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Revenue Incentives and Referee Propensity to Make Foul Calls in the NBA Finals

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Abstract

In this study I examine foul calls by NBA referees alongside the difference in aggressiveness of twelve NBA basketball teams as they compete for the Championship Title. I aim to identify referee biases that increase the likelihood of the NBA Finals ending in a later game due to league revenue incentives. My data consists of 91 individual NBA Finals games played between the 2001 and 2016 NBA Finals. After controlling for changes in play as well as the difference in aggressiveness, I find that NBA referee's foul calls are more dependent on a call on the opposing team in situations with a larger series score spread. Additionally, I identify a consistent officiating bias towards the home team. My results imply an effort by the NBA to increase the probability of the series ending in a later game, possibly motivated by increased revenues for the league and all parties involved.

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Introduction

On June 19th, 2016 the Cleveland Cavilers did the unthinkable, they came back from a (3,1) lag against the Golden State Warriors and won the 2016 National Basketball Association (NBA) Finals. A mere nine days before, the Warriors had just won their third game of the series, and they were a shoo-in for the victory. At that time Vegas was predicting a 1.2% chance of the Cavilers winning the series, a next to impossible feat. As I watched the seventh and final game of the series I could not help but notice all of the hype surrounding the event. Every other sentence from the announcer pertained to some record being broken whether it be ticket sales, viewership, ad pricing, all of the past sales records had been left in the dust.

The 2016 NBA Finals game seven was the third most watched game in NBA history peeking with almost 45 million viewers, and averaging 31 million viewers throughout the game. [1] Ticket sales skyrocketed after the Cavilers beat the Warriors in game six and sent the series to a deciding game seven. Courtside VIP seats for game seven were listed for $122,000 and average ticket prices jumped over $1000.[2] As I watched the immense amount of money surround game seven, I could not help but think the NBA had some how made this happen. Had game five decided the series, the NBA and all parties involved would have missed out on potential revenues in excess of $100 million.[3] This thought sparked my interest in investigating whether or not the NBA was fixing games. After speaking with various friends who were knowledgeable and passionate about the NBA, I decided it was unlikely the NBA would directly fix games.

1 NBA Communications, 2016 Finals Summary
2 Tuttle, Brad. "NBA Finals Game 7 Ticket Prices Shoot Up an Extra $1,000."
3 Tuttle, Brad. "Here's How Much Money ABC & the NBA Make with an NBA Finals Game 7"

However, I still believed the NBA would do everything in their power to increase the likelihood of the Finals going to game seven. This led me to my investigation into referee biases in the NBA Finals.

Upon my review of previous literature on the subject I found various studies aiming to identify referee bias in the NBA as well as the NCAA. Anderson and Pierce (2009) examined foul calls in the NCAA and find referees will traditionally favor the lagging team as well as the home team. Their insights give direction for how to identify bias in basketball; however, the authors chose to examine regular season games opposed to post season games. A similar study by Price et al. (2012) assessed referee calls in the NBA, and aimed to identify a bias using discretionary and nondiscretionary turnovers. I find similar results to those found by Price et al. (2012), although, I use fouls as my measure of bias opposed to turnovers.

After deciding to examine foul calls by the referees, I had to establish how I expected to uncover the bias I believed was present. My advisor, who has done extensive work in tournament competition research, encouraged me to investigate how the aggressiveness of the two teams shifted throughout the series. Cabral (2003) and Ozbeklik and Smith (2014) both find that competitors in multi-period competitions vary in risk-taking behavior as well as effort exerted depending on their position in the standings. This led me to establish an aggressiveness metric to measure the difference in team's aggressiveness as the series progressed.

My study builds on current literature pertaining to NBA referee biases, and also contributes to existing literature on competitor behavior in competition settings. Although my study relates directly to the NBA Finals, it offers an outline for identifying officiating biases in a variety of tournament settings. My results shed light on what may be an effort by the NBA to increase the likelihood the Finals ending in a later series game due to revenue incentives, however, there still stands an immeasurable amount of work to ascertain such an effort.

Background on the NBA Finals

The NBA Finals have been played after every NBA season since the NBA's inception, beginning with the first Finals in 1947. The Finals consist of a seven game series in which the winners of the Eastern and Western Conference Finals compete for the Larry O'Brien Championship Trophy. The first team to win four games in the series emerges victorious. The current structure of the Finals is a 2-2-1-1-1 format in which the first two games are played at the home of the higher seeded team, then the following two games are played at the home of the lower seeded team, then the last three games alternate with the 5^{th} and 7^{th} games being played at the home of the higher seed, and the 6^{th} game at the home of the lower seed.

The Finals have been anything but consistent throughout their history. From name changes to structural changes, the finals have transformed along with the shifting board and commissioners. In 1984 David Stern took over control from Larry O'Brien as Commissioner of the NBA. One of the first changes he instituted as Commissioner was a structural change to the 1984-1985 NBA Finals. Stern argued, teams, as well as media, were caused unnecessary stress by the 2-2-1-1-1 format due to the requirement to fly back-and-fourth across the country to play the final games of the series. In order to ease the burden on all parties involved, Stern changed the format of the Finals from the original 2-2-1-1-1 format to a 2-3-2 format. Although this change did ease stress on the players and media alike, many also argued it increased the likelihood of the series ending in a later game because it provided the lower seeded team with one additional home game before returning to the home court of the higher seeded team. The NBA continued with the new structure until 2013 when Adam Silver took the reins from Stern. Again with the shift in power, one of the first changes instituted was the shift back to the original 2-2-1-1-1 format. Thus far the Finals have remained in their original format of 2-2-1-1-1, but the consistency of structure remains to be seen with future shifts in the administration.

Additionally, the NBA has also made recent changes to the instant replay rules. Instant reply was first introduced to the NBA in 2002; since then it has become instrumental in making calls, especially foul calls. After the reorganization of the NBA Competition Committee in 2012, the NBA began making major changes to the calling power allotted to the instant replay reviewers. For the 2012-2013 season the Competition Committee introduced extended use of reply, which allows referees to make flagrant foul calls after the game is over upon review of the game footage.[4] Along with this change came several others allowing for more autonomy over calls, however, the rules also place more control in the hands of the reviewers allowing them to alter the outcome of a game even after it has finished.

The most recent change to the NBA Finals is a change to the playoff seeding. Originally, the top teams from each division of the NBA were guaranteed a top four seed in their respective conference playoffs. If the division winner did not have a better record

[4] NBA Communications, NBA Board of Governors approves expanded use of replay

than their opponent then they lost home court advantage, but they maintained their seed. For the 2015-2016 season the NBA Board of Governors voted to do away with the guaranteed top four seed for the division winners, and shift to a playoff seeding structure based purely on record.[5] This changes allowed for a higher likelihood of having the best teams in the finals, and in turn increase the overall probability the finals end in a later game.

