The Effect of NBA Playoff Experience on Playoff Scoring

by Samuel Wang

ECON107: Applied Econometrics

Professor Bowman Cutter

December 15th, 2023

1. Introduction

After a grueling 82-game schedule, the top NBA teams compete in the playoffs to determine the league champion. The high stakes encourage full effort from teams and players, often leading to unpredictable outcomes as underdogs overperform: a recent example being the first round of the 2023 playoffs when the 8th seeded Heat knocked off the 1st seeded Bucks (Basketball Reference).

An oft-cited component of playoff success is playoff experience. When the 6th seeded Warriors played the 3rd seeded Kings in first round of the 2023 playoffs, the massive gap in playoff experience was touted by many basketball analysts as a key factor working in the Warriors favor (Biderman, 2023). Of course, when the Warriors won the series, that only confirmed the idea that playoff success is crucial if you want to win a championship. But to what degree is that true?

In this paper, I scraped data from more than 400 NBA playoff series across 30 years to analyze the relationship between starters' playoff experience, bench playoff experience, and playoff scoring. I also examine the idea that inexperienced teams struggle especially hard in road playoff environments. I find that both starters' and bench playoff experience's effect on scoring is significant and insufficient evidence that teams with less experience struggle on the road after accounting for home field and lack of playoff experience.

The rest of the paper is laid out as follows: Section 2 is a literature review to build off previous studies. Sections 3-5 explain the data collection process and prepare the data for regressions. Sections 6-8 explain the framework for equations and analyze the results of the regressions.

2. Literature Review

NBA teams that hope to eventually contend for a championship regularly sign tenured veterans to help develop young players as well as provide a perceived boost in the playoffs. With sports betting also increasing every year, it seems more important now than ever to have an accurate view on the true impact that players with playoff experience have.

To evaluate the effect that playoff experience has, several variables will be used. The dependent variable is the number of points scored in an NBA playoff game, which is a key metric for evaluating team performance in NBA games. A summary paper from Kubatko et al. (2007) found that win percentage could be accurately predicted using points scored and points allowed, making the expected number of points scored a powerful predictor of success. Teramoto and Cross (2010) also established that offensive production remains crucial throughout the playoffs, and defensive ratings become more impactful in later rounds. Therefore, for the NBA playoffs, focusing on offensive production through points scored supplemented by defensive metrics may offer important perspectives for teams looking to win an NBA title.

To estimate the team strength of an NBA team in the playoffs, two regular season metrics will be used. According to a study on March Madness (NCAA college playoff) games, regular season win percentage, strength of schedule, offensive rating, and defensive rating were the four key statistics for predicting the winner of a March Madness game (Pifer et al., 2019). However, there are two major issues when applying this to NBA playoff games. First, strength of schedule in the NBA isn't nearly as relevant, as each NBA team plays teams from its own conference and 36.56 of its games against teams from the other conference (NBAStuffer). This combined with NBA teams generally being much closer in skill than college basketball teams means that strength of schedule likely doesn't play a significant factor. This study also found that previous playoff experience plays a significant role in winning college playoff games. A major difference between March Madness games and the NBA playoffs is that while both are single elimination format, March Madness rounds only have single games, whereas the NBA playoff rounds have a best-of-7 format. NBA players could plausibly adjust to a "playoff atmosphere" in the course of multiple games, which could mean that the importance of past postseason experience in the NBA is likely different compared to March Madness games. While March Madness teams are also played at a theoretically neutral site, there could also be a small home court advantage for teams that have played more March Madness games. It's very possible that teams that have had recent success in March Madness will have more fans, and therefore players that have qualified for the NCAA tournament in past years and played well will have a small home court advantage, which has been shown to be significant, at least in NBA games (Hill, 2018). This means that the bias on playoff experience for players in this study is likely to be positive.

For this paper, regular season average points scored and opponent average points allowed will be used instead of offensive and defensive ratings to account for pace differences across 30 years (ratings are pace-neutral) and due to the limitations of the dataset. Several studies also highlight the influence of home court advantage in the postseason, so home/away games will be a categorical variable used in all equations (Hill, 2018; Pifer et al., 2019).

