Empirical Economics (2020) 59:1019–1036
https://doi.org/10.1007/s00181-019-01641-4

The sunk-cost fallacy in the National Basketball Association: evidence using player salary and playing time

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Received: 29 March 2018 / Accepted: 7 February 2019 / Published online: 15 February 2019

Abstract
We analyze the effect of player salary, a sunk cost, on player utilization in the National Basketball Association (NBA). According to economic theory, rational agents make decisions based on marginal expected benefits and costs, and non-recoverable costs should not influence decision-making. Therefore, NBA teams should be playing their most productive players, regardless of salary. Whether decision-makers in the real world uphold this normative theory and ignore sunk costs has been the topic of much empirical work. Previous similar studies have looked at whether NBA teams irrationally escalate commitment to their highest drafted players by giving them more playing time than their performance warranted, coming to mixed conclusions. We build upon these studies by using salary to measure the impact of financial commitment on playing time, by using a fixed-effect panel data model to control for unobserved individual heterogeneity which may have been biasing previous results, and by using a spatial econometric model for a robust check of playing time dependence among players within each team. Our results indicate that a small but significant sunk-cost effect is found.

Keywords NBA · Panel data model with fixed effects · Performance statistics · Playing time · Salary · SLX model · Sunk-cost fallacy

1 Introduction

Do sunk (non-recoverable) costs matter? Economic theory tells us no. Sunk costs do not matter as once a cost is sunk it has no effect on future marginal benefits and costs and therefore plays no role in rational decision-making. While decision-makers *should* ignore sunk costs, the question has become whether humans in the real

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world make decisions holding to this normative theory of rational behavior/decision-making. Experimental work of Staw (1976, 1981), Arkes (1996), Arkes and Blumer (1985) and others demonstrated situations where sunk costs were not ignored by decision-makers, with this flaw in decision-making coming to be known as the *sunk-cost fallacy*. There are differing explanations as to why this occurs. For instance, self-justification of the original decision (Staw 1981), not wanting to appear wasteful (Arkes 1996), or due to the framing of decisions/prospect theory (Whyte 1986). Regardless of the psychological mechanisms explaining the behavior, if sunk costs are being taken into account in economic decisions, this is a violation of economic theory.

With much of the previous work demonstrating the fallacy being experimental in nature, observational studies were needed to prove it exists in the real world with experts making high-stakes decisions, and not simply in the low-stakes environment of students answering hypothetical questionnaires in laboratories. Many of these observational studies have been in the domain of professional sports; due to the timely performance feedback on all employees, professional sports give researchers a unique opportunity for labor market research (Kahn 2000). Relevant empirical works include Staw and Hoang (1995), Camerer and Weber (1999) and Leeds et al. (2015) for NBA games, Borland et al. (2011) for the Australian Football League games, and Keefer (2015, 2017) for the National Football League (NFL) games. In the NBA, new players are chosen by teams in a yearly draft. Using the order that a player was selected as a proxy for initial sunk cost, Staw and Hoang (1995) showed NBA teams committed the sunk-cost fallacy as players drafted higher in the draft receive more playing time through the first 5 years of their career than is justified by their NBA performance. Camerer and Weber (1999) tested the same idea with additional controls and made attempts to rule out rational explanations which could have caused the results found in Staw and Hoang (1995) such as the informational content of draft number, and corroborated Staw and Hoang's results, albeit with only half the magnitude. Leeds et al. (2015) also investigate whether NBA teams irrationally escalate commitment to their highest drafted players, using a regression discontinuity design (hereafter RD) to try to account for omitted variables which may have caused biased estimates in previous studies. Using RD around the thresholds of being a lottery (top 14) or first-round (top 30) draft selection, they find that there is no change in playing time given to players based on draft status when they cross the threshold into being a lottery or first-round pick, contradicting the findings showing NBA teams irrationally escalate commitment to higher drafted players. Taking salary cap value as the measure of financial commitment, Keefer (2015, 2017) use the number of games started for defensive players and rush attempts as the measures of player utilization, respectively, and their results all indicate the existence of the sunk-cost fallacy in NFL games.

Outside of sports, sunk-cost effects have also been shown in finance and other fields. For example, Jin and Scherbina (2010) showed that new mutual fund managers were much more likely to sell losing stocks in their inherited portfolios than were incumbent managers. Schoorman (1988) showed that managers making hiring decisions for firms were much more likely to evaluate subsequent employee performance highly than were individuals who disagreed with the original hiring decision. Klein et al. (2002) showed that Internet users spent longer periods of time on a gaming Web site if there had been more time delays to access/play the game.

