The Effect of Trades on NBA Franchise Revenues

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Abstract

My research question tries to find the impact of player trades on NBA franchise revenues between 2011 to 2024 seasons. The data analyzed includes all 30 NBA teams, exploring trade activity, win percentages, ticket prices, and other factors that influence financial performance. The results show that teams who do participate in trades, on average, receive a 30 million increase in their revenue. This could suggest that teams should value trades and marketing efforts in order to increase their revenues. Overall the study offers results into how a good trading strategy can influence the financial success in the NBA market.

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I. Introduction

The NBA recently reached $11 billion in total revenue, growing by approximately $700 million from previous years. This jump shows how successful the league has become and sets a baseline for understanding the financial recipe behind its success. Among the many factors feeding this growth, player trades stand out as not just calculated moves to build teams but also important financial decisions that eventually dictates the financial success of a team. Trades, often characterized as the movement between players from one team to another, are a common tool used throughout the NBA. While much of the hype between these trades only focuses on their impact to make a team better or have a chance at playoffs or championships, the financial consequences or rewards are often overlooked.

As a basketball fan myself, I've always been deeply affected by trades, especially when my favorite players, like DeMar DeRozan, switch teams. The emotional impact of seeing your favorite player in another jersey as well as the unwillingness that follows to support a team has been my personal motivation to explore how these feelings are presented in factors such as fan behavior (buying tickets, merchandise, etc.) and how that therefore affects team revenues. In addition, this project can serve as a valuable test of how effective trades are in boosting team revenues, which could inform changes in policies like salary caps, potentially encouraging more sign-and-trade deals and other strategies to promote team success and financial growth. Overall, this study tries to find the relationship that these trades can have on revenues combined with factors such as media exposure, win percentages, and so on.

II. Literature Review

The research by Tyler Matthew Stanek played a role in helping to understand the broader economics of NBA franchises, although his focus was on player salaries and marginal revenue products. Essentially, Stanek examines player compensation and how it ultimately affects team revenues. Stanek's findings were important in showing how NBA players, through a different independent variable of focus, influence revenue generation. For example, his study found that veterans are often paid more than they should be in relation to younger players, which hints that certain decisions can unequally affect a team's financial success. This claim complements my research focus on trade activity and its impact on team revenues, as trades typically involve player movement influenced by factors such as contract size, age, and market value. While my study directly examines trades, Stanek looks at specific players and how complicated roster management can be. Overall, understanding player worth in the market could change what type of trades teams are conducting.

The next research paper I reviewed was by Jake Harrison, who studied the effects of play style on NBA franchise revenues. Similar to my research, we examine the same dependent variable though Harrison focuses on three-point shooting as his independent variable of choice. The ultimate goal of both studies is to understand how different factors indirectly affect fan demand, leading to the creation or loss of franchise revenues. His results showed that teams taking more three-point shots tend to generate lower revenues, which unlike my findings, suggests that not all team choices guarantee higher earnings. This shows that team revenues depend on multiple factors, some of which may benefit a franchise while others may not.

Additionally, Harrison's study only covered a few years before and after the league's shift toward increased three-point shooting, limiting the scope of his analysis. In contrast, my research spans a broader range of seasons and includes all teams, making it more generalizable to the entire league.

The study by Tianqi Li was an interesting research topic involving the familiar variable of trades. However, his study focuses on a different dependent variable: team performance and how trades, through salary dispersion, affect team performance . Li uses panel data, similar in structure to how I set up my data, though this only spans to a couple years being the 2014-2015 and 2015-2016 seasons. In his results, Li discovers that salary dispersion, influenced by team performance, negatively impacts team success. This shows that trades, especially when involving salary imbalances, disrupt current team structures and ultimately affect performance. While Li uses game-level data and my research focuses on franchise-level data, both studies share a common interest: understanding the ultimate impact of trades on team success, mine through financial outcomes and his through team performance. Li suggests that the NBA should tighten its policies on sign-and-trade deals and salary caps to create more balanced trades, thus improving team performance. Overall, his study provides insights into the other side of my motivation, helping me better understand the need for smarter trade decisions and how they can influence league policies.