As mentioned earlier, playoff basketball and the atmosphere it brings is said to be significantly different compared to the regular season. Previous studies, like the one done on March Madness teams, have looked at the overall playoff experience of the starting five, which will be the same metric used for this paper, although experience will be measured in minutes instead of games to more accurately quantify a player's experience (Pifer et al., 2019). In addition to just the playoff experience of the starting five, the experience of the other players on the team (the players on the bench) will also be taken into account, as veteran players are often brought in specifically for the playoffs, used in “short rotations”, and can contribute significantly to scoring (Huff, 2022).

There is also anecdotal evidence that players with limited playoff experience struggle to adjust to a road environment in an aggressive playoff atmosphere. Many players in the NFL have noted that road playoff games often have extremely hostile environments, and some NBA players have had similar experiences, although to a lesser degree (Shook, 2023; Rio, 2022). For that reason, I will also look at the interaction between road teams with much less playoff experience and away games specifically.

3. NBA Playoff Setting

The structure of the NBA playoffs has changed significantly over time from its inception in 1947, from the total number of teams included, the series format of home and away games, the number of games per round, and more. For example, in 2013 the format of the NBA Finals was changed from 2-3-2 to 2-2-1-1-1 (NBA, 2013). A 2-2-1-1-1 format means the team with the higher seed (i.e. more regular season wins) hosts games 1, 2, 5, and 7, which is the standard for all NBA playoffs in the current 2023-2024 season.

The current playoff format is a best of 7 series for all rounds, but before 2003 earlier rounds used a best of 5 format (NBA, 2013). Due to the significant changes in format over time, data from individual playoff games is used instead of series outcomes or win percentage to utilize a larger sample size of NBA playoff games.

In 2020, the NBA playoffs were held exclusively in the “Bubble” after regular season play was halted due to the Covid-19 pandemic (Beck, 2020). While the structure of the playoffs, (e.g. the number of games, seeding) was unchanged besides a shortened regular season, home court advantage for that year should be nonexistent, as teams didn't need to travel between games, there was little to no crowd, and other stadiums specific advantages (e.g. elevation differences in Denver or Salt Lake City) weren't present. This means that even though teams "played at home", they should have no real benefit. For this reason, 2020 is excluded from regressions testing the interaction of playoff experience differences and home court advantage (Table 5), but included in all other regressions.

4. Data

I link 3 data sets: (1) points scored at the individual playoff game level, (2) player playoff minutes at the series level, and (3) regular season points scored and points allowed. All datasets were created by me with data scraped from basketballreference.com using Python and BeautifulSoup4, which was cross checked with official NBA data (Basketball Reference; Van Rossum et al., 1995; Richardson, 2007).

4.1 Points Scored

For the purpose of my study, I will be using the logged value points scored in individual playoff games as the dependent variable. While using points scored alone has obvious limitations, how teams react differently to heightened defense in the playoffs is a key factor in game and ultimately series outcomes. It also has the benefit of being understood by casual fans, as a 4% increase in expected points scored at home compared to road (away) games can be easily interpreted.

The points scored for each playoff game for both teams was scraped from the Basketball Reference page for each series of the past 30 years (1994-2023), with away linked to each game

(ex:
https://www.basketball-reference.com/playoffs/2023-nba-eastern-conference-first-round-heat-vs-bucks.html). Due to a difference in the formatting of NBA Finals data, scores for the finals were not scraped. While not ideal, the number of NBA Finals series makes up less than 7% of the total number of series in this dataset, and finals games make up less than 10% of all playoff games. The teams that play in the finals also necessarily play in 3 other series in the same year on the way to the finals, so data for finals teams is included in other observations. In total, there were 420 playoff series scraped with 4,476 total points scored observations (1 for both teams in each game) from 2,238 playoff games.