While there have been many experiments and field studies demonstrating the fallacy, the evidence for the fallacy is not as definitive as many believe (Friedman et al. 2007). Many of the results which claim to demonstrate a sunk-cost fallacy can be *rationalized.* For instance, experiment #2 in Arkes and Blumer (1985) has been called by Eyster (2002) "The most convincing single experiment (of the sunk-cost fallacy)." In this experiment, students purchasing season tickets to the university theater were randomly assigned to pay full price, or received small or large discounts on the tickets. Those who paid the full ticket price ended up attending significantly more shows than those who received a discount, demonstrating a sunk-cost fallacy. However, even this "most convincing experiment" can be attacked (or *rationalized)* as one could argue that students receiving discounts could have taken the information of discounted prices on their tickets to infer negative things about the quality of the shows, and subsequently attended less plays. Therefore, the reduction in shows attended by the discounted group is potentially not demonstrating a sunk-cost fallacy, but the informational content of the discounts. For the basketball scenarios outlined above, teams who draft players high in the draft have very high initial projections of their talent, and teams may need a few seasons of information of NBA performance to update their optimistic Bayesian priors which lead the team to draft these players highly in the first place. Perhaps, this process of updating optimistic Bayesian priors takes a few seasons, and therefore there is no irrational escalation at all.

Clearly, more experimental and observational studies are needed to rigorously demonstrate the existence of this "flaw" in decision-making beyond any reasonable doubt. In this paper, we are interested in exploring the possible existence of the sunk-cost fallacy in the NBA, where decisions made by management are under intense and constant scrutiny from the media and fans, making it difficult to admit a previous decision (such as a large sum of money invested into a low performing player) was a mistake. It therefore is reasonable to expect that the desire to not appear wasteful as in Arkes (1996) and to appear competent in past decisions as in Staw (1981) is conducive to teams committing the sunk-cost fallacy by giving more playing time to their players with higher base salary than is justified by their NBA performance. Therefore, we use *current season base salary* of the players as a direct sunk-cost measure, which is different from Staw and Hoang (1995), Camerer and Weber (1999), and Leeds et al. (2015) who used players' draft order to capture the initial cost of players when searching for a sunk-cost effect. Given the timely performance feedback on all NBA players, if sunk costs are taken into account in this environment, it would be a clear demonstration of *experts* making *high-stakes decisions* violating the laws of rational choice.

In this paper, with an abundant panel dataset from four NBA seasons, we can apply a panel data model with fixed effects to account for unobserved player heterogeneity which may have been biasing the previous results of Staw and Hoang (1995) and Camerer and Weber (1999). In addition, as a robust check we apply a spatial lag of X (hereafter SLX) model to explicitly explore whether a player's playing time is also affected by the performance of other players within a team. To our best knowledge, our paper is the very first to explore the within-team player time dependence in the sunk-cost fallacy literature.

The rest of our paper proceeds as follows. Section 2 reports our empirical results from estimating a panel data model with fixed effects, Sect. 3 reports estimation results from analyzing a SLX model, and Sect. 4 concludes.

2 Panel data model with fixed effects

Our work continues the work of Staw and Hoang (1995), Camerer and Weber (1999), and Leeds et al. (2015) by examining whether the sunk-cost fallacy exists in the NBA. These three studies use draft position as a proxy for sunk cost, while we will use base salary of the players. This provides the methodological advantage of being able to take advantage of the panel dataset.

Previous work has used the ordinary least squares (or OLS) method to calculate the effect of draft number on playing time. However, unobservable player characteristics such as popularity or leadership may be related to both draft order and playing time, which leads us to believe that using pooled panel data model to explore irrational escalation of commitment in Staw and Hoang (1995) and Camerer and Weber (1999) may be biased. We therefore will employ the fixed-effect panel data model to control for the unobserved characteristics of players.

A second reason for the direct use of salary is that while the escalation effect of draft number on playing time was shown to decrease over time as this decision becomes further in the past, the salary of a player is relevant in each season. The NBA salaries are determined in the off-season, so the value of the contract is fixed during the season when the games are played. NBA contracts are guaranteed; therefore, even if a player is cut midway through a season, they are still owed their salary.[1] It is a sunk cost. Managers who explicitly know how much of their limited salary cap is spent on each player may have a hard time ignoring this fact when they make their playing time decisions. Finally, we can increase the sample size from previous studies which only look at recently drafted players, as we can include all NBA players in our study.

Hypothesis test The goal of NBA teams is to win the NBA championship, which requires a strong regular season followed by play-off success. While some coaches will strategically rest their top players periodically during the regular season in order to have them rested in the play-offs, over the course of a full NBA season the top performing players on each team will be given the most amount of playing time. The amount of playing time is positively correlated with salary in our data. However, our data also reveal positive correlation between salary and all key performance statistics (*ws48*, points-per-minute, assists-per-minute, and rebounds-per-minute). We therefore hypothesize that when we account for

[1] The highlights of the NBA collective Bargaining agreement are described in http://www.nba.com/media/CBA101.pdf.

performance, the effect of salary should not be significant in determining playing time of NBA players, if teams are able to ignore sunk costs.