Background on NBA Finals Viewership & Revenues

In 2010 the NBA set records with their broadest Finals reach ever. The Finals were broadcast in 215 countries and territories in 41 languages.[6] This marked the beginning of an NBA initiative to expand Finals viewership worldwide. After a successful 2010 season the NBA began investing in a variety of vehicles to expand viewership to stretches of the world that had never experienced the NBA. This investment included the ability to watch the Finals on NBA.com and NBA Mobile, and in 2013 NBA Digital, the NBA's multimedia conglomerate, set yet another record year.

After 2013 the NBA saw a market opportunity and began to build out their social media platform. Over the course of the next two years the NBA launched social media campaigns on: Facebook, Twitter, Google, Instagram, and Snapchat to gain user interaction. This investment paid off, and in 2015 the NBA shattered viewership records with an average 20 million viewers per Finals game. During the series NBA Digital delivered 336 million combined video views during the 2015 Finals. By the end of the

[5] NBA Communications, NBA to seed conference playoff teams by record
[6] NBA Communications, NBA Finals: Broadest reach ever

2015 Finals the NBA had 835 million combined social media followers after adding 250 million over the course of the season.[7]

The 2016 season brought another record-breaking year with the culmination of the Finals. Game seven averaged 31 million viewers on ABC making it the third most watched NBA game of all time, and in China garnered 15.3 million unique viewers over all platforms making it the most watched NBA game in China's history.[8] The NBA also surpassed 1 billion social media followers making it the first sports league in the world to pass 1 billion followers.

Hypothesis Development

Average ticket prices for the 2016 NBA Finals shot up over $1000 when the Cleveland Cavilers won game six and pushed the series to a deciding game seven.[9] There is no question that everyone benefits from the NBA Finals being pushed to an additional game. The fans get to watch a more intense match. The broadcasting agencies get to run more adds. The NBA gets to sell more merchandise and tickets. It is really a win-win for everyone. This is precisely the thought I had as I watched the Cleveland Cavilers win game six after coming back from a (3-1) lag in 2016. So, if everyone wins, why not push the series to a game seven?

Over the course of the 2015 NBA postseason 81 games were played between 16 total teams. The Finals went to games six, but ended when the Golden State Warriors

[7] NBA Communications, NBA Finals 2015 by the numbers
[8] Historic NBA Finals 2016 set TV, Social, Digital and merchandise records
[9] Tuttle, Brad. "NBA Finals Game 7 Ticket Prices Shoot Up an Extra $1,000."

beat the Cleveland Cavilers in game six. Ad sales from the 81 televised games combined to generate a whooping $613 million dollars in sales.[10] AdAge, a prominent Ad statistics reporter, estimated that had there been a game seven ABC would have generated an additional $45 million in ad sales.[11] This means that while game seven only makes up 1.2% of the total games played, it generates over 7% of the total ad sales. Ad revenue is still only a portion of the total revenues received in the event of an extra Finals game. The NBA is also able to capitalize on additional merchandise sales, ticket sales, and in the event of a revenue sharing agreement with the broadcasting agency the excess ad revenues once the Finals achieve a certain ad sales benchmark.

Due to the possible revenues available at little to no cost I see no reason why the NBA would not be inclined to do everything in their power to increase the probability of a Finals game five, six, or seven. So, when considering ways the NBA could affect this probability I chose to focus on foul calls. After reviewing previous literature on the subject I found that competitors who are leading often exert less effort, and teams who are lagging exert more effort. This led me determine my first hypothesis:

> **Teams lagging in the NBA Finals will exert more effort as the possibility of them losing increases, and teams who are leading in the NBA Finals will exert less effort as the possibility of them winning increases.**

Next, I had to determine where I expected to see a bias in the referee's calls. If the referees were incentivized to increase the probability of the Finals reaching a game five, six, or seven, then I would expect them to favor the lagging team. Naturally, if my first

[10] Crupi, Anthony. "With the Warriors on Fire, NBA Generates Big Bucks for TNT, ESPN."
[11] Tuttle, Brad. "Here's How Much Money ABC & the NBA Make with an NBA Finals Game 7"

hypothesis holds, then I would expect to see more fouls by the lagging team and less fouls by the leading team as the series spread increases. In the event of the referees favoring the lagging team I would expect to see little to no change in the proportion of foul calls on the lagging team while their overall aggressiveness increased throughout the series. This led me to my second hypothesis:

> **While the aggressiveness of the lagging team increases and the aggressiveness of the leading team decreases, I expect to observe little to no change in the proportion of foul calls on the lagging team to the leading team due to a referee bias towards the lagging team.**

Previous Literature

When considering how to acquire the most informative literature for my study I chose to construct my search around two primary bases. The first assumption of my study is: as the distance between two tournament competitors increases the laggard will increase their effort and risk taking behavior, and the leader will decrease their effort and risk taking behavior. To support this assumption I present several studies concerning the complexities of effort and risk taking behavior put forth by competitors in a variety of tournament competition settings. The second notion of my study is the assumption of referee bias towards the laggard of the NBA Finals in an effort to increase revenues and the likelihood the finals end in game five, six, or seven. To establish an empirical approach to identifying referee biases I consider a multitude of studies aimed at ascertaining specific biases in sports officiating, and in particular NBA and NCAA basketball officiating.

Economic literature investigating competitor behavior in tournament competition settings is far from limited. Cabral (2003) considers R&D investment in an infinite time horizon multi-period race where competitors are given the option to chose a low payoff, low variance technology or a high payoff, high variance technology. The study seeks to determine a player's optimal strategy as a function of their relative positioning. Cabral asserts a firm's payoff is a function of the quality difference between its product and the rival's, so payoffs are monotonic and symmetric, just as they are in the NBA Finals. Based on the results Cabral concludes in equilibrium the leader will most often chose the safer strategy, and the laggard the more risky strategy. Although he uses an infinite time horizon, Cabral concurs a similar result would be derived from a finite tournament structure "…thus formalizing the sports intuition that the laggard has nothing to lose."

Similarly to Cabral's study, Ozbeklik and Smith (2014) examine risk-taking behavior in tournament competition through the lens of professional golf. The study aims to measure risk taking in one-on-one, single elimination golf tournaments using data taken from 579 professional golf matches and over 18,000 holes from 2003 to 2013. To assign a measure of risk-taking the authors use two approaches. First, they observe the percentage of holes conceded. This statistic offers insight into the holes where contestants took a risk and were unsuccessful. Second, they consider the standard deviation of relative-to-par scores of a hole over the course of the competition. Measuring the standard deviation of relative-to-par scores allows the researchers to identify holes with a high score variance, therefore, implying the larger the variance of a hole the more risk taken on that particular hole. Using both approaches Ozbeklik and Smith find players who were ahead adopted more conservative play, and players who were lagging adopted more risky behavior. This finding was emphasized as the players came closer to the end of the tournament, and also as the difference between the two players scores increased.

