# Does NBA attendance respond to an increased emphasis on offense?

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The economics of sports, and more specifically sports attendance, is a topic that at first glance would seem a niche field in economics with relatively limited literature. When examined more closely however, the study of sports economics is a growing field, commanding more and more attention as the intricacies of sports have proven puzzling and fascinating to economists. Despite similarities in firm behavior and structure in the sector of professional sports, there are important differences between the different sports and their respective demographics that must be considered when looking at what drives attendance and ticket sales. As an NBA team is a product competing in the market for leisure and entertainment dollars, it is important for an NBA team to find the relative mix of what factors contribute to their game's attendance, as this is one of their main sources of revenue.

After Michael Jordan retired from basketball for the second time in 1998, strong power forwards and centers have dominated the NBA. For each of the past nine years since the "Jordan Era," either Tim Duncan or Shaquille O'Neal, widely recognized as the two most dominant "big men" ever, reached the NBA Finals. While both Tim Duncan and Shaquille O'Neal are almost unanimously respected and praised for their unmatched skills, their style of play is generally described as "vanilla", as noted by Eifling (2003). The NBA responded to this criticism with subtle alterations to the rules of basketball, which empowered smaller players and promoted a faster paced game with increased scoring and more fast breaks[1]. As described by Dupree (2006), the league decided to decrease their tolerance for hand checks after the 2003-2004 season with increased speed and offense in mind. By calling more fouls on defenders who instigated contact with offensive players, offensive players were given more power to score and control the tempo

[1] Fast break is defined as a quick drive to score before the defense organizes itself.

of the game, leading to more fast breaks and more overall scoring.  This change in the NBA's product from a physical sport reliant on brute strength and stifling defenses to a sport reliant on speed, finesse, and offensive prowess, immediately changed the competitive landscape of the NBA, leading teams to sign players fit for this new style of play.  The results of these changes in many dimensions currently remain unexamined.  This paper seeks to answer the question: does this increased emphasis on offense lead to higher attendance as predicted by the league?

The paper is organized as follows.  Section two explores the basic model for sporting attendance and existing literature related to game quality's effect on consumption of sports. Section three outlines the theoretical framework employed in this particular paper.  Section four describes the data used in the empirical work.  Section five presents the regression results and analysis.  Section six addresses any potential robustness issues.  Section seven provides a conclusion and a direction for further research.

**Review of Existing Literature**

This study, in its most generalized form, investigates what consumers value when purchasing tickets to a professional basketball game.  Surprisingly, the sports economics community largely ignores this subject from a game quality standpoint[2].  The basic framework models attendance as a linear function of metropolitan area incomes and population surrounding the team, the price of admission relative to the prices of recreation substitutes, stadium attributes, the rank of the team, and the "goodness of substitutes" (Rottenberg 1956).  Neale (1964) refined Rottenberg's rudimentary model by arguing the existence of the Louis-Schmelling Paradox (named after the boxers Joe Louis and Max Schmelling).  The Louis-Schmelling Paradox states

[2] The use of "game quality" in this context refers to aspects of the game related to the act of playing basketball.

that sporting competition drives attendance more than sporting monopoly. This principle is epitomized by the New York Yankees in the 1950's, who saw declining attendance despite winning six World Series in seven years. Seeing this paradox's effect, Neale argued that parity was always more important dominating the competition every year. An alternate take on this theory is presented by Whitney (1986) who argued that winning percentages and parity are secondary to the championship prospects of a team. If a team's attendance were predominately a function of winning percentages, then there would exist no trade offs between playoffs and simply extending the regular season. Whitney examined season attendance at major league baseball games, observing that pennant race probabilities played a statistically significant role in determining attendance. The attendance theories regarding rank and winning percentages outline the Uncertainty of Outcome Hypothesis (UOH), a prominent theory in sports economics. The theory states that consumers want their team to win, but they receive the greatest utility when their team wins a close contest in which the outcome is uncertain (Fizel 2006). Despite its best efforts, the NBA is the least competitively balanced league of the four major North American professional sports according to Berri et al. (2004). Instead of drawing fans based on uncertainty of outcome, multiple studies have shown a positive significant effect of visiting superstars. First investigated by Hausman and Leonard (1997) using total revenue as the dependent variable, Berri and Schmidt (2005) studied the superstar eternality's impact on attendance during Michael Jordan's prime, finding that superstars playing for the road team increased attendance for the home team.

The most similar body of research to the investigation of fast break points and scoring is the research conducted on the effects of similar institutional changes made by the NHL regarding violence and scoring. During the past decade, the NHL and the NBA in particular have been "perfecting" their product through rule changes that attempt to increase attendance. For the NHL, policies were put in place to curb violence and increase scoring, because the NHL believed that attendance was negatively correlated with violence and positively correlated with scoring. Paul (2003) found that the opposite was true, as violence was positively correlated attendance and scoring was negatively correlated. While violence is a strong selling point for hockey, the NBA rules do not provide the same kind of leniency for fighting.

With the amount of rule changes that have occurred over the past decade, the dearth of econometric studies on the effects of these changes is surprising. Investigating these changes and their subsequent consumer response helps assess the effectiveness of these changes. This study seeks to fill the gap in sports economics literature by asking the question: Does NBA attendance respond to fast break points and prolific scoring? Assuming that the NBA changes its product with the goal of increasing profits through increasing attendance, an increased emphasis on offense should, *ceteris paribus*, increase attendance.

