How Does Winning Affect NBA Team Revenues?

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Abstract

This project investigates the relationship between team success in the National Basketball Association and team revenue, analyzing whether on-court performance, measured by win percentage and championship victories, translates into financial gain. Using revenue and win percentage data from 2010 to 2019, the study employs linear regression models and hypothesis testing to explore how success affects revenue both in the current and following seasons. Two linear regression models show that while win percentage in the current season is not a statistically significant predictor of revenue, higher win percentages do significantly correlate with increased revenue in the following year, as well as percentage change in revenue. However, hypotheses tests reveal that neither having a successful season nor winning a championship significantly increases a team's revenue in the next season when all teams are considered together. Further analysis at the individual team level identifies a subset of teams that do experience significant revenue increases during successful seasons compared to unsuccessful seasons. All revenue differences were analyzed using percentage change to account for disparities in team market sizes. This study contributes to sports economics by clarifying that success alone does not guarantee higher revenue across all teams.

Keywords: basketball, regression, win percentage.

1 Introduction

Professional sports teams generate billions of dollars of revenue each year through ticket sales, merchandise sales, broadcasting rights, sponsorships, and many more sources. The National Basketball Association (NBA) is one of the most profitable businesses in the United States, drawing attention both domestically and internationally. For example, during the 2023-2024 season alone, the 30 NBA teams generated a combined $11.34 billion (Statista, 2024). This highlights the large financial scale of the league and the potential for individual teams to experience significant revenue growth. Teams' profits can fluctuate year to year due to many different factors including market size, media exposure, and stadium capacity. Additionally, well known teams in bigger cities like the New York Knicks and the Los Angeles Lakers often have higher revenue than teams in smaller cities. But how greatly does a team's success affect its revenue? A team's on-court success may also significantly influence its financial performance due to increased attention and fan bases. Determining how success affects team profit can help teams understand the financial impacts of success and optimize revenue strategies. This question is particularly important in the modern sports landscape, where data-driven decision making is becoming increasingly common. By analyzing historical performance and financial trends, teams can better strategize both on and off the court.

In the 2022-2023 season, the Golden State Warriors were the highest-earning team in the NBA with $765 million in revenue after winning their seventh NBA championship in 2022 (Conte, 2024). However, despite winning their first NBA championship in 2023, the Denver Nuggets had only the 15th highest earnings the following season. Even though these teams had very different earnings, did they profit more than previous seasons after they had a successful season? This project aims to examine whether there is a measurable relationship between NBA team success and team revenue. Through the use of statistical tests and visualizations I analyze how NBA teams' revenues change when they have more successful seasons and what effect winning a championship has on a team's revenue.

Considerable work has been done researching NBA revenues and how the NBA has grown, however, few studies have isolated the financial effect of a team's success. Li (2011) studied how on court performance affects teams' revenues based on individual player contribution and wins. He measured the relationship between player statistics and their expected value and concluded that having well known players can increase revenue due to higher performance and ticket sales (Li, 2011). This analysis was done in May 2011 using data from the 1990s and 2010s, however the NBA has significantly grown since this time, prompting the possibility of new conclusions. In order to contribute to this work hypotheses tests and linear regression models are conducted to analyze whether a team's wins or winning a championship have an effect on their revenue in the next season. This analysis also compares revenue changes of each team with past seasons and measures how much a team's revenue increases in percentage terms when their win rate increases. In addition, I examine whether a successful season affects revenue in the current year or in the following season, due to delayed profits from playoff success. These results aim to provide insights into how NBA teams can better predict and maximize revenue through improved performance.

In Section 2 the data sets used in this analysis are detailed with a graph displaying the average NBA revenue per year and summary statistics of teams' win percentages. Next, Section 3 details the methods used to analyze how team success affects their revenue, and the regression models, hypotheses tests, and results are reported in Section 4. The discussions of these results and future directions, along with a short conclusion, are included in Section 5. All code and data is linked in Section 6 and a short thank you is included in Section 7. Lastly, all references are included with links in the Reference Section.

2 Data Description

This analysis uses two main data sets that include NBA teams' revenue and season data. Both data sets are composed of observational data from teams' past seasons collected from publicly available sources. These data sets allow for an in-depth comparison of team success

Table 1: Summary statistics of the win percentages in the NBA from 2009-2019.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.1060	0.3780	0.5120	0.4999	0.6100	0.8900

and financial performance across multiple seasons.

