**MEASURING THE IMPACT OF DISCIPLINE ON NBA PLAYER PERFORMANCE**

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**Abstract**

This study examines the impact of suspending players in the National Basketball Association (NBA) on post-suspension performance. This is done by observing both productivity changes and behavior changes via box score statistics pre and post-suspension, identifying characteristics of player suspensions that contribute to those changes, and measuring their marginal impact. Through this method, coaching staffs, NBA front offices, and die-hard fans will have an improved understanding of how they can expect basketball players to perform for or against a team following disciplinary action.

1. **Introduction**

The National Basketball Association (NBA) has spiked in popularity in recent years, and league viewership is at an all-time high. Moreover, the emergence of the field of basketball analytics has shifted teams’ in-game objectives toward shooting more three-pointers and high-percentage shots close to the rim on offense, and forcing long midrange jumpshots on defense. In fact, the 2017-18 Houston Rockets became the first team in NBA history to attempt more 3-point shots than two point shots in a season (Basketball-reference, 2018). This has made the game more exciting and viewer-friendly, while helping teams make the most of each possession.

While the statistical strategy of how to play the game at peak efficiency has been thoroughly studied by basketball researchers and enthusiasts such as Dean Oliver (2004), some exogenous factors which influence player performance such as player discipline have not been fully analyzed. With social media providing increasing amounts of access to basketball fans, there are now more eyes on player actions and emotions within the game than ever. Despite being the third most popular league (behind the National Football League (NFL) and Major League Baseball (MLB)) in 2015, the NBA has amassed over 92 million followers across Facebook, Twitter, and Instagram through July of 2018 (Public Policy Polling, 2016). This number exceeds the NFL’s (52.5 million followers) and MLB’s (19.4 million followers) combined. As a result of increased monitoring by its fan base, it has become imperative for the NBA and NBA franchises to closely monitor and discipline players when they fail to uphold the high behavioral standards expected of professional basketball players.

To preface the motivation of this study, the NBA league office is responsible for handing out discipline to players upon review or investigation of questionable incidents (NBA Rule Book, 2015-2016). The league office is comprised of the league commissioner and his cabinet. (NBA Rule Book, 2015-2016). In addition to league discipline, individual teams may punish their players for violating team rules. Bearing this in mind, the league and especially its teams need to understand the perhaps unforeseen on-court impact that disciplinary actions may have on player performance, if a team intends to optimize its on-court performance and if the league wants its players to play to their capabilities. This study estimates the average effect that NBA player suspensions have on player performance, and by accomplishing this task, team management can better anticipate the impact that suspensions have on player productivity post-suspension. Such information will potentially yield results that would allow teams to adjust their gameplans to improve overall team performance.

NBA players are unique individuals, but if there is indeed an impact of suspensions on in-game performance post-suspension, we would expect it to only be temporary. Just as the amount of time it takes players to fully recover from a similar physical injury varies from player-to-player, there may be variability in the recovery time from a suspension effect. Moreover, it is hypothesized that the effect, should it exist, would be most noticeable in the first game the player plays after serving his suspension.

Two hypotheses will be statistically tested. The first is the positive effect hypothesis, which would entail the player being more productive in the game following a suspension than before he was suspended. This may be a result of the player having extra motivation to make up for missed games due to the suspension, or having extra motivation due to the nature or cause of the suspension. The second hypothesis is the negative effect hypothesis, which entails the player being less productive in the game than before being suspended. This effect may be a result of loss of rhythm and/or physical conditioning, or the player feeling shame for his actions which negatively affect his on-court performance.

1. **Literature Review**

While there is limited research pertaining to the effects that discipline has on NBA player performance, some studies have found relationships involving the characteristics of NBA player discipline. McCutcheon (2016) found that NBA players who have a history of being punished via fine or suspension are less likely to be deterred from once again committing a punishable offense, compared to players who have fewer previous offenses. The average amount of time between punishments is less for players with more offenses (McCutcheon, 2016). This implies that players with a history of being punished are more likely to continue the deviant behavior that resulted in a suspension in the future. However, this research focused on both fines and suspensions, and did not focus on game performance post-suspension.

The majority of NBA suspensions come as a result of fighting and intimidation (Nagel, 2004). The NBA has also had more fighting caused suspensions than the other three major North American sports from 1995-1999, despite basketball being categorized as a non-contact sport (Nagel, 2004). The 2015-16 NBA rule book has a section dedicated specifically to the consequences of fighting, motivated by the negative image that fighting tends to paint the league (NBA Rule Book, 2015-2016).

Public perception of professional athletes (and the NBA in particular) is another relevant area of prior research. In a 2015 national survey of 1,009 adults, more than half responded that professional athletes serve as worse role models than “10 to 20 years ago” (Cohn, 2015). Cohn (2015) also notes that the growth of technology and social media has played a large part in this change in public perception of professional athletes. Player wrongdoings rarely go unnoticed with the advent to 21st century technology. News of athlete misbehavior was reported on 22 out of 28 days in February, 2009 according to Kim and Parlow (2009). The public nature of player punishments may have some psychological bearing on the disciplined player due to their image being tarnished. This is somewhat unjust, considering that arrest rates among athletes in the four major North American sports leagues were lower than the national average arrest rate for males between the ages of 20 and 39 (Leal et al., 2015, Tracy, 2014).