**Theoretical Framework**

We begin with the basic model for attendance:

$$Attendance_{gh} = t_{gha} + t_{hat-1} + l_h + p_h$$

where *g* denotes the game, *h* represents the home team, *a* represents the away team. $Attendance_{gh}$ is the attendance at game *g* of home team *h*, with $\mathbf{t}_{gha}$ is a vector of current team attributes for both home team *h* and away team a playing in game *g*, $\boldsymbol{t}_{hat-1}$ is a vector of the team attributes indicated by past performance for both home team *h* and away team *a*, and $\boldsymbol{l}_h$ is a vector of the location attributes of the home team *h*, and $\mathbf{p_h}$ denotes the price charged by the home team *h*. Because the quality of game *g* is unknown, it is the expected quality of game *g* based on previous performance captured by $\mathbf{t_{gha}}$. The term $\mathbf{t_{gha}}$ represents many qualities of a basketball game, including fast break points per game, total points per game, as well as their current success in winning games.

Ticket prices are set before season starts. We assume that teams set ticket prices in order to maximize profits based on a monopolistic model where marginal revenue is equal to marginal cost. Because the relative cost of adding one extra fan is negligible up to capacity, we also assume that all teams face marginal costs of zero. We must also assume for the purpose of this study that a single, profit maximizing price is charged by each team at the beginning of the season based on a monopolistic demand function derived from the expected mean quality of the games for the coming season of the home team.

$$p_h = t_{h\bar{a}} + l_h$$

where $\mathbf{p_h}$ is the price charged by the home team, $\boldsymbol{t_{ha}}$ is the expected quality of the home team as it relates to the mean expected quality of the away teams the team will face throughout the season. These expectations are derived from previous season performance. See Figure I.

Because marginal cost is assumed to be zero, the profit maximizing condition is synonymous with the revenue maximizing condition.

$$\max_{p} \ \mathrm{R_h} = p_h \bullet \sum_{G} A_{gh} \quad \text{s.t. } \mathrm{S_h}$$

where $\mathbf{R_h}$ is the home team's total season gate revenue, $\mathbf{p_h}$ is the price charged for admission by home team *h*, and $\mathbf{A_{gh}}$ is the attendance at home game *g* for home team *h*, subject to stadium capacity $\mathbf{S_h}$ for home team *h*.

Existing sports economics literature states that econometric analysis of attendance often yields the disturbing result of an upward sloping demand curve, which is blamed on an omitted variable, as detailed in Fizel (2006). This conclusion fails to take into account what is modeled when performing econometrics analysis of game-to-game attendance variation. Instead of modeling demand and movements along the demand curve, econometric analysis of game-to-game attendance variation actually models the price-quality schedule, where the *shifts* in the demand curve identify the price-quality schedule. See Figures II and III for a graphical representation.

Including home team fixed effects has many implications regarding the estimation equation formulation. All the predetermined variables are captured with the home team fixed effects, which includes previous season success (or failure) of the home team, locational qualities, and ticket prices. Since we are not controlling for the away team, the fixed qualities of the away team are included in the final estimation equation. In addition, it should be noted that because of this approach, we are modeling the shifts in the demand function as a result of quality variations over the course of the season. The changes in demand due to home team quality are expected to be smaller, and possibly insignificant, due to the use of home team fixed effects. Because the home team's previous seasons' quality and success are included in the fixed effect terms and the fact that the largest change game to game is the opponent rather than the home team quality, the home team's variation is unlikely to be found significant. From this we find the only remaining terms in the equation are:

$$Attendance_{gh} = t_{gha} + t_{at-1} + FE$$

where the first two variables remain the same, but we now include $t_{at-1}$ instead of $t_{hat-1}$, as the fixed effects are controlling for the home team previous season performance, and add the home team fixed effects terms represented by $H_h$. This yields the following linear estimation equation:

$$\text{Attendance}_t = ß_0 + ß_1 \text{ OPENER} + ß_2 \text{ EARLY} + ß_3 \text{ LATE} + ß_4 \text{ WEEKEND} + ß_5 \text{ LASTWINAWAY} + ß_6 \text{ LASTPOINTAWAY} + ß_7 \text{ PLAYAWAY} + ß_8 \text{ PLAYAWAY2nd} + ß_9 \text{ PHOME}_{t-1} + ß_{10} \text{ PAWAY}_{t-1} + ß_{11} \text{ FBHOME}_{t-1} + ß_{12} \text{ FBAWAY}_{t-1} + ß_{13} \text{ WINHOME}_{t-1} + ß_{14} \text{ WINAWAYt-1} + ß_{15} \text{ STARSAWAY} + ß_{(16\text{-}40)} \text{ HOMETEAM} + \varepsilon_t$$

Refer to Table I for explanations of each of the variables included in the estimation equation.

Many of these variables come in pairs, one for the home team and one for the away team, which is necessary to show the relationship the competition has on the attendance of each game. As discussed earlier, previous season variables are only used for the away team due to the inclusion of home team fixed effects.

