4-26-2021

Sunk or Dunk?: An Empirical Analysis of the Effect of Sunk Cost Fallacy in Professional Basketball

Hailey DiCicco
Ursinus College, hadicicco@ursinus.edu

Sunk or Dunk?: An Empirical Analysis of The Role of The Sunk Cost Effect in Professional Basketball

By Hailey DiCicco and Professor Jennifer VanGilder

Submitted to the Faculty of Ursinus College in fulfillment of the requirements for Distinguished Honors in Applied Economics

Abstract

This project is dived into two sections. The first section is a comparison between the NBA and WNBA, using performance metrics from game statists. Using performance characteristics, empirical analysis was used to determine if the number of minutes played was determined by consistent parameters across these organizations. This finding showed inconsistency. The WNBA showed higher valuation for blocks, steals, and assists while the NBA showed higher valuation for three-point percentages and defensive rebounds.

The second section of the paper evaluates the sunk cost fallacy and its impacts in the NBA. The WNBA was not able to be included in this part of the study due to lack of salary data. The sunk cost fallacy is described as; as the spending for a person or thing increases, the perceived need to get the most out of that financial decision increases. It was found that a 1% increase in salary statistically increases minutes played by 1.5 minutes. This reveals that the sunk cost fallacy could be at play in the NBA, however more investigation is needed to make more firm conclusions

Introduction

On December 1, 2012, the New York Times reported that the National Basketball Association (NBA) fined the Spurs for “sending starters home”. This fine totaled $250,000 and was defined as a “disservice” fee for head coach Greg Popovich’s decision to rest their “Big Three” during a regular season road game against Miami. The decision by Coach Popovich highlights that decisions of who plays and for how long is more complex than simply a measurement of the productivity of the players. Ben Shields and Paul Michelman, of COUNTERPOINTS, analyzed the connections between the financial aspect of the league and the total number minutes each player gets. Michelman and Shields discussed what occurred when Greg Popovich decided to bench his “Big Three”, Tim Duncan, Manu Ginobili, and Tony Parker, in a 2012 regular season game against the Heat. Popovich appeared to want to rest his three super star players during this less competitive game, for their own health’s sake, while also giving other members of the team the opportunity to play. However, this decision had a ripple effect that Popovich did not intend. The commissioner of the NBA fined Popovich’s team, the Spurs, a quarter of a million dollars for what Popovich felt was a “strategic” decision. Fans of the opposing team were angered by Popovich’s decision and sued the NBA for what they felt was an unfair act. This lawsuit was eventually dropped, but the message sent to the NBA was not soon forgotten. This example illustrates how minutes played by NBA players might be linked to how much they are paid. This is practice, however, still occurs. Boren (2017) reported in the Washington Post, Greg Popovich and the Spurs were the catalyst for many coaches in the years following that event to rest their top players despite the negative reaction they knew they would receive.

Another instance where the league punished a team for resting their top players happened with the Cleveland Cavaliers in 2017. During a regular season game against the Los Angeles Clippers Coach Tyronn Lue decided to rest their teams' "big three" which consisted of Lebron James, Kevin Love, and Kyrie Irving. This caused an outrage with the NBA analysts as well as by Doc Rivers, the coach of the Clippers. The complaint by many sports analysts such as Jeff Van Gundy was that they advertised one game, with big names, and then once the tickets were purchased and people were already sitting in the stadium, they switched out the players. He claimed it was false advertising and would not be tolerated in any other industry. The general manager of the Cavaliers was not pleased with the decision either, showing that this decision had come directly from the coach and not the administration. This situation occurred another time with Steve Kerr resting his top stars of the Golden State Warriors, Steph Curry, Draymond Green, Klay Thompson, and Andre Iguodala. In this instance they lost the game against the Spurs calling the decision into question.

Based on these events, two major questions come to light. The first is how the number of minutes played by players is determined. This productivity assessment will be addressed in Part I of this paper using data from both the NBA and WNBA. The second is whether playing decisions utilize the sunk cost fallacy, where salary is a determining factor in playing time. Although this question is equally important in the WNBA, individual salary statistics are not public, therefore this this question will only be addressed using data from the NBA. However, results will be used to draw inferences about the WNBA.

