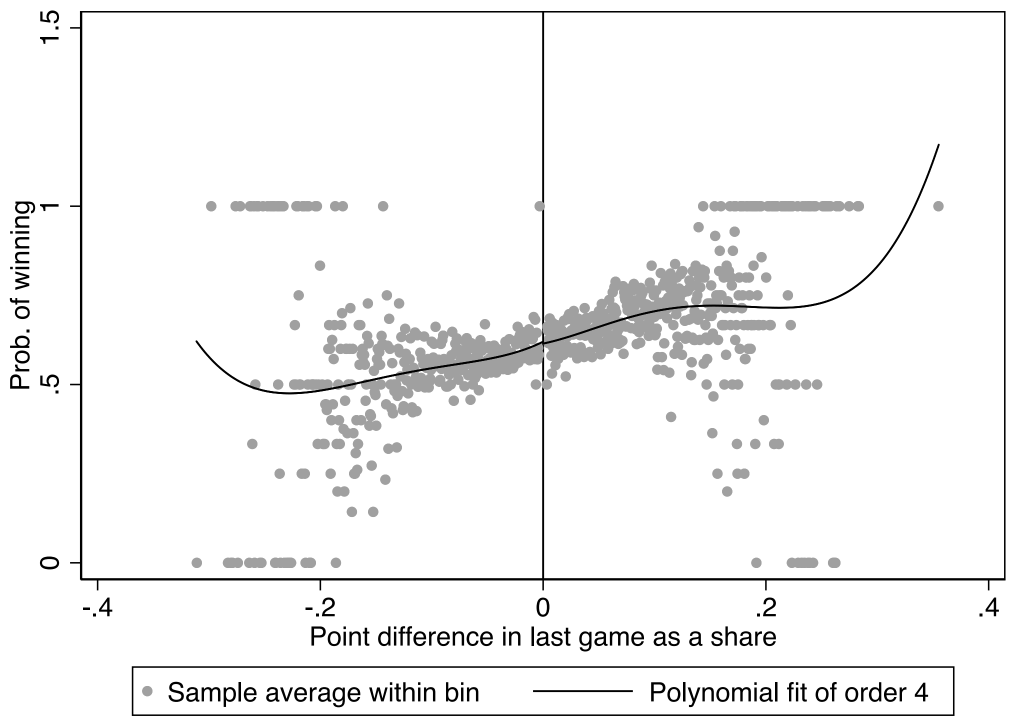
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logit	logit	logit	logit	LPM	LPM
Heat (victories in last 5 games) - home		0.039***	0.008	0.003	0.003	0.001
		(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Heat (victories in last 5 games) - away		-0.027***	-0.030***	-0.035***	-0.034***	-0.033***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Home winning percentage in regular season			0.006***	0.006***	0.006***	0.005***
			(0.001)	(0.001)	(0.001)	(0.001)
Away winning percentage in regular season			0.003***	0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
Rest time (in days) - home				0.015**	0.013**	0.012*
				(0.007)	(0.006)	(0.006)
Rest time (in days) - away				0.012	0.012	0.014*
				(0.009)	(0.008)	(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)
Coef.	-.00101	.00114	.0342
S.E.	.0175	.018	.0231
Prob.	.954	.95	.138
N left	28725	28725	28725
N right	28602	28602	28602
h left	.0427	.0413	.0247
h right	.0427	.0398	.0247

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



4% increase in the probability of winning the next game when we use the smallest possible window.

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

	(1)	(2)	(3)
Coef.	0.04	0.02	0.01
Prob.	0.02	0.16	0.31
N	2744	6418	9819
N left	1357	3206	4947
N right	1387	3212	4872
Window	1	2	3

II.2 Playoffs

Figure 6 displays visual evidence of the effect of winning a game on the probability of winning the next game in repeated match-ups during playoffs. We see 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