We collected data of four NBA seasons, spanning from the 2013–2014 season to the 2016–2017 season. Player statistics come from Basketball-reference.com, while contract information comes from Basketball-reference.com, as well as Spotrac.com. As explained in Leeds et al. (2015), a player must have played at least 500 min in at least one of these seasons to be maintained in the study. Similar to Staw and Hoang (1995) and Camerer and Weber (1999), players must have played in at least two seasons to be maintained, as some control variables are lagged one season. In total, there are 465 players and 1573 player-year observations in our sample. There is some attrition in the panel, but it is due to exogenous regressors like experience and/or age and decreasing performance, which are not directly linked to the dependent variable.

We first consider a panel data model with both individual and time fixed effects to examine the effect of salary on playing time:

$$mpg_{it} = f(X_{it}, w_{it}) + \mu_i + \alpha_t + \varepsilon_{it}, \tag{1}$$

where mpg_{jt} is the dependent variable and equals the average minutes of the ith player played per game during season t. Previous studies have used total minutes for each season, but average minutes per game is a better measure as it will not be affected by games missed due to injuries, illness, or strategic decisions made by coaches to rest players for specific games. w_{it} is the logarithm of a player's base salary. X_{it} contains several measures of player productivity/performance and other characteristics, μ_i is the unobserved characteristic of the ith player, α_t is an unobserved time effect, and ε_{it} is the idiosyncratic error. Below, we give the detailed description of variables contained in X_{it}.

(1) *Performance* Historically, basketball performance statistics have been countable statistics such as *points, rebounds, assists, blocks, and steals*. While these statistics are important to success, they do not capture everything a player does on the court that helps a team win, which is the objective of all teams. More recently with the advent of *big data* in the world of sports, more advanced statistics have been developed by researchers in sports analytics in the attempt to more accurately capture the effect of individual players on the outcome in a team game, a fundamentally difficult problem. For instance, realizing that the difficulty of each specific shot in a basketball game is context dependent, Zuccolotto et al. (2017) generate statistics to compare players based on how they perform in high-pressure situations. In Deshpande and Jensen (2016), the authors aim to capture the effect of an individual on his team's chances of winning by having an estimate of the win probability of the home team at every moment during a game, and measure how this changes for the time an individual player is on the court, summing these changes in win probability over the course of the season for each individual player, to get a measure of each player's effect on their team's chances of winning. In Page et al. (2013), the authors create career production functions of NBA players as a function of their position, their usage, and how many minutes they play. Using these production curves, they aim to predict future performance of players based on their current output.

While many metrics of player performance exist, a gold standard production metric does not exist (Garcia and Caro 2011), so any choice of performance statistic will be somewhat arbitrary. We chose to select *Win Shares* as our performance statistic. It uses player, team, and league-wide statistics to capture the offensive and defensive contributions of a player, in order to estimate how many wins they add to their team during a season. Like the previous works, the performance statistics must be rate statistics and not total statistics to prevent bidirectional causality. We use the rate statistic, *win shares per 48 min* (labeled as *ws48*) of playing time, to capture each player's effect when they are on the court.[2] Both current period and previous period performance statistics are included in our model, where the current period performance statistics should determine court time, while the lagged performance statistics may also rationally be affecting coach's playing time decisions, because year-to-year performance is very consistent in the NBA, especially relative to other professional sporting leagues (Bern et al. (2007)), and therefore, players with high levels of performance in the last period can be expected to have high levels of performance this period.

(2) *Team dummy variables* These variables are included to take into account different playing strategies and talent levels across teams.

(3) *Team winning percentage* This is a measure of a team's overall performance over a season, and its value will change as players switch teams during a season.

(4) *All-star status* This variable captures the time-varying popularity and reputation of players. Each season, players are chosen for the all-star game either through fan voting, or coach and media voting. Therefore, being named to the all-star team designates either a very popular player, or a highly regarded one, or both.

(5) *Experience* This variable equals the number of years a player has been in the NBA. More experienced players may be given more playing time. *Experience*^{2} is also used in some of our models as it is hypothesized that playing time will increase as players gain experience and then decrease as they approach the end of their careers.

(6) *Position dummies* These dummy variables account for the fact that different positions may play different amounts of time.

(7) *Changing team dummy* This dummy variable accounts for the fact that players who have changed teams between seasons or in the middle of a season will have to adjust to the new team's strategies and may be played less than players who have more tenure at the team.

(8) *Current manager dummy* The variable equals one if during the current season the manager who signed the player's contract is the current manager of the team the player is on. Different scenarios, such as players being traded, or managers being fired, can mean the player is playing under a different manager than the one who signed their current contract. As was shown in Jin and Scherbina (2010), incumbent managers are more likely to hold on to poorly performing stocks than managers who inherited these stocks. An analogous situation may be at play here, as players who

[2] For more on *win shares*, see Basketball-reference (https://www.basketball-reference.com/about/ws.html).

Table 1 Summary statistics

Variables	Minimum	Maximum	Mean	SD
mpg	1.00	38.7	22.3	8.37
ws48	– 0.30	2.12	0.09	0.08
ln(*salary*)	9.69	17.2	14.9	1.21
All-star status	0	1	0.061	0.24
Winning percentage	0.122	0.890	0.505	0.156
Change teams	0	1	0.303	0.460
Experience	0	20	5.31	4.11
Current manager	0	1	0.737	0.440

are playing under the manager who signed the contract may be given extra playing time than deserved by their performance.