4.2 Player Playoff Experience

Player playoff experience (Exp) includes the IDs of starters and all players on both teams for a series and individual player total playoff minutes entering a series. Player playoff minutes were scraped from the same series level data as linked above, with total playoff minutes for a series for an individual player linked to their unique player ID. This tracks players across seasons as they change teams. The player minutes for players that changed teams, missed playoff series, and whose teams changed names were double checked (e.g. Lebron James, Hakeem Olajuwon, Baron Davis, etc.) with official NBA player stats for their entire career, and were all within 10 minutes of official data, with any differences due to rounding (Statmuse).

Playoff minutes were scraped from the last 50 NBA seasons (1974-2023). Finals minutes are included (which were manually scraped) since unlike the points scored in the finals, not including finals playoff minutes would significantly influence the coefficients of playoff experience variables for future playoff series. Data from ABA playoff series pre-merger (1974-1976) were also included, although this data is limited since not all ABA series had player minutes tracked. This has a very small effect, as there were only a few players that played in both the ABA and in a post-1993 NBA season.

The minutes for each player are updated after each series, so a player's playoff experience for each game is their playoff experience entering the series. Starters for a playoff series were defined as the 5 players that had the most minutes played for each team. While game level total playoff experience (instead of at the series level) for each player might be more ideal for the regression and defining starters, the starters for both teams are likely to see similar minutes over the course of a series, and the 5 players with the most minutes per team are likely to have the most minutes on a per game basis as well. The total playoff experience by both teams over a series will change by the same amount regardless of being updated at the game or series level.

4.3 Regular Season Statistics

Regular season points scored (pf) and points allowed (pa) averages were linked to each team for each season. Data was checked for teams that changed names and locations. Although regular season statistics are averages and the number of regular season games can vary in some seasons, *this data was not weighted for heteroskedasticity*, because they are used within each observation to estimate team strength, not to represent populations.

5. Descriptive Statistics

Before running the regression, it's important to check the key variables for correlations and that the variables are correct. The full summary statistics can be found in Table 1. The distributions for the key variables appear correct, with the mean of *away* being exactly 0.5, which is expected since each playoff game has a corresponding home and away observation for each team. *least_starters_exp_quartile*, which will be explained in the next section, has a mean of 0.249 instead of 0.250, but this is due to the fact that multiple playoff games have the same *Starters-exp-difference*$_{io}$, since playoff experience isn't updated until the end of a series (which is between 3-7 games). The means for the experience difference statistics (mean = 0) and year (mean = 2009) are all correct.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
score	4,476	98.28	13.62	56	154
series_id	4,476	217.9	128.3	1	449
starters_playoff_exp_dif	4,476	0	7,218	-21,800	21,800
bench_playoff_exp_dif	4,476	0	4,759	-16,241	16,241
reg_season_pf	4,476	102.7	7.238	86.30	120.7
opp_reg_season_pa	4,476	98.59	7.211	83.40	118.5
year	4,476	2,009	8.537	1,994	2,023
ln_score	4,476	4.578	0.139	4.025	5.037
ln_reg_season_pf	4,476	4.629	0.0698	4.458	4.793
ln_opp_reg_season_pa	4,476	4.588	0.0723	4.424	4.775
least_starters_exp_quartile	4,476	0.249	0.433	0	1
away	4,476	0.500	0.500	0	1
least_starters_exp_quartile_away	4,476	0.130	0.337	0	1
total_playoff_exp_dif	4,476	0	10,149	-30,607	30,607
Number of year	29	29	29	29	29

(Table 1)

	at_home
at_home	**1.0000**
ln_reg_sea~s	**0.0100**
ln_opp_reg~a	**0.0097**
starters_p~f	**0.0326**

(Table 2)

Examining the correlation between home games in Table 2, natural log of points scored, natural log of opponent's points allowed, and starters' playoff experience difference reveals no major correlation. This makes sense, since at most 60% (3 out of 5) of games in a series can be home games for the higher seeded team, so it follows that even stronger teams don't get home court advantage all the time.

6. Equations

Since points scored in a playoff game is the dependent variable, I theorize that the main influences on the number of points scored are the strengths of both teams (estimated through regular season metrics), home court advantage, differences in playoff experience (measured in minutes), and year (to adjust for pace).