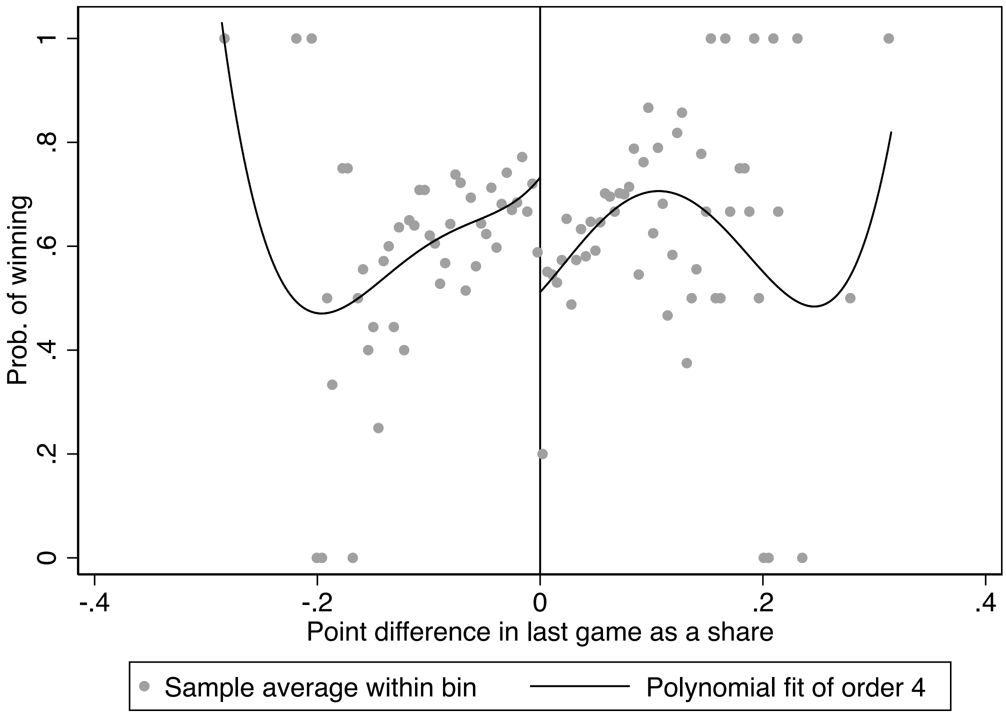


Table 10 uses the same optimal bandwidths as Table 8 to report the point estimates of the momentum effect. It confirms what we observe in Figure 6: a statistically significant 18% decrease in the probability of winning.

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

	(1)	(2)	(3)
Coef.	-.179	-.183	-.174
S.E.	.0733	.0714	.0876
Prob.	.0145	.0106	.0477
N left	1664	1664	1664
N right	1438	1438	1438
h left	.0482	.0553	.0323
h right	.0482	.0467	.0323

Table 11 reports the results of the estimation using the local randomization approach, which are largely consistent with what we find for the continuity-based approach in Table 10. We find a decrease of 14% in the probability of winning the next game for the smallest window (one point), with a p-value of 0.13. When we consider larger windows (two or three points) we find a statistically significant negative effect of 16-17% (see column 2 and 3 in Table 11), which is similar in magnitude to the continuity-based estimate. The fact that our estimates are only statistically significant at 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)
Coef.	-0.14	-0.16	-0.17
Prob.	0.13	0.00	0.00
N	147	358	551
N left	84	182	276
N right	63	176	275
Window	1	2	3
Power vs. d=0.15	0.45	0.84	0.96

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 regression discontinuity design plot that shows a discontinuity similar to in Figure 6. Tables 13 and 14 in the Appendix report 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 likely due to the limited power of our restricted sample to detect the effect, as our analysis of power corroborates[4]. It also suggests that controlling for location does not dramatically change our estimates.

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

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 regression discontinuity design 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 regression discontinuity design approach makes a valuable contribution by evaluating the effect of momentum interpreted in its strictest, most narrow sense.

II Validity of the regression discontinuity design in regular season

While our empirical approach clearly passes validity checks for playoff games, some of the checks do not support the use of regression discontinuity design in the case of regular season games, casting some doubt on conclusions derived from that subset of 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 regression discontinuity design result for the playoffs contradicts previous findings in the NBA, as well as in other sports.[5] 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 the apparent disadvantage from winning the previous game.

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.[6] 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). Future research could estimate the effect of winning the previous game conditional on the playoff series tally. This is not feasible in our regression discontinuity design because of the constrained sample size.

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 momentum effect we observe. While this speculation cannot be tested with our data, it

[5]Indeed, according to the contest theory literature, we should expect a positive winning effect from our regression discontinuity design analysis of playoff games. See Klumpp and Polborn [2006] for sequential elections and Malueg and Yates [2010] for best-of-three tennis matches.

[6]This explanation is related to 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] provide similar argument among professional golfers

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 regression discontinuity design analysis for non-discretionary turnovers and discretionary turnovers conditional on the point differential of the previous game in a playoff series.

VII Final Remarks

In this paper we examine the existence of momentum effects 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 our regression discontinuity design.