(9) *Experience * ln(salary) interactive term* To see whether tenure in the league will have an impact on any sunk-cost effect.

Analyzing NFL game data, Keefer (2017) argues that a positive coefficient in front of salary cap value may not reveal a true sunk-cost effect as the positive effect may reflect the correlation between financial compensation and player utilization being generated by expected productivity. We believe we have controlled for expected productivity due to the extensive performance and player/team characteristics contained in X_{it}. Importantly, we include current period performance measures (whereas many other studies have used previous period statistics only), which reduces the concern that expected productivity is the cause of a potential positive coefficient for salary. In addition, although some NBA contracts contain bonus structures, only the base contract is used in our analysis to prevent endogeneity concerns.

2.1 Empirical results

The summary statistics for important variables are included in Table 1, and results of two different specifications of FE panel data models are included in the first two columns of Table 2. To see whether tenure in the league has an impact on any sunk-cost effect, we construct model M2 by including an interactive term, ln(*salary*)*experience, to model M1. Our results indicate that changing manager has no significant impact on players' playing time at the 5% significant level and that the coefficient of the interactive term is insignificant as well. Also, as expected, the performance variable win shares per 48 min and its lagged specification are both significant at any reasonable significance level across both models. Being designated as an all-star player has a positive coefficient, but it is not significant at the 5% level in either model. When both experience and experience^2 are included in the model, the effect of experience takes a concave shape, with only the quadratic term being significant. The coefficient of ln(*salary*) is found to be positive and significant at the 5% significance level in both models, indicating that the sunk-cost fallacy persists in the NBA even after player performance and a host of other factors have been controlled for.

Table 2 Panel data models with fixed effects

Variables	M1 *ws48*	M2 *ws48*	M1 box-score statistics	M2 box -score statistics
ln(*salary*)	0.834*** (0.26)	1.15** (0.49)	0.719** (0.30)	0.819 (0.55)
Average treatment effect of ln(*salary*) [95% CI]	0.834 [0.32, 1.35]	0.848 [0.33, 1.37]	0.719 [0.13, 1.31]	0.718 [0.13, 1.31]
ws48	45.1*** (4.53)	44.6*** (4.59)	No	No
Lagged *ws48*	19.8*** (4.53)	19.6*** (4.23)	No	No
Points-per-minute	No	No	11.1*** (3.61)	11.1*** (3.62)
Rebounds-per-minute	No	No	−5.82 (8.15)	−5.78 (8.17)
Assists-per-minute	No	No	7.64 (10.2)	7.57 (10.2)
Blocks-per-minute	No	No	20.2 (31.6)	20.4 (31.6)
Steals-per-minute	No	No	−2.04 (27.7)	−2.58 (27.8)
Fouls-per-minute	No	No	−99.4*** (15.0)	−99.7*** (15.1)
Three-point percentage	No	No	3.22 (2.11)	3.21 (2.12)
Free throw percentage	No	No	8.62*** (3.30)	8.52** (3.34)
Two-point percentage	No	No	12.0*** (3.67)	11.9*** (3.68)
All-star status	0.539 (0.91)	0.527 (0.91)	0.105 (0.90)	0.099 (0.90)
Winning Percentage	−16.2*** (2.33)	−16.1*** (2.34)	−8.59*** (2.45)	−8.57*** (2.45)
Change teams	−0.441 (0.37)	−0.461 (0.37)	−0.431 (0.40)	−0.438 (0.40)
Experience	0.311 (0.37)	1.00 (0.98)	−0.527 (0.422)	−0.294 (1.15)
Experience^2	−0.087*** (0.024)	−0.083*** (.025)	−0.042 (0.028)	−0.040 (0.029)
Current Manager	−0.426 (0.49)	−0.471 (0.50)	0.045 (0.52)	0.036 (0.522)
ln(*salary*)*Experience	No	−0.050 (0.07)	No	−0.017 (0.077)
R^2 within	0.412	0.412	0.468	0.469
N	960	960	820	820

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively; standard errors are in parentheses

We also include year dummies, position dummies, and team dummies in the above estimation. To save space, we dropped the estimation results for some of the lagged performance statistics

Holding all else constant, a unit increase in ln(*salary*) (or an increase in raw salary by a magnitude of 2.7 times) leads to an estimated increase of 0.834 (95% CI [0.32, 1.35]) and 0.848 (95% CI [0.33,1.37]) minutes per game on average, as predicted by model M1 and M2, respectively, where average experience is used to calculate the impact in model M2. As the two 95% confidence intervals almost coincide with each other, these estimates are not statistically different from each other.

In addition, as a robustness check, we also added an additional interactive term, ln(*salary*)*current manager to model M2, but did not report the results as this term was insignificant, and added very little to the current models in terms of explaining variation in the dependent variable..