The first four variables, OPENER, EARLY, LATE, and WEEKEND, control for various time effects. The first home game of the season for a team is always a celebration of the return of basketball and all of the fan's favorite players. The festivities usually include numerous promotions, prizes and other activities that add value to attending the home opener. The home opener variable's sign should be positive and significant. The variable for games played early in the season should have a negative and significant coefficient as the early season games have less clear playoff implications. Conversely, a game played in the last few weeks of the season has more clear playoff implications as the playoff seedings are finalized in these games. This added excitement is expected to cause late season games, *a priori*, to have a positive and significant sign. Games played on the weekend should have greater attendance, as the opportunity cost of attending games on the weekend is less for those who work during the typical workweek. The coefficient for weekend games should be positive and significant.

While employing home team fixed effects controls for previous season performance characteristics of the home team, it is still necessary to control for the away team's previous season success. The away team's number of wins and average points scored in the last season both should have positive and significant coefficients according to the theory of game quality as defined in this study. The playoff appearance dummy variables control for the attendance that results from seeing teams that competed in the previous season's playoffs. The intuition behind including a second round playoff variable is controlling for the potentially negative effect of an early post season exit, a theory explored in empirical studies of other sports including Paul (2003). While reaching the second round of the playoffs should have a positive and significant sign, previous studies have shown that only reaching the playoffs and not advancing has a negative and significant sign. The previous season variables are relevant as many tickets are sold before the season begins, and previous season performance for both teams is the information that many fans base their individual game purchasing decisions on.

The next four variables are the average total points scored by each team as well as the average number of those points that were scored on a fast break. If a team averages abundant scoring or many fast break points, the team is more interesting according to the theory promoted by this paper. *A priori*, each of these variables' coefficients should have a positive and significant sign. The next two variables control for how many wins each team has. A large number of total wins in the season for either team should positively affect the desire of a fan to see the more successful teams.

Also included is a variable for the presence of All-Star[3] players on the away team. This effect is captured by including a variable for the number of All Star players on each team plus one. Theory and previous research suggest this variable will have a positive coefficient, as the . more "star power" playing in the game, the better the quality of the game.

**Summary Statistics**

Data for the 2005-2006 NBA season contain observations for each of the 1,230 games played during the regular season by the 30 teams in the NBA, all of which were entered manually using box scores provided by the National Basketball Association on NBA.com[4]. . The 2004-2005 season results used for previous season performance variables and the number of All- Star players on each team were compiled from information provided by the National Basketball Association, also available on NBA.com. I entered the data myself.

Two major changes were made to the data set to produce more accurate results. After Hurricane Katrina, the New Orleans Hornets moved their home games to Oklahoma City's Ford Center. Midway through the season, the Hornets played six games in Louisiana including one in Baton Rouge. This creates an inconsistency when attempting to control for home team fixed effects, which would vary depending on where the game is played. The New Orleans/Oklahoma City Hornets' home games were excluded from the final data set. Teams that sell out every game of the season, the Detroit Pistons, the Sacramento Kings and the San Antonio Spurs, lack of variation in the dependent variable, which is necessary to produce accurate regression results. These teams' home games are also excluded from the data set.

[3] An All-Star is defined as a player selected to be on the roster for either the Eastern Conference All-Star Team or the Western Conference All-Star Team. The starting 5 players for each team are voted for by fans, while the remaining 7 slots on each team are devoted to players chosen by the coach of each All-Star team.

[4] Some observations had data missing from the box score, which were filled in by referencing an alternate database hosted by ESPN.com.

The final data set, after dropping the four previously mentioned teams and observations with missing data from the beginning of the season due to lags in the independent variables for current season performance, totaled 1,051 observations. The data were inspected for irregularities and accuracy during the data entry process, and again after compiling the entire set using histograms and summary statistics. See Table I for a description of the data and the basic characteristics of each variable. The attendance figures range from 9,812 to 22,479, which is within expected limits as none of the teams have a capacity above 22,500. The attendance values are also generally normally distributed. The variables for points average are both within expected ranges, as the use of cumulative averages causes the first few observations to exhibit greater variation from typical values that usually range from 85 to 110. Not every team excels at scoring fast break points, which is why the relatively large ranges for fast break points for home and away teams of 4.8 to 22 and 4.5 to 22 respectively are reasonable. The two win variables have similar ranges, although the away win variable has a higher upper value as the home games for team with the most wins during the 2005-2006 season, the Detroit Pistons, were dropped, for reasons previously discussed. The most interesting feature of the dummy variables is the fact that almost half of the NBA's games are played on weekends, as this variable has a mean of .478. Refer to Table I for complete summary statistics and histograms for each of the variables included in the regression. All regressions and robustness checks were performed using Intercooled Stata 9.2.

**Results and Analysis**

Before the first regression, the variables were tested for multicollinearity and stationarity. The VIF and simple correlation coefficients reveal multicollinearity, as would be expected with many of the game quality variables. Previous season performance variables exhibited the most multicollinearity, with the highest simple correlation coefficient of .796 existing between previous season wins for the away team and previous season playoff appearance. The theoretical validity of the variables included leads us to take no action to correct for multicollinearity. See Table III for the pair-wise correlation matrix.

