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Abstract

What is the effect of home court advantage in the National Basketball Association (NBA)? Based on the Economic Theory of Professional Sports and the concept of shirking, teams should perform better at home than they do on the road. Descriptive statistics support this expectation. It is hypothesized that a home court advantage is due to fan attendance, field goal and free throw percentages, and fouls called by the referee. Following every NBA team and every game played over a three-year span (2008-2011), this paper estimates the probability of producing a win at home based on the aforementioned variables. Using a logit regression analysis, it is found that a one standard deviation increase in attendance increases the home team's chances of winning the game by 2.7%. A referee bias is also found, increasing the home court advantage for NBA teams.

Keywords: Home Court Advantage, Basketball, Attendance, Referee-Bias

I. Introduction

During the 2012-13 National Basketball Association (NBA) season, the Houston Rockets compiled a record of 45-37 and were the eighth seed out of eight in the Western Conference playoffs. The Rockets had a road record of just 16-25, but went 29-12 at home. The Utah Jazz won 30 games at home last year, but only 13 on the road. Cooper (2013), a freelance writer for the Atlanta Hawks, found that in the 2013 playoffs, "Through the first 20 games of the First Round (heading into games of Friday, April 26), the home team had won 17 times." How can this major difference between records be explained? Home court advantage is the answer. Carron et al., (2005) define home court advantage as, "the consistent finding that home teams in sport competitions win over 50% of the games played under a balanced home and away schedule." Each NBA team plays 41 games at home and 41 games on the road each year. Each team also plays each team at least once at home and once on the road. Based on Carron's definition of home court advantage, each team is expected to win at least 21 games at home each year.

But, where does this home court advantage come from? This paper seeks to answer that question by using logit regressions to analyze the determinants of winning at home. The dependent variable is a dummy variable for wins. I hypothesize that home court advantage exists, and that it can be explained mostly by fan attendance, performance statistics, and referee bias.

Section II examines previous literature on the subject of home advantage. Section III lays out the theoretical framework, while Section IV defines the empirical models. Section V gives descriptive statistics and Section VI reports the results. Finally, Section VII offers concluding thoughts.

II. Literature Review

The home advantage is a well-established concept in the literature. There is no debate over whether or not it exists; rather much of the literature examines the causes and effects of home court advantage. Carron et al. (2005) offer a conceptual framework for analyzing home court advantage. Most of the variables in the models presented in this paper come from the Carron et al. article. They present variables representing game location factors, critical psychological and behavioral states, and performance outcomes. This study builds on their work.

A. Game Location Factors

Game location factors, as defined by Carron et al. (2005), are crowd factors, learning/familiarity factors, travel factors, and rule factors. Crowd factors acknowledge that generally competitors at home have more support from spectators than do visitors, and thus have a greater home court advantage. Schwartz and Barsky (1977) compare home advantages among baseball, football, hockey, and college basketball. They find that the home advantage is greatest in indoor sports and primarily has to do with support of the home crowd. The literature dealing with crowd factors and attendance is extensive (Forrest et al., 2005; Greer 1983; Nevill 1999; Nevill et al., 1996; Smith 2005). All of these studies report that fan attendance has a positive effect on wins. Nevill et al. (1996) specifically find that absolute crowd size is positively related to home advantage. Salminen (1993) is the only study that finds fans' cheering for the home team is not related to greater home team success.

Another aspect of Carron's game location factors is travel. Ashman et al. (2010) find that when playing games at home on consecutive nights the home team plays poorly in the second game when the visitor has one or two days rest. But, Nutting (2010), finds that game frequency itself has a negative impact on wins, so the home factor does not matter as much as the frequency. Therefore, a days of rest variable, measuring the amount of rest each home team has before each competition, is included in the models.