Lastly, Harrison Li's research on the relationship between on-court performance and team revenues was the only paper I found that showed a positive relationship between the independent variable and franchise revenues. Li uses player-level data such as points, assists, rebounds, steals, and so on. From this data, he concluded that better individual performance was a significant indicator of how well a team performed by increasing fan engagement. Similar to Stanek, Li also uses MRP (marginal revenue product), but through player performance measures rather than salaries. This could explain why Li reached a more positive conclusion compared to Stanek. Li also did well in covering more seasons, more players, and thus capturing a wider range of data that better reflects actual outcomes. Even though his dataset was broader than the previous three studies we examined, his focus on individual players remains somewhat limited.

III. The Model and Variable Selection

Description:

To determine the impact of trade activity on NBA franchise revenues, we need to identify a regression model that takes franchise revenue as the dependent variable. The model should also have carefully selected independent variables based on factors I believe directly or indirectly influence franchise revenues. The goal would be to consider both market characteristics alongside measurable team data. This balance makes sure the model isn't overly complex and makes sure to look at all angles that could play a part with our dependent variable.

Variable Selection:

For the model to make sense below will be the list of the variables used with a small description of what they represent. Each one of them is an independent variable and were chosen based on their relevance to financial performance. Each one will get analyzed and refined further in the data section but for now having a brief description should help with understanding the model. First of all, trade activity is a binary variable where a value of 1 indicates that a team made at least one significant trade during the season, impacting team composition or performance, while a value of 0 indicates no impactful trades were made. Top 15 merchandise ranking is another binary variable showing whether a team has players in the NBA's top 15 jersey sales, serving as an indicator for player popularity and marketability. Games televised measures the total number of nationally televised games a team plays during the season, reflecting media exposure and popularity. Win percentage is calculated as the number of games won divided by the total games played, indicating a team's competitive success. Playoff appearance is a binary variable indicating whether a team qualifies for the playoffs, as postseason participation typically leads to additional revenue streams. Total ticket sales capture the cumulative number of tickets sold throughout the season, reflecting fan attendance and game popularity. Average ticket price measures the average cost of a ticket for home games, with higher prices often reflecting greater demand and perceived team value. Metro population represents the estimated population of the team's metropolitan area, using it as a measure of market size and potential fan base. Lastly, All-Star count records the number of players from a team selected for the All-Star game, emphasizing team star power and individual player marketability.

Main Model and Prediction:

My prediction would be that teams that participate in trades will experience a boost in their revenues. This is because trades can start a chain of excitement among fans, create media hype, and potentially improve teams overall rating. The art of trading brings the possibility of rebuilding a team's future, whether through acquiring superstar players or essential role players. The model should lead us to these outcomes: through the coefficients, each variable will tell their story of how much they contribute to franchise revenues. For example, if we note that trade activity has a positive coefficient, it would indicate that through trading, teams were able to make more money. The main model includes all of the variables with no adjustments made. I also include three additional models that adjust the main model's layout to explore different perspectives. These models restrict certain variables or change the dependent variable to see if we can discover anything useful beyond what the main regression outcomes show. Below is the model with no adjustments made.

Franchise Revenue = β_0 + β_1(Trade Activity) + β_2(Top 15 Merchandise) + β_3(Games Televised) + β_4(Win Percentage) + β_5(Playoff Appearance) + β_6(Total Ticket Sales) + β_7(Average Ticket Price) + β_8(Metro Population) + β_9(All Star Count)

Model 2: Restrictive Model

In Model 2, I took a different approach by removing specific variables to see how the absence of certain factors would affect the results. Specifically, I excluded variables such as All-Star count and playoff appearances to evaluate how much revenue can be explained without them. This change gives more importance to other variables like trade activity, ticket sales, and market size, allowing us to see if these factors alone still drive revenue growth. For example, if a team doesn't have their star players, we want to determine whether its revenue could still increase through well-executed trades. Overall, this model aims to separate revenue boosts driven by star players from those generated by trades.