The regression results are reported in Table II. Using the Atlanta Hawks as the base team for the home team fixed effects, all teams but the Houston Rockets, Orlando Magic, and Portland Trailblazers were found to be positive and significant. The teams collectively have an F-test statistic of 43.394, which is statistically significant. The variables for the away team's playoff success both had negative coefficients, but neither were significant. These results could be attributed to a general indifference of fans to the results of the post season for the away team. The significance of the playoffs is not as strongly supported by the literature as previous season wins are, which were positive and significant, so this result is not of great concern.

The variables for early and late season games both had insignificant t-scores, but did have coefficients with the signs the theory predicted, negative and positive respectively. The variable for opening night games had a positive coefficient and was significant with 99% confidence, as predicted. Opening night draws an extra 2,212 fans when compared to other games throughout the season. Weekend games were also shown to be significant with a positive coefficient as predicted. Weekend games are estimated to have 1,219 more fans in attendance than games played during the week.

Current season wins for the home and away team produced mixed results. The home team current season wins were insignificant, but with a positive sign as predicted by theory. This could be attributed to the use of home team fixed effects, which reduces the responsiveness of the home team variables due to the fixed effects controlling for all previous season performance variables. The away team's wins were significant with a positive coefficient. Each additional win of the away team increase attendance by almost 21 people.

The variables for offensive performance were mostly insignificant with mixed signs. The home team's fast break point and total point average both failed to reject the null hypothesis of a coefficient equal to zero, as each had a negative and insignificant coefficient. Previous season total points average for the away team was negative but insignificant. The away team's average total points for the current season were positive and significant, with approximately 49 more fans attending the game for each point the away team averages. As the away team points average has a mean of 96.30 and a standard deviation of 4.62, an away team that averages one standard deviation from the mean in points per game, *ceteris paribus*, draws almost 250 more fans than an away team that scores the mean. The away team's fast break points had a negative sign, but failed to reject the null hypothesis. The insignificance of the home and away team fast break points suggests that the speed of the game does not have a statistically significant effect on attendance.

The away team's number of All-Stars was positive and significant with a 99% confidence level. For each All-Star an away team's roster, the game's attendance goes up by more than 267. For teams like the Miami Heat and the Phoenix Suns who have two All-Stars on their team, attendance rises by nearly 535 fans. The Detroit Pistons, who had a record 4 All-Stars in 2005-2006, drew an estimated 1,068 more fans when playing on the road!

## Robustness

The use of panel data presents a multitude of possible robustness deficiencies, with no simple solutions in most cases. Because panel data span both time and space, it is important to test for predominately cross sectional issues such as heteroskedasticity as well as predominately time series issues such as serial correlation and stationarity. For the time series issues in particular, testing each panel's time series individually is an important step in checking the robustness of the regression results.

Stationarity, primarily a time series problem, was tested for panel by panel for each variable using the Dickey-Fuller test. Attendance rejected the null hypothesis of unit roots for many of the panels, while the independent variables largely failed to reject the null hypothesis of unit roots[5]. Due to this inconclusive result, the residuals were tested to check for stationarity in the residual. None of the panels had non-stationarity issues in the residuals, which showed that the variables are likely cointegrated. Cointegration made the use of first differences unnecessary.

After running the initial regression, the residuals were tested for serial correlation and heteroskedasticity. Similar to the Dickey Fuller test, we used the Durban-Watson test repeated for each panel to test for first order serial correlation. Because the panels were not ordered in a meaningful way, we did not test for serial correlation across panels. All of the panels' d-statistics were within the inconclusive region[6], failing to reject the null of no first order serial correlation. We tested for heteroskedasticity using both the Breusch-Pagan and the White test, isolating a single cross sectional unit, given that the proportionality factor is unknown. Both tests failed to reject the null hypothesis of constant variance, providing evidence of homoskedasticity. The

[5] The prolific nature of this approach makes the inclusion of these test outputs inappropriate.

evidence provided by these robustness tests suggests that the initial regression results are in fact robust.

**Conclusions and Directions for Further Research**

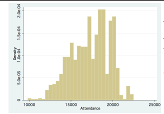
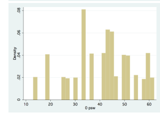
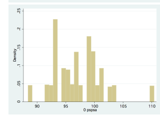
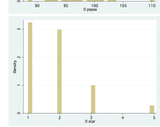
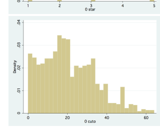
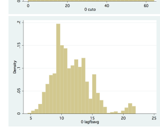
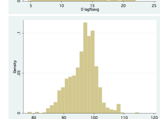
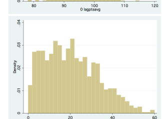
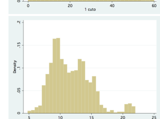
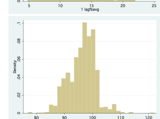
This study estimated the impact of increased offense and speed in the NBA on attendance. Using data from the 2005-2006 NBA season, this study found evidence of away team points scored does have an economically significant effect on attendance, while game speed as represented by fast break points does not have any significant effect on attendance.

It should be noted that this is not the end of the exploration of structural changes in the NBA. This study focused on one structural change, while over the course of NBA history the institution of rules like the 24-second shot clock and the three point line changed the rules of basketball even more drastically than the changes explored in this paper. These changes warrant separate studies from a more historical perspective. In addition, the functional form and specification employed by this paper is by no means ideal, as the multicollinearity between points scored and wins is necessarily high. One could instead eliminate this multicollinearity by employing a set of variables to predict wins through points scored and other variables that determine the outcome of a given game. This would have the added benefit of allowing for the maximization of attendance through the principles presented by proponents of the Uncertainty of Outcome Hypothesis.