The first data set is from Kaggle and contains NBA season records and statistics for each year from 1946-2018 (Kaggle, 2017). For my analysis I use only the seasons on and after 2009-2010. This data set has 17 variables however, the analysis uses only three of these variables; season, team, and W/L (win percentage). This data set only contains data through the 2017-2018 season, therefore it is supplemented with the records of each team through the 2018-2019 season using data from Basketball Reference (Basketball Reference, 2025). Additionally, to ensure consistency throughout seasons, all past team names in the data set, 'New Jersey Nets", "Charlotte Bobcats", and "New Orleans Hornets", were updated to their current team names, "Brooklyn Nets", "Charlotte Hornets", and "New Orleans Pelicans", respectively.

Table 1, shows the summary statistics of NBA win percentages from 2009-2019. This table shows that the minimum win rate was 10%, while the maximum win rate was 89%. The median and mean are similar, with a slight skew to the left. This is beneficial to the analysis because it shows that the data is well distributed and roughly symmetric.

The second data set contains information from multiple sources including multiple Forbes articles (Forbes, 2024) and Run Repeat (Run Repeat, 2024). It contains each teams' generated revenue for each year from 2011 to 2021 and is given in million United States dollars. The average revenue (in million USD) of NBA teams for each season from 2011-2019 in displayed in Figure 1. It is calculated each year by adding the revenues of each team each year and dividing by 30, the number of teams in the NBA. Here we see that average revenue has increased gradually each year from 2011, with only a slight dip in 2012. By visualizing the average revenue of NBA teams we are able to understand the revenue of each team better by knowing how it relates to the season average.

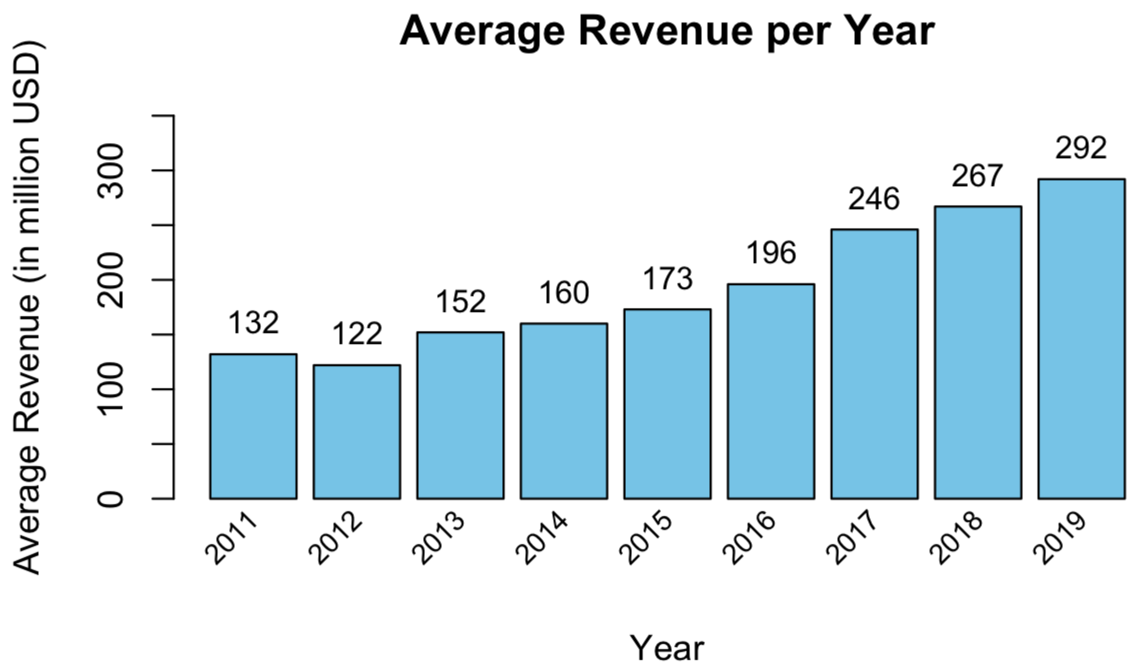

Figure 1: Bar chart of the average NBA Team Revenue each season from 2011-2019.