Previous research indicates that teams with large amounts of playoff experience significantly outperform projections based on regular season statistics alone (Silver, 2017). This study hopes to further explore specific aspects of playoff experience. While some projection systems like FiveThirtyEight's CARM-Elo use weighted career playoff experience by "averaging the number of career playoff minutes played for each player on its roster, weighted by the number of minutes the player played" this has the limitation of only using regular season minutes when my regression can use *the actual playoff minutes played of a player*, since it's a regression and not a projection. This is beneficial in cases when a player sees regular playing time in the regular season but little to no playoff minutes.

6.1 Base Model

In my base equation, I estimate the logarithmic points scored in a playoff game using regular season team metrics and series level previous player playoff experience over 30 NBA seasons (1994-2023):

$$(1)\ ln(Y_{ioy}) = \beta_0 + \beta_1 ln(pf_{iy}) + \beta_2 ln(pa_{oy}) + \beta_3\, away + \beta_4\, Starters\text{-}exp\text{-}difference_{io} + \gamma_y + \varepsilon_{ioy}$$

where Y_{ioay} is the natural log of points scored by a team *i* in a playoff game against team *o* in year *y*. All point statistics are logged to adjust for pace of play, shot selection, and other factors across years. For example a coefficient of -0.04 for away games means that a team is expected to score 4% less in road playoff games with all else staying the same. $ln(pf_{iy})$ and $ln(pa_{oy})$ are the natural logs of the points scored averages of team *i* and points allowed average of team *o* in the regular season of year *y*, and are included as a basic estimation of the offensive production of team *i* and the defensive strength of team *o*. I expect both of these coefficients to be positive, as a stronger offense and a weaker opponent defense are likely correlated with more scoring. *away* is a categorical variable for whether a game is at the opponent's stadium (away = 1) or at home (away = 0). I expect this coefficient to be negative, as previous studies noted above have found that teams score less on the road.

$Starters\text{-}exp\text{-}difference_{io}$ is the difference between the total playoff experiences in minutes of starters of both teams as defined in the previous section at the start of the series. If the starters of the opposing team *o* have more playoff experience than the starters of team *i*, then $Starters\text{-}exp\text{-}difference_{io}$ will be negative. I expect this coefficient to be positive, as teams with more playoff experience than their opponents are also likely to outperform their estimated scoring based off of regular season statistics alone (which is what three models use). The reason that the experience for both teams is combined into one variable is that teams are often measured in differences in experience in the playoffs, i.e. team "x" has much more experience than team "y". Using the difference in experience allows us to directly test that idea. Combining the experiences of both teams into one variable also allows us to reduce the number of variables used in the equations and create a categorical variable, $Least\text{-}starter\text{-}exp\text{-}dif_{io}$, used in equation (3) to capture the experience of both team i and team o. y_y are the year fixed effects for year y to adjust for differences in pace of play across seasons.

6.2 Base Model and Bench Experience Difference

The second equation only differs from the first equation with the inclusion of the differences in bench player playoff experience. Similar to the previous equation, $Bench\text{-}exp\text{-}difference_{io}$ is the difference between the total playoff experience in minutes of teams i and o.

$$(2)\ Y_{ioy} = \beta_0 + \beta_1 \ln(pf_{iy}) + \beta_2 \ln(pa_{oy}) + \beta_3\, away + \beta_4\, Starters\text{-}exp\text{-}difference_{io} + \beta_5\, Bench\text{-}exp\text{-}difference_{io} + y_y + \varepsilon_{ioy}$$

$$H_0:\ \beta_4 = \beta_5$$

$$H_1:\ \beta_4 \neq \beta_5$$

The purpose of the second equation is to test whether the coefficients of $Starters\text{-}exp\text{-}difference_{io}$ and $Bench\text{-}exp\text{-}difference_{io}$ (β_4 and β_5) are different. A 2012 study found that team chemistry is an important factor in playoff wins (Rivera, 2012). NBA players also often cite a "veteran presence" from battle-tested players, even if they spend most of their time on the bench (Rio and Ritscher, 2022). Therefore, our null hypothesis is that β_4 and β_5 are equal, and the alternate hypothesis is that they are not. If the coefficients between the two variables are the same, it may suggest that veteran players may bring value similar to starters and that unobservables like leadership and chemistry might play an important role.

