# NBA Trade Impact on Franchise Revenues

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# Motivation

-This project can serve as a valuable indicator 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.

-Everyone has a favorite team even so a favorite player and understanding how fans interact financially through franchise revenues with their teams after trades is important to maintain a successful business.

# Challenges

- Limited access to detailed financial data for individual teams, such as merchandise sales or localized revenue numbers

-Another challenge was defining a trade and determining which team should be credited for its impact.

# Past Efforts

- Harrison (2019) examines how variations in play style impact NBA revenues, focusing on the economic effects of team strategies on ticket sales and viewership. However, it does not address the specific role of player trades.

- Mahmoud M. Nourayi (2019) analyzes correlations between attendance, winning percentages, and roster changes, showing that adopting strategies of superior teams boosts performance and some skills are key for playoff success.

- Bolduc (2021) analyzes the impact of the three-point shot on NBA team revenues, focusing on the period before and after Stephen Curry's MVP seasons. The study examines metrics like three-point makes, effective field goal percentages, playoff wins, and attendance, finding that the rise of the three-point shot became a significant driver of revenue in the modern NBA.

# DATA

-Panel dataset from the 2011-2024 NBA seasons to analyze the franchise revenue impacts of player trades.

-Tracks 30 teams across 13 seasons, resulting in **N = 390 observations** (30 teams x 13 seasons).

-Variables include total ticket revenue, average ticket price, attendance, playoff appearances, winning percentage, and star player presence (e.g., top 15 jersey sales).

-Focuses on trades involving starters or significant bench players, excluding trades for cash considerations or draft picks without immediate player impact.

# Model

Franchise Revenue = $\beta_0$ + $\beta_1$(Trade Activity) + $\beta_2$(Top 15 Merchandise) + $\beta_3$(Games Televised) + $\beta_4$(Win Percentage) + $\beta_5$(Playoff Appearance) + $\beta_6$(Total Ticket Sales) + $\beta_7$(Average Ticket Price) + $\beta_8$(Metro Population) + $\beta_9$(All Star Count) + $\varepsilon$

# Hypothesis

-Teams that participate in player trades are likely to see an increase in their revenues. The excitement of acquiring new players, along with the potential for improved team performance and better fits within existing teams, are key factors in driving fan engagement. This encourages fans to spend more, ultimately leading to increased revenue for the team.

# Models

**Model 1**: Baseline model with core predictors like wins and attendance to establish fundamental revenue drivers.

**Model 2**: Removes All-Star count and playoff appearances to focus on the other variables impacting revenue.

**Model 3**:Uses log-transformed franchise revenue and metro population to better handle skewed data and understand percentage changes.

**Model 4**: Focuses on how trade activity and other factors influence team performance, rather than revenue.

# Regression Analysis

Regression Results: Franchise Revenue and Winning Percentage
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|  | 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)

# Meaning

**Trade Activity**: Significant in Models 1-3, increasing franchise revenue by **~$30 million** when a trade occurs (e.g., **30.288** in Model 1). However, it has minimal effect on winning percentage (**-0.160**, Model 4), indicating that while trades can drive revenue, they don't necessarily correlate with team performance.

**Games Televised**: Significant across all models, increasing revenue by **~$2.8 million** per additional televised game (Models 1-2). In Model 4, it also improves winning percentage by **~0.16%**, suggesting that more media coverage has both financial and performance benefits for teams.

**Playoff Appearances**: Drives winning percentage significantly (**15.860**, Model 4), showing its strong influence on team performance. However, its direct impact on revenue is more modest, contributing about **$6.8 million** in Model 1, suggesting that playoff appearances may be more important for on-court success than financial gain.

**Average Ticket Price**: Strong driver of revenue, contributing about **~$0.42 million** to revenue per **$1** increase in ticket price (Model 1). This emphasizes the importance of pricing strategies for generating revenue.

**Metro Population**: Significant when logged in Model 3 (**0.097**), showing that larger markets (cities) have a proportional impact on franchise revenue. This indicates that teams in bigger markets generally have higher potential for revenue growth.

**Win Percentage**: Surprisingly negative in Models 1-3 (~ **-$1.07 million**), suggesting that other factors like trades or ticket sales outweigh performance in driving franchise revenue. This could mean that off-court factors (e.g., media deals, trades) matter more for revenue than on-court performance, at least in this analysis.

# BAR PLOT: Trade Activity



Impact of Trade Activity on Franchise Revenue