These data sets are combined for use in the linear regression models and hypotheses tests. A binary variable "Champion" is added to the data set, where 0 = no championship in that season, and 1 = championship won in that season. This data is collected from the list of NBA champions on the NBA website (NBA, 2024). The data is added in order to conduct hypotheses tests to examine the relationship between revenue change and winning a championship.

Although both revenue and win percentage data was collected for each team through the 2024 season, due to limitations from the COVID-19 virus, statistics of each team are severely skewed and are not beneficial to the analysis. This is due to shortened seasons, changes in attendance capacities, and less total games which cause fluctuations in revenue that compromise the consistency of the analysis. Due to this all data from the 2020 season and on are omitted. This results in a data set with revenue data from 2011 to 2019 and win percentage data for each team from 2010 to 2019. There is an extra year in the win percentage data in order to analyze the 2011 revenue data using both the 2010-2011 season and 2009-2010 season data.

3 Methods

This analysis compares teams' revenues across multiple years in relation to their win percentages, with the goal of identifying whether team success is associated with increased revenue. In order to assess whether win percentage is more associated with current revenue or future revenue, two linear regression models are used. These models are performed across all teams and all years, with the outcome being revenue. One regression model measures the association between a team's win percentage and its revenue in the same season. While the second linear regression model measures the association between a team's win percentage and its revenue in the next year. Furthermore, to analyze the linear relationships between the change in revenue and win percentage, an additional linear regression model is used, with percentage change in revenue as the outcome. All models use the equation

$$y = \beta_0 + \beta_1 WinPct. \tag{1}$$

In this equation y is the dependent variable; for the first regression, it represents revenue in the current year, in the second model, it represents revenue in the next year, and in the third model, it represents percentage change in revenue. Next, β_0 is the intercept, indicating the revenue when win rate is zero, and β_1 is the slope, which quantifies how much revenue is expected to change for one unit-increase of win rate. These models are evaluated using a significance level of 0.05. Lastly, $WinPct$ is the independent variable, which corresponds to the teams win rate. Diagnostic plots and statistical tests are used to check the assumptions of linearity, normality, constant variance, and independence for these models.

To further explore the financial impact of team performance, three hypotheses tests are conducted. The first test examines whether teams with successful seasons experienced greater revenue growth in the following season. For this test, "success" is defined as having a win percentage greater than 0.60. The second test examined whether winning a championship significantly affects revenue growth in the next year. This is concluded by testing whether championship teams experience a high average percentage increase in revenue the year after winning a championship. Revenue change for each team is calculated using the formula

$$Percentage\_Change = \frac{NextRevenue - CurrentRevenue}{CurrentRevenue} * 100. \tag{2}$$

The last hypotheses tests are individual two sample t-tests to compare each team's average revenue during winning seasons versus losing seasons. This analysis identifies which teams experience statistically significant revenue changes after a winning season. In this test, a "winning season" is defined as having a win percentage greater than 0.50. Each test will be conducted at a 0.05 significance level. If the p-value is less than 0.05 the null hypothesis is rejected.

Lastly, graphs are used to visualize the statistical results and to illustrate trends in team performance and revenue over time. They are used to show the average percentage revenue change for each team following a winning season and following a championship win. These visual tools support the conclusions drawn from the hypotheses tests and regression models.

Teams in larger cities, like New York and Los Angeles, have the potential to generate more revenue than other teams regardless of success. In order to counteract this bias in the data, all results quantify the change of revenue using percentages rather than an increase in raw numbers.

4 Results

Using the methods described in Section 3, the relationships between team success and revenue in both the same and subsequent seasons, as well as the financial impact of winning a championship are examined in the following subsections.

4.1 Linear Regression Analysis

Three linear regression models are fitted to evaluate the relationship between team success and revenue using Equation (1). They are evaluated using a significance level of 0.05. If the models have a p-value less than 0.05 it is concluded they are statistically significant. All assumptions for these models, including assumptions of linearity, normality, constant variance, and independence are verified. The first model examining revenue as a function of win percentage in the same season provides the equation

$$current\_revenue = 168.46 + 49.43 WinPct. \tag{3}$$

In this equation, the intercept of 168.46 indicates that when a team has a win rate of 0%, they are expected to have a revenue of \$168.46 million. Additionally, the win percentage coefficient of 49.43 indicates per one-unit increase in win percentage, a team's revenue is expected to increase \$49.43 million. While this model shows a positive relationship between win percentage and revenue in the same season, it has a high p-value of 0.101. This is greater than the significance level of 0.05 concluding there is not a statistically significant relationship between win percentage and revenue in the same year across all teams.