Model 3: Log-Model

The third model provides a well rounded interpretation of our data by log transforming our franchise revenues and metro population. This small change in the model can create a big difference because it makes the relationship between variables easier to understand as percent changes. If our result shows that the coefficient for ticket sales is 0.07, this means for every 1% increase in ticket sales, franchise revenues are predicted to increase by 0.07%. Thus, a 10% increase in ticket sales would mean a 0.7% increase in franchise revenues. This model would effectively show us proportions between variables excluding the influence of big outliers which can make the model results and their relationship easier to interpret. The model would reflect common revenue shifts based on proportionate changes in ticket sales or other variables.

Model 4: Team Performance

In this model, we are trying to determine how trades influence team success rather than checking how they affect revenues. Through this measure, we can evaluate how trades improve a team's competitiveness, offering a different perspective on how they impact financial outcomes. If a trade brings in better players, leading to a playoff run or even a championship, the result would be increased ticket sales, sponsorships, and televised games—all indirectly boosting franchise revenues. Through this model, I wanted to see how changing the dependent variable can help uncover details that may not be immediately apparent when focusing only on revenues. Similar to the research conducted by Harrison Li, I aim to see whether improved team performance acts as a link between trades and financial success, effectively connecting better team performance to a team's profitability. Although this is separate from my research question it could provide interesting details that can answer further questions with results of the main model.

IV: Data

In this section I will discuss the data portion of the research question, what went into collecting it, and any complications and further refinement of variables that impact the data collection process. For my research I compiled a panel data set ranging from the 2011-2024 NBA seasons. For every year data was collected on the 30 NBA teams which resulted in 390 total observations. Below is a summary stats table showing rough representation of the data collected for this project.

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Top.15.Merchandise Games.Televised Win.Percentage  Playoff.Appeareance Total_Ticket_Sales_Million Average.Ticket.Price Metro_Population_Million
Min.   :0.0000     Min.   : 0.00   Min.   :10.60   Min.   :0.0000      Min.   :0.0000             Min.   :  0.0        Min.   : 0.877
1st Qu.:0.0000     1st Qu.: 3.00   1st Qu.:39.55   1st Qu.:0.0000      1st Qu.:0.6277             1st Qu.:107.0        1st Qu.: 1.780
Median :0.0000     Median : 8.00   Median :51.20   Median :1.0000      Median :0.7098             Median :153.5        Median : 3.425
Mean   :0.3128     Mean   :10.85   Mean   :50.00   Mean   :0.5308      Mean   :0.6613             Mean   :163.6        Mean   : 5.030
3rd Qu.:1.0000     3rd Qu.:19.00   3rd Qu.:60.58   3rd Qu.:1.0000      3rd Qu.:0.7766             3rd Qu.:204.0        3rd Qu.: 5.893
Max.   :1.0000     Max.   :42.00   Max.   :89.00   Max.   :1.0000      Max.   :0.9944             Max.   :611.0        Max.   :18.937
All.Star.Count   Franchise.Revenue
Min.   :0.0000   Min.   : 78.0
1st Qu.:0.0000   1st Qu.:164.0
Median :1.0000   Median :225.0
Mean   :0.9026   Mean   :242.2
3rd Qu.:1.0000   3rd Qu.:293.8
Max.   :4.0000   Max.   :800.0
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Data Sources:

I collected revenue data from NBA financial reports and team-specific revenue data available through sports analytics sites like Forbes and Statista. Player trades and roster data were collected from ESPN, NBA.com, and official team press releases to identify significant trades. Market size and population metrics were based on the U.S. Census Bureau data for metro area population and city GDP data from the U.S. Bureau of Economic Analysis. Top-selling merchandise rankings were pulled from NBA merchandise reports and fan engagement metrics from sources like Fanatics and Sports Business Journal. Playoff appearances and team performance data, including win percentages and playoff records, were accessed via Basketball Reference and NBA.com statistics pages. Ticket sales data, including average ticket prices and sales figures, were sourced from Team Marketing Report and secondary market sites like Ticketmaster for league-wide price averages.