Historically, the NBA’s image hasn’t always been as pristine as it currently is, and its restoration is likely a function of today’s stricter league suspension policy. Berry and Smith (2000) acknowledge the aim of discipline in professional sport leagues is to discourage negative player activity. For example, the NBA dealt with a huge cocaine problem in the 1970’s and early 1980’s by banishing multiple players from the league, in order to improve its image. Once policies and other conduct codes were implemented by commissioner David Stern (hired in 1984), the popularity of the NBA began to grow, ultimately reaching the level it is today. Because of past issues, the NBA league office does not want its image tarnished again, and administers punishments accordingly. The results from Nagel’s (2004) study reaffirm this claim; he concludes that the four major North American professional sport leagues likely use punishments as a public relations tool and not as a meaningful deterrent to player behavior.

Other studies done in the realm of sport science have documented changes in the overall athletic performance of NBA players during the course of a season. It has been shown that compared to non-starters (i.e. players who are on the bench at tipoff), starting NBA players are better at maintaining their physical performance level and body composition over the course of a full season, showed greater improvement in vertical jump power and reaction time compared to non-starters, but tended to be more fatigued (Gonzalez, 2013). Gonzalez’s (2013) study documents that there are physical differences between starters and non-starters, which is likely to have an influence on their on-court performance.

1. **Research Methodology & Technical Terms**

Before the question “What effect does a suspension have on NBA player performance?” can be answered, a measure of player performance post-suspension is needed. Because this suspension effect is hypothesized to be most observable in the first game following suspension, the dependent variable of interest must also hold significance for a single game. However, basketball players can contribute to a game in a number of ways both positively and negatively, and there are many different linear combinations of box-score statistics that could qualify a performance as being “good” or “bad”. To account for this, a single measure of overall productivity needed to be used to measure game performance. One of the best per game metrics of measuring player productivity is John Hollinger’s game score statistic. Hollinger’s game score formula is reported as equation 1 below:

|  |
| --- |
| **Hollinger’s Game Score Formula**  Game Score = Points + (**0.4**\*Field Goals Made) - (**0.7**\*Field Goals Attempted) - **0.4**\* (Free Throws Attempted - Free Throws Made) + (**0.7**\*Offensive Rebounds) + (**0.3**\*Defensive Rebounds) + Steals + (**0.7**\*Assists) + (**0.7**\*Blocks) – (**0.4**\*Fouls) – Turnovers **(1)** |

Game score accounts for nearly every quantifiable box-score statistic of game performance, and weights each box-score statistic to follow the same scale as points scored (“What is Game Score”, 2015). A game score of 10 is considered average, while a game score of 40 is considered outstanding.

**Game Score Calculation Example: Carmelo Anthony**

The data set from this study includes a game played by Carmelo Anthony, who returned from a one game suspension for the New York Knicks against the Chicago Bulls in the 2012-13 season. Anthony finished the game with 39 points on 14-32 field goal shooting and 7-9 free throw shooting, along with 6 defensive rebounds and 2 offensive rebounds, 1 steal, 5 assists, 1 block, 3 fouls, and 3 turnovers. Therefore, Anthony’s game score for this game was

39 + (**0.4**\*14) – (**0.7**\*32) – **0.4**\*(9-7) + (**0.7**\*2) + (**0.3**\*6) + 1 + (**0.7\*** 5) + (**0.7\***1) – (**0.4**\*3) – 3 = 25.6.

In addition to the change in overall player productivity of a player observed through game score, more limited measures of player performance/activity can be used as dependent variables, and the impact of suspensions on these measures can be measured. For example, changes in personal fouls (PF), field goal attempts (FGA), free throw attempts (FTA), and turnovers (TOV) may be observed post-suspension. Moreover, in equation (1), each of these four measures captures negative behavioral response. These four box-score statistics may be used to construct separate response variables to capture changes in on-court player behavior, since players may be pressing harder and commit more fouls, turnovers, or shoot more upon returning from a suspension.

Instead of separately using field goal attempts and free throw attempts as response variables, a single statistic called true shot attempts which combines the two measures is likely a better overall measure. True shot attempts is computed as a separate function, i.e.

**True Shot Attempts Formula**

TSA = FGA + 0.44\*FTA  **(2)**

The true shot attempts formula recognizes that a field goal attempt is not counted when a player is fouled, unless the player scores the basket while being fouled on a field goal attempt. The coefficient of 0.44 indicates the population proportion of free throw attempts that result from a shooting foul. For this reason, true shooting attempts is a better measure of overall player aggressiveness in attempting to score than simply field goal attempts or free throw attempts. Further information regarding the true shot attempts statistic is reported in the glossary section of the appendix.

To make the game score statistic (or other response statistics) comparable across players, the measure must be adjusted for minutes played. Clearly if a player plays more minutes in a game than another player, he has more opportunities to boost his numbers in each statistical category. To account for this, all potential response statistics (game score, true shot attempts, fouls and turnovers) need to be normalized to a per-36 minute scale, and were transformed as shown in equation 3:

**Per-36 Minute Transformation:**

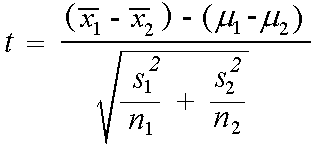
Response statistic per 36 minutes = 36\*(Response statistic/Minutes Played) **(3)**

To derive the dependent variable(s) used in the empirical regression models (the change in the response statistic pre and post suspension), the normalized average statistics needed to calculate game score were calculated for all games preceding suspension and the game immediately following suspension were obtained. The difference in the normalized average game score (or other response measures) before the player was suspended and the normalized game score (or other response measures) in the game immediately following the suspension were calculated. If a player was suspended multiple times in a season, the average difference was calculated using the statistics from the games starting from their return from their prior suspension, up until the suspension of interest. The box score data used in this analysis was collected from player game logs found on [www.basketballreference.com](http://www.basketballreference.com) and compiled into a Microsoft Excel spreadsheet.