The second linear regression model examines revenue in the next season as a function of win percentage and outputs the equation

$$future\_revenue = 162.78 + 60.78 WinPct. \tag{4}$$

In this equation, the intercept of 162.78 indicates that when a team has a win rate of 0%, they are expected to have a revenue of \$162.78 million in the next season. The win percentage coefficient of 60.78 tells us that per one-unit increase in win percentage, a team's revenue in the next is expected to increase \$60.78 million. This model has a low p-value of 0.041 concluding that at a 0.05 significance level, teams with higher win percentages tend to earn

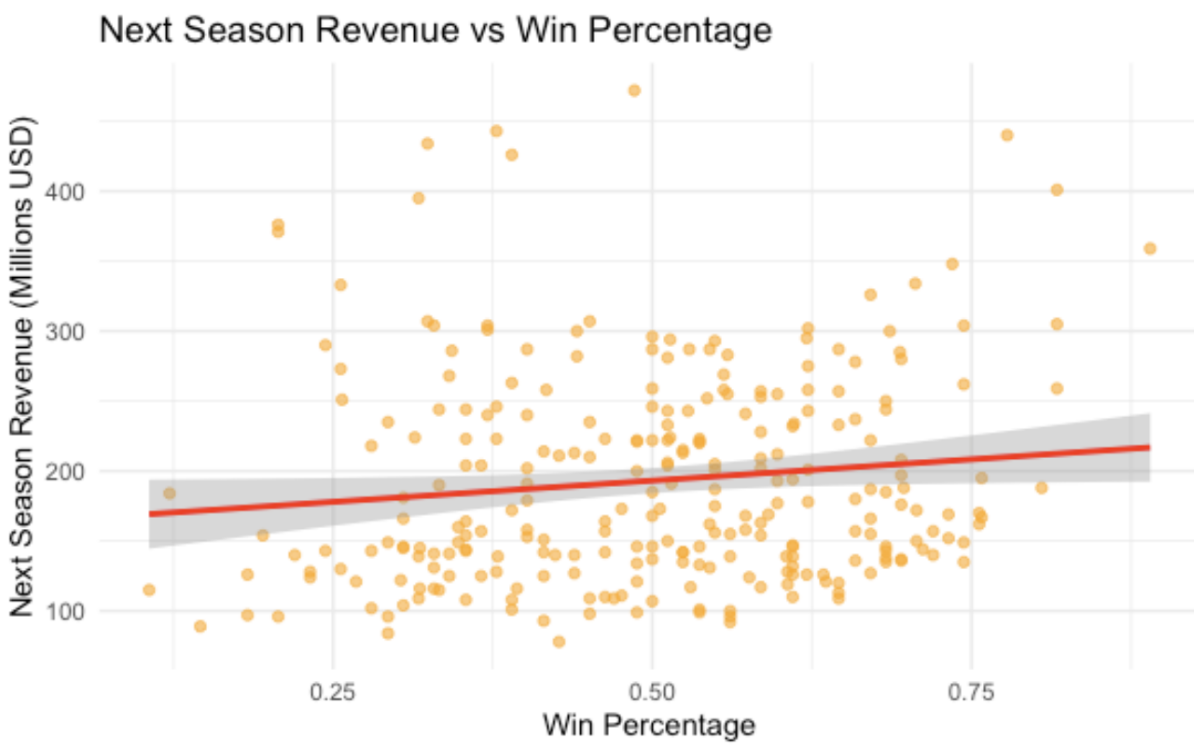

Figure 2: Linear Regression model over graph of win percentage versus next season revenue.

significantly more revenue in the following year.

However, the adjusted R-squared value is only 0.01182, meaning that win percentage explains just 1.18% of the variation in next season's revenue. This indicates that while the relationship is statistically significant, it is not practically strong; win percentage alone is not a reliable predictor of team revenue.