SECTION I: An Economic Analysis of Minutes Played in the NBA and WNBA

Literature Review

The determination of value can come in many forms, however for a top athlete value can be seen though usage. A highly valuable player will find themselves being utilized more than a less valuable player. Berri (1999) looked to analyze how to determine a player's value. This research found that "most valuable" is not defined as 'most popular', 'most talented', or 'most prolific scorer'. Rather, most valuable is simply defined as the player whose production is estimated to represent the most wins.". Berri created several econometric models; per-minute production, per-minute team tempo factor, per-minute team defense factor, and production of wins. All these models used statistics, both offensive and defensive, from NBA players who played from the 1994-1995 season to the 1997-1998 season. Berri's research concluded that there is one way to analyze "value". He found that the marginal value of each productivity statistic is an important contributor. Berri argues that this value is different based on the team. Essentially, a player's marginal value will depend on the skill level of their teammates. However, Berri also stated that it would be misleading and incorrect to surmise a player's value from points scored or given up because basketball is a team sport. The main finding from Berri (1999) is that the empirical value of an NBA player can be determined and therefore used to determine worth.

Minutes have been observed to be a very important metric for determining value in professional basketball. Minutes are effective in measuring a player's long-term productivity, usage rate, and production curve (Page, Barney, McGuire, 2013). In their model, they wanted to estimate the players long term production curves, in order to observe what effect position, usage rate, and minute played has on the individual curves. By estimating their model using a hierarchical Bayes model regression and Gaussian Process they were able to estimate the entire career production curve. They did not want to just focus on the “prime” point in a player’s careers in order to get a full picture of their production. Through their investigation they concluded that players with high minutes and high usage rates, have more dramatic changes over their career compared to those with low minutes. This implies that a player who is getting a lot of minutes, is going to see more dramatic shifts because of the wear and tear on their body.

In a similar study, (Page, Fellingham, and Reese, 2007), they looked at what skills each positions needs most to contribute to a team’s success. Both (Page, Fellingham, Reese, 2007) and (Berri, 1999) hoped to find a correlation between the productivity of an individual player and team wins. Berri was able to link individual NBA statistics to their team’s success with his regression model. This study also utilizes NBA player statistics, 10 different performance variables, and also a hierarchical Bayes model to estimate position specific skills contributions to wins. The results indicated that for all positions out assisting their opponents had very positive results on team wins, and in general players who are able to preform multiple skills/ multiple positions are more valuable. In all of these studies, they used player statistics, relative data, a regression model created to estimate value. Value of professional basketball players can be determine in multiple different ways, with a many different focuses, but the centralized method is the same.

Comparison of WNBA and NBA

At first glance it could be surmised there are few differences between the NBA and WNBA. However, upon further investigation the first difference is size of the league. The NBA is a larger organization than the WNBA. The WNBA includes fewer teams and players. To uncover whether statistical differences between the leagues exist, apart from the personal differences, a two-sided t-test was computed between the average statistics of the NBA and the

WNBA. This type of test is used to determine whether to reject or fail to reject the null hypothesis that the means of the two variables are the same. If the means are the same, the variables are not statistically different. However, if the means are not the same it provides evidence that the variables are statistically different. The results of these tests are included in Table 1 below.

Table 1 Two-Sided t-test between NBA and WNBA

	MIN	FGPCT	3PA	FTPCT	PTS	REB
WNBA Avg.	19.59	41.85	0.25	74.40	3.15	2.30
NBA Avg.	18.65	25.2	0.30	45.40	15.05	2.85
p-value	0.44	0.0016	0.00000023	0.0000072	0.014	0.019

From this table it can be noted that Minutes is only variable that is not statistically different between the NBA and WNBA. To dive into these differences more summary statistics were computed. Table 2 and Table 3 can be used to show that WNBA players average more minutes per player as well as a better field goal percentage and free throw percentage per player.