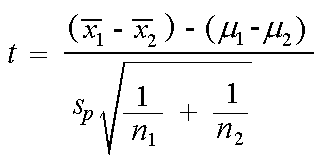
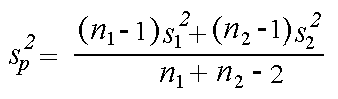
It is also important to control the difference in minutes played per game before and after suspension. If a player’s average minutes per game pre-suspension significantly differed from the minutes played in the game post-suspension, any results obtained using the normalized response measures would be vulnerable to imbalances in statistical extrapolation, which could introduce considerable error into the response variable. To account for this, a *t*-test is used to check whether minutes played per game pre-suspension (MP1) significantly differed from the minutes played in the first game post-suspension (MP2).

To perform the *t*-test, an additional test was conducted to determine the appropriate procedure. That is, an F-test should be conducted to determine if the pre and post suspension dependent variables’ variances are equal. If the two variances are not statistically different, the pooled variance *t*-test specification is used, as shown in equation 5. However, if the F-test rejects the null hypothesis of equal variances, the Welch’s *t*-test is used, as shown in equation 4.

**T-statistic for Welch’s T-test:**

  **(4**)

**T-statistic for pooled variance test:**

 **(5)**

After the prior *t*-tests are used to account for any error in extrapolating with minutes and then identifying potential response dependent variables (those which had a significant change in their pre and post suspension levels), a set of explanatory variables is specified to explain the change. Broadly speaking, it is hypothesized that the change in player performance can be explained by two dominant considerations: Suspension characteristics and player characteristics. A set of zero-one dummy variables was used to quantify suspension characteristics, and are listed in Table 1:

Table 1: Description of Suspension Characteristic Explanatory Variables

|  |  |
| --- | --- |
| Variable | Description |
| multi | Equal to 1 if the suspension was for more than one game, equal to 0 otherwise |
| ref | Equal to 1 if the incident which caused the suspension involved a referee, equal to 0 otherwise |
| phys | Equal to 1 if the suspension happened as a result of extreme physical contact with another player, equal to 0 otherwise |
| game | Equal to 1 if the incident which caused the suspension happened outside of a game environment, equal to 0 otherwise |

In addition to these suspension dummy variables, variables which describe a player’s characteristics are used as explanatory variables in the empirical analysis, and are outlined in Table 2:

Table 2: Description of Player Characteristic Explanatory Variables

|  |  |
| --- | --- |
| Variable | Description |
| vet | Equal to 1 if the suspended player had played at least 4 seasons, equal to 0 otherwise |
| FirstSus | Equal 1 1 if the suspension was the first of the player’s NBA career, equal to 0 otherwise |
| Start | Equal to 1 if the player had started in at least half of his games in the season before being suspended, equal to 0 otherwise |
| MP1 | The number of minutes the player averaged before being suspended |
| OppSRS | A measure of the strength of the opponent the suspended player played against in the game in which he returned from suspension (see glossary for further explanation of SRS) |
| age | The age of the suspended player in years |

The suspension data was obtained from [www.spotrac.com](http://www.spotrac.com) and consists of seven years of NBA suspension data (2010-11 to 2016-17) compiled into the afore-mentioned Excel spreadsheet. All suspensions occurring in the offseason and the postseason were eliminated from the dataset, as well as the rare cases in which a player was suspended, then failed to play in a game following suspension. In addition, if a player failed to accumulate at least 100 minutes played prior to suspension, the observation was removed from the data set.

1. **General Empirical Model Construction**

A standard multiple least squares regression model is proposed for establishing the relationship between the change in the normalized response variable and the explanatory variables chosen for each empirical model. The response variables are all continuous, and the general form of the regression models is:

Y = *β0 + β*1X1 + *β*2X2 +…+*βK*XK + ui **(6)**

where K is the number of explanatory variables chosen for a given model. The coefficients on the explanatory variables in the regression equation yield marginal effects on the response variable, and their t-statistics identify the statistical significance of specific factors which impact the response variable post-suspension. In effect, the empirical hypotheses being tested are a null hypothesis which claims that each *βK* = 0, against an alternative hypothesis that at least one *βK* ≠ 0. The sign on a statistically significant coefficient indicates the direction of impact each variable has on the change in the response variable.

The linear regression model is the model of choice because the parameters have an interpretation that can be translated from unit increases in the explanatory variables, to unit changes in box-score statistics. For example, a statistically significant coefficient of positive 10 on the explanatory variable “multi” in a regression with game score per 36 minutes as the dependent variable could be directly translated as the fact that a multi game suspension boosts offensive and defensive rebounds by 10 each (0.7\*10 + 0.3\*10 = 10) per 36 minutes post-suspension, after plugging functioning values into equation (1). This holds true for reasonable linear combinations of box-score statistics that when plugged into equation (1), sum to 10.

In this research, there are potentially four response variables that can be used. This potential set of dependent variables consists of change in game score per 36 minutes, change in true shot attempts per 36 minutes, change in personal fouls per 36 minutes, and change in turnovers per 36 minutes.