2.2 Sunk-cost fallacy or incorrect performance measure?

In Table 2, win shares per 48 min is used to capture the performance of players, and a significant sunk-cost fallacy was found. However, while this statistic is perhaps superior to almost all other statistics in measuring the performance of players, it may not be the most correlated with what coaches are using to evaluate player performance and therefore to allocate playing time for their team. In Bern et al. (2007), the authors looked at voting for the all-rookie team, which is an end of season award given to the top 5 rookies, as voted by the NBA coaches. They discovered that using only scoring of players, they were able to explain more of the variation in the voting results than with using more advanced statistical measures. While there are many ways players can contribute to a basketball team to help the team win games, it appears in their results that scoring dominates all other factors from a coach's evaluation perspective. However, voting for an all-rookie team is not a stressful or important decision for the coach, and coaches likely spend very little time on it. Therefore, it could be argued that this simple "scoring above all else" coach evaluation may not hold up when coaches are making more important decisions. Accordingly, Bern et al. (2007) tested this idea with off-season free agent signings of players by teams, measuring how much of the salary given to players could be explained by various performance measures. A model with "Wins Produced" (a statistic similar in idea to the "Win Shares" variable used in our regression) explained 41% of the variation in salary sizes, while a model using only scoring (and not assists, rebounds, shooting percentages or any defensive measures) explained 59% of the variation in wages. Clearly, scoring dominates the evaluation of players even in very important decisions. Following this logic, scoring is correlated strongly with salary as well as with minutes per game. And, while some degree of scoring is of course captured by our win shares per 48-min statistic, it may be that coaches are making playing time decisions with scoring overly valued and so what appears to be a sunk-cost fallacy in model (1) is actually a potential misuse of players, as players are being played based almost exclusively on scoring and not on their total contribution as captured by win shares. Consequently, we run a further model as a robustness check for the sunk-cost fallacy found in model (1), this time replacing the performance variable win shares per 48 min by nine box-score statistics: scoring, assists, rebounding, blocks, fouls, steals, field goal percentage, three-point percentage, and free throw percentage. The first six statistics are divided by minutes played, in order to get rate statistics (i.e., points scored per minute) to prevent simultaneous causality, and to capture a player's contribution while they are on the floor. Similar to the previous regression, lagged performance statistics are used as well as real-time statistics. The remaining regressors are unchanged. A fixed-effect panel data model is used again. We run two nested models, and the results of these models are reported in columns 3 and 4 of Table 2, where again model M2 contains the interactive term, ln(*salary*)*Experience, while model M1 does not.

In this new specification, points-per-minute is as expected positive and significant across both models. Fouls-per-minute is negative and extremely significant (p value = 0.000), due to their being a cap on allowable fouls during each game players who are foul-prone cannot play many minutes as they are at greater risk of fouling out.[3] The only other current period performance statistics to be significant are free throw percentage and two-point percentage. None of the lagged performance statistics are significant at the 5% level. Including the ln(*salary*)*experience interactive term in model M2 has not improved the fit of the model relative to model M1, based on the within-R^2 of the models. Relative to the previous regression which included only win shares per 48 min as the performance variable, the new regression is superior in regards to explaining the variation in the dependent variable, as the R^2 within has increased from 0.412 to 0.469. The coefficient of ln(*salary*) is significant at the 5% significance level in model M1. Although the coefficient of ln(*salary*) is not significant at the 5% level in model M2, the variable is still important as its t statistic takes a value greater than one. With the new specification of explicitly including all per-minute performance characteristics, the (average) marginal effect of a one-unit increase in ln(*salary*) is estimated to be an increase of 0.718 and 0.719 min per game on average, holding other factors fixed and depending on the model used. These estimates have identical 95% confidence intervals of [0.13, 1.31] minutes per game. Even with timely performance feedback on all players, the sunk-cost fallacy is found to persist, albeit with a small magnitude as the average playing time of players across our sample is 22.3 min per game.

2.3 Issues with truncated data?

The FE estimator we have used implicitly assumes the dependent variable can take any value along the real line; however, our dependent variable, *mpg*, can only take values in the interval of [0, 48]. This may motivate the use of fractional probit/logit model with the dependent variable transformed from *mpg* to *mpg*/48, a ratio in the interval of [0, 1].[4] However, in all four of the specifications run with the FE model in Table 2, all our fitted values of *mpg* lie within the range [0, 48], allowing us to conclude that we do not have an issue with truncated data, and that modeling the

[3] Once a player has incurred their 6th foul during a game, they have "fouled-out" and are no longer able to play during that game.

[4] We thank one of the referees to pointing out this issue.

dependent variable as *mpg* and using fixed effects model is a legitimate approach to the current problem.