Table 2 Summary Statistics for WNBA Productivity Measurements

Statistic WNBA	N	Mean	St. Dev.	Max	Min	Median	Pctl(25)	Pctl(75)
Year	289	2015	0.5	2016	2015	2016	2015	2016
MIN	289	19.59	8.19	34.7	2.4	18.9	12.9	27
FGM	289	2.77	1.73	8.5	0	2.5	1.4	3.8
FGA	289	6.41	3.77	19.4	0.4	5.8	3.5	8.4
FGPCT	289	42.34	8.35	66.5	0	41.8	37.9	47.1
THREEPM	289	0.49	0.55	2.7	0	0.3	0	0.9
THREEPA	289	1.5	1.53	7.7	0	1.1	0.1	2.5
THREEPPCT	289	22.86	17.04	100	0	27.9	0	34.5
FTM	289	1.53	1.24	6.7	0	1.2	0.6	2.1

FTA	289	1.92	1.46	7	0	1.5	0.8	2.5
FTPCT	289	76.72	15.06	100	0	79.2	71.4	85.7
OREB	289	0.86	0.67	3.1	0	0.7	0.4	1.2
DREB	289	2.39	1.55	8.9	0.1	2.1	1.3	3.1
REB	289	3.25	2.1	10.1	0.1	2.8	1.8	4.2
AST	289	1.64	1.26	6.3	0	1.3	0.6	2.3
STL	289	0.71	0.44	2.3	0	0.6	0.4	1
BLK	289	0.4	0.51	4	0	0.2	0.1	0.5
PTS	289	7.56	4.79	23.4	0.1	6.7	3.7	10.4

Table 3 Summary Statistics for NBA Productivity Measurements

Statistic NBA	N	Mean	St. Dev.	Max	Min	Median	Pctl(25)	Pctl(75)
Year	962	2015	0.5	2016	2015	2016	2015	2016
MIN	962	20.03	9.14	42.4	0.8	19.8	12.9	27.6
FGM	962	3.12	2.11	10.3	0	2.6	1.5	4.3
FGA	962	6.93	4.47	24	0	5.9	3.6	9.4
FGPCT	962	44.18	9.47	100	0	44	40	48.48
THREEPM	962	0.73	0.74	5.1	0	0.5	0.1	1.2
THREEPA	962	2.08	1.91	11.2	0	1.65	0.5	3.27
THREEPPCT	962	27.37	15.55	100	0	32.55	22.05	37.1
FTM	962	1.43	1.37	9.2	0	1	0.5	1.8
FTA	962	1.89	1.69	10.9	0	1.4	0.8	2.5
FTPCT	962	71.89	18.35	100	0	75.65	66.7	82.7
OREB	962	0.86	0.77	4.9	0	0.6	0.3	1.2
DREB	962	2.73	1.79	10.3	0	2.4	1.5	3.5
REB	962	3.59	2.42	14.8	0	3.05	1.9	4.7
AST	962	1.83	1.76	11.7	0	1.2	0.6	2.3
STL	962	0.64	0.42	2.1	0	0.6	0.3	0.9
BLK	962	0.4	0.43	3.7	0	0.3	0.1	0.5
PTS	962	8.39	5.86	31.6	0	7	4.03	11.1

Referring to Table 1, the null hypothesis in this case was that the mean of the variable for the WNBA is the same as the mean of the variable for the NBA. The level of significance used is 99%. For minutes, the p-value is greater than .10 therefore we fail to the null hypothesis that the means are statistically the same. For FGPCT, 3PPCT, FTPCT, PTS, and REB the p-value is less than 0.10, so we reject the null hypothesis that the means of these variables are statistically the same. What this data indicates is that all variables except minutes are statistically different between the NBA and WNBA. What these statistics indicates is that on average players in the WNBA had a better shot accuracy than the NBA players, however the NBA had higher three-point percentage, points, and rebounds. Leavy (2015) observed that men shot more 3 pointers than the women because of the different ways they play the game. In the WNBA, the 3-point shot has been de-incentivized by making the point gain worth less for the risk of taking the shot. Analysists claim that one difference between the WNBA and the NBA is the difference of the emphasis on game play versus entertainment. The WNBA contracts are not nearly as large as NBA contracts. Additionally, in the NBA much of the game has shifted to accommodate what the fans want to see. NBA fans are looking for entertainment, and so the NBA has adapted from a more game play focused event to something else entirely. The line between positions has been blurred, and the number one focus seems to fall on shooting. In fact, coaches may be putting too much focus on scoring and misusing their players skills to see them shooting more baskets (Hinton, Sun 2019).