**Regression Model 1**

The basic empirical model proposed for predicting the change in the response variables post-suspension is labeled as Regression Model 1:

**Regression Model 1: Basic Individual Characteristics Model**

∆Response per 36 mins = *β0 + β*1(vet)+ *β*2(OppSRS) +*β*3(MP1) + *β*4(Age) + *β*5(vet\*Age)+ ui

(Denoted *β0 + β*1(vet) +…+ *β*5(vet\*Age) + ui)

Model 1 estimates the change in the response variable as the function of playing time (MP1), and opponent strength (OppSRS), in addition to maturity characteristics (vet, age). The coefficients *β*1, *β*2, *β*3, and *β*4 are the marginal effects of these explanatory variables on the change in the response variable, while the coefficient *β*5 captures the interaction effect of age and veteran status. Less experienced players are expected to have their productivity be more negatively affected by a suspension than a more experienced player. It is also hypothesized that returning to play against a tougher opponent is negatively related to the change in player productivity. The sign of the coefficient for minutes played is more difficult to predict than the other coefficients, but is expected to be negative since a player being thrust back into playing heavy minutes after sitting out would require more of an adjustment upon returning to action, compared to a player who sees limited game action. The minutes a player plays generally is a good measure of the player’s value to the team, and higher-caliber players are more likely to receive more media attention after being suspended compared to a lower-caliber player simply due to his popularity, possibly weighing on a player in his return to action.

**Regression Model 2**

Some of the most infamous suspension incidents in NBA history have resulted from excessive contact with another player (i.e. fighting, hard fouls, flagrant two fouls, etc.). A relatively recent example of this (not included in the dataset for this study) occurred in the 2012 NBA Playoffs when the Los Angeles Lakers’ Metta World Peace elbowed Oklahoma City Thunder guard James Harden in the head after scoring a basket, resulting in a seven game suspension, along with a swarm of media frenzy and controversy surrounding the incident. The most heinous physical incidents often result in multi-game suspensions from the NBA to set a precedent that such violent behavior is not tolerated. For these reasons, it is reasonable to add the variables phys, multi, and their interaction to capture the potential performance effects related to flagrant physical-based suspensions. Adding these variables to model 1 yields Regression Model 2:

**Regression Model 2: Basic Individual Characteristics Model, Accounting for Incident Severity Effects**

∆Response per 36 mins = *β0 + β*1(vet)+…+ *β*5(vet\*Age) + *β*6(phys) + *β*7(multi) + *β*8(phys\*multi)+ ui

(Denoted *β0 + β*1(vet)+…+*β*8(phys\*multi) + ui)

In Model 2, the coefficients *β*6 and *β*7 are the marginal effects that suspensions categorized as having resulted from extreme physical contact, and multi-game suspensions have on the response statistic per 36 minutes, respectively. The parameter *β*8 captures the interaction effect that suspensions stemming from physical incidents which result in multi-game suspensions have on the response variable. The sign of *β*6 is difficult to predict due to a number of conflicting factors, but because this coefficient would represent the effect for single game suspensions (i.e. less serious infractions), its magnitude is expected to be small. On the other hand, multi-game suspensions have the chance to disrupt a player’s rhythm, and both *β*7 and *β*8 are expected to be larger in magnitude.

**Regression Model 3**

Model 2 does not control for out-of-game incident suspensions, or referee related suspensions. Suspensions which occur outside of a game environment, as well as suspensions involving a referee may result in different suspension behavior than suspensions related to a physical altercation. Regression Model 3 adds these two additional explanatory variables to Model 2:

**Basic Individual Characteristics Model, Accounting for All Suspension Effects (Regression Model 3):**

∆Response per 36 mins = *β0 + β*1(vet)+…+ *β*8(phys\*multi)+*β*9(Game) + *β*10(Ref) + ui

In Model 3, *β*9 and *β*10 represent the marginal effects of out-of-game incidents and incidents that involve a referee, respectively. The magnitude of *β*9 is expected to be large, due to the fact that incidents that happen outside of a game environment tend to have legal implications, which generate much media attention. *β*10’s magnitude is expected to be small, simply because these suspensions tend to be the least deviant in their nature (ex. Earl Boykins’ 2010 suspension for touching a referee’s arm).

**Regression Models 4-6**

Prior research indicates that NBA players with a long history of being disciplined by the NBA are less likely to deter their negative behavior (McCutcheon, 2016). In addition, starters are also more likely to show signs of improved physical strength and reaction time than non-starters over the course of an NBA season (Gonzalez, 2013). Should both of these findings hold true for the study data set, it is necessary to control for these factors. Models 4, 5, and 6 were constructed to test for the consistency of prior research findings published in the literature. Model 4 is a modification of Regression Model 1, and Regression Model 5 is a modification of Regression Model 4. Model 6 extends Model 5.

**Regression Model 4 (Regression Model 1, Plus Accounting for Incident History & Player Role, {*β*6,*β*7,*β*8,*β*9})**

∆Response per 36 mins = *β0 + β*1(vet)+*…*+ *β*5(vet\*Age)+ *β*6(FirstSus)+ *β*7(vet\*FirstSus)+*β*8(START) + *β*9(START\*MP1) + ui

(Denoted *β0 + β*1(vet)+*…*+*β*9(START\*MP1)+ ui)

**Regression Model 5 (Regression Model 4, Plus Accounting for Incident Severity) , {*β*10, *β*11, *β*12, *β*13})**

∆Response per 36 mins = *β0 + β*1(vet)+*…*+*β*9(START\*MP1)+*β*10(phys)+*β*11(multi)+ *β*12(phys\*multi) +*β*13(multi\*START)+ ui

(Denoted *β0 + β*1(vet)+*…*+*β*13(multi\*START)+ ui)

**Regression Model 6 (Regression Model 5, Plus Accounting for All Suspension Effects, {*β*14, *β*15})**

∆Response per 36 mins = *β0 + β*1(vet)+*…*+*β*13(multi\*START)+*β*14(Game) + *β*15(Ref) + ui

InModel 4, *β*6 and *β*8 represent the marginal effect of a player’s first suspension, and the marginal effect of being a starter, respectively. The signs on both of these are likely to be negative, despite the fact that Gonzalez’s (2009) study showed that starters maintain their physical performance better than non-starters. The disruption in the rhythm of a starting caliber player due to the suspension is likely to negate the positive effects of being a starter.