Casas-Arce and Martinez-Jerez (2009) test how particular tournament features affect contestant incentives and efforts over the course of the tournament. Specifically, the study considers a multi-period sales contest organized by a manufacturer amongst its retailers to observe how participant's incentives evolve as the contest progresses. The contest provides a static environment in which homogeneous competitors reach a symmetric equilibrium, however, introducing the multi-period structure generates heterogeneity amidst the competitors due to the interim performance of each competitor. Casas-Arce and Martinez-Jerez find the introduction of the contest significantly impacts retailer's efforts and incentivizes them to sell more goods. Additionally, they also observe a significant decrease in the efforts of leading competitors as well as an increase in the efforts of the lagging competitors to try to catch up. These tendencies increase as the distance between the competitors grows. However, as the gap grows to be too large to make up the researchers witness a decrease in motivation and effort by the lagging players, although, this finding is most likely irrelevant in a seven game series.

In addition to the previously referenced studies on risk-taking behavior, Genakos and Pagliero (2012) consider the effects of interim rank on weight announcements in professional weightlifting. The study uses panel data from the Olympics and the World and European Weightlifting Championships from 1990 to 2006. In weightlifting competitions competitors are scored off of the amount of weight successfully lifted. Therefore, higher weight announcements represent riskier behavior because they imply a larger difference in the case of success or failure. The study finds that competitors lagging behind are more likely to make risky announcements than competitors who are in the lead. The evidence displays an inverted-U relationship with interim rank. Announcements increase from first to sixth place, but then fall and become equivalent to first place by the 17^{th} rank.

To attempt to measure risk-taking behavior in basketball I must first understand how certain factors contribute to a teams success or failure. Stern (1994) creates a Brownian Motion model to predict who will win an NBA basketball game as a function of time remaining in the game $t \in (0,1)$, and the difference in score $X(t)$. When observing data from 493 NBA games Stern finds home teams consistently outscore visiting teams by roughly 1.5 points in the end of the first, second and third quarters, but lose the majority of the lead in the fourth quarter. The authors attributed this to coaching decisions to remove top players towards the end of the game because of their lead. This finding led me to consider not only the player's risk-taking behavior during a game, but also the coach's risk-taking behavior. I elaborate on this finding in the Methods section later in this paper.

Zak, Huang and Siegfried (1979) similarly attempt to create a production function for an NBA team; however, they do so using a Cobb-Douglas production function. The researchers use data from 375 games over the 1976-77 NBA season. In regard to personal fouls the study finds a 1% increase in the ratio of personal fouls in the game leads to a .11% decrease in the point ratio between the teams. Additionally, when considering the possibility of a home court advantage the study finds teams perform better at home opposed to on the road, specifically in shooting accuracy and number of rebounds. The study does not find any correlation of on-the-road point deficit and officiating.

In conflict with Zak, Huang and Siegfried's finding, Lehman and Reifman (1987) observe a difference in home vs. away officiating, but only with star players. The researchers hypothesize star players are less likely to have a foul called at home rather than away because fans are biased towards their favorite players. The study measures the difference between foul calls on star players[12] at home and away, and non-star players at home and away. Leman and Reifman find star players are less likely to be called for fouls at home than away, this is significant at the 5% level. Additionally, the study also finds non-star players are just as likely to be called for a foul at home as they are on the road. These findings, in contradiction to the study done by Huang and Siegfried, imply there is a home court advantage in game officiating.

Officiating biases can favor one specific team, or both teams simultaneously. Anderson and Pierce (2009) examine patterns in foul calls during 365 NCAA basketball games throughout the 2004-2005 season. They estimate expected foul differential based on a binomial distribution. The researchers then compare the expected foul differential with the empirical and find the actual variance is significantly less than the expected variance, therefore, suggesting the foul calls are not independent. Anderson and Pierce find fouls are more likely to be called on: the team with the fewest fouls, the visitor, and the leading team. The data suggests the probability of the next foul being called on the visitor can reach .7 in specific conditions due to the observed biases. Secondly, the study maps the probability of the next foul being called on the home team based on the current foul differential. They find referees consistently favor the home team as indicated by the equilibrium probability of .438. One key distinction of this study is they only compare

[12] Star players are identified by all-star status, draft rank, and scoring status

fouls called in the first half of the game to control for fouls called in the last few minutes of the game, assuming they are intentional.

Foul calls, as explained previously, can have a large impact of the outcome of a game. If the officials of a game are biased this can cause a game to transpire unnaturally, and in some cases profitably. Price et al. (2012) and Thu et al. (2002) identify officiating biases and explain how they relate to league profitability. Price et al. (2012) distinguish between discretionary turnovers[13] and nondiscretionary turnovers[14] to identify a referee bias. They also consider fouls called by the referees. The researchers track the difference between both types of turnovers over varying game situations to discern between differences in play by the players and referee bias. When tracking the DTO and NTO the study finds refs favor home teams, teams that are lagging in a game, and teams that are lagging in a series. While NTO remained relatively constant over different game scenarios, the study finds DTOs are called more often on the disadvantaged team. While the study does consider shooting fouls vs. non-shooting fouls, the results are not significant and provide little insight. The researchers also consider the profit benefits to referee bias and find all biases are profitable to the NBA. In conjunction, the study finds referees who work playoff games were more likely to be assigned to games where a weak home team was playing a strong visitor, "…this indicates the league makes ref assignments in a strategic way, and rewards refs who help teams when they need it most."

Thu et al. (2002) aim to identify two systematic biases of NCAA Division 1 referees: if referees call a disproportionate amount of fouls on the leading team, and if the disproportionality of fouls called increases with nationally televised games. In the initial

[13] DTO - call made by the referee
[14] NTO - call made obvious by the players, out of bounds etc.

observation the researchers find foul calls in the last two minutes differ vastly from the rest of the game because the losing team typically intentionally fouls the winning team as the game comes to an end.[15] To control for this the researchers leave all fouls called in the last two minutes out of their analysis. After controlling for fouls called in the last two minutes the researchers find on average leading teams have 6% more fouls called on them, this in significant to the 1% level. Additionally, the researchers also find NCAA Division 1 games that are televised on primary networks have a significant increase in fouls called against the leading team opposed to games that are not televised or televised on local channels, this is significant to the 1% level also.