The difference between the way the game is played between the leagues can be attributed to the different rules and regulations that the women and men play with. The ball that the women play with is smaller than what the men play with. The ball for WNBA and women's NCAA basketball has a circumference of 28.5 inches while the circumference for the NBA is 29 7/8th

inches. This difference in size does not just apply to the basketballs. The women's 3-point line is 19 feet 9 inches in distance from the hoop, while the NBA line is 22 feet. Additionally, the shooting lane on WNBA courts is 12 feet wide, 4 feet narrower than in the NBA. These differences have been a part of the game since the WNBA's beginning in 1996. This information can also be found below in table 4 for easier side by side comparison.

	Ball Size	Game Length	3 Point Line	Shooting Lane	Shot Clock	Draft Age	Roster Size
WNBA	28.5 in	40 mins	19 ft 9 in	12 ft wide	30 sec	22 yrs.	12 max
NBA	29.87 in	48 mins	22 ft	16 ft wide	24 sec	19 yrs.	15 max

Table. 4

The differences in the sport can be traced back to women's beginnings in sport. In fact, when women started making their way into the world of football in Europe, they were met with intense opposition. In the text *Futbolera* by Brenda Elsey and Joshua Nadel an in-depth history is provided about how difficult it was for women to break into the world of football (American Soccer) for women, and all the criticism and discrimination they faced. The author details what the Brazilian government wanted to do for a physical education program for women, which followed the Swedish model. Essentially, they wanted to allow women to only participate in sports such as gymnastics and dance or walking and light jogging. This was to help maintain their "feminine physique" and teach them how to be graceful. Despite this plan, many women in Brazil pursued soccer as it was a very popular sport in their country. They were mocked for being too manly, and often time were only able to secure playing time at circuses. The belief was the women need to maintain their small, dainty figure, and playing sports that built muscle would not agree with the female identity. The connection back to the WNBA is that most female sports were created after the men had been playing for years, and they were "adapted" for the women so that they wouldn't be as intense or as "masculine". The remnants of this are the smaller equipment and court in the WNBA, which is justified today by the thought that on average women have smaller hands. Nadel and Elsey feel that these types of differences are simply justifications to maintain the suppression of women's sports and idea of superiority of men in sports. (Nadel and Elsey, 2019)

Data

The data that will be used in the first section of this study was compiled from NBA.stats and WNBA.stats. The data includes all players and their statistics from the 2015-2016 and 2016-2017 seasons. Table 5 lists the variables that will be used in the model. It is important to note that all of these variables are the relative averages per game calculated from an entire season of data for each player. The reason relative averages are so important is because it provides data that takes into account the variation in a player's performance over time and based on their specific position. We cleaned the data, and formatted it with the variables that we needed, in relative form, as well as with the players who played under our minute's threshold removed.

Table 5.

Variable	Description
MIN	average minutes played per game
FGPCT	field goal percentage per game
THREEPA	average three-point attempts per game
FTPCT	average free throw percentage per game
REB	average number of rebounds per game

AST	average number of assists per game
STL	average number of steals per game
BLK	average number of blocks per game
FGA	average number of field goals attempted per game (shots not including free throws)
THREEPPCT	average three-point percentage per game
OREB	average number of offensive rebounds per game
DREB	Average number of defensive rebounds per game

In order to adjust for outlier bias, players who averaged less than 5 minutes per game were excluded. Linear models were run, one using the data for the WNBA and one using the data from the NBA, with minutes as the dependent variable and productivity measurements as the independent variables. The independent variables were THREEPPCT, FGPCT, FTPCT, BLK, STL, AST, OREB, and DREB.

Results

The variables THREEPPCT, and FGPCT were not significant in the WNBA model while STL and both OREB and DREB were significant at the 99% level. The NBA model saw THREEPPCT significant at the 99% level, but FGPCT was also not significant. Another interesting conclusion from this data is that both leagues has very similar FTPCT, which for both models is significant at the 99% level.

Table. 6

Observations	205	760
R^2	0.79	0.74
Adjusted R^2	0.79	0.74
Residual Std. Error	3.69 (df = 196)	4.30 (df = 751)
F Statistic	94.73^{***} (df = 8; 196)	273.88^{***} (df = 8; 751)
Note:		$^{*}p^{**}p^{***}p<0.01$

WNBA Model

	Estimate	Std. Error
(Intercept)	-2.349344	2.260509
THREEPPCT	0.017562	0.036952
FGPCT	0.043099	0.048510
FTPCT	0.096271	0.024756
BLK	-2.398105	1.477272
STL	4.230182	0.880600
AST	2.316085	0.298135
OREB	2.177949	1.022308
DREB	1.952062	0.339905