Variable Description:

For this section, we will look closer at variables that are not easily characterized and require specific guidance when gathering data. First is the trade activity variable, which is highly subjective due to the significance of player movement. As stated earlier, trade activity is represented as a binary variable where a value of 1 indicates that a team made an impactful trade, while a value of 0 means no such trade took place. To ensure consistency, I developed a strategy for classifying certain trade activities. If one team clearly benefited from a trade by acquiring an impactful player while giving up draft picks, only that team would receive a 1. For example, if the Lakers traded LeBron James to the Houston Rockets for cash considerations and draft picks, the Rockets would receive a value of 1. These cases were rare, but when encountered, I examined the specific trade more closely to assess how impactful the player was based on contributions such as points, rebounds, and minutes played. In cases where both teams traded players who were clearly starters, All-Stars, or key bench players, both teams would receive a value of 1. If a trade occurred mid-season, only the team that kept the traded player into the following season would receive a 1. Most importantly, trades were typically excluded if they only involved future draft picks or cash considerations. Overall, this classification method maintained consistency. In rare or borderline cases, I made the final decision on whether a team received a 0 or 1, ensuring that similar situations were evaluated based on player statistics and overall trade impact.

The only two other variables that required extra time to evaluate were Games Televised and Top-15 Merchandise. In terms of games televised, media deals presented challenges. I had to research when certain teams secured streaming agreements and how much TV exposure they received. Initially, collecting data on the number of games aired for each team in recent seasons was straightforward. However, as I examined older seasons, data availability significantly decreased due to the exclusion of certain streaming services introduced in later years. After recognizing this issue, I realized that some data was missing because I had included TV streaming games from NBA League Pass and similar platforms as part of the games televised count. To ensure consistency, I decided to restart the data collection process, focusing only on nationally televised games aired on established networks like ESPN, TNT, and ABC. This approach allowed me to gather more reliable data while avoiding newer streaming platforms such as YouTube TV and NBA League Pass, which did not have historical consistency.

Top-15 merchandise also had a similar problem where data was easy to collect in the beginning but did not have statistics for older years. For example, in the most recent seasons, a few websites provided rankings of merchandise sales, including the team and player, which was very convenient. However, for 2014, there was no data available, and for 2018, only the top 10 merchandise rankings were listed. In these cases, where only the top 10 was available when I required the top 15, I filled in the gap by directly searching for the remaining five players. For the year with no data I searched through ESPN data for jersey sales and selected the top 15. Apart from these challenges, the websites from which I gathered data for the other variables had spreadsheets containing all the data and years I was looking for, making the data collection process much more straightforward.