6.3 Least Starter Experience Difference and Away Interaction

The third equation replaces the raw numbers of starter experience difference with a categorical variable, $Least\text{-}starter\text{-}exp\text{-}dif_{io}$, of whether the starter experience difference is in the first quartile (bottom 25%) of all starter experience difference, or in other words, if a team's starters have significantly less playoff experience than their opponents:

$$(3)\ Y_{ioy} = \beta_0 + \beta_1 ln(pf_{iy}) + \beta_2 ln(pa_{oy}) + \beta_3\, away + \beta_4\, Least\text{-}starter\text{-}exp\text{-}dif_{io} + \beta_5\, Least\text{-}starter\text{-}exp\text{-}dif_{io} \times away + \gamma_y + \varepsilon_{ioy}$$

$$H_0:\ \beta_5 = 0$$

$$H_1:\ \beta_5 \neq 0$$

an interaction variable between the *Least-starter-exp-dif*$_{io}$ categorical and *away* is also included. The coefficient of *Least-starter-exp-dif*$_{io}$ is expected to be negative, because teams with little playoff experience are likely to underperform in the playoffs relative to other teams based on their regular season scoring alone. It's a fairly common sentiment among NBA fans that rookies and those new to the playoffs struggle especially hard in a road playoff environment (Rio and Ritscher, 2022). The purpose of this equation is to test whether β_5 is 0, or similarly, if newer players perform better or worse on the road than otherwise predicted without the interaction ($\beta_5 \neq 0$).

7. Results

7.1 Base Model: Differences in Starter Playoff Experience are Significant

ln(Playoff Score)	
Base Model with Starter Exp Difference	
	(1)
VARIABLES	ln_score
ln_reg_season_points	0.944***
	(0.0456)
ln_opp_reg_season_pa	0.771***
	(0.0479)
away	-0.0415***
	(0.00337)
starters_playoff_exp_dif	1.16e-06***
	(2.35e-07)
Constant	-3.308***
	(0.284)
Observations	4,476
Number of year	30
R-squared	0.187
Year FE	YES

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

(Table 3)

Table 3 shows the coefficients for our base model with year fixed effects. As expected, the coefficients for regular season averages and away games are all highly significant. The coefficients of 0.94 and 0.77 for $ln(pf_{iy})$ and $ln(pa_{oy})$ suggest that for a 1% increase in points scored or opponents points allowed during the regular season, we expect points scored during a playoff game to increase by 0.94% or 0.77%, respectively. The *away* coefficient of -0.04 also lines up with previous studies, suggesting teams score 4% less on the road than at home with all else being equal.

The coefficient of *Starters-exp-difference*$_{io}$, while extremely small, is also positive and highly significant, even at the 1% level. This means that teams with much more playoff experience than their opponents are expected to score more than regular season averages and home field advantage would indicate. The statistic wasn't reshaped because dividing *Starters-exp-difference*$_{io}$ by 5 (the number of starters) or even 48 (the length of an NBA game without overtime) still doesn't produce interpretable results and player minutes vary. Dividing by any large number having to do with expected number of minutes played during a also fails because series length differs significantly by year. The main goal of the regression is just to check whether or not the coefficient of *Starters-exp-difference*$_{io}$ is significant to set up a basis for the remaining two regressions, not to interpret the value of a playoff minute in terms of experience. There could be many reasons that the coefficient is significant (i.e. resting during the regular season, coaching experience, etc.) that will be explored in the next section.