To augment the simple effects in model 4, *β*7 and *β*9 control for the interaction effects of interest. *β*7 captures the additional effect that a veteran player experiences when he’s suspended for the first time in his career. This effect builds upon the maturity effect model 1 estimates, and is likely to be positive since it has been hypothesized that veteran status lessens the negative effect of being suspended. *β*9 controls for the player characteristic effect, which describes the additional effect that playing increased minutes has on the change in the response variable for starters. This effect is expected to be negative, since *β*3 and *β*8 have been hypothesized to be negative.

Model 5 adds the same variables to regression Model 4 that Model 2 added to Model 1, but with the inclusion of another interaction variable to account for the difference between the effects of multi-game suspensions on starters compared to non-starters. This marginal effect is estimated by *β*13, and is likely to be negative due to the starting player’s rhythm being disrupted further by missing multiple games.

Model 6 adds the same explanatory variables to regression Model 5 that Model 3 added from Model 2.

1. **Results**

Before discussing the empirical regression models, a brief overview of the summary statistics for the explanatory variables used in this analysis is presented in Tables 1 and 2:

Table 1: Summary statistics for all suspension characteristic variables of interest

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

The means of Table 1 indicate the proportion of suspensions with that particular characteristic (recall that the variable game is the label for an out-of-game suspension). Note that the sum of the means of the suspension characteristic dummy variables is greater than one, implying that every dummy variable pair is not necessarily mutually exclusive. If this had not been the case, then any dummy variable interaction involving two suspension characteristics in a proposed linear regression models would be useless. For example, a player could be suspended multiple games as a result of a physical altercation, which would make both multi and phys equal to one for that observation. Physical altercations are the most common cause of suspension, confirming Nagel’s (2004) findings, whose study used data from nearly two decades prior.

The summary statistics for the player characteristic variables analyzed in this study are reported in Table 2:

Table 2: Summary statistics for player characteristic variables of interest



Table 2 indicates that over half of the sample is players with over four years of NBA playing experience. Moreover, over half of the sample are starters and players whose recorded incident was the first suspension of their career. We can interpret the mean of the oppsrs variable by saying that the opposing team of a suspended player upon his return from suspension was on average 0.432 points better than an average team.

To discover if there was a significant overall impact of suspension on the four potential response variables, a *t*-test on the minutes played variables pre and post-suspension was performed to ensure that any interpolation or extrapolation of the response statistics used in this study would be equal on average. The appendix shows the results of the EOV test on minutes played pre and post-suspension, and rejects the null hypothesis that the variances of the two groups are equal. Therefore, a Welch’s *t*-test was the most appropriate method of determining any difference in minutes played pre and post-suspension. The results of this *t*-test are reported below in Table 3:

Table 3: Welch’s *t*-test on minutes played before and after suspension



Based on the results of the Welch’s *t*-test, we cannot conclude that there is any difference in the minutes played before suspension than after suspension. A lack of a significant statistical difference allowed for the per-36 minute adjustment to be performed on each response variable without introducing any potential bias into the constructed response variables.

This statistical finding allowed for the construction of the four potential response variables. The means for the change in the four potential response variables are reported in Table 4 below:

Table 4: Mean of the changes between response variable before and after suspension

|  |  |
| --- | --- |
| Variable (per 36 minutes) | Average Change (per 36 minutes) |
| Game Score | -2.198 |
| True Shooting Attempts | -0.516 |
| Personal Fouls | 0.436 |
| Turnovers | 0.253 |

Based on the above table, average game score and average true shot attempts decreased post-suspension, while fouls and turnovers increased. However, it was necessary to perform another set of *t*-tests to determine if the average change in each potential response variable was statistically significant.

Equality of variance tests were once again performed (once for each potential response variable) to determine which *t*-test procedure to use, and the results of these EOV tests in the appendix clearly show that the null hypothesis, which claims that the variances of the statistics pre and post-suspension are equal, can be rejected for every response variable. Due to unequal variance, the Welch’s *t-*test for a statistical difference in the response variable was used. The results of the test on each response variable are summarized below in Table 5. The only potential response variable that was statistically significant at the 5% level was the change in game score. Thus, all empirical analysis is limited to models where the dependent response variable is the change in game score.

Table 5: Welch’s *t*-test on difference in sample statistics before and after suspension

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Game Score/36 mins | True Shot Attempts/36 mins | Personal Fouls/36 mins | Turnovers/36 mins |
| t-value | 2.0849 | 0.6868 | -1.1649 | -0.9758 |
| p-value | 0.03091 | 0.4931 | 0.2463 | 0.3312 |
| 95% Confidence Interval | (0.112, 4.284) | (-1.998, 0.967) | (-0.305, 1.176) | (-0.260, 0.765) |

Table 6 presents the empirical results for the six regression models estimated. The models were estimated using STATA and the dependent variable in each model was the change in game score per-36 minutes.