This relationship is visualized in Figure 2, which displays a scatterplot of win percentage versus next season revenue with a fitted regression line. While the line shows an upward trend, the wide spread of data points around it further supports the conclusion that win percentage has only a small effect on revenue. The shaded region around the line represents the 95% confidence interval.

These models conclude that a higher win percentage has a greater effect on revenue in the following season than revenue in the current season. In order to test whether win percentage has a linear relationship with the change in revenue across all teams, the last linear regression

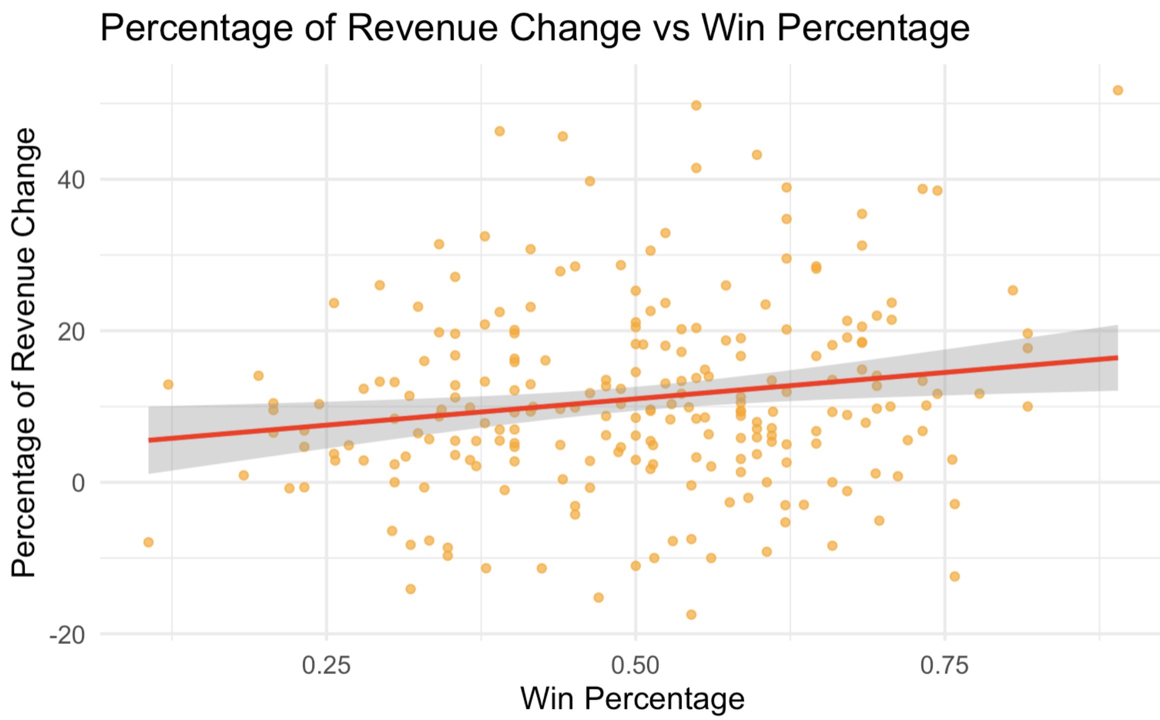

Figure 3: Linear Regression model over graph of win percentage versus percentage of revenue change in the next season.

model uses percentage change in revenue as the dependent variable. This model produces the equation

$$revenue\_percentage\_change = 4.086 + 13.899WinPct. \tag{5}$$

For this equation, the intercept of 4.086 indicates that when a team has a win rate of 0%, they are expected increase revenue by 4.086%. This model has a low p-value of 0.009 indicating that at a 0.05 significance level, teams with a higher win percentage tend to have a higher percentage change in revenue. While this model shows a strong positive relationship, it has a low R-squared value of 0.024, meaning that win percentage explains only 2.4% of the variation in percentage change in revenue. This concludes, similarly to the last models, that while the relationship between these variables is statistically significant, win percentage does not significantly predict the percentage change in revenue.

Figure 3 shows the regression model over a scatterplot of win percentage and percentage change of revenue in the next season. This graph shows the linear relationship between the variables, however helps conclude that there is not prediction capabilities in the model. The visual confirms that many other factors, such as market size, sponsorships, media exposure, and player popularity, likely contribute more significantly to financial performance than win percentage alone.