B. Critical Psychological and Behavioral States

The next set of variables that Carron et al. (2005) present in their conceptual framework are critical psychological and behavioral states. These two are related and deal with how coaches, competitors and officials affect the outcome of the game. An interesting example is the possibility of a referee bias. Do referees call fewer fouls on the home team, and are they influenced to make calls based on the home crowd reaction? Page and Page (2010) study the roles of referees in determining home field advantage in European soccer. They find that there is a significant impact of the referee on home field advantage. This means that some referees cave under the pressure of a large and boisterous crowd, giving the home team more of an advantage with certain calls. Moskowitz and Wertheim (2011) also find this referee bias. They study all five major professional sports (basketball, baseball, football, hockey, soccer) and agree that the home field advantage in virtually all sports is largely due to the bias of officials toward the home team.

C. Performance Outcomes

The final variables Carron et al. (2005) present in their conceptual model are variables measuring performance. These performance outcomes are statistically based variables that in this study are field goal and free throw percentages. By studying college basketball teams, Harville and Smith (1994) find that the advantage of playing at home (in relation to playing on a neutral court) is estimated to be 4.68 ± 0.28 points. Continuing with performance based home court advantage, Cao et al. (2011) find that being the home team has a positive effect on free throw performance. The authors state that this is because the home fans may be able to distract shooters from the away team.

D. Control Variable

One variable that Carron et al. (2005) do not include in their model, but other literature states must be included, is a control variable measuring the quality of the visiting team. This is included in the model because Nevill (1999) states, "In order to correctly calculate the home advantage of individual teams, the ability of the opposition must also be included." A variable controlling for the quality of the home team, however, is not necessary in determining home court advantage. This is because the quality of the team is already being controlled for due to the balanced nature of the competition. A balanced competition is one where teams play at least one home game and one away game versus each opponent. Nevill (1999) states that for sports like basketball, the quality of the team at home "is effectively eliminated by counterbalancing the game location."

III. Theory

Stefan Kesenne's "Economic Theory of Professional Sports" states that professional sports teams can either be profit maximizing or win maximizing (Kesenne 2007). If teams are win maximizing, then they will do everything they can to produce more wins and create an advantage over their opponents. One way teams can get this advantage is through creating a larger home court advantage. A home court advantage produces wins, and thus a higher home court advantage produces more wins. Ultimately, a production function is being proposed.

But, why do teams play better at home? One explanation could be rationalized through the fans. Katie Stankiewicz (2009) explores shirking in Major League Baseball (MLB). Shirking is when a player purposefully does not perform to the best of his ability. Stankiewicz does not find any evidence that players in the MLB shirk. Stankiewicz explains lack of player shirking through fan monitoring. Players are less likely to shirk in front of their home fans because they do not want to lose fan approval. Fans express their approval or disapproval by attending games, cheering or booing at games, or buying a player's jersey. Attendance and merchandise sales are a large part of a player's salary. So, a player is going to make sure he performs especially well at home to keep the fans happy and his salary high. Thus, being at home should have a greater chance of producing a win than being on the road.

Referee biases can be explained through psychological theory that people want to be liked and to be confirmed in their judgments. Referees do not like to be booed, and therefore will base some of their decisions on crowd reaction. If the home crowd is loud and boisterous, the referee is more likely not to call a foul or infraction on the home team. But, in the same situation, the referee is more likely to call a foul on the away team and receive cheers from the home crowd.

IV. Empirical Model

Data for the models are retrieved from the game logs of regular season NBA games from the 2008-09 season through the 2010-11 season. Every game during those seasons is accounted for, except the first games of each season for which DAYS REST is missing. Thus the sample size is limited to 3,642 game entries. Performance based data statistics such as field goal percentage, free throw percentage, fouls, and win percentage are retrieved from basketball-reference.com (Kubatko, J., 2014). The attendance, win percentage, and days of rest data are obtained from nba.com (NBA Stats, 2014). Using data from the selected time period allows for a recent analysis while avoiding lockout years in the NBA.

Two models are presented in this study. Both have a dummy dependent variable representing a win as 1 and a loss as 0. As such, a logit model is used. The logit model enables a more accurate analysis than ordinary least squares (OLS) regression because the dependent