This study only examines a small element of the determinants of professional basketball's value and institutional renovations of professional basketball. More analysis of these topics could help inform our understanding of consumer preferences for professional basketball and the nature of leisure goods in general.

## Table I

**Summary Statistics**

| Variable | Mean | Std. Dev. | Min | Max | Histogram | Variable Explanation |
|---|---|---|---|---|---|---|
| Attendance | 17,309.300 | 2,310.630 | 9,812 | 22,479 |  | Attendance is measured by the number of people in attendance at a given game. |
| LASTWINAWAY | 41.027 | 12.445 | 13 | 62 |  | The previous season's win total for the away team. |
| LASTPOINTAWAY | 97.170 | 4.287 | 88.4 | 110.4 |  | The previous season's points per game average for the away team. |
| STARSAWAY | 1.810 | 0.925 | 1 | 5 |  | The number of All-Stars on the away team roster plus one. |
| $WINAWAY_{t-1}$ | 21.014 | 13.479 | 0 | 64 |  | The away team's win total, lagged one game. |
| $FBAWAY_{t-1}$ | 11.658 | 3.105 | 4.5 | 22 |  | Average fast break points scored by the away team per game for the current season, lagged one game. |
| $PAWAY_{t-1}$ | 96.307 | 4.628 | 78 | 115 |  | Average points scored by the home team per game for the current season, lagged one game. |
| $WINHOME_{t-1}$ | 20.135 | 12.579 | 0 | 60 |  | The home team's win total, lagged one game. |
| $FBHOME_{t-1}$ | 11.678 | 3.164 | 4.8 | 22 |  | Average fast break points scored by the home team per game for the current season, lagged one game. |
| $PHOME_{t-1}$ | 96.357 | 4.864 | 77 | 122 |  | Average points scored by the home team per game for the current season, lagged one game. |
| EARLY | 0.166 | 0.372 | 0 | 1 | N/A | Whether the game was played during the first month of the season |
| LATE | 0.123 | 0.328 | 0 | 1 | N/A | Whether the game was played during the last month of the season |
| OPENER | 0.010 | 0.102 | 0 | 1 | N/A | Whether the game was the first home game of the season. |
| PLAYAWAY | 0.535 | 0.499 | 0 | 1 | N/A | Whether the away team was a playoff team the previous season. |
| PLAYAWAY2nd | 0.266 | 0.442 | 0 | 1 | N/A | Whether the away team won their first round playoff series. |
| WEEKEND | 0.478 | 0.500 | 0 | 1 | N/A | Whether the game was played on either a Friday, Saturday, or Sunday |
| HOMETEAM | N/A | N/A | 0 | 1 | N/A | A dummy variable for each home team |

* $\varepsilon_1$ is a classical stochastic error term.

Observations: 1051

## Table II

### Attendance Modeled with Home Team Fixed Effects

| | | | | | |
|---|---|---|---|---|---|
| Boston Celtics | 1868.084 | Milwaukee Bucks | 1360.082 | Away Playoffs 1st Round | -286.154 |
| | (5.60)** | | (3.72)** | | (1.77) |
| Charlotte Bobcats | 1323.953 | Minnesota Timberwolves | 1085.641 | Away Playoffs 2nd Round | -243.868 |
| | (3.52)** | | (3.33)** | | (1.76) |
| Chicago Bulls | 6269.699 | New Jersey Nets | 1548.171 | Early | -19.633 |
| | (19.24)** | | (4.29)** | | (0.12) |
| Cleveland Cavaliers | 4248.223 | New York Knickerbockers | 3909.304 | Late | 187.309 |
| | (11.09)** | | (11.98)** | | (1.13) |
| Dallas Mavericks | 4933.186 | Orlando Magic | 371.996 | **Opener** | 2212.312 |
| | (12.53)** | | (1.13) | | (4.91)** |
| Denver Nuggets | 1824.642 | Philadelphia 76ers | 1575.793 | **Away Wins** | 20.671 |
| | (3.07)** | | (4.49)** | | (2.73)** |
| Golden State Warriors | 3285.189 | Phoenix Suns | 2766.794 | Home Wins | 9.461 |
| | (8.27)** | | (6.13)** | | (1.06) |
| Houston Rockets | 469.001 | Portland Trail Blazers | -278.509 | Home Fast Break Average | 26.445 |
| | (1.38) | | (0.80) | | (0.56) |
| Indiana Pacers | 1092.213 | Seattle Supersonics | 1096.702 | Away Fast Break Average | -30.954 |
| | (3.33)** | | (3.09)** | | (1.72) |
| Los Angeles Clippers | 2141.852 | Toronto Raptors | 1956.801 | **Away Points Average** | 49.015 |
| | (6.35)** | | (6.04)** | | (3.29)** |
| Los Angeles Lakers | 3702.921 | Utah Jazz | 3433.956 | Home Points Average | -10.464 |
| | (11.21)** | | (10.25)** | | (0.51) |
| Memphis Grizzlies | 748.542 | Washington Wizards | 2086.965 | **Weekend Game** | 1219.625 |
| | (2.18)* | | (4.95)** | | (13.80)** |
| Miami Heat | 4828.923 | | | **Away All-Star** | 267.845 |
| | (13.18)** | | | | (3.84)** |
| | | | | **Away Previous Season Wins** | 28.366 |
| | | | | | (3.07)** |
| | | | | Away Previous Season Points Average | -23.072 |
| | | | | | (1.36) |
| | | | | Constant | 10992.287 |
| | | | | | (4.90)** |
| Adjusted R-Squared | 0.65 | | | Observations | 1051 |

Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table III

| | Attendance | PLAYAWAY | PLAYAWAY2nd | EARLY | LATE | OPENER | WINAWAYt-1 | WINHOMEt-1 |
|---|---|---|---|---|---|---|---|---|
| Attendance | 1 | | | | | | | |
| PLAYAWAY | 0.1278 | 1 | | | | | | |
| PLAYAWAY2nd | 0.1177 | 0.5656 | 1 | | | | | |
| EARLY | -0.0681 | -0.0182 | -0.0029 | 1 | | | | |
| LATE | 0.1024 | -0.01 | -0.0227 | -0.1722 | 1 | | | |
| OPENER | 0.0901 | -0.0104 | 0.0419 | 0.3406 | -0.0587 | 1 | | |
| WINAWAYt-1 | 0.1892 | 0.2201 | 0.2496 | -0.5767 | 0.4657 | -0.2304 | 1 | |
| WINHOMEt-1 | 0.2458 | -0.0149 | -0.0295 | -0.5866 | 0.5043 | -0.2358 | 0.7521 | 1 |
| FBHOMEt-1 | 0.0904 | 0.0008 | -0.0025 | 0.023 | 0.0101 | 0.0251 | -0.0138 | 0.1344 |
| FBAWAYt-1 | 0.0228 | 0.1391 | 0.1929 | -0.017 | 0.0081 | 0.0686 | 0.1129 | -0.0087 |
| PAWAYt-1 | 0.1307 | 0.2951 | 0.3801 | -0.1053 | 0.0507 | 0.0149 | 0.2347 | 0.1017 |
| PHOMEt-1 | 0.2803 | 0.0122 | 0.0092 | -0.014 | 0.049 | 0.0097 | 0.0621 | 0.2038 |
| WEEKEND | 0.2152 | 0.0208 | -0.0221 | -0.0049 | -0.0101 | -0.0517 | -0.0099 | -0.0345 |
| STARSAWAY | 0.2037 | 0.4566 | 0.5534 | -0.0163 | -0.0088 | -0.0259 | 0.2835 | -0.0146 |
| LASTWINAWAY | 0.176 | 0.7963 | 0.6343 | -0.0386 | -0.0177 | -0.0284 | 0.3055 | 0.0008 |
| LASTPOINTAWAY | 0.0741 | 0.2915 | 0.3128 | -0.0736 | -0.009 | 0.0245 | 0.1098 | 0.037 |

| | FBHOMEt-1 | FBAWAYt-1 | PAWAYt-1 | PHOMEt-1 | WEEKEND | STARSAWAY | LASTWINAWAY | LASTPOINTAWAY |
|---|---|---|---|---|---|---|---|---|
| FBHOMEt-1 | 1 | | | | | | | |
| FBAWAYt-1 | -0.0514 | 1 | | | | | | |
| PAWAYt-1 | -0.0489 | 0.5814 | 1 | | | | | |
| PHOMEt-1 | 0.5806 | -0.0165 | 0.011 | 1 | | | | |
| WEEKEND | -0.0263 | 0.0241 | -0.0094 | -0.0038 | 1 | | | |
| STARSAWAY | -0.0031 | 0.0388 | 0.2755 | 0.0149 | 0.0121 | 1 | | |
| LASTWINAWAY | 0.0001 | 0.1356 | 0.3796 | 0.007 | -0.0052 | 0.6282 | 1 | |
| LASTPOINTAWAY | -0.0206 | 0.3177 | 0.5755 | -0.019 | -0.0336 | 0.17 | 0.5526 | 1 |