4.2 Hypotheses Tests

After concluding teams' win percentages have a more significant relationship with revenue in the following season, three hypotheses tests were run. The first test investigates whether teams that experience a successful season, defined by having a win percentage greater than 0.60, have significantly different percentage revenue growth than teams with less successful seasons. This hypothesis is tested at a 0.05 significance level. The null hypothesis, H_0, is there is no difference between mean percentage revenue change between teams with a successful season and those without. The alternative hypothesis, H_a, is there is a significant difference in revenue growth between the two groups. A two sample t-test yielded a p-value of 0.8064, which is greater than 0.05, meaning we fail to reject the null hypothesis. This concludes that there is no statistically significant difference in the percent revenue growth of teams following a successful season compared to teams with a less successful season.

The next hypothesis test examines whether winning an NBA championship correlates with a statistically significant increase in revenue the following year. This hypothesis is tested at a 0.05 significance level. The null hypothesis H_0 is there is no difference in the average percentage revenue change between championship-winning teams and non-championship teams. The alternative hypothesis, H_a, is that teams winning a championship do experience different revenue growth in the following year. The two sample t-test calculated a p-value of 0.8814, which is greater than 0.05, determining we fail to reject the null hypothesis. This result indicates that there is no statistically significant evidence that winning a championship

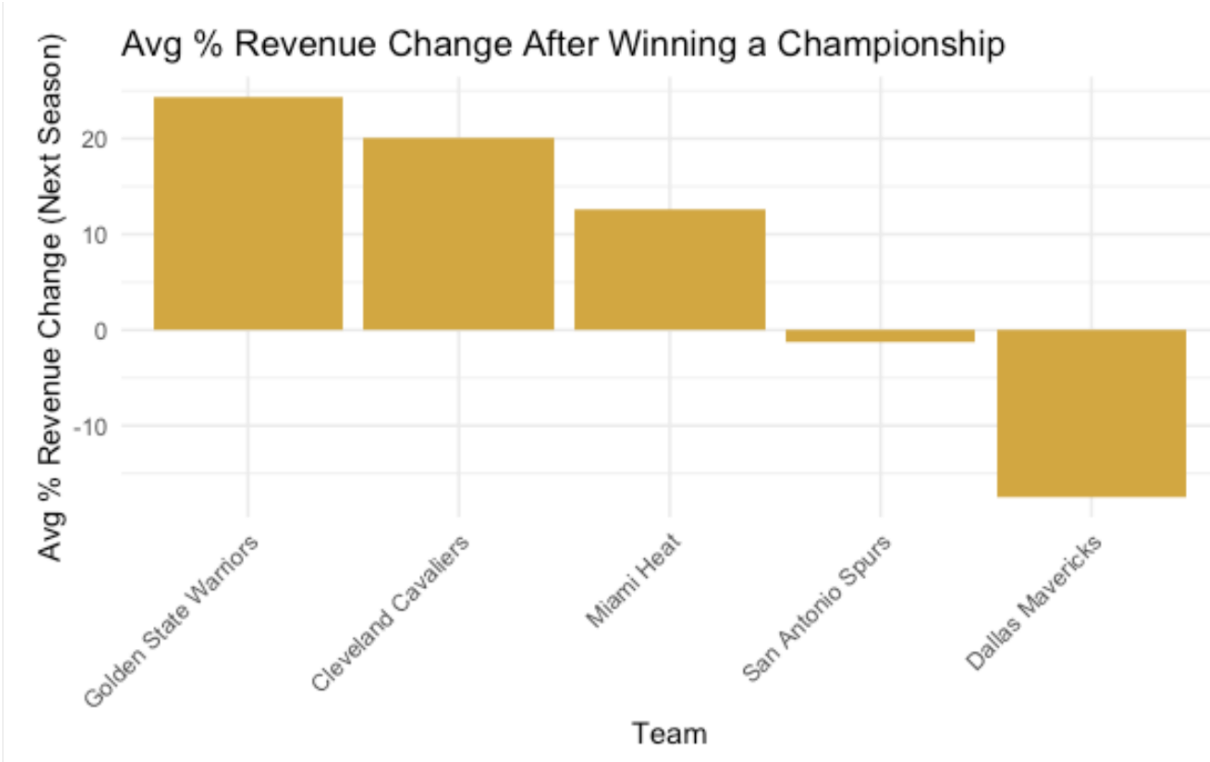

Figure 4: Bar chart of the average percent revenue change in the next season for each championship team.

results in higher revenue growth in the following season compared to non-championship teams.