Table 6: STATA output for linear regression models 1-6

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |
| VARIABLES | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|  |  |  |  |  |  |  |
| vet | 39.82\*\* | 36.31\* | 37.39\* | 25.19 | 23.74 | 25.09 |
|  | (19.06) | (18.59) | (18.85) | (20.08) | (19.26) | (19.63) |
| oppsrs | 0.355\* | 0.380\* | 0.388\* | 0.281 | 0.322\* | 0.331\* |
|  | (0.201) | (0.196) | (0.198) | (0.198) | (0.191) | (0.194) |
| mp1 | -0.150 | -0.109 | -0.102 | -0.632\*\* | -0.442 | -0.429 |
|  | (0.125) | (0.123) | (0.126) | (0.262) | (0.268) | (0.272) |
| age | 1.491\*\* | 1.562\*\* | 1.576\*\* | 1.309\* | 1.283\* | 1.300\* |
|  | (0.670) | (0.658) | (0.667) | (0.686) | (0.666) | (0.679) |
| Age\*vet | -1.685\*\* | -1.603\*\* | -1.647\*\* | -1.363\* | -1.353\* | -1.399\* |
|  | (0.746) | (0.727) | (0.738) | (0.752) | (0.722) | (0.736) |
| multi |  | -7.046\*\* | -6.948\*\* |  | -1.068 | -0.927 |
|  |  | (3.082) | (3.216) |  | (3.834) | (4.005) |
| phys |  | -2.553 | -1.172 |  | -3.300 | -2.151 |
|  |  | (1.988) | (2.918) |  | (2.017) | (2.899) |
| Multi\*phys |  | 13.09\*\*\* | 12.95\*\*\* |  | 11.77\*\* | 11.76\*\* |
|  |  | (4.755) | (4.879) |  | (4.777) | (4.884) |
| ref |  |  | 2.713 |  |  | 2.056 |
|  |  |  | (3.636) |  |  | (3.543) |
| game |  |  | 1.395 |  |  | 1.243 |
|  |  |  | (3.237) |  |  | (3.117) |
| firstsus |  |  |  | -5.570 | -5.390 | -5.232 |
|  |  |  |  | (3.748) | (3.641) | (3.688) |
| Vet\*firstsus |  |  |  | 9.811\*\* | 10.41\*\* | 10.10\*\* |
|  |  |  |  | (4.343) | (4.181) | (4.264) |
| start |  |  |  | -13.84 | -7.194 | -6.804 |
|  |  |  |  | (8.646) | (8.599) | (8.888) |
| Start\*mp1 |  |  |  | 0.683\*\* | 0.463 | 0.449 |
|  |  |  |  | (0.339) | (0.342) | (0.350) |
| Multi\*start |  |  |  |  | -9.860\*\* | -10.13\*\* |
|  |  |  |  |  | (4.463) | (4.553) |
| Constant | -33.24\* | -33.87\*\* | -35.67\*\* | -16.18 | -17.81 | -19.73 |
|  | (17.00) | (16.72) | (17.32) | (18.95) | (18.41) | (19.13) |
|  |  |  |  |  |  |  |
| Observations | 95 | 95 | 95 | 95 | 95 | 95 |
| R-squared | 0.125 | 0.199 | 0.205 | 0.221 | 0.318 | 0.321 |

**Basic Regression Models, Regression Models with Starter & Suspension History Effects**

Standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

The linear regression results in Table 6 reveal that minutes played (mp1) is not significant in explaining the change in game score from pre to post-suspension level in Model 1. Interestingly, despite only being significant at the 10% level in most of the models, the sign on the coefficient for opponent strength variable is positive, indicating that player productivity increased on average when playing against higher quality opponents post-suspension, contradicting the hypothesis on the coefficient’s sign made during model 1’s construction. Individually, age and veteran status positively affect the change in game score at the 5% significance level in model 1, but their interaction is negative and significant at the 5% level. The coefficient of this interaction term added with the effect of the age coefficient yields a very slightly negative net effect on game score ((1.491-1.685)\*Age = -0.194\*Age), which fails to align with the hypothesis that older players see less of a negative suspension effect. However, this interaction would also mean that older, non-veteran players experience *positive* effects in their productivity (=1.491\*Age). The coefficient on the veteran status variable is also much larger in magnitude relative to the other coefficients; however, it is also offset by the negative interaction between veteran status and age, as well as the constant term. Considering that the minimum age of a NBA player is 18 years old, we can take the sum of the constant term (-33.24) and the coefficient of the age variable (1.491) multiplied by 18 (26.838) to obtain some semblance of a more reasonable baseline for the y-intercept of this regression (-6.402).

Model 2 controls for physical altercations and multi-game suspensions. For the Model 2 coefficients in common with Model 1, the coefficients are nearly identical, and their signs and statistical significance are comparable, except for veteran status, which is now only statistically significant at the 10% level. Multi-game suspensions appear to have a negative effect on productivity, while returning from a multi-game suspension resulting from a physical altercation has a highly positive effect on player productivity. The coefficient on physical altercations alone had no significant explanatory power on the change in game score.

Model 3 has the same significant variables as Model 2, but the standard errors are generally larger, suggesting the presence of multicollinearity in Model 3. The added variables of game and ref were not significant. Thus, these types of suspensions are unlikely to affect the change in game score.

Model 4 is the only model in which minutes played is significant, and its sign is negative. Its significance is likely what caused the intercept to become insignificant. In addition, the interaction effects of first suspension and starter (which was added to Model 4 relative to Model 1), were not statistically significant. However, the interaction of veteran status and the first suspension dummy variables is significant and positive, as was the interaction between minutes played and starter classification, the latter of which contradicts the negative hypothesis advanced when Model 4 was specified. It was hypothesized that a veteran player is less likely to be adversely impacted by a suspension, holding the other variables in the model constant. It is also noteworthy to observe that the simple effect of having veteran status is no longer statistically significant as was the case in model 1, and can likely be attributed to the inclusion of the veteran status and first suspension interaction effect.

In Model 5, the simple multi-game suspension effect is no longer statistically significant as it was in model 2. However, the coefficients on the effect of returning from a multi-game suspension due to a physical altercation is positive and significant as it was in model 2. Also similar to Model 2, the simple marginal effect of physical altercations is not significant. The interaction between minutes played and starter classification is no longer statistically significant, as was the case in model 4. The added marginal effect of multi-game suspensions on starters was found is significant and negative.