V. Results

After running the models and including all necessary data, here are the results that I received. I will give a quick rundown of the most important findings for each variable according to the results. The variable of importance being Trade Activity had three stars of significance in Models 1-3, with a coefficient of 30.288 in Model 1 and very similar values in Models 2 and 3 (30.303 and 0.129, respectively, when logged). Top-15 Merchandise showed no significance in any model, with coefficients of 11.524 in Model 1, 11.441 in Model 2, 0.046 in Model 3, and -0.253 in Model 4. Games Televised had three-star significance across Models 1-3, with coefficients of 2.820 in Model 1, 2.736 in Model 2, and 0.011 in Model 3 (logged revenue). In Model 4, it had two-star significance with a coefficient of 0.161. Win Percentage was most significant in Model 2 with three stars and a coefficient of -1.008, had two stars in Model 3 with a coefficient of -0.004, and one star in Model 4 with a positive coefficient of 15.860. Playoff Appearance had no significance in Models 1 and 3, was not included in Model 2, and showed the highest significance with three stars in Model 4, where it had a coefficient of 15.860 .Total Ticket Sales had negative coefficients across all models, with values of -8.327 in Model 1 and -7.459 in Model 2, and no significance. In Model 3, it had a coefficient of 0.069, and in Model 4, -0.680. Average Ticket Price had three-star significance in Models 1-3, with coefficients of 0.420 in Model 1 and 0.001 in Model 3 (logged revenue). It had no significance in Model 4, where its coefficient was 0.007. Metro Population showed three-star significance throughout all four models. Its coefficients were 3.406 in Model 1, 3.404 in Model 2, 0.097 when logged in Model 3, and -0.365 in Model 4.. All-Star Count only had three-star significance in Model 4, with a coefficient of 5.565. In the other models, it showed no significance, with coefficients of -3.814 in Model 1, -0.008 in Model 2, and 0.032 in Model 3. Also, looking at the R^2 values across all the models lets us know how well the independent variables help explain the variation in the dependent variable. In Models 1 and 2, the results show a value of 0.385, meaning the variables explain 38.5% of the variation in franchise revenue. In Model 3, this value becomes smaller, explaining only 31.8% of the variation in franchise revenue. Model 4, which now looked at win percentage as the dependent variable, had a value of 0.695, meaning the independent variables were a better fit in explaining team performance rather than franchise revenue. Below is the complete results table that displays the numbers we have been discussing.

Regression Results: Franchise Revenue and Winning Percentage

	Dependent variable:			
	Franchise Revenue		Log Franchise Revenue	Winning Percentage
	(1)	(2)	(3)	(4)
Trade Activity	30.288***	30.303***	0.129***	-0.160
	(8.274)	(8.255)	(0.034)	(0.842)
Top 15 Merchandise	11.524	11.441	0.046	-0.253
	(11.771)	(11.678)	(0.049)	(1.198)
Games Televised	2.820***	2.736***	0.011***	0.161**
	(0.660)	(0.629)	(0.003)	(0.067)
Win Percentage	-1.069**	-1.008***	-0.004*	
	(0.503)	(0.335)	(0.002)	
Playoff Appearance	6.814		0.034	15.860***
	(13.148)		(0.055)	(1.064)
Total Ticket Sales	-8.327	-7.459	0.069	-0.680
	(24.737)	(24.655)	(0.103)	(2.518)
Average Ticket Price	0.420***	0.419***	0.001***	0.007
	(0.054)	(0.054)	(0.0002)	(0.006)
Metro Population	3.406***	3.404***		-0.365***
	(0.943)	(0.938)		(0.094)
log(Metro_Population_Million)			0.097***	
			(0.022)	
All.Star.Count	-3.814		-0.008	5.565***
	(7.625)		(0.032)	(0.722)
Constant	164.216***	161.790***	5.044***	36.086***
	(24.238)	(21.432)	(0.102)	(1.635)
Observations	390	390	390	390
R2	0.385	0.385	0.318	0.695
Adjusted R2	0.371	0.373	0.301	0.688
Residual Std. Error	80.833 (df = 380)	80.671 (df = 382)	0.336 (df = 380)	8.230 (df = 381)
F Statistic	26.476*** (df = 9; 380)	34.110*** (df = 7; 382)	19.644*** (df = 9; 380)	108.381*** (df = 8; 381)
Note:				*p<0.1; **p<0.05; ***p<0.01
				Dependent Variable: Franchise Revenue (in millions of USD)
				Data Years: 2011-2024
				Sample Size: 30 NBA teams over 13 seasons (390 observations)