Figure 4 displays the average percentage revenue change in the season following a championship win for the teams that won at least one championship between 2010 to 2018. Interestingly, the Golden State Warriors and Cleveland Cavaliers saw substantial post championship win revenue increases, with increases above 20%. However, teams like the Dallas Mavericks experienced a significant drop in revenue after winning, suggesting that a championship title does not always guarantee financial growth in the following year. This variability helps to explain why the above hypotheses tests concludes there is no statistically significant difference in revenue increases after winning a championship.

Due to the previous hypotheses tests determining there is no significant relationships between revenue and high win percentages across all NBA teams, the last hypotheses tests analyze the relationships of each team. These hypotheses tests perform two samples t-tests

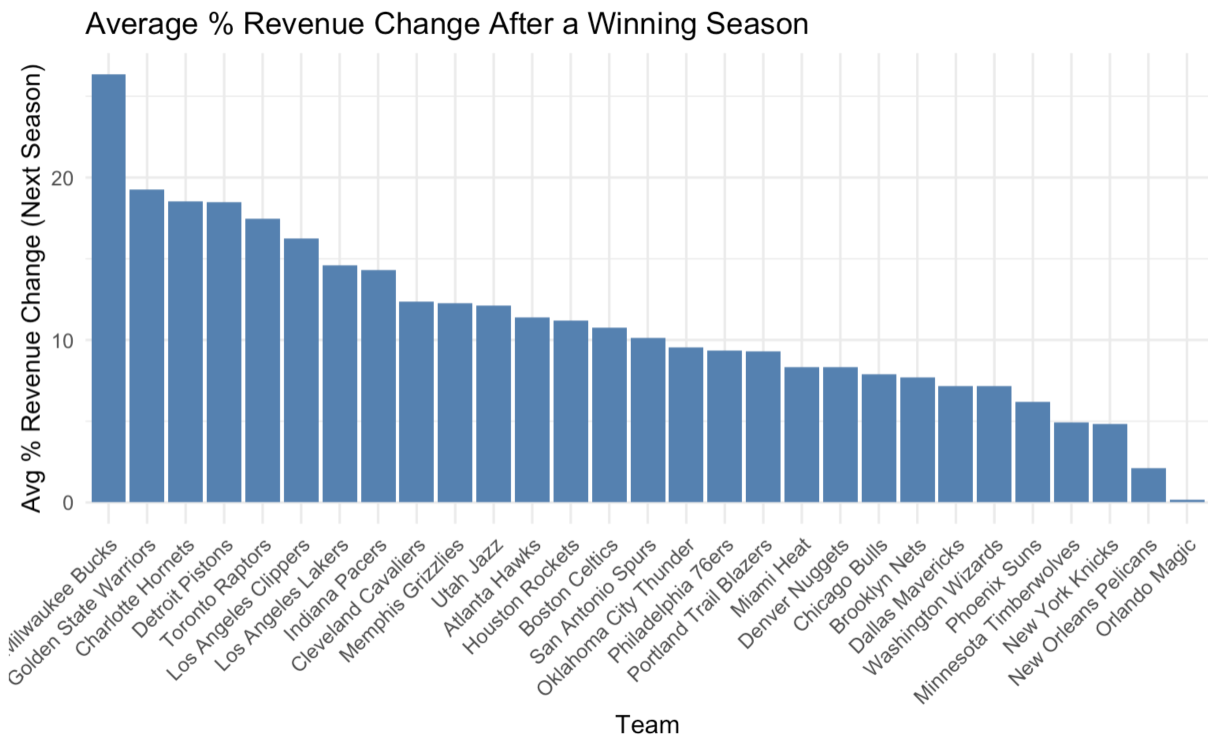

Figure 5: Bar chart of the average percent revenue change for each team after a winning season.

for each individual team, comparing their average revenue during winning seasons to their average revenue during losing seasons. In this test, a winning season is defined by having a win percentage above 0.50. Similarly to the previous tests, these tests will be conducted at a 0.05 significance level. The null hypothesis, H_0, for each team is there is no difference in the average revenue between winning and losing seasons. The alternative hypothesis, H_a, for each team is that the team's average revenue differs significantly based on whether the team had a winning or losing season. The only teams with p-values less than 0.05 were the Chicago Bulls, Memphis Grizzlies, New York Knicks, Golden State Warriors, Toronto Raptors, and the Los Angeles Lakers. The data for these teams shows that the revenue difference between winning and losing seasons is statistically significant. This suggests that while there may not be a pattern across all teams, some NBA teams do experience an increase in revenue during more successful seasons.