NBA Model

	Estimate	Std. Error
(Intercept)	-1.053693	1.618841
THREEPPCT	0.093269	0.024727
FGPCT	0.038972	0.029383
FTPCT	0.064546	0.016026
BLK	0.129417	0.882688
STL	7.804409	0.583921
AST	0.843841	0.155770
OREB	-0.420811	0.482332
DREB	2.183273	0.220812

Econometric Testing and Conclusion

In order to assess the strength of both of these models, there was several econometric tests performed. Both models were tested for serial correlation, multicollinearity, specification error, and heteroskedasticity. In the WNBA model, the Ramsey reset result in a p-value less than .05, which indicates an error with the specification of the model. This is not unexpected because when working with data in the realm of professional sports, there are so many small variables that we either unable to control for or unable to observe. The Durbin-Watson test was preformed and with a low p-value, this is evidence that the model has serial correlation among the variables. This again is not surprising, because the variables we used are game statistics, which can overlap in areas. The Breusch-Pagan test also resulted in a low p-value indicating the model has heteroskedasticity. In order to correct for the serial correlation and heteroskedasticity the coeftest was ran in R to generate new corrected coefficients and standard errors for the model. The same tests were performed on the NBA model, with very similar results. There were also mis-specification issues, heteroskedasticity, and serial correlation. The reasoning behind this is the same as for the WNBA, there are so many variables we were not able to control for or cannot be measured and the metrics used to measure performance overlap in several areas. The variance inflation factors for all variables for both models were below 5, which indicates that there is not multicollinearity in either model. The heteroskedastic and serial correlation corrected coefficients and standard errors were also generated for the NBA model.

The differences among men's and women's sports is always a very interesting topic to research. In this capacity, we were interested in observing the statistical differences between how female pro-basketball players perform compared to men, as well as how the productivity metrics interacted with minutes between the leagues. Some notable conclusions were that women averages more minutes per game than men, but men average high points scored per game. The way these variables influences minutes was more difficult to determine due to the inconsistency of minutes between positions. After observing the way these specific variables interact with the minutes a professional basketball player is given, we were interested to investigate the value of a player even further. If analyzing how their minutes player is or isn't affected by the players performance metrics, the next logical step is to bring salary into the equation. Unfortunately, we were not able to continue the regression with the WNBA because after researching, contacting experts, and digging on all WNBA sites, the salaries for the women are simply not readily available for the public to see. The following section of this paper is focused on how players performance effects their salary, through the lens of the sunk-cost effect. This was a topic that came up in further research on economic questions about professional sports. The analysis we completed is not focused on making specific policy recommendations, but rather to study and observe how this economic and psychological effect exists in the world of professional basketball.

SECTION II: An Empirical Investigation of the Sunk Cost Fallacy in the NBA

Sunk Cost Introduction

The desire to have highly paid players in the game has more than one motivation. One motivation may be related to the sunk cost fallacy. The sunk cost fallacy is described as; as the spending for a person or thing increases, the perceived need to get the most out of that financial decision increases. It is well explained how this theory presents itself in professional basketball by Hinton and Sun (2019). Sunk costs are costs that once incurred, cannot be recovered. The sunk cost fallacy is when decision makers ignore this fact and continue to include them when making economic decisions. This section of the paper aims to find what role the sunk cost fallacy plays in the minutes played by NBA players. In the NBA this can be seen in situations where highly paid players get more minutes simply because the organization diverted a larger portion of their team salary towards this player. The fallacy is seen where the highest paid players receive the most minutes, regardless of productivity, to feel as though some of this cost is being recovered

Literature Review

Research has been conducted to uncover if the sunk cost fallacy exists. A reason why NBA teams may be falling victim to the sunk cost fallacy so often could have something to do with the elusive goal of creating a "winning" franchise. Staw and Hoang (1995) mention that there have been several studies on why people continue to throw money at a goal even if its not going to change the results, (see Staw and Ross, 1987, 1989; Brockner, 1992), and with the NBA, in particular, most operate under the assumption that spending more money on big name players will result in improving a team's performance. This study by Staw and Hoang(1995) used players draft order as their initial cost measurement, and then analyzed the influence this initial cost had on a player's utilization by a team.