We then focus on a restricted sample of repeated, same location playoff match-ups, which allows us to better control for team strength and home-court advantage. Our regression discontinuity design 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.

References

Jeremy Arkes. Revisiting the hot hand theory with free throw data in a multivariate framework. *Journal of Quantitative Analysis in Sports*, 6(1), 2010.

Jeremy Arkes. Misses in "Hot Hand" Research. *Journal of Sports Economics*, 14(4):401–410, 2013. ISSN 15270025. doi: 10.1177/1527002513496013.

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

Michael Bar-Eli, Simcha Avugos, and Markus Raab. Twenty Years of "Hot Hand" Research: Review and Critique. *Psychology of Sport and Exercise*, 7:525–553, 2006. ISSN 14690292. doi: 10.1016/j.psychsport.2006.03.001.

Matias D Cattaneo, Nicolas Idrobo, and Rocío Titiunik. A Practical Introduction to Regression Discontinuity Designs: Volume II. *Cambridge Elements: Quantitative and Computational Methods for Social Science*, II:113, 2018.

Romain Gauriot and Lionel Page. Psychological Momentum in Contests: The Case of Scoring before Half-time in Football. *Journal of Economic Behavior and Organization*, 149:137–168, 2018. ISSN 01672681.

Thomas Gilovich, Robert Vallone, and Amos Tversky. The Hot Hand in Basketball: On the Misperception of Random Sequences. *Cognitive Psychology*, 17:295–314, 1985.

Brett Green and Jeffrey Zwiebel. The Hot-Hand Fallacy: Cognitive Mistakes or Equilibrium Adjustments? Evidence from Major League Baseball. *mimeo*, 2017.

Seppo E Iso-ahola and Charles O Dotson. Psychological Momentum: Why Success Breeds Success. *Review of General Psychology*, 18(1):19–33, 2014. doi: 10.1037/a0036406.

Daniel Kahneman and Amos Tversky. Subjective probability: A judgment of representativeness. *Cognitive psychology*, 3(3):430–454, 1972.

Tilman Klumpp and Mattias K Polborn. Primaries and the new hampshire effect. *Journal of Public Economics*, 90(6-7):1073–1114, 2006.

Kevin M. Kniffin and Vince Mihalek. Within-series Momentum in Hockey: No Returns for Running up the Score. *Economics Letters*, 122(3):400–402, 2014. ISSN 01651765. doi: 10.1016/j.econlet.2013.12.033. URL http://dx.doi.org/10.1016/j.econlet.2013.12.033.

Benjamin Leard and Joanne M Doyle. The Effect of Home Advantage, Momentum, and Fighting on Winning in the National Hockey League. *Journal of Sports Economics*, 12(5):538–560, 2011.

David S. Lee and Thomas Lemieux. Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, 48:281–355, 2010.

David A. Malueg and Andrew J. Yates. Testing Contest Theory: Evidence from Best-of-three Tennis Matches. *Review of Economics and Statistics*, 92(3):689–692, 2010. ISSN 00346535. doi: 10.1162/REST_a_00021.

Justin McCrary. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of Econometrics*, 142:698–714, 2008. ISSN 03044076.

Joshua B. Miller and Adam Sanjurjo. Surprised by the Hot Hand Fallacy? A Truth in the Law of Small Numbers. *Econometrica*, 86(6):2019–2047, 2018.

Lionel Page and John Coates. Winner and loser effects in human competitions. Evidence from equally matched tennis players. *Evolution and Human Behavior*, 38:530–535, 2017. ISSN 10905138. doi: 10.1016/j.evolhumbehav.2017.02.003. URL http://dx.doi.org/10.1016/j.evolhumbehav.2017.02.003.

Stephanie Parsons and Nicholas Rohde. The Hot Hand Fallacy Re-examined: New Evidence from the English Premier League. *Applied Economics*, 47(4):346–357, 2015.

Devin G Pope and Maurice E Schweitzer. Is tiger woods loss averse? persistent bias in the face of experience, competition, and high stakes. *American Economic Review*, 101(1): 129–57, 2011.

Joseph Price, Marc Remer, and Daniel F Stone. Subperfect game: Profitable biases of nba referees. *Journal of Economics & Management Strategy*, 21(1):271–300, 2012.

Steven Salaga and Katie M. Brown. Momentum and Betting Market Perceptions of Momentum in College Football. *Applied Economics Letters*, 25(19):1383–1388, 2018. ISSN 14664291. doi: 10.1080/13504851.2017.1420885.