7.2 Base Model and Bench Experience Difference

ln(Playoff Score)
with Starter and Bench Exp Difference

VARIABLES	(1) ln_score
ln_reg_season_points	0.945***
	(0.0456)
ln_opp_reg_season_pa	0.760***
	(0.0482)
away	-0.0414***
	(0.00337)
starters_playoff_exp_dif	9.67e-07***
	(2.57e-07)
bench_playoff_exp_dif	7.26e-07*
	(3.91e-07)
Constant	-3.265***
	(0.285)
Observations	4,476
Number of year	30
R-squared	0.188
Year FE	YES

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

(Table 4)

Table 4 shows the coefficients of the base model with *Bench-exp-difference*$_{io}$ added in (year fixed effects are still included). All previous coefficients are still significant at the 1% level, but the coefficient of *Bench-exp-difference*$_{io}$ is only significant at the 10% level. An F-test of our null hypothesis from equation (2) that the coefficients of β_4 and β_5 are equal gives a probability > F of 0.659 (F(1, 4441) = 0.19). Since 0.659 > 0.05, we cannot reject the null hypothesis: we do not have evidence that the coefficients of *Starters-exp-difference*$_{io}$ and *Bench-exp-difference*$_{io}$ are different. One possible reason for this result is that some bench players may play only slightly fewer minutes than starters, so the line for starters and bench players may be more blurred than a categorical variable allows. Other possible reasons will be explored in the next section.

7.3 Least Starter Experience Difference and Away interaction

ln(Playoff Score)
with Least Starters Exp Difference Quartile

VARIABLES	(1) ln_score
ln_reg_season_points	0.958***
	(0.0460)
ln_opp_reg_season_pa	0.783***
	(0.0483)
away	-0.0449***
	(0.00397)
least_starters_exp_quartile	-0.0145**
	(0.00575)
least_starters_exp_quartile_away	0.00685
	(0.00792)
Constant	-3.419***
	(0.285)
Observations	4,322
Number of year	29
R-squared	0.190
Year FE	YES

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

(Table 5)

Table 5 shows the coefficients of *Least-starter-exp-dif*$_{io}$ and its interaction with *away* (year fixed effects are still included). As noted above, 2020 is not included due to home field advantage not being present during the playoffs. The coefficient of *Least-starter-exp-dif*$_{io}$ of -0.015 is significant at the 5% level, and means teams that are much less experienced than their opponents (bottom quartile) are expected to score 1.5% less in a home playoff team *than other teams with the same regular season averages*. An F-test of our null hypothesis from equation (3) that β_5 (coefficient of interaction between *Least-starter-exp-dif*$_{io}$ and *away*) gives a probability > F of 0.4083 (F(1, 4287) = 0.68). Since 0.4083 > 0.05, we cannot reject the null hypothesis: we do not have evidence that the coefficient of the interaction term *Least-starter-exp-dif*$_{io}$ and *away* is not 0.

8. Discussion and Conclusion

This paper examines 3 different mechanisms in which playoff experience could affect scoring, which is important to NBA teams and could impact the way that they choose to develop their players. My results reinforce the idea that playoff experience could be an important variable to take into account when thinking about playoff success.

Results from Table 4 indicate that bench players' playoff experience is an important factor to take into account along with starters' playoff experience. Veteran players off the bench may be valuable, whether it be for chemistry, leadership, or just that it provides teams with a deeper bench to pull from. However, all starters' playoff experience and bench experience are treated the same within their separate categories, but that's a simplified approach. A 6th man (a player off the bench that often plays as part of the rotation with significant minutes) plays much more in a game than the worst player on the team, and my data isn't able to capture that. In the future, I might implement a weighted playoff experience variable similar to FiveThirtyEight.

Table 5 shows that teams that are much less experienced than their opponents don't seem to struggle more in away playoff games than home playoff games once home field advantage is taken into account. While this contradicts some anecdotal evidence, it also makes sense. Stakes are high in any playoff game, and most players already have plenty of experience playing away games from the regular season.