> “Because of the vagaries of forecasting talent, teams may have invested more in some players than is merited by their performance on the basketball floor. Therein lies the sunk-cost dilemma. Do teams use players they have expended the most resources to attract, even if their performance does not warrant it? Likewise, do teams retain high-cost players, beyond the level warranted by their performance on the court” (Staw and Hoang, 1995)

Staw and Hoang (1995) used minutes played as the dependent variable, and then as independent variables they used a performance index they created from gathering player statistics. This research found that scoring was the performance variable most associated with higher minutes. Additionally, they found that draft order was “a significant predictor of minutes player over the entire five-year period [that they had data from].” With every one-unit decrease in draft number, the players minutes in their second year decreased by up to 23%. This study looked at 5 consecutive years following players being drafted, and they found that the draft number was a significant factor up to 5 years later. .

The existence of the sunk cost fallacy is seen through the results of study done by Hinton and Sun (2019). This research looked at the effect of player salary on player utilization in the NBA. Their research looked at the sunk cost fallacy when dealing with NBA player salaries in relation to players minutes. A fixed effects model holding constant player performance and comparing salary to minutes was analyzed. It was found that salary should have no effect on playing time IF teams are able to ignore sunk costs. They found that the coefficient for the variable *ln(salary)* to be positive 0.824 and significant at the 5% level when looking at win shares per 48 minutes without a lagged experience variable. The meaning behind this coefficient is that salary increases by 8.2% for each one unit contributed to win shares. It was also found *ln(salary)* was significant at the 5% level with a positive coefficient of 1.15 when a lagged variable for experience was included. The author concluded that the sunk cost fallacy exists in the NBA even when the other factors that contribute to game time are considered. The fact that the variable for salary is affected by the model when player performance is held constant indicates that there are other variables effecting salary outside of player performance statistics. This finding supports the conclusion that when a player is paid more in the NBA, they are played based off what the team "should" get out of the player due to their salary.

In a well renowned paper on the theory of sunk cost, Arker and Blumer (1985) demonstrate an economic motivation behind sunk cost. The figure below is called the value function of prospect theory. This graph models the value, gains, and losses that a person feels while making economic decisions.

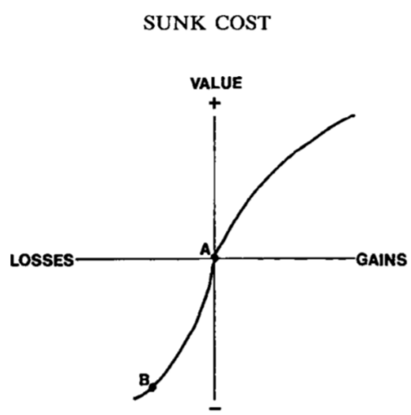

FIG. 1. The value function of prospect theory (Kahneman & Tversky, 1979).

This graph demonstrates that when someone is already at a perceived "loss", they are more willing to take other small losses to reach a bigger gain. Someone who has just paid a sunk cost would be at point B, feeling as though they have already lost something due to these non-recoupable costs. They want to get themselves to a large gain to compensate for their costs, so they are more willing to expend more small losses, or sunk costs in order to get the most "bang for their buck". How this comes into play in the NBA is with contracts being signed before players begin their time with the team. NBA team managers make the decisions on how much money to spend on what players before the player has performed for them. Theses sunk costs are then what motivates the players minutes, because the franchise is unable to escape the feeling of loss. They are then also willing to continue spending money on these players, such as training costs and game bonuses, if they believe it will get their players to a top level of performance that will then get them the most out of their “investment”.

Garland (1990) researched the idea that sunk cost influences a person’s decision to escalate a commitment to an ongoing project. This is an that could apply to NBA team decisions, as discussed above with the value function of prospect theory. If players are paid their contract salary, and it is a sunk cost, then the team manager might feel inclined to continue spending on that player to assure that they see a profitable return on their investment.

Data

The data for the model was retrieved from NBA.com/stats. The player statistics from the years 2016, 2017, and 2018 were gathered, and cleaned. The individual player salaries per year were taken from basketballreference.com and added to the data set. We then generated the relative statistics in R, using the original data and the equation for relative player statistics from David Berri. Log of wage is the dependent variable, and the performance statistics of the players will be the independent variables. The reason for this is to find how the players performance and minutes correlate to their salary, and to observe what patterns, arise from higher salaries players. Once the connection between player salary and minutes is established, it will be possible to look at specific variables to see if certain positions indicate more minutes played. If a player has performance statistics that do not correlate with higher minutes, but they do have a very high salary and audience, then it could be said that the sunk cost fallacy effect influenced their minutes.