Model 6 mimics Model 3 in that it the same significant variables as the previous model (Model 5), but the standard errors are again inflated likely due to multicollinearity.

1. **Discussion**

In determining whether or not suspensions have an effect on player performance, the mean calculations show that suspensions have a negative effect on player performance. That is, a suspension on average causes game score and true shot attempts to decrease, and causes personal fouls and turnovers to increase on average in a player’s first game following a suspension. However, the results of the Welch’s t-test clearly indicate that the only difference which is statistically significant at the 95% significance level was the decrease in average game score. This result implies that the behavioral changes in player aggressiveness or composure that the study sought to quantify were statistically nonexistent. However, because these other three response variables comprise the negative terms in game score’s calculation, the fact that their differences are statistically equivalent to zero indicates that at least one of the *positive* terms in equation (1) is decreasing from pre-suspension to post-suspension, provided that the true difference in game score is negative. Analyses on the other box score statistics could be run in a similar fashion to determine exactly which statistic(s) decreased in the game score calculation from pre to post-suspension.

Using linear regression to determine the possible determinants of the negative suspension effect on game score showed that some of the change in game score can be attributed to the maturity characteristics described in model 1. In particular, it is interesting to observe the differences between veteran and non-veteran players as age increases. The appendix shows the graph of game score effect versus age by veteran status, and from the graph it is apparent that older, non-veteran players suffer the least among all groups when returning from a suspension. In fact, after the age of 24, game scores for non-veterans ***increased*** from their pre-suspension level on average. Veterans and non-veterans have nearly identical changes to their game score post-suspension at age 23, but once a player has four years of experience, there is a negligible marginal effect on game score due to aging.

Older non-veterans are generally players who remain in college for a few years, or played overseas for an extended period of time before initially landing in the NBA. These players can be described as “blue collar” players and tend to play the game with a bigger chip on their shoulder than players who enter the league at a young age because of their talent. This difference in mindset could affect a player’s approach to the game, and may provide an explanation for the contrast between these two groups in how their productivity changes after being suspended.

In Model 2, it is clear that the change in game score can also be partially attributed to effects stemming from multi-game suspensions and suspensions resulting from physical altercations (in addition to the maturity effect described earlier). Multi-game suspensions decrease game score post-suspension by 7.046 per 36 minutes on average, and this marginal effect is significant at the 5% level. Although the coefficient on the variable for suspensions from physical altercations is not significant, this variable’s interaction with the multi-game suspension dummy variable is significant at the 1% level, and implies that players returning from a multi-game suspension resulting from a physical altercation boost their game score by 13.09 per 36 minutes on average.

As previously described, multi-game suspensions which result from physical altercations are among the most publicized and controversial suspensions. The sign of the coefficient is positive, implying that these suspensions improved average post-suspension performance. This may be a result of the player feeling extra motivation to make up for the physical actions which resulted in his suspension. This explanation would align with the positive effect hypothesis described in the introduction; however, the opposite may be true of multi-game suspensions that did not stem from physical altercations. Because the coefficient of the multi-game suspension variable is negative and significant, the negative effect hypothesis is likely to be the dominant effect.

Across both regression models, minutes played is not significant in explaining the change in game score from pre to post-suspension. However, minutes played is significant in Model 4. Among all of the explanatory variables used in the study, minutes played is the only one that can be changed after a suspension occurs, and would yield an interesting result in a player-personnel scenario if Model 4 is indeed valid.

For example, if player A is playing his first game since being suspended, his game score this game (GS’A) will be affected by the minutes he plays in this game divided by 36 (minsA/36), multiplied by the sum of the game score effect per 36 minutes (α = Model 4 equation) and his average game score per 36 minutes before the suspension (α + GSA). Mathematically,

GS’A = (minsA/36) \* [GSA + α] **(7)**

If player B is not a player coming off of a suspension and is the best and only possible replacement for player A, he will play (48 - minsA) in this game, and is expected to have a game score of [(48 - minsA)/36] times his average game score per 36 minutes (GSB). Mathematically,

GS’B = [(48 - minsA)/36] \* GSB  **(8)**

The personnel decision would come from choosing an amount of minutes for player A, in order to maximize productivity for this position (GS’A + GS’B), under the constraint minsA + minsB = 48. This could be very useful for NBA team front offices and coaching staffs who seek to optimize the team’s productivity at the position of the player who was previously suspended.

For example, if a 25 year old veteran starter returns from the first single game suspension of his career against an average opponent (OppSRS = 0), Model 4 indicates that the player’s game score per 36 minutes is expected to be affected by the function -1.939 + 0.051(minutes). This implies that this category of player would have to play 38 minutes in order to produce at his pre-suspension level (Game score effect = 0).

The two coefficients that were statistically significant in each model that they appeared in, were the coefficients for veteran status and first suspension interaction, and the coefficient on the multi-game suspension and physical altercation interaction. This implies that across all models, there is some maturity effect present, as well as a suspension effect present stemming from severe physical incident suspensions, and they both have strong positive effects on the change in game score for a player returning from suspension. While this result should not encourage deviant behavior, it certainly identifies some factors that could serve as possible motivation for a player to be more productive in his return from suspension.

**Limitations**

There were certainly limitations to this study, starting with choices made regarding the data. The difference in the statistics of interest would have a greater variation if a majority of the suspensions occurred in the beginning of a season. This is because the pre-suspension sample average would use fewer observations and would likely to be less representative of the season average. Because of this, some bias could exist depending on the proportion of observed suspensions that happened early in the season. Additionally, more definitive conclusions could be made with a sample size greater than the 95 observations. The small sample size limited the number of regression interactions considered, and other possibly relevant effects, such as a fixed effect for head coach.