As mentioned earlier in the results section, there could be many other factors that affect scoring beyond player playoff experience that affect the coefficients of player playoff experience differences. One major missing variable is coach playoff experience. Since teams in a playoff setting play multiple games against each other, scheme adjustments and specific strategy changes between games matter much more than in the regular season (Avery, 2000). This missing variable is likely to be positively correlated with both player playoff experience and scoring, since teams are unlikely to fire coaches that get to the playoffs consistently and coaching playoff experience could help teams adjust better to opponent defensive schemes and score more points. This means that the coefficients for player playoff experience variables are likely lower than we estimated due to missing variable bias. Coaching playoff experience was not included in the regressions in this paper because coaches were not listed for each playoff series on Basketball Reference, where all the data for this paper was scraped from. In the future, I would like to include coaching playoff experience along with player playoff experience to get closer to a causal relationship.

Another major limitation of the data used in this study is that it fails to account for "resting" players, where teams intentionally sit star players out during some regular season games to prevent injuries. Resting players is most common among teams that have older players and/or consistently make the NBA playoffs. This would artificially lower the regular season points scored average and increase points allowed for teams that have more playoff experience. The NBA plans to roll out new policies against resting players in the 2023-2024 season which would limit this effect, but the data used in this study doesn't correct for stars sitting out

(Aschburner, 2023). A possible way I could address this is by only including regular season games where key players for a team played. That wasn't done for this paper as it would drastically increase the amount of scraping needed.

While the significance of the results of this study are limited due to major shortcomings in data (I did scrape everything myself), I believe it provides a possible framework for looking at how player playoff experience can be examined through different lenses to develop better projections and form more well-informed player development strategies. I also plan on sharing the player playoff experience data online (after I clean it up) for others to use.

Figures and Tables

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
score	4,476	98.28	13.62	56	154
series_id	4,476	217.9	128.3	1	449
starters_playoff_exp_dif	4,476	0	7,218	-21,800	21,800
bench_playoff_exp_dif	4,476	0	4,759	-16,241	16,241
reg_season_pf	4,476	102.7	7.238	86.30	120.7
opp_reg_season_pa	4,476	98.59	7.211	83.40	118.5
year	4,476	2,009	8.537	1,994	2,023
ln_score	4,476	4.578	0.139	4.025	5.037
ln_reg_season_pf	4,476	4.629	0.0698	4.458	4.793
ln_opp_reg_season_pa	4,476	4.588	0.0723	4.424	4.775
least_starters_exp_quartile	4,476	0.249	0.433	0	1
away	4,476	0.500	0.500	0	1
least_starters_exp_quartile_away	4,476	0.130	0.337	0	1
total_playoff_exp_dif	4,476	0	10,149	-30,607	30,607
Number of year	29	29	29	29	29

(Table 1)

ln(Playoff Score)
Base Model with Starter Exp Difference

VARIABLES	(1) ln_score
ln_reg_season_points	0.944***
	(0.0456)
ln_opp_reg_season_pa	0.771***
	(0.0479)
away	-0.0415***
	(0.00337)
starters_playoff_exp_dif	1.16e-06***
	(2.35e-07)
Constant	-3.308***
	(0.284)
Observations	4,476
Number of year	30
R-squared	0.187
Year FE	YES

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

(Table 3)

ln(Playoff Score) with Starter and Bench Exp Difference	
	(1)
VARIABLES	ln_score
ln_reg_season_points	0.945***
	(0.0456)
ln_opp_reg_season_pa	0.760***
	(0.0482)
away	-0.0414***
	(0.00337)
starters_playoff_exp_dif	9.67e-07***
	(2.57e-07)
bench_playoff_exp_dif	7.26e-07*
	(3.91e-07)
Constant	-3.265***
	(0.285)
Observations	4,476
Number of year	30
R-squared	0.188
Year FE	YES

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

(Table 4)

ln(Playoff Score) with Least Starters Exp Difference Quartile	
	(1)
VARIABLES	ln_score
ln_reg_season_points	0.958***
	(0.0460)
ln_opp_reg_season_pa	0.783***
	(0.0483)
away	-0.0449***
	(0.00397)
least_starters_exp_quartile	-0.0145**
	(0.00575)
least_starters_exp_quartile_away	0.00685
	(0.00792)
Constant	-3.419***
	(0.285)
Observations	4,322
Number of year	29
R-squared	0.190
Year FE	YES