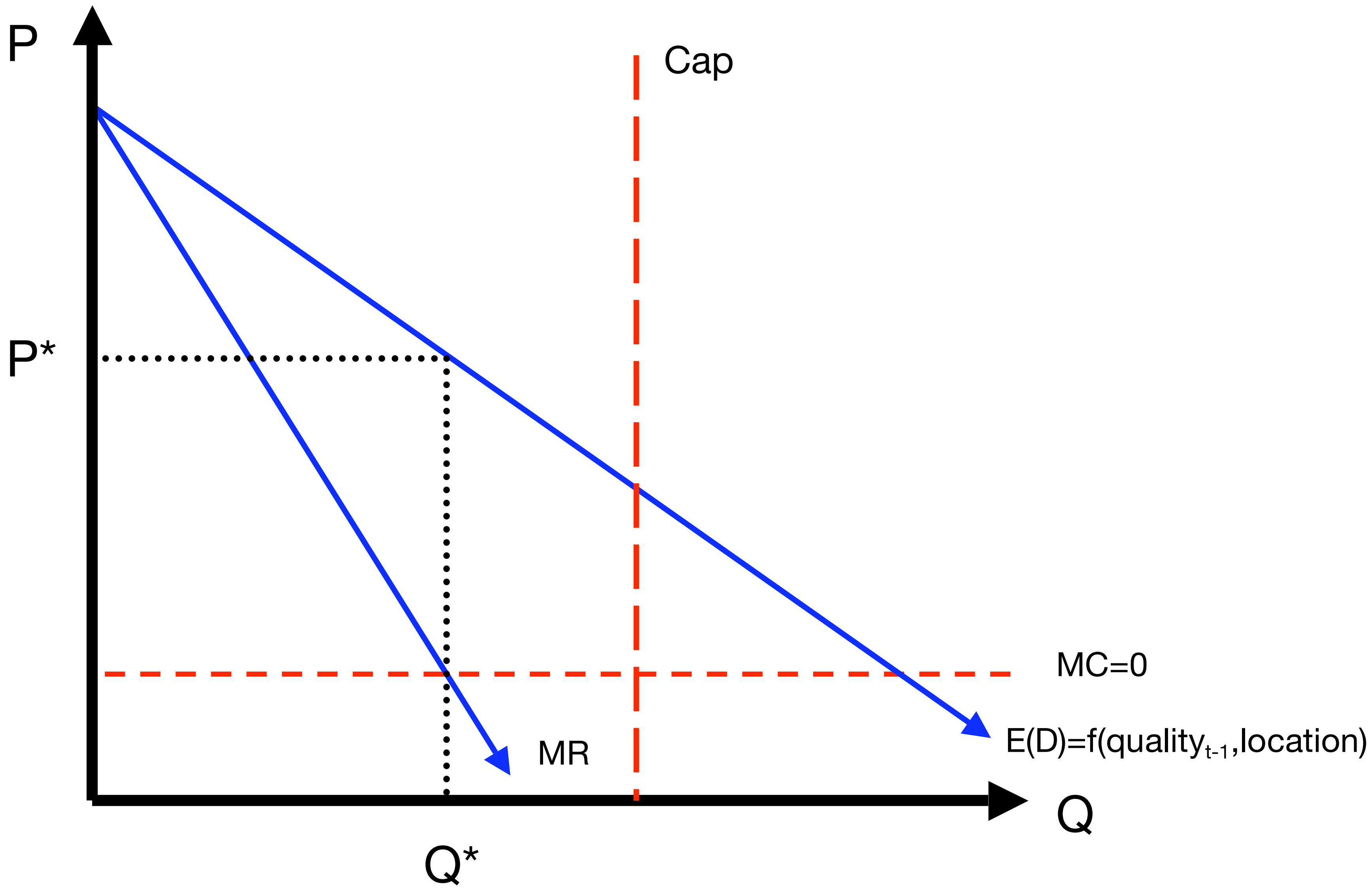



Figure I:  Price Setting Condition

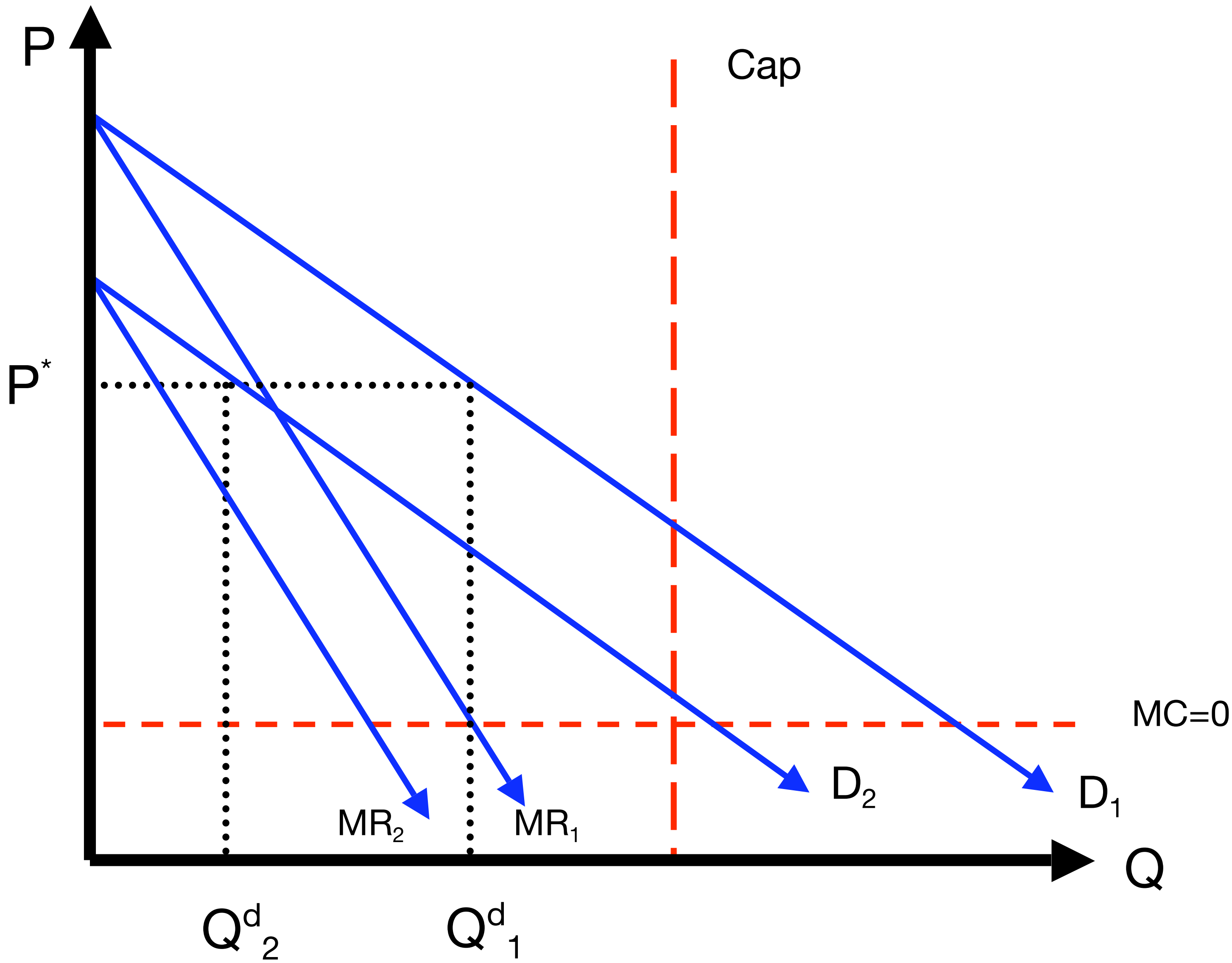



Figure II: Game Quality Decreases

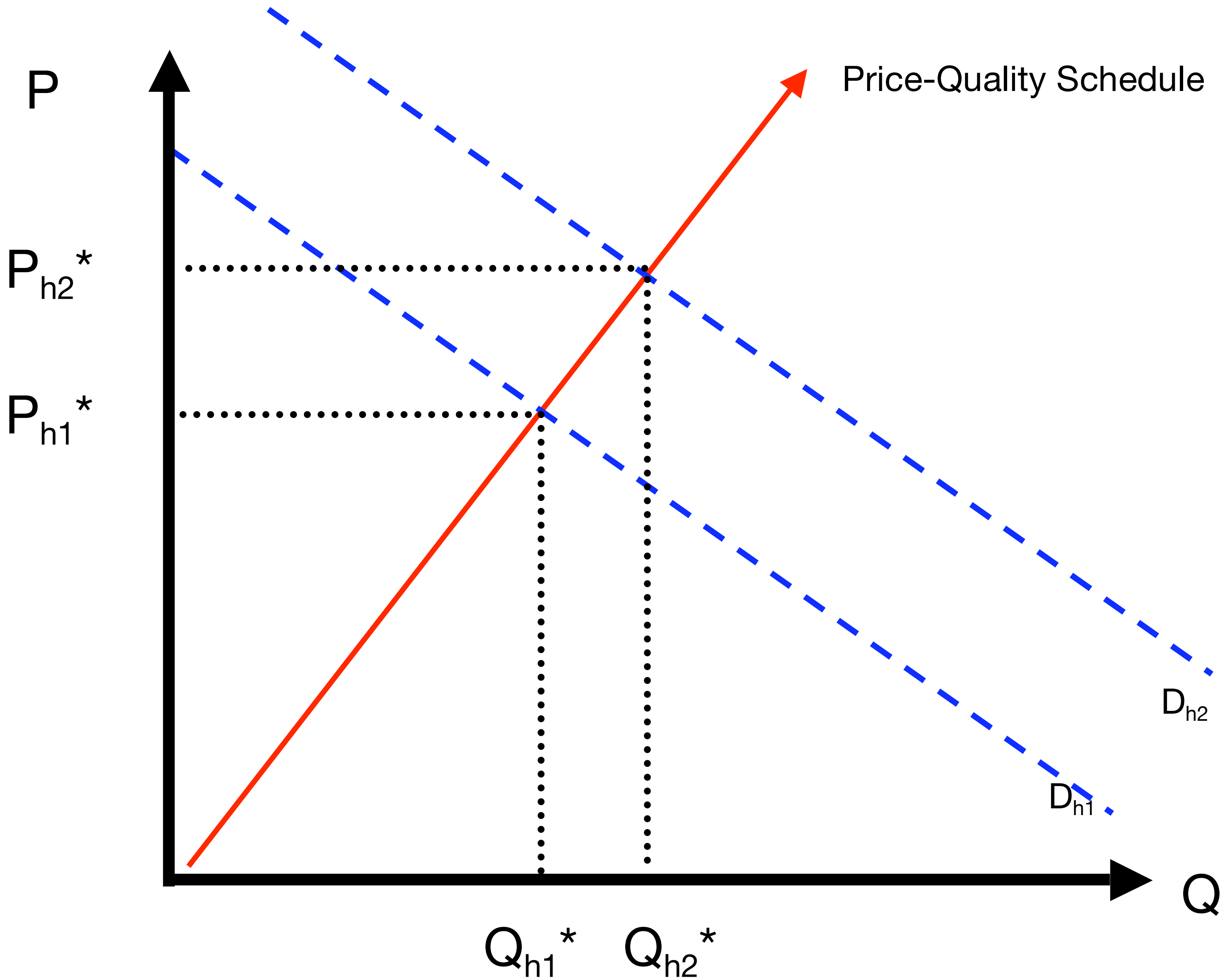



Figure III: Price Quality Schedule

Where h1 and h2 are different home teams.

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## Data Set


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