Mark F Schilling. Does Momentum Exist in Competitive Volleyball? *Chance*, (November 2014):37–41, 2013.

Roger C Vergin. Winning streaks in sports and the misperception of momentum. *Journal of Sport Behavior*, 23(2), 2000.

Appendix

Figure 7: Share of close games per season

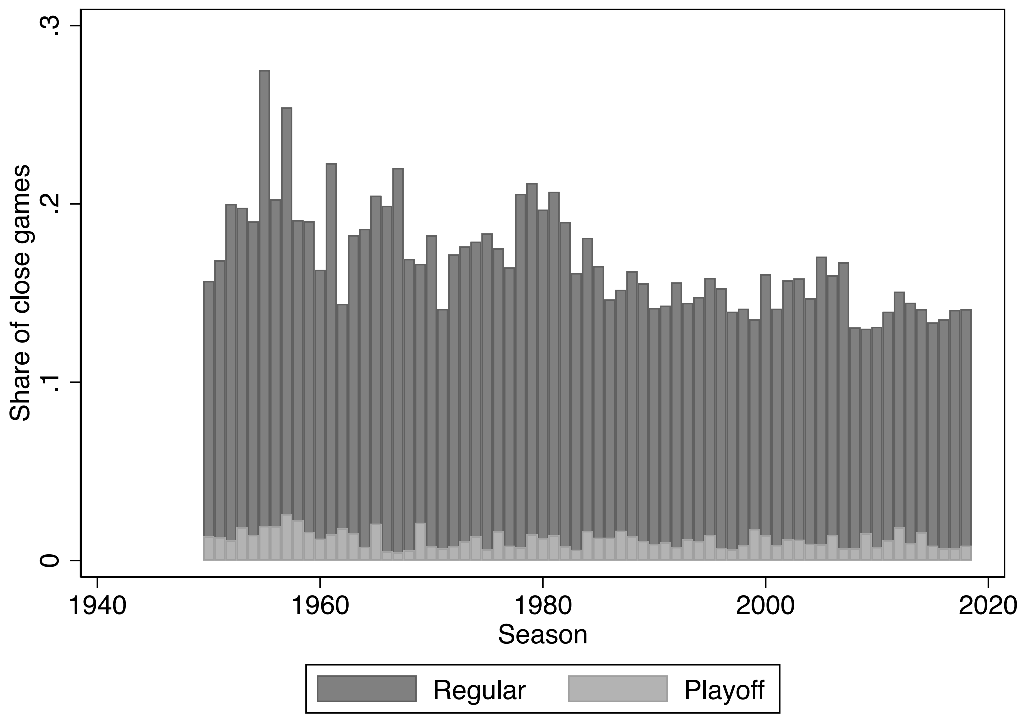


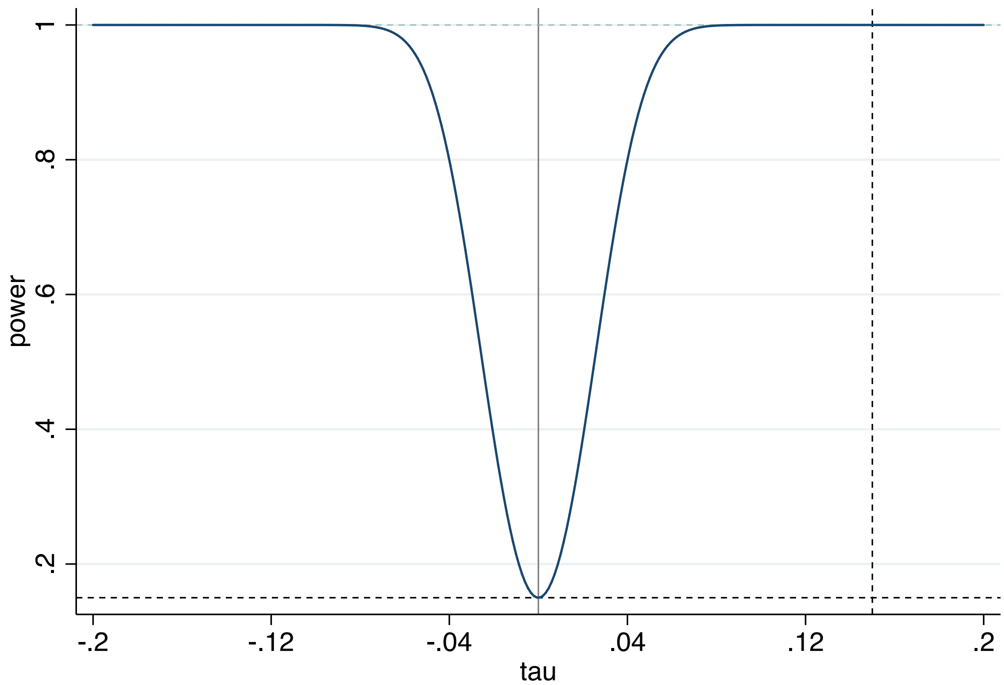
Table 12: Correlation matrix

	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
N	61999										

t statistics in parentheses

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

Figure 8: Power function for regular season games



Power function for N_l = 14054, N_r = 13996, alpha = .15 (horizontal black dashed line).