Figure 5 shows the average percentage revenue change for each NBA team following a winning season, defined as a season with a win percentage greater than 0.5. This graph shows that while some teams tend to experience revenue growth after a successful season, the magnitude of change varies greatly. For example, the Milwaukee Bucks, Golden State Warriors, and Charlotte Hornets showed the highest average revenue increases, between 18% to 30%. However, teams like the New Orleans Pelicans, New York Knicks, and Orlando Magic saw minimal growth. This differs slightly from the results of the last hypothesis tests. This could indicate that even though some teams have high revenue changes after a winning season, it is not statistically different than their revenue changes after losing seasons.

5 Discussion and Conclusion

This analysis combined data collection, statistical modeling, and visual analysis to explore the financial impact of team success in the NBA. With the use of NBA team revenue and win percentage data, I applied linear regression models to assess the relationship between win percentage and revenue, and conducted multiple hypotheses tests to evaluate revenue growth after successful seasons and championship wins. From these models I concluded there is a statistically significant positive relationship between win percentage and revenue in the next season. However, win percentage shows minimal accuracy for predicting revenue. Additionally, from the hypotheses tests I determined the percent change in revenue is not statistically different for teams when they have a successful season or win a championship. The team-specific hypothesis tests revealed that the only teams who experience statistically significant revenue boosts following winning seasons are Chicago Bulls, Memphis Grizzlies, New York Knicks, Golden State Warriors, Toronto Raptors, and the Los Angeles Lakers. This comprehensive approach not only deepened our understanding of sports economics but also determined whether success translates into financial gain across different NBA teams.

This project contributes to the broader understanding of how NBA team performance translates into revenue for professional basketball teams. It directly addresses the need identified in Section 1: to determine whether team win percentage or championship wins correlates with increased revenue. While the linear regression and hypotheses tests did not show a strong correlation between success and revenue across all teams, the individual team analyses did uncover some statistically significant revenue differences. These results only partially confirm my expectations. I anticipated a general upward trend in revenue with success, but found that only certain teams significantly benefited from higher win rates. This suggests that the financial impact of winning is not league-wide. These conclusions help teams by determining that team success is not a major factor in increased revenue. By understanding this, teams can optimize their resources to gain revenue by improving other areas of their franchises, even when their team is having an off-year.

The main limitations of this study are the differences in team market sizes and limited variables. Revenue is affected by many factors beyond win percentage, including sponsorships, local economies, and media contracts; variables that were not included in this dataset. This analysis attempted to conclude the effect win percentage only had on revenue, by performing simple linear regression instead of multiple linear regression. Future studies could consider incorporating additional variables including player popularity, city population sizes, and tourism rates, to increase the accuracy of the linear regression model. Future work could also explore the impact of playoff performance, international exposure, and social media following on revenue growth. As the NBA becomes more global and digital, these factors are increasingly relevant. Additionally, tracking long-term revenue trends post-championship, rather than just the immediate following season, could offer deeper insight into delayed or sustained financial impacts. Furthermore, expanding the data set beyond the NBA to include other professional leagues may help generalize these findings. The takeaway from these limitations is that success can influence financial performance, but this effect is not guaranteed nor always statistically significant; it is magnified in teams with pre-existing strong market presence.

This analysis integrates programming and data management by compiling different data sets in order to create the best data set for my analysis. Data analysis is done by conducting hypotheses tests and regression models to determine if teams have different revenues based on their success rate. Furthermore, this data is visualized in graphs and tables in order to best convey results. Lastly, all the data is ethical because it is all publicly available, contains no confidential information, and lacks bias due to the observational nature of the data. Any bias that may be caused by the difference in the sizes of teams cities was addressed by comparing teams' changes in revenue percentages.

6 Supplemental Materials

All code and data used in this manuscript are available at https://github.com/ogmassad/Capstone-Information.

7 Acknowledgments

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