To summarize, the notion that as the distance between two tournament competitors increases the laggard is more likely to increase their effort and risky behavior and the leader in more likely to decrease their effort and risky behavior, is widely supported by tournament theory literature. Whether or not this increase or decrease is distinctly effort or distinctly risk remains more vague, but for the purpose of my study is obsolete. In regard to my second assumption, it can be determined officiating biases exist in sporting events and quite possibly the NBA. Whether these biases are a direct result of profit seeking stands unclear, however, the financial benefits to a referee bias in the NBA are explainable and quite plausibly a motivator for the bias I expect to observe.

[15] Equal distribution of foul calls over entire game vs. 32%-66% laggard-leader in the last two minutes

Data

I gather all of my data on individual National Basketball Association (NBA) Finals games using Basketball Reference, a comprehensive statistical database containing NBA game summary statistics dating back to 1946. My data includes 91 individual games played in the 2001 to 2016 NBA Finals. Over the course of the fifteen years I collect data on, twelve individual teams appear in the NBA Championship, with nine emerging victorious.

For each individual game I record: the fouls, field goal attempts, three point attempts, steals, blocks, offensive rebounds, defensive rebounds, and starter to bench playtime ratio for each team competing in the series. To account for changes in play or tournament structure I also collect and include in my analysis: the year of the series and which team is playing at home. For the purpose of controlling for intentional fouls made in the last two minutes, I use play-by-play data and deduct all fouls made in the last two minutes. Due to the NBA not beginning to keep play-by-play statistics until the 2000-2001 season, my data is limited to the fifteen Finals series I include.

Methods & Regressions

To test my hypotheses I aim measure the aggressiveness of each team playing, as well as identify referee bias based on the existing series score.

Measurements of Aggressiveness

Field Goal Attempts to Three Point Attempts

For my first measure of aggressiveness I calculate each team's field goal attempts to three-point attempts. In basketball there are three ways to gain points: free throw, field goal, and three-point shot. Each method delivers one, two, and three points respectively. As determined by Casas-Arce and Martinez-Jerez (2009) and Genakos and Pagliero (2012) risk-taking is often exhibited through the decision to take on a high variance, high payout option opposed to a low variance, low payout option. During the 2016 NBA season the success percentages for free throws, field goals, and three point shots are 77%, 48%, and 36% respectively.[16] Therefore, because three-point shots have the lowest success percentage and the highest payout, one can assume teams exhibiting risky and aggressive behavior will take more three-point shots than their counterparts. The ratio of *FGA/TPA* allows for me to determine when teams are playing more conservatively, i.e. taking easier shots with a higher success percentage, and when they are playing more aggressively, i.e. taking more risky shots.

Steals

In basketball a player can attempt to steal the ball from the opposing player, however, this has a high likelihood of resulting in move past the aggressing player by the

[16] Gracenote. Basketball Reference, 2016 regular season stats

ball handler. In that case the ball handler becomes goal-side of the aggressor, and he is able to freely take a shot or pass the ball. Because of this, attempting to steal the ball is a gamble. If the aggressor is able to get the ball they are often rewarded with an easy layup or assist, but if they fail to do so they let down their team and provide the opposing team with an easier attempt on goal. By including the *steals* of each team throughout the NBA Finals I am able to again measure each teams risk-taking behavior and aggressiveness.

Blocks

I also include *blocks* in my measurement of team aggressiveness. A block results in a similar outcome to a steal. When blocking the aggressor attempts to swipe the ball from the opposing players hands as they go for a shot. If the ball handler pump-fakes when the aggressor attempts to block, the ball handler can easily step to the side of the aggressor and take an unguarded shot. Therefore, a block can result in a defended shot and often a turnover for the aggressing team, but if the attempt goes wrong the ball handler gets a free shot.

Offensive & Defensive Rebounds

In Zak, Huang and Siegfried's (1979) study of NBA team production efficiency the authors find offensive and defensive rebounds to be statistically significant in determining a teams win potential. After an unsuccessful shot on goal the ball is free and in play so as long as it stays in bounds. This means teams who are willing to box out harder, jump higher, and move faster to the ball will prevail. Therefore, *offensive and defensive rebounds* are a direct measure of team aggressiveness throughout a game.

Starter Playtime vs. Bench Playtime

Stern (1994) introduces the idea that coaching decisions are one of the primary factors effecting game outcomes. This assertion led me to consider the coach's risk taking behavior and what affect it might have on foul calls. To measure coaches' risk-taking behavior I include the ratio of *starter playtime to bench playtime* for each game. When a coach plays a star player he runs the risk of injuring or tiring out his player. Therefore, in low-risk situations a coach would be more inclined to allow their star players to rest, and play their bench players. However, in high-risk situations one would expect a coach to take the risk of injuring or tiring out their star players, and play them to the end of the game. For this reason I include the ratio of *starter playtime to bench playtime* to account the coach's propensity to take risks.

Measuring Aggressiveness

To measure the aggressiveness of each team competing in the championship I use a stacked line chart to compare the difference of the leader from the laggard for each aggressiveness measure. In every possible series score scenario, i.e. (0,0), (0,1), (0,2), (1,1) etc. I calculate the average of each aggressiveness measurement and subtract the laggard average from the leader average. That is, I calculate the average *steals* for the leading team and the average *steals* for the lagging team in all (0,0) scenarios, then I subtract the lagging average from the leading average.

Because the measures are all on different scales I use the stacked line chart to identify trends in team play as the series progresses. To compare varying scenarios I list the series scores in order of equal to most unequal, i.e. starting with (0,0) where one would expect to see an even amount of aggressiveness by each team, and end with (0,3) where one would expect to see the most aggressiveness by the lagging team and the least aggressiveness by the leading team.

Identifying Referee Bias

To identify a referee bias towards the laggard I use a multiple-linear regression and control for series score, as well as the aggressiveness measures listed above. The regression I use is as follows:

$$\text{Fouls} = \alpha + \beta_1\text{Fouls on Op. Team} * \text{ZeroZero} + \beta_2\text{Fouls on Op. Team} * \text{ZeroOne} + \beta_3\text{Fouls on Op. Team} * \text{OneZero} + \beta_4\text{Fouls on Op. Team} * \text{ZeroTwo} + \beta_5\text{Fouls on Op. Team} * \text{TwoZero} + \beta_6\text{Fouls on Op. Team} * \text{OneOne} + \beta_7\text{Fouls on Op. Team} * \text{ZeroThree} + \beta_8\text{Fouls on Op. Team} * \text{ThreeZero} + \beta_9\text{Fouls on Op. Team} * \text{TwoOne} + \beta_{10}\text{Fouls on Op. Team} * \text{OneTwo} + \beta_{11}\text{Fouls on Op. Team} * \text{OneThree} + \beta_{12}\text{Fouls on Op. Team} * \text{ThreeOne} + \beta_{13}\text{Fouls on Op. Team} * \text{TwoTwo} + \beta_{14}\text{Fouls on Op. Team} * \text{TwoThree} + \beta_{15}\text{Fouls on Op. Team} * \text{ThreeTwo} + \beta_{16}\text{Fouls on Op. Team} * \text{ThreeThree} + \beta_{17}\text{Steals} + \beta_{18}\text{Blocks} + \beta_{19}\text{Offensive Rebounds} + \beta_{20}\text{Defensive Rebounds} + \beta_{21}\text{Field Goal Attempts/Three-Point Attempts} + \beta_{22}\text{Starter/Bench Playtime} + \beta_{23}\text{Game Time} + \beta_{24}\text{At Home} + \beta_{25}\text{Year}$$

My regression consists of 182 observations due to the fact I consider fouls on both teams from all 91 game observations.