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

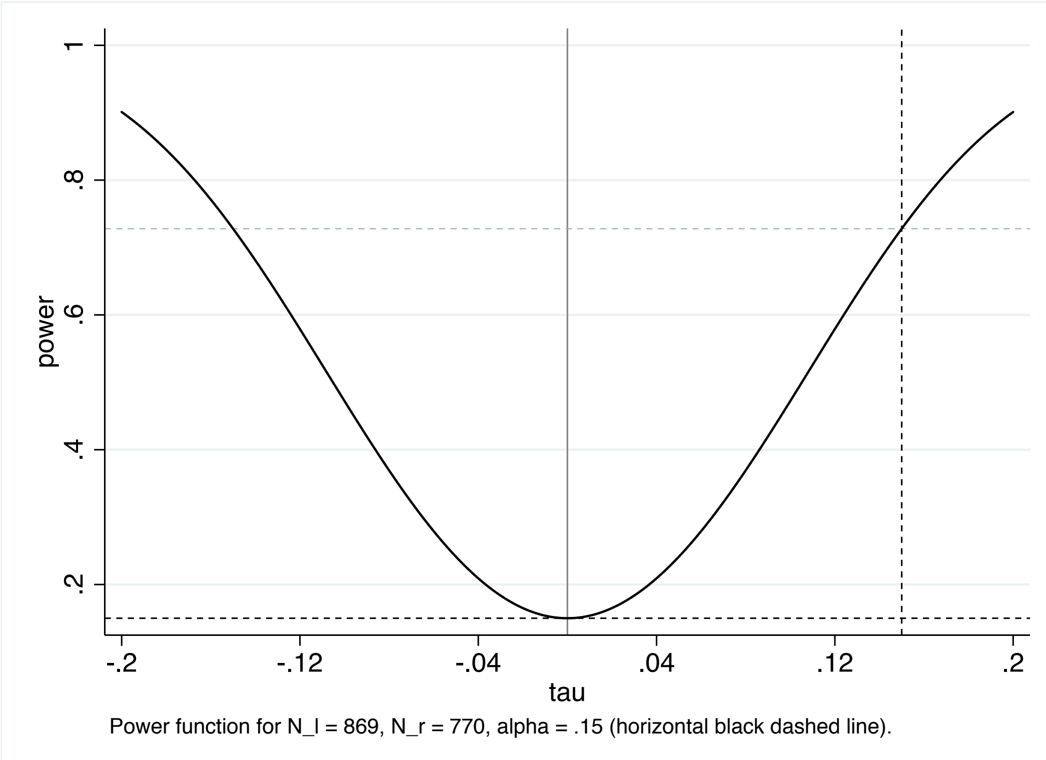


Figure 10: Power function for repeated match-ups/location in playoff games

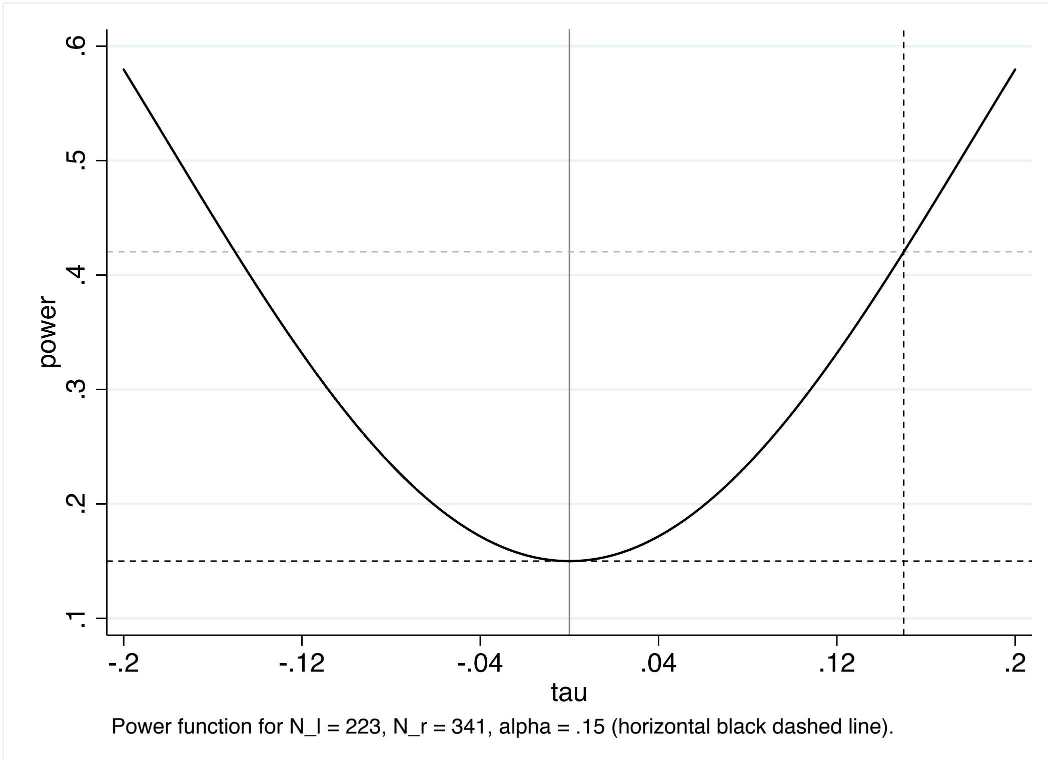


Figure 11: The effect of winning on the next game result in playoff

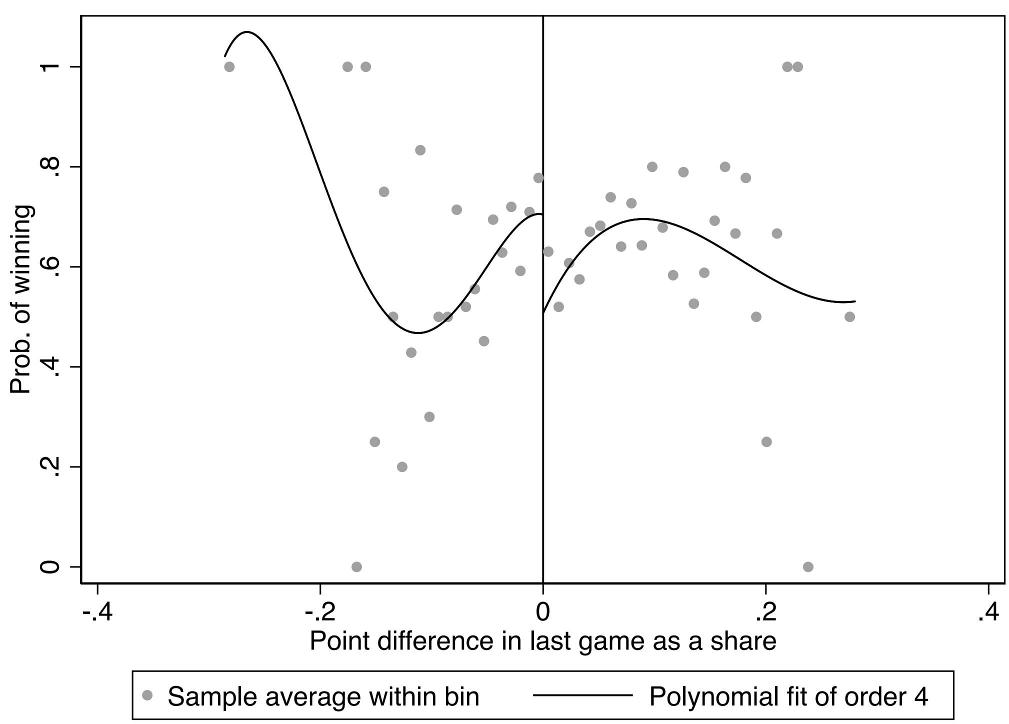


Table 13: The effect of winning on the probability of winning the next game during the playoffs

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

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

	(1)	(2)	(3)
Coef.	-0.11	-0.14	-0.15
Prob.	0.42	0.10	0.02
N	56.00	147.00	231.00
N left	25.00	61.00	91.00
N right	31.00	86.00	140.00
Window	1.00	2.00	3.00
Power vs. d=.15	0.23	0.48	0.66