Empirical Model

	Estimate	Std. Error
(Intercept)	-17.201525	3.778213
rel_fgm	-0.137443	38.570514
rel_2pm	22.591237	12.828120
rel_astm	6.068829	2.790320
rel_blkm	-1.698112	6.665762
rel_drbm	-6.451458	2.651847
rel_ftm	3.432887	13.197649
rel_orbm	-13.788569	6.109319
rel_pfm	-35.224765	18.791924
rel_ptsm	1.468045	12.733868
rel_stlm	0.344862	5.211072
rel_tovm	-18.033507	7.686108
logwage	1.525533	0.177480

Constant	-17.20***
	(1.57)
Observations	1,470
R^2	0.78
Adjusted R^2	0.77
Residual Std. Error	4.37 (df = 1424)
F Statistic	109.56*** (df = 45; 1424)
Note:	*p**p***p<0.01

**The team and positions were controlled for using dummy variables*

This regression yielded some significant results. We observed that the variable logwage is significant at the 99% level, and the coefficient indicates that for everyone on unit increase in the players wage correlates with a 1.53% increase in relative minutes played per game. Based on the research on sunk cost and its effect in the NBA, this unexplained increase in minutes with higher salary could be an indication of the sunk cost fallacy in effect. If a player is receiving more minutes with an increase in wage this could indicate the general manager trying to recoup these sunk costs, by getting more minutes out of higher paid players.

Econometric Testing

In order to test the legitimacy of our model further we preformed a fixed effects and random effects model, as well as the econometric testing for multicollinearity, serial correlation, omitted variable bias, and heteroskedasticity. The fixed effects model is used to remove omitted variable bias over time by using dummy variables for the missing characteristics. A random effects model is used to control for unobserved heterogeneity in the data, and since our data has so many different individuals there are countless factors that we did not observe. After using both the fixed and random effects model, a Hausman test was preformed, and this tells us which estimator is more consistent. Based on the results of the Hausman test we fail to reject the null hypothesis that the preferred model is random effects and therefore use fixed effects. In order to test our model for a specification error, the Ramsey reset test was performed. The p-value for this test was well below .05, which means we fail to reject the null hypothesis that the value of the coefficients is equal to zero and the model is mis-specified. It makes sense for there to be mis-specification issues with the regression because there are many small variables that we were not able to control for in this instance. To test our model for serial correlation, the Durbin-Watson test was preformed in R. The Breusch-Pagan test was also performed to test the model for heteroskedasticity, and the p value was very small indicating this problem existed in our model as well. Using the *coeftest* in R we were able to generate coefficient and standard errors that were corrected for heteroskedasticity and serial correlation.. Finally, the model was tested for multicollinearity by calculating the variance inflation factors of all the independent variables. The variables rel_astm, rel_tovm, and rel_ftm all had variance inflation factors over 5, which indicates there could be a multicollinearity issue with these three variables.

Ramsey Reset Test

```
        RESET test

data:  NBAmodel
RESET = 230.62, df1 = 3, df2 = 1421, p-value < 2.2e-16
```

Durbin-Watson Test

```
        Durbin-Watson test

data:  NBAmodel
DW = 1.4097, p-value < 2.2e-16
alternative hypothesis: true autocorrelation is greater than 0
```

Breusch-Pagan Test

```
        studentized Breusch-Pagan test

data:  NBAmodel
BP = 878.6, df = 45, p-value < 2.2e-16
```