Originally, I attempted to observe a referee bias in a foul ratio, which consisted of the fouls on the leading team over the fouls on the lagging team. I anticipated that while the series progressed I would see the aggressiveness of the lagging team increase and the aggressiveness of the leading team decrease. If this was in fact true, then one would expect to observe a decrease in the foul ratio as stated above.

Unfortunately, when I ran my first regression I realized I had no measure for the change in foul ratio I expected to see. I could observe a change as the series progressed, but I had no concept of if that change was large or small. Because of this, I needed to alter my regression to show foul calling variation in each series scenario opposed to the other scenarios. To identify any variation in calls dependent on the series score I chose to look at the number of *fouls* called on both teams throughout the series.

In my regression I regress the number of *fouls* on the opposing team multiplied by a dummy variable for the *series score* at the time of the game. I also include controls for the aggressiveness of the team whose *fouls* I am measuring to account for changes in play throughout the series. My regression ultimately measures what affect *fouls* on the opposing team have on the probability of having an additional foul called on the team in question. Although this regression is unable to identify a bias towards the laggard, it does have the ability to shed light on the effect of a foul call on the opposing team on fouls called on the team in question depending on the series scenario.

Regression Variables

The dataset I run my regression on is setup with two observations of each game. *Fouls*, the dependent variable in my regression, represents the number of fouls called on team A in game X. *Fouls on Op. Team* represents the fouls called on team B in game X. The *Fouls on Op. Team* is multiplied by a dummy variable relating to the *series score* at the time of the game. For irrelevant *series score* variables the *Fouls on Op. Team* is multiplied by zero, and for the relevant *series score* I multiply the number of fouls by one.

The coefficients on each of the *series score* variables can be interpreted as the effect a foul on the opposing team has on the probability of an additional foul called on the team in question depending on the current series score. Although this does not help to identify laggard referee bias, it does help to identify game situations in which the referees are systematically keeping the game close, as well as game situations where the foul calls are independent from each other.

To control for changes in play by teams over the course of the series I include all of the aggressiveness measures I mention above. *Steals* represents the number of steals called on team A when regressing on the fouls called on team A. *Blocks* represents the number of blocks by team A. *Offensive Rebounds* and *Defensive Rebounds* represent the number of offensive and defensive rebounds by team A respectively. *Field Goal Attempts/Three-Point Attempts* is the ratio of team A's field goal attempts over the number of team A's three-point attempts during the game in question. *Starter/Bench Playtime* represents the total starter minutes of play over the total bench minutes of play for team A. *Game Time* represents the total playtime of the game; this allows me to control for games that went into overtime. *At Home* is a binary variable, which controls for whether or not the teams were playing at home. Lastly, I control for changes to tournament structure and play by including the *Year* of the series.

Each iteration of the regression represents the above variables for team A or team B respectively. As mentioned previously, I control for intentional fouls called in the last two minutes of each game by subtracting out all fouls called in the last two minutes. I include overtime in the overall game time, therefore in games that went to overtime I simply subtract out fouls from the last two minutes of overtime.

Results

To analyze the change in aggressiveness of the leading and lagging teams throughout the NBA finals I use a stacked line chart to measure the overall trends in team aggressiveness. For each series scenario I find the average: fouls, field goal attempts/three-point attempts, steals, blocks, offensive rebounds, defensive rebounds, and starter/bench playtime for both the leading and the lagging team. Then I take the averages and find the difference in aggressiveness between the leading and the lagging team in each series scenario. These differences are then mapped using a stacked line chart to display the overall difference in aggressiveness between the leaders and the laggards, refer to Figure 8.

When mapped together using a stacked line chart one observes an initial uptick in aggressiveness by the leading team in situations with a series score of (1,1), (2,2), and (3,3). As the series spread increases one observes a shift in the difference in aggressiveness resulting in a negative difference between the leader and the laggard. This is consistent with my initial hypothesis: as the series spread increases one expects to see a decrease in the aggressiveness of the leading team, and an increase in aggressiveness by the lagging team.

In concern with team aggressiveness, my regression model does not display any statistically significant observations. However, in regard to the correlation between a foul being called on the other team and receiving a foul, I find multiple statistically significant observations. In all series score scenarios, aside from Three Zero for which I had limited observations, one observes a positive correlation between a foul being called on the opposing team, and a foul being called on the team in question. Although not all coefficients are statistically significant, one observes a consistent increase in correlation as the series spread increases. This can be interpreted as an observable trend in the referees keeping the game closer through dependent foul calls in games with a larger series spread, while calling fouls more independently in games with little to no series spread. This does not confirm nor deny any bias in the referee's calls towards the leader or the laggard, but it does establish an observable increase in dependency on foul calls on the opposing team with an increase in series spread when measuring the potential for an additional foul call on the team in question.

Discussion

This paper examines a referee's propensity to make foul calls on the leading team of the NBA Finals due to a proposed increase in league revenue incentives during the finals. The data consists of NBA Finals played over 15 years, in which 91 individual games were played between 12 teams. As proposed in my hypothesis, I observe an increase in the aggressiveness of the lagging team as the series spread increases, as well as a decrease in the aggressiveness of the leading team. This is in line with the theory that in a finite time horizon multiple-period contest, the laggard will increase their risk taking behavior and effort as long as they have nothing more to lose.

Although I attempt to capture a referee bias towards the laggard, I am unable to do so due to a lack of measure for the observable change in foul calls. However, my regression results do point to various significant referee biases in the NBA Finals. First off, I observe a trend in referee's propensity to make foul calls dependent on an additional foul call on the opposing team. This dependency increases as the series spread increases, implying the referees are systematically keeping the games closer by way of foul calls in games with a high series score differential. This result is far from surprising. One might expect the referees to make calls more independently when there is no leader of the series, and to keep the game close as the potential for a series winner increases.

Additionally, when including the *At Home* variable I observe a significant decrease in the total number of fouls called on the team in question. This finding is also supported by previous literature as other studies have found a home court advantage when investigating the NBA and NCAA. This finding again is far from surprising. One expects referees to favor the home team due to an implicit bias as well as fan biases towards their team during the game.