The attempt to measure the behavioral effect through personal fouls may have been difficult for the fact that there may exist a relationship between minutes played and personal fouls. Many NBA players get reduced playing time if they pick up fouls early in a basketball game, and this could have had an impact on the mean estimate for the change in that variable. In addition, it is possible that race could play some role in how a player performs after a specific type of suspension, and that would be another interesting effect to estimate. Player salary could also impact how a player performs, given that the player loses game salary as part of his punishment. On a related note, a categorical variable distinguishing players who were playing in a “contract year” might also explain post-suspension performance. Even the number of endorsements a player has could impact post-suspension performance. A larger sample of NBA suspensions would facilitate a larger breakdown of suspension types, which may further aid in identifying other possible suspension characteristics that impact performance, and possibly help stabilize some of the effects estimated in this study.

One of the biggest limitations is the inability to quantify basketball defensive statistics, which makes it difficult to fully measure overall performance, as suspended players hypothetically could have played better defense in the games immediately after being suspended. If this is true, there would be no easy way to measure this defensive improvement outside of the box score defensive statistics that report steals and blocks, which are incomplete measures of good defense. This study covers the last seven seasons of the NBA, and more detailed player tracking data is now becoming public. With this data, the impact of player suspensions on a player’s average speed on the court can be measured, or the change in the types of shots that a player takes on average. The proportion of contested shots that a player takes, for example, could be measured before and after a suspension, and could yield interesting results.

In addition to not being unable to quantify defensive statistics or having access to relevant tracking data, it may be possible that the models presented in this study are incapable of capturing performance effects on their own. The study primarily focused on in-game and suspension characteristics to measure the change in productivity of a player, but in reality, performance may be a function of both of these two characteristics combined with other individual personality characteristics such as player rhythm that are difficult to measure. These personality characteristics would need to be measured at the micro level and could prove to be both expensive and difficult to obtain.

**Future Research**

Alternative research could be done in international basketball and/or college basketball, despite suspensions happening less frequently to student-athletes, and it may be the case that more than just game score is impacted by a suspension at the college level. A similar study done on MLB players would be a great parallel to this study, since individual player performance in baseball is easily measured, although doping and corked bat suspensions would have to be eliminated from the study, because being suspended for those reasons is likely to have boosted a player’s performance capabilities in the time before being suspended.

There may also be disciplinary effects observed in the workplace. A worker who is suspended without pay may take a different approach to their work, and it would be interesting to see if worker productivity increases or decreases on average after being disciplined. Public opinion on major companies is important to business, so the swiftness of disciplinary actions could have implications on company revenue, depending on factors like the value of the company, type of company, the incident’s characteristics, the position of the offender and company hierarchy, etc. This idea resembles that of the NBA’s image and how it was successfully able to restore its brand.

An additional extension would be to observe a player’s salary and evaluate the cost for him to be suspended, and if it’s assumed that a player’s productivity is what warrants his salary, the marginal cost of particular suspension characteristics could be obtained using the change in the game score statistic.

1. **Conclusion**

The experiment conducted in this study aimed to determine if the suspension of an NBA player affected his performance negatively or positively in his first game following the suspension, and attempted to identify performance measures that were impacted so that individual characteristics of a suspension can be attributed to game performance. While most of the response variables did not differ significantly from their pre-suspension levels, the results showed that suspensions negatively impact players’ overall box score productivity (game score) in the game immediately following the suspension. These effects were attributed to maturity effects, such as veteran status and suspension history, as well as specific characteristics of a suspension, including physical altercations and multi-game suspensions.

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**Appendix**

Appendix A**:** EOV Test Results

Table A-1: EOV Test on Minutes Played Before & After Suspension



Table A-2: EOV Test on Game Score per 36 minutes Before & After Suspension



Table A-3: EOV Test on True Shot Attempts per 36 Minutes Before & After Suspension



Table A-4: EOV Test on Personal Fouls per 36 Minutes Before & After Suspension



Table A-5: EOV Test on Turnovers per 36 Minutes Before & After Suspension



Figure A-1: Graph of Game Score Effect versus age by veteran status



Age represents player age in years and GS Effect = (Game Score per 36 minutes after suspension - Game Score per 36 minutes before suspension). The red line represents players who have played at least 4 seasons in the NBA while the blue line represents players with fewer than 4 seasons played. The respective shading portions represent 95% Confidence intervals for a particular x-value. The two lines cross at an age of 23 years old. The figure shows that once a player reaches four years of experience (vet = 1, red line), they experience very little change in their game score after being suspended as their age increases. Non-veteran players (vet = 0, blue line) see increasingly positive effects as they age, so long as veteran status has not been reached.

**Glossary**

**SRS-** “Simple Rating System”, a team rating statistic measured by taking into account average point differential and strength of schedule. For example, the 2006-07 San Antonio Spurs won games by an average of 8.43 points per game and played a schedule with opponents that were 0.08 points worse than average, giving them an SRS of 8.35. This 8.35 means they were 8.35 points better than the average team, who would have a SRS of 0.0. (Lynch, 2015)

**TSA- “**True Shot Attempts”, equal to (0.44FTA + FGA). Serves as a measure of player aggressiveness in attempting to score during a game, by accounting for both free throw attempts and field goal attempts. A great example of TSA’s use would be to examine former NBA player Corey Maggette’s performance against the New Jersey Nets in 2009. Maggette ended the game with only 4 field goal attempts, but managed to attempt 20 free throws. In this scenario, Maggette’s true shot attempts would be 12.8. Field goal attempts alone would fail to capture Maggette’s attempts to score for his team, since fouls on shot attempts which fail to score do not count as field goal attempts.