VI. Summary and Conclusion

From the model results, they offer a very successful analysis of what I expected to see regarding how trades influence franchise revenues. Trade activity looked like one of the most important variables, with consistent significance and a coefficient representing approximately 30 million dollars in model 1. In other words, teams engaging in trades in a specific year versus those who did not, on average, can see a 30 million dollar increase in franchise revenues. However, Model 4, which changed the dependent variable to win percentage, tells us something interesting. Trade activity had no significance in this model and had a small and negative coefficient. This difference between financial gains and how well a team performs shows that although trades are good for making money, they do not help a team become better or win more games. This can then bring additional questions behind the art of trading. Do teams understand this and know they will get worse but still continue for the financial gains? Are they trying to balance between making enough money and doing alright on the court? All interesting questions that bring ideas to further research that should be needed to answer them.

Another interesting detail from the data had to do with the variables Average Ticket Price and Total Ticket Sales. Going back to the model, Average Ticket Price was significant across all models with three-star significance and a coefficient of 0.420. In other words, for every dollar increase in average ticket price, franchise revenues increased by about $0.42 million. This shows that teams should not only focus on making smart trading choices but also understand how valuable their pricing strategy for tickets is. With the variable Total Ticket Sales, we see a negative coefficient across all models and no significance. This felt odd because teams in larger markets not only have high prices but also sell many more tickets. However, without significance, this could mean that the number of tickets sold becomes less important when revenue is already driven by premium pricing. On top of this, small-market teams may sell out many of their games, but doing so at lower prices limits total revenue potential regardless of how many people buy tickets.

The last important variables to discuss are Games Televised and Metro Population, with Model 3 where it's logged. These variables were included to show how media exposure and market size influence franchise revenues. As noted earlier, Games Televised had three-star significance across Models 1-3 and two-star significance in Model 4. Its coefficient is 2.820 in Model 1, meaning that for each additional nationally televised game, teams experience an average increase of $2.8 million in franchise revenue. This makes sense because watching games on television is much easier than attending games in person, allowing TV broadcasts to attract millions of NBA fans. Take, for example, a team like the Los Angeles Lakers, which has many nationally televised games due to their popularity. This extra exposure generates attention from sponsorship deals and out-of-state merchandise sales. Small-market teams can also benefit from extra airtime, especially if they have a superstar who can attract fans through TV appearances.

The Metro Population variable also had clear, consistent significance, showing the distinct advantage that larger cities have in increasing franchise revenues. In Models 1 and 2, the coefficient for metro population was about 3.4, indicating that teams with one million more people in their metro area generate, on average, $3.4 million more in revenue. This means teams in larger markets bring in millions more simply because they have more potential fans. This is not surprising, as cities such as Los Angeles or Chicago have much larger fan bases than smaller markets like Memphis or Portland. In Model 3, I adjusted this variable by using Log Metro Population, which helped me interpret the relationship through proportional changes. It had a coefficient of 0.097, meaning that a 1% increase in metro population results in a 0.097% increase in revenue. This adjustment helps account for differences in sizes between population sizes of teams. For example, adding 250,000 people to a smaller market city like Memphis could show significant revenue gains, while adding the same population to a much larger city like Chicago would likely have a far smaller impact.

Conclusion:

To conclude my research, it's clear that my data provided a strong answer to the question of how NBA trades impact franchise revenues. When I started this project, I couldn't find a clear motivation beyond simply liking basketball. However, as I reflected more with others, it became clear that the motivation for research is always about finding answers to questions that haven't been solved yet. More specifically, within my model, I found that trades showed a positive coefficient of 30.288, meaning that teams do, in fact, benefit from trades and that this impact is statistically significant. Understanding that teams, on average, gain that much more revenue when they trade compared to when they don't brings a new perspective on how important certain decisions are. Additionally, several other factors showed significance, such as ticket prices and games televised. The significance of these variables demonstrates that the NBA isn't just about showing up, playing the game, and generating revenue; there's much more at play behind the scenes. The NBA is a business, and like any successful business, it must understand how to generate revenue to support its growing economy and meet rising demand to remain competitive and sustainable.

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