Variance Inflation Factors

```
> vif(NBAmodel)
     rel_fgm      rel_2pm     rel_astm     rel_blkm     rel_drbm      rel_ftm 
2.045065e+05 1.224682e+04 7.510055e+02 1.635577e+01 2.342693e+02 5.789023e+03 
    rel_orbm      rel_pfm     rel_ptsm     rel_stlm     rel_tovm      logwage 
3.911606e+01 1.061005e+02 1.749728e+05 1.555670e+02 6.567646e+02 1.443117e+00 
         ATL          BOS          BRK          CHI          CHO          CLE 
1.993691e+00 1.851006e+00 1.995604e+00 1.908231e+00 1.994534e+00 1.987512e+00 
         DAL          DEN          DET          GSW          HOU          IND 
2.171907e+00 2.043160e+00 1.953563e+00 1.991161e+00 2.088512e+00 1.881383e+00 
         LAC          LAL          MEM          MIA          MIL          MIN 
1.969090e+00 2.051948e+00 2.169195e+00 1.874826e+00 2.060048e+00 1.927946e+00 
         NOP          NYK          OKC          ORL           PF           PG 
2.256044e+00 1.955405e+00 1.993129e+00 1.947164e+00 1.458059e+00 1.519566e+03 
         PHI          PHO          POR          SAC          SAS           SF 
2.004258e+00 2.157421e+00 1.930748e+00 1.968630e+00 1.943165e+00 1.208681e+00 
          SG          TOR          UTA 
1.247729e+00 1.930702e+00 1.997483e+00 
```

Conclusion

Through our research on the sunk cost fallacy's presence in the NBA, several interesting conclusions could be drawn. The fact that the log of wage variable is so statistically significant in our regression was evidence that pointed to the sunk cost fallacy influencing salary in the NBA. Our model had relative minutes set as the dependent variable, and so the logwage variable being significant was an important relationship for this model. The coefficient on logwage of 1.52 indicates that with a 1% increase in salary there is a 1.52 minute increase in a players minutes, keeping constant all performance metrics. The entire theory of the sunk cost fallacy is that when we pay recoupable costs, we feel as though we are at a loss now and need to make sure we get "the most bang for our buck" even though there is no way to actually get back the sunk costs already spent. If teams are putting a hefty amount of money into specific player contracts, then they will feel the need to pressure the coaches into giving that player more minutes in order to get the most out of their sunk cost. The aim of this study was not to be able to give concrete policy recommendations but rather to investigate this phenomenon in professional sports. The results of our regression are not concrete evidence, but they indicate an unexplained positive relationship between minutes and salary. Further investigation would require looking even more in-depth on the factors that contribute to player minutes, salary and any outside factors that may influence a player's minutes.

Bibliography

Adler, Moshe. 1985. "Stardom and Talent." *The American Economic Review* 208-212.

Arkes, Hal R., and Catherine Blumer. 1985. "The Psychology of Sunk Cost." In *Organizational Behavrior and Human Decision Process*, 124-140. Ohio University .

Berri, David. 1999. "Who Is 'Most Valuable'? Measuring the Player's Production of Wins in the National Basketball Association." *Managerial and Decision Economics* 411-427.

Boren, Cindy. 2017. "'A prosecutable offense': Cavs ripped for resting LeBron, fellow stars in high-profile game." *The Washington Post*, March 19.

Elsey, Brenda, and Joshua Nadel. 2019. *Futbolera: A History of Women in Sports in Latin America.* Univesity of Texas Press.

Fellingham, Gilbert W., and C. Shane Reese. 2007. "Using Box-Scores to Determine a Positions Contribution to Wunnung Basketball Games ." *Journal of Quantiative Analysis in Sports.*

Garland, Howard. 1990. "Throwing Good Money After Bad: The Effect of Sunk Cost on the Decision to Escalate Commitment to an Ongoing Project." *The Journal of Applied Psychology* 728-731.

Hinton, Alexander, and Yiguo Sun. 2019. "The sunk-cost fallacy in the National Basketball." *Empirical Economics* .

Humphries, Brad, and Candon Johnson. 2019 . "The Effect of Superstars on Game Attendance: Evidence from the NBA." *Journal of Sports Economics.*

Kaplan, Scott, interview by Paul Michelman and Ben Shields. 2019. *The Economic Impact of Sitting NBA Superstars* (May 2).

Kaplan, Scott, Vaibhav Ramamoorthly, Cheernar Gupte, Amit Sagar, Deepak Premkumar, Joshua Wilbur, and David Zilberman. 2019. "The Economic Impact of NBA Superstars: Evidence from Missed Games using Ticket Microdata from a Secondary Marketplace." *UC Berkley* .

Rosen, Sherwin. 1981. "The Economics of Superstars." *The American Economic Review* 845-858.

Schmidt, Martin, and David Berri. 2007. "Does One Simply Need to Score to Score?" *International Journal of Sports Finance* 142-148.