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

(Table 5)

Bibliography in APA

Aschburner, S. (2023, September 15). Adam Silver discusses new policy as load management goes “too far.” https://www.nba.com/news/adam-silver-load-management-bog-news-conference-2023

Basketball Reference. (n.d.). Contact and media information. https://www.basketball-reference.com/about/contact.html

Beck, H. (2020, August 18). The truth about NBA home-court advantage. THE TRUTH ABOUT NBA HOME-COURT ADVANTAGE. https://bleacherreport.com/articles/2905080-the-truth-about-nba-home-court-advantage

Biderman, C. (2023, April 19). Playoffs: Kings hope to overcome experience gap vs. warriors | the ... Kings-Warriors playoff preview: Sacramento preparing for experience gap vs. Golden State. https://www.sacbee.com/sports/nba/sacramento-kings/article274336560.html

Haislop, T. (2021, September 18). NBA bubble, explained: A Complete Guide to the rules, teams, Schedule & More for Orlando Games. NBA bubble, explained: A complete guide to the rules, teams, schedule & more for Orlando games. https://www.sportingnews.com/us/nba/news/nba-bubble-rules-teams-schedule-orlando/zhap66a9hcwq1khmcex3ggabo

Huff, C. (2022, April 19). The value of veterans and short rotations in NBA playoffs: Cole Huff’s notebook. The Athletic. https://theathletic.com/3258328/2022/04/19/the-importance-of-veterans-and-short-rotations-in-the-nba-playoffs-and-more-in-cole-huffs-nba-notebook/

Hill, Brian. "Shadow and spillover effects of competition in NBA Playoffs." Journal of Sports Economics 19.8 (2018): 1067-1092.

Kubatko, J., Oliver, D., Pelton, K., & Rosenbaum, D. T. (2007). A starting point for analyzing basketball statistics. Journal of quantitative analysis in sports, 3(3).

NBA. (2013, October 23). NBA owners change finals format to 2-2-1-1-1. NBA owners change Finals format to 2-2-1-1-1.

NBAStuffer. (2023, August 24). How the NBA schedule is made. NBAstuffer. https://www.nbastuffer.com/analytics101/how-the-nba-schedule-is-made/ https://web.archive.org/web/20131030061032/http://www.nba.com/2013/news/10/23/nba-board-of-governors-format-change.ap

Richardson, L. (2007). Beautiful soup documentation. April.

Rio, A. (2022, June 6). How NBA basketball changes in the postseason. How NBA Basketball Changes in the Postseason. https://www.bruinsportsanalytics.com/post/nba_postseason_change

Rio, A., & Ritscher, K. (2022, March 29). The statistical validity of “Veteran presence” in the NBA. The Statistical Validity of “Veteran Presence” in the NBA. https://www.bruinsportsanalytics.com/post/vet_presence

Rivera, E. (2012, March 7). How important is “playoff experience”? https://www.espn.com/blog/truehoop/post/_/id/38430/how-important-is-playoff-experience

Shook, N. (2023, February 28). Joe Burrow, Bengals Embrace Challenge of road playoff game: “it’s you against the world.” Joe Burrow, Bengals embrace challenge of road playoff game: “It’s you against the world.”

https://www.nfl.com/news/bengals-qb-joe-burrow-embraces-challenge-of-road-playoff-game-you-against-world

Silver, N. (2017, October 13). Why the warriors and cavs are still big favorites. FiveThirtyEight. https://fivethirtyeight.com/features/why-the-warriors-and-cavs-are-still-big-favorites/

Statmuse. (n.d.). Most career playoff minutes played. most career playoff minutes played. https://www.statmuse.com/nba/ask/most-career-playoff-minutes-played

Teramoto, M., & Cross, C. L. (2010). Relative importance of performance factors in winning NBA games in regular season versus playoffs. Journal of Quantitative Analysis in Sports, 6(3).

Van Rossum, G., & Drake Jr, F. L. (1995). Python reference manual. Centrum voor Wiskunde en Informatica Amsterdam.