One surprising finding of my study is the negative correlation of *Starter/Bench Playtime* to *Fouls.* I originally included *Starter/Bench Playtime* to measure the aggressiveness of the coaches. I expected to see a positive correlation with fouls received and the playtime ratio, however, I observe a negative coefficient in my regression. In previous studies[17] researchers have found that referees are less likely to make foul calls on star players, especially at home, because the fans disapprove. This theory is a possible explanation for why I observe a negative coefficient for *Starter/Bench Playtime.* Star players are most likely to be starters. As coaches play more aggressively and use their starters more, the referees may make less total foul calls because they are less inclined to make calls on star players and increase the potential of them being forced out of the game.

[17] Lehman and Reifman (1987)

If one is looking to expand on this study in the future I highly recommend approaching the problem from the beginning with an appropriate measure for the difference in foul calling. I was unable to achieve my goal of identifying a referee bias towards the laggard, however, I am still unconvinced it does not exist. Because I was unable to measure to what degree the foul calls were changing in conjunction with a change in aggressiveness of the two teams, I was prevented from making any significant findings regarding a laggard bias. Had I had more time I would have completed a similar study on the regular season. Had I done this I would have been able to establish a standard for the correlation between the change in aggressiveness and the change in foul calls. Additionally, I would include more measures for variation in team play. Originally, I collected all the regular season averages for the statistics included in my analysis to control for variation in team steals, starter/bench playtime, blocks, etc., but I chose to exclude the data from my study due to possible variation in regular season play opposed to Finals play. If I had completed the same study for the regular season, then I would have been able to account for possible variation in play between the regular season and the finals.

My study adds to existing literature pertaining to officiating baises in the NBA Finals as well as supports past claims made by previous researchers. Although I did not achieve my goal of proving both of my hypotheses correct, I found my first hypothesis regarding team aggressiveness to be true, and I stumbled upon a few findings that in general support my overall hypothesis that the NBA Finals are subject to referee bias in line with extending the potential length of the series. It is my hope these finding will be expanded upon, and that someday someone is able to identify the bias I still strongly believe is present.

Figures

Figure 1: Difference in Means - Fouls

Series Score	Leader Avg. Fouls	Laggard Avg. Fouls	Difference	T-Stat
(0,0)	18.06	20.57	**-2.5**	-1.68
(1,1)	23.25	17.88	**5.36**	2.99
(2,2)	25.71	21.28	**4.42**	2.01
(3,3)	19.5	18	**1.5**	0.74
(0,1)	20.56	22.25	**-1.68**	-1.21
(1,2)	20.71	21.85	**-1.14**	-0.82
(2,3)	20.88	21.11	**-0.22**	-0.10
(0,2)	22	20.42	**1.57**	0.75
(1,3)	21.85	24.42	**-2.57**	-1.35
(0,3)	15.5	19.5	**-4**	-1.56
Overall	**20.8**	**20.728**	**0.074**	**0.12**

Figure 2: Difference in Means - Field Goal Attempts to Three Point Attempts

Series Score	Leader Avg. Field Goal Attempts/Three Point Attempts	Laggard Avg. Field Goal Attempts/Three Point Attempts	Difference	T-Stat
(0,0)	5.25	5.2	**0.06**	0.07
(1,1)	4.5	4.49	**0.01**	0.01
(2,2)	4.32	4.72	**-0.4**	-0.37
(3,3)	3.73	4.33	**-0.6**	-0.58
(0,1)	3.92	4.99	**-1.06**	-1.46
(1,2)	3.91	5.65	**-1.74**	-2.03
(2,3)	3.49	3.66	**-0.16**	-0.37
(0,2)	3.82	5.1	**-1.28**	-2.41
(1,3)	3.73	3.75	**-0.01**	-0.01
(0,3)	3.66	7.02	**-3.36**	-1.04
Overall	**4.033**	**4.891**	**-0.85**	**-3.01**

Figure 3: Difference in Means - Steals

Series Score	Leader Avg. Steals	Laggard Avg. Steals	Difference	T-Stat
(0,0)	6.88	8.31	**-1.44**	-1.57
(1,1)	7.89	7.67	**0.22**	0.14
(2,2)	6.43	7.43	**-1**	-0.82
(3,3)	6.5	8.25	**-1.75**	-1.11
(0,1)	8	7.63	**0.38**	0.36
(1,2)	6.21	7.36	**-1.14**	-1.06
(2,3)	8.56	8.33	**0.22**	0.11
(0,2)	7	8.57	**-1.57**	1.26
(1,3)	6.43	8	**-1.57**	-1.47
(0,3)	6	5	**1**	1.00
Overall	**6.99**	**7.655**	**-0.67**	**-1.63**

Figure 4: Difference in Means - Blocks

Series Score	Leader Avg. Blocks	Laggard Avg. Blocks	Difference	T-Stat
(0,0)	5.5	4.63	**0.88**	0.91
(1,1)	6.33	4.78	**1.56**	1.61
(2,2)	3.67	6.33	**-2.67**	-1.52
(3,3)	4.75	5.5	**-0.75**	-0.61
(0,1)	6.38	4	**2.38**	2.37
(1,2)	4.64	4.71	**-0.07**	-0.05
(2,3)	4.78	6.38	**-1.6**	-0.99
(0,2)	4.57	4.86	**-0.29**	-0.18
(1,3)	6	4.57	**1.43**	0.91
(0,3)	2.5	3	**-0.5**	-0.44
Overall	**4.912**	**4.876**	**0.037**	**0.09**

Figure 5: Difference in Means - Offensive Rebounds

Series Score	Leader Avg. Offensive Rebounds	Laggard Avg. Offensive Rebounds	Difference	T-Stat
(0,0)	11.75	10.31	**1.44**	1.09
(1,1)	9.89	11.78	**-1.89**	-0.97
(2,2)	12.29	9.43	**2.86**	1.16
(3,3)	12.25	9.25	**3**	0.78
(0,1)	11.06	11.94	**-0.88**	-0.67
(1,2)	11.5	10.21	**1.29**	0.78
(2,3)	11.22	10.67	**0.56**	0.33
(0,2)	9.14	12	**-2.86**	-1.23
(1,3)	12.14	10.43	**1.71**	0.65
(0,3)	9	13	**-4**	-1.78
Overall	**11.02**	**10.902**	**0.123**	**0.21**

Figure 6: Difference in Means - Defensive Rebounds

Series Score	Leader Avg. Defensive Rebounds	Laggard Avg. Defensive Rebounds	Difference	T-Stat
(0,0)	33.19	28.06	**5.13**	3.63
(1,1)	28.44	30.11	**-1.67**	-0.89
(2,2)	26.71	26.43	**0.29**	0.12
(3,3)	31	32	**-1**	-0.36
(0,1)	29.88	29.25	**0.63**	0.39
(1,2)	30.64	30.79	**-0.14**	-0.08
(2,3)	33.22	32.44	**0.78**	0.28
(0,2)	27.43	29.86	**-2.43**	-0.78
(1,3)	31.43	30	**1.43**	0.71
(0,3)	33	28.5	**4.5**	2.49
Overall	**30.49**	**29.744**	**0.752**	**1.09**

Figure 7: Difference in Means – Starter to Bench Playtime

Series Score	Leader Avg. Starter/Bench Playtime	Laggard Avg. Starter/Bench Playtime	Difference	T-Stat
(0,0)	2.51	2.78	**-0.26**	-0.83
(1,1)	2.15	3	**-0.85**	-2.12
(2,2)	2.89	3.41	**-0.52**	-0.82
(3,3)	2.71	4.86	**-2.16**	-2.90
(0,1)	2.5	2.44	**0.06**	0.17
(1,2)	2.7	2.43	**0.27**	0.83
(2,3)	2.48	2.7	**-0.22**	-0.58
(0,2)	2.28	3	**-0.72**	-1.65
(1,3)	2.55	2.65	**-0.11**	-0.24
(0,3)	3.47	2.08	**1.39**	0.99
Overall	**2.624**	**2.935**	**-0.31**	**-0.76**

Figure 8: Stacked Line Chart – Combined Difference in Means

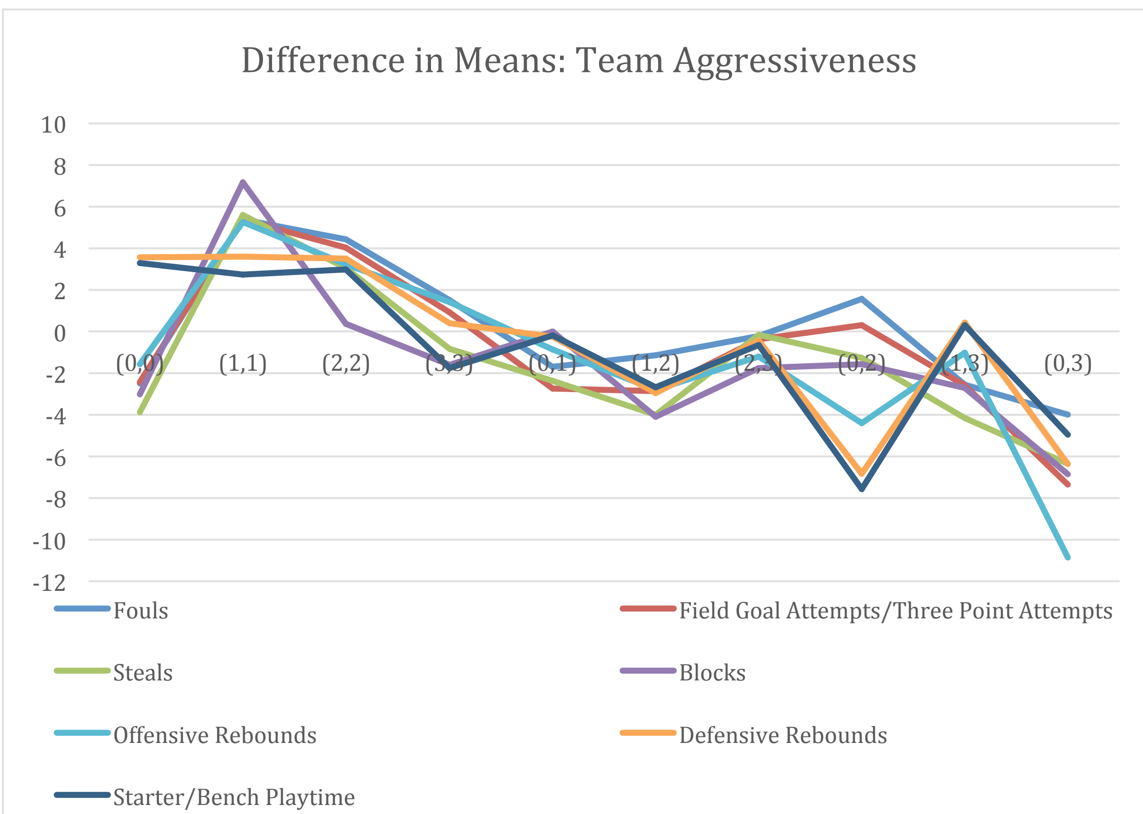


Figure 9: Regression Summary

Independent Variables	Coefficient	Std. Error	95% Conf. Interval		
Series Score: (0,0)	0.104	[.106]	-.105	to	.313
Series Score: (0,1)	0.128	[.119]	-.107	to	.363
Series Score: (1,0)	0.200**	[.093]	.016	to	.384
Series Score: (0,2)	No Data				
Series Score: (2,0)	0.200**	[.091]	.019	to	.380
Series Score: (1,1)	0.137	[.101]	-.063	to	.338
Series Score: (0,3)	No Data				
Series Score: (3,0)	-0.023	[.152]	-.325	to	.277
Series Score: (1,2)	0.177*	[.095]	-.010	to	.365
Series Score: (2,1)	0.209*	[.115]	-.018	to	.437
Series Score: (1,3)	0.281***	[.092]	.099	to	.463
Series Score: (3,1)	0.266***	[.103]	.062	to	.470
Series Score: (2,2)	0.247***	[.094]	.061	to	.433
Series Score: (2,3)	0.148	[.123]	-.096	to	.392
Series Score: (3,2)	0.228**	[.104]	.022	to	.434
Series Score: (3,3)	0.139	[.118]	-.094	to	.372
Steals	0.126	[.098]	-.068	to	.321
Blocks	-0.15	[.118]	-.383	to	.083
Offensive Rebounds	-0.001	[.071]	-.140	to	.139
Defensive Rebounds	-0.058	[.080]	-.218	to	.101
FGA/TPA	0.289**	[.148]	-.003	to	.583
Starter/Bench Playtime	-0.516*	[.307]	-1.122	to	.090
Game Time	0.079*	[.045]	-.011	to	.170
At Home	-1.762***	[.580]	-2.909	to	-.614
Year	-0.114	[.089]	-.289	to	.061

All values statistically significant at the: *10%, **5%, & ***1% levels.
Number of observations: n = 182
R^2 = .274

Fouls represents the number of fouls called on team A in game X. *Fouls on Op. Team* represents the fouls called on team B in game X. *Fouls on Op. Team* is multiplied by a dummy variable relating to the *series score* at the time of the game. The coefficients on each of the *series score* variables can be interpreted as the effect a foul on the opposing team has on the probability of an additional foul called on the team in question depending on the current series score. *Steals* represents the number of steals called on team A. *Blocks* represents the number of blocks by team A. *Offensive Rebounds* and *Defensive Rebounds* represent the number of offensive and defensive rebounds by team A. *Field Goal Attempts/Three-Point Attempts* is the ratio of team A's field goal attempts over the number of team A's three-point attempts. *Starter/Bench Playtime* represents the total starter minutes of play over the total bench minutes of play for team A. *Game Time* represents the total playtime of the game. *At Home* controls for whether or not the team is playing at home. *Year* controls for the year of the series.