3 Robustness check: SLX model

As a robustness check on the results in Sect. 2, we propose a spatial econometric method to take into account possible inter-dependence of players' playing time, which has not been used in the previous studies looking for the sunk-cost fallacy in the NBA. The motivation for using a spatial econometric model is that the amount of playing time given to each player on a team is not independent observations. Anecdotally, many players are complements of each other and will spend the majority of the game playing alongside each other. As well, players on the same team and playing the same position are substitutes for each other. Hence, playing time for each player is not only dependent on their own performance, but can also be impacted by the performance of other players on their team.

The effect of team dynamics was accounted for in model (1) by including team dummies, as well as winning percentage of the team, and our results in Table 2 indicate that players on teams with higher winning percentages were given less playing time holding all else constant. Camerer and Weber (1999) used "backup player" performance explicitly as a regressor to account for the dependence between observations (where "backup player" is defined as a player on the same team playing the same position). They found as expected that stronger performance of backup players results in less playing time. We originally estimated a spatial Durbin as well as spatial autoregressive model; however, the coefficient for the *spatial lag parameter* in front of the spatial lag term of dependent variable was found insignificant. Therefore, we estimate an SLX model, to account for the fact that the playing time of each player depends on the performance of "neighboring" players.

The SLX model is specified below:

$$\begin{aligned} mpg_i = {} & \alpha_0 + \beta_1' X_i + \alpha_1 \sum_{j \neq i} w_{ij} \ln(salary_j) + \alpha_2 \sum_{j \neq i} w_{ij} ws48_j + \alpha_3 \sum_{j \neq i} w_{ij} (\text{points per minute}_j) \\ & + \alpha_4 \sum_{j \neq i} w_{ij} (\text{two-point percentage}_j) + \alpha_5 \sum_{j \neq i} w_{ij} (\text{free throw percentage}_j) \\ & + \alpha_6 \sum_{j \neq i} w_{ij} (\text{Fouls per minute}_j) + \alpha_7 \sum_{j \neq i} w_{ij} (\text{Draft Round}_j) + \varepsilon_i, \end{aligned} \tag{2}$$

where mpg_i is the ith player's average minutes per game, X_i is the vector of control variables including ln(*salary*), win shares per 48 min, the nine box-score statistics defined in Sect. 2, all-star status, experience, experience^2, team dummy variables, change teams dummy, player position dummy, current manager dummy, draft round, and two interactive terms, ln(*salary*)*experience and ln(*salary*)*current manager. Draft round has been added as a regressor to account for the findings of Staw and Hoang (1995) and Camerer and Webeer (1999) showing draft order is significant on playing time. This variable was not included as a regressor in the fixed effect model, as it is time invariant.

A downside to model (2) is due to the yearly changes in players, and starting lineups each year, we are unable to use an SLX panel data model as we do not have the same players across years for the construction of the spatial weight matrix. Therefore, we run separate cross-sectional spatial regressions for each year (excluding 2013, where we do not have information on players who changed teams). This means we lose the ability to control for the individual fixed effects of players. Note that team winning percentage is excluded as a regressor, due to singularity with including team fixed effects. We therefore include in X_i the nine performance statistics: scoring, assists, rebounding, blocks, fouls, steals, field goal percentage, three-point percentage, and free throw percentage, mentioned in Sect. 2.2 to proxy for players' individual effects.

In addition, $\sum_{j\neq i} w_{ij} ws48_j$, $\sum_{j\neq i} w_{ij}(\text{points per minute}_j)$, $\sum_{j\neq i} w_{ij}(\text{Fouls per minute}_j)$, $\sum_{j\neq i} w_{ij}(\text{two-point percentage}_j)$, and $\sum_{j\neq i} w_{ij}(\text{free throw percentage}_j)$ are spatial lag terms of four performance statistics, and $\sum_{j\neq i} w_{ij}\ln(salary_j)$ and $\sum_{j\neq i} w_{ij}(\text{Draft Round}_j)$ are two spatial lag terms of costs. The spatial performance statistics (*ws48*, points-per-minute, two-point percentage, free throw percentage, and fouls-per-minute) are included as they were found to be significant determinants of playing time in model (1). If the coefficients in front of these spatial performance statistics are significant, we find evidence that a player's playing time depends not only on his own performance but also on other players' performance.

The *spatial weight*, w_{ij}, is a predetermined weight representing the impact of the *j*th player's playing time on the *i*th player's playing time, and $w_{ii} = 0$ holds for all *i*. Let W_n be an *n* by *n* spatial weight matrix whose (*i,j*)th element equals w_{ij}, where n is the sample size. Here, w_{ij} is a "*position-based*" weight used to capture substitute/complementary impacts across players on the same team. Specifically, the "*position-based*" weight, w_{ij}, equals negative one if player *j* either plays the same position as player *i* on the same team (as they are substitutes), and equals positive one if player *i* and player *j* are both members of the "starting lineup" on the same team (they are complements). Players on the starting lineup are generally the best players on a team, in terms of performance. Therefore, being a member of a starting lineup is correlated with *mpg* (as starters will usually play more minutes than bench players), but this correlation is through performance. There is no reverse causation from *mpg* to being a member of the starting lineup, so we believe our weight matrix is exogenous.

Empirical Results We estimate model (2) for each year separately, under two different specifications per year, and these results are reported in Table 3, where model M2 adds the current manager dummy variable, as well ln(*salary*)*current manager and ln(*salary*)*experience interactive terms into model M1. Our results clearly support joint significance of spatial lag terms of regressors via F tests. Therefore, it is demonstrated that the playing time given to individual observations is not independent observations, but is dependent on the performance of "neighboring" players.

The average direct impact (or ADI) of ln(*salary*) in SLX models equals the coefficient in front of ln(*salary*) in model M1, see Elhorst (2014). Our results indicate that the ADI of ln(*salary*) is all significantly different from zero at the 1% significance

Table 3 SLX models with two different specifications per year

Variables	2014—M1	2014—M2	2015—M1	2015—M2	2016—M1	2016—M2
ln(*salary*)	1.17***	0.460	1.41***	2.13**	1.23***	1.08*
	(0.28)	(0.51)	(0.27)	(0.50)	(0.26)	(0.57)
Weight*salary	0.495	0.643	1.52*	1.46*	2.35***	2.32**
	(1.51)	(1.51)	(0.87)	(0.87)	(0.90)	(0.91)
ws48	− 2.19	− 2.16	12.2**	10.1	7.84	8.01
	(6.59)	(6.58)	(6.15)	(6.15)	(7.45)	(7.51)
Weight**ws48*	241.7***	237.9***	58.0**	58.4**	31.6	31.6
	(41.4)	(41.4)	(28.8)	(28.9)	(31.5)	(31.8)
Points-per-minute	9.31***	9.19***	7.19***	7.10**	7.16***	7.17***
	(2.70)	(2.69)	(2.75)	(2.76)	(2.72)	(2.75)
Weight*points-per-minute	66.0**	63.7**	15.7	17.9	22.3	22.4
	(31.6)	(29.6)	(17.0)	(17.0)	(18.9)	(18.9)
Rebounds-per-minute	7.23	7.44	3.48	5.24	3.78	3.47
	(5.28)	(5.31)	(5.51)	(5.51)	(5.47)	(5.58)
Assists-per-minute	25.0***	24.3***	27.2***	27.8***	19.2***	19.1***
	(6.85)	(6.85)	(7.16)	(7.14)	(6.79)	(6.83)
Steals-per-minute	17.9	17.1	3.22	5.13	9.55	10.0
	(19.3)	(19.2)	(19.8)	(19.7)	(18.3)	(18.5)
Blocks-per-minute	10.5	12.9	16.3	21.9	31.1	31.4
	(17.4)	(17.5)	(18.8)	(18.8)	(22.3)	(22.4)
Fouls-per-minute	− 65.5***	− 65.6***	− 40.9***	− 44.0***	− 48.0***	− 47.9***
	(9.88)	(9.93)	(9.75)	(9.89)	(9.99)	(10.0)
Weight*fouls-per-minute	236.3***	229.3***	− 82.6	− 94.5	− 130.4**	− 131.4**
	(77.3)	(77.3)	(57.8)	(58.3)	(51.0)	(51.4)
Three-point percentage	3.72*	4.00*	1.85	1.66	5.30**	5.27**
	(2.07)	(2.07)	(2.00)	(1.99)	(2.45)	(2.48)

Table 3 (continued)

Variables	2014—M1	2014—M2	2015—M1	2015—M2	2016—M1	2016—M2
Two-point percentage	14.7*** (3.97)	14.7*** (3.97)	8.07** (3.88)	8.19** (3.86)	8.29** (3.65)	8.15** (3.70)
Weight*two-point percentage	− 123.3*** (43.0)	− 119.8*** (43.0)	− 9.61 (22.2)	− 6.57 (22.1)	− 38.5* (21.0)	− 37.9* (21.2)
Free throw percentage	1.51 (1.79)	1.24 (1.80)	2.83 (2.18)	2.66 (2.17)	4.20* (2.19)	4.33* (2.22)
Weight*free throw percentage	14.5 (21.3)	11.8 (21.4)	− 11.2 (14.3)	− 13.1 (14.3)	− 8.44 (13.1)	− 8.26 (13.2)
Experience	0.281 (0.19)	0.098 (0.76)	0.520*** (0.19)	2.33*** (0.70)	− 0.182 (0.24)	− 0.478 (0.86)
Experience^2	− 0.021* (0.012)	− 0.022 (0.013)	− 0.04*** (0.012)	− 0.031** (0.012)	− 0.003 (0.02)	− 0.004 (0.02)
ln(*salary*)*experience	No	0.0123 (0.05)	No	− 0.131*** (0.05)	No	0.021 (0.06)
Draft round	− 0.471 (0.35)	− 0.472 (0.36)	− 1.04*** (0.36)	− 0.747** (0.37)	− 0.585 (0.38)	− 0.598 (0.38)
Weight*draft round	− 7.26** (3.58)	− 7.21** (3.58)	− 1.20 (2.28)	− 0.810 (2.28)	1.52 (2.42)	1.50 (2.43)
All-star status	1.30 (1.15)	0.919 (1.17)	0.160 (1.24)	0.505 (1.24)	1.26 (1.28)	1.21 (1.30)
Change teams	− 0.20 (0.56)	− 0.091 (0.56)	− 1.53*** (0.539)	− 1.71*** (0.55)	− 0.982 (0.62)	− 0.99 (0.62)
Current manager	No	− 14.5** (6.72)	No	− 3.36 (7.06)	No	0.008 (7.67)
ln(*salary*)*current manager	No	0.967** (0.44)	No	0.185 (0.46)	No	0.011 (0.50)
Adjusted R^2	0.731	0.732	0.716	0.720	0.721	0.718

Table 3 (continued)

Variables	2014—M1	2014—M2	2015—M1	2015—M2	2016—M1	2016—M2
F test statistic: SLX versus no spatial terms	27.1***	27.3***	21.9***	21.9***	21.8***	21.5***
ADI of ln(*salary*)	1.17	1.22	1.41	1.56	1.23	1.22
N	419	419	418	418	365	365

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively; standard errors are in parentheses

We also include position dummies and team dummies in the above estimation level and ranges from 1.17 to 1.41 min per game. These estimates are not statistically different from each other by comparing their 95% confidence intervals. In model M2 with interaction terms, using the average value of *current manager* and *experience*, we calculate an estimated increase of 1.22 to 1.56 min per game for a one-unit increase in ln(*salary*), holding all else constant. The results of the SLX regression models also support a small but significant sunk-cost effect similar magnitude to the results from model (1).

As in model (1), our regression model implicitly assumes the dependent variable can take any value along the real line; however, our dependent variable *mpg* can only take values in the interval of [0, 48]. However, in the six SLX regressions run, there were a total of only six instances where the fitted value lay outside of the [0, 48] range, indicating that truncated data were not of major concern.

Even with simply constructed binary spatial weight matrices, the addition of spatial lag terms in the model has significantly improved the fit, as evidenced by the F tests across all 3 years relative to the model without any spatial lag terms. The hypothesis that players' playing time depends on other players' performance was clearly supported by the data. If future researchers are aiming to look for escalation of commitment biases and sunk-cost fallacies in the domain of professional sports, spatial regressions with spatial weights which capture the interdependencies in playing time between players are a nice addition to the researcher's toolbox. Additionally, the spatial weights could be selected by nonparametric methods when the weights are a function of a continuous random variable for cross-sectional data, as is suggested in the literature of spatial econometrics by Pinkse et al. (2002) and Sun (2016).

4 Conclusion

Using player salary as a direct sunk-cost measure, we have demonstrated that the sunk-cost fallacy exists in a real world, high-stakes setting such as the NBA. Previous studies looking for the sunk-cost fallacy in the NBA have used draft order as the original measure of cost to the team, and then used the OLS method to look for escalation of commitment to high drafted players via playing time above and beyond what their on-court performance warrants. We instead use player salary as a direct sunk-cost measure to the teams, and we use a fixed-effects model to control for individual heterogeneity of players, and then a spatial regression to control for possible impacts of other players' performance, in order to more accurately model the playing time relationship, and therefore more convincingly demonstrate a sunk-cost effect. In both specifications, we find positive and significant effects of salary on playing time, above and beyond what is justified by their own (and other players') performance. The magnitudes of the effect may not seem massive, as in model (1) a one-unit increase in ln(*salary*) (holding all else constant) was estimated to increase playing time by around 0.7–0.8 min per game on average, but in the context of the NBA, they are not ignorable given NBA players can sometimes receive massive increases in salary from 1 year to the next. The environment of the NBA with media and fan scrutiny as well as low job security of managers makes it difficult for managers and other decision-makers to admit mistakes, and even with timely performance feedback and high-stakes decisions made by experts, the sunk-cost fallacy is found to persist. This result could be due to teams not wanting to appear wasteful as in Arkes (1996), and feel they must get value from the assets they have purchased. Or perhaps it is more in line with justification of past decisions and not wanting to admit mistakes as in Staw (1976). While the psychological mechanism for why this occurs in this situation is not in the spectrum of this research, we have demonstrated that the sunk-cost fallacy does exist in the NBA.

If the sunk-cost fallacy can persist in an environment such as the NBA, with its nightly updating of performance feedback for coaches and managers to constantly review, it is not hard to believe that sunk costs will be affecting decisions at other industries, where performance feedback is less accurate and updated much less regularly than the feedback of employees in the professional sporting arena.

Acknowledgements We would like to thank two anonymous referees and the associated editor for their comments. Yiguo Sun would like to thank the financial support by the Social Science and Humanities Research Council of Canada Insightful Grant 435-2016-0340.

Compliance with ethical standards

Conflict of interest The author declares that they have no conflict of interest.

Human and animal rights This research does not contain any studies involving human participants or animals performed by any of the authors.

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