Figure 10: NBA League Revenue by Year

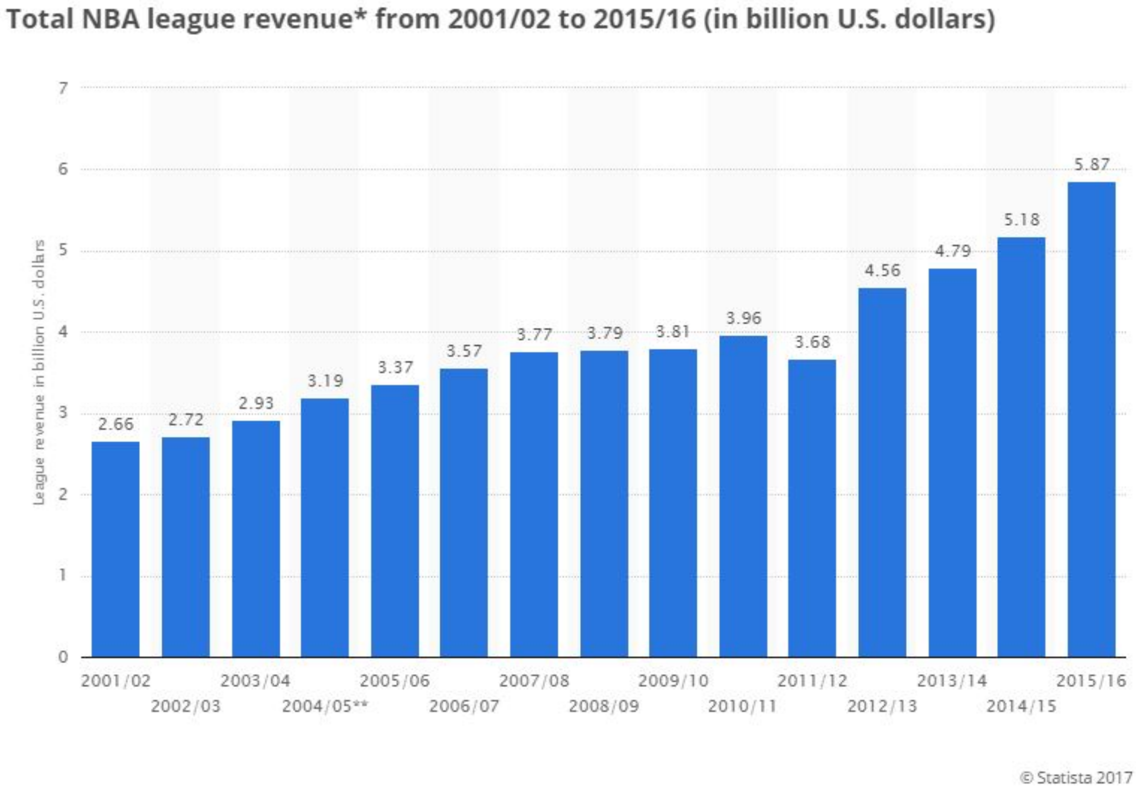
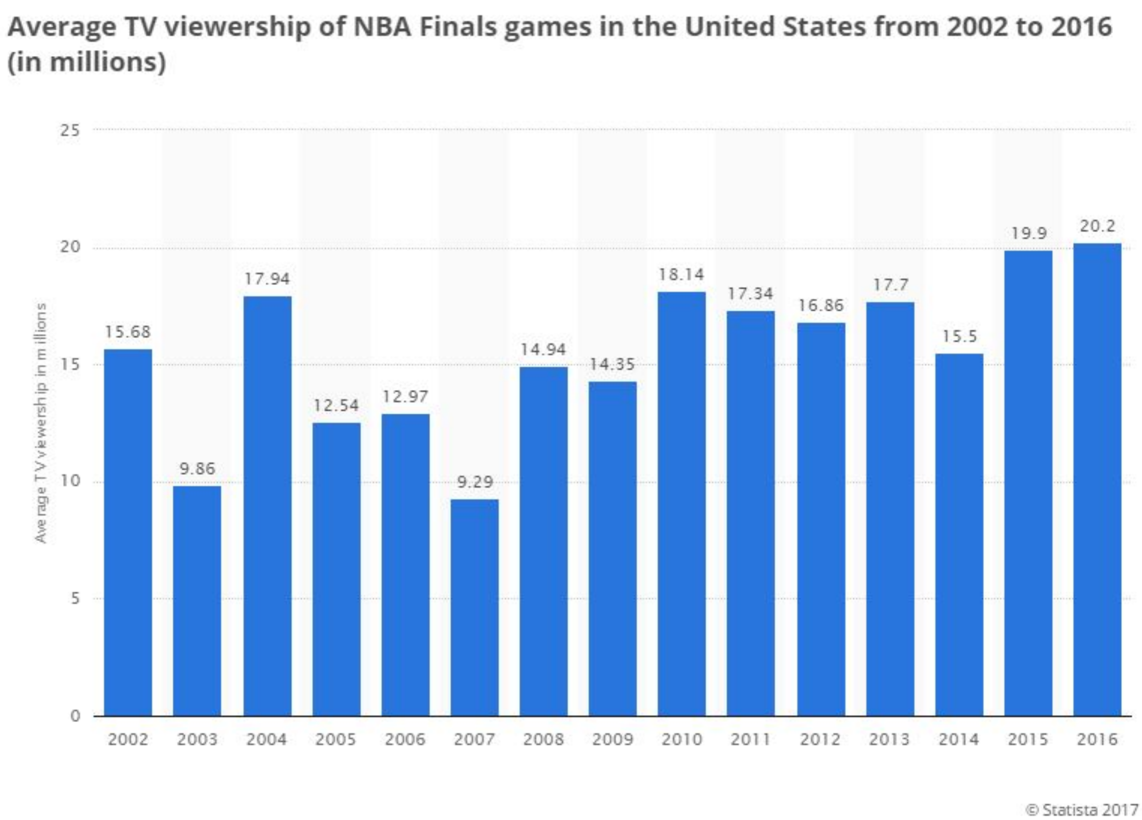


Figure 11: Average Viewership of NBA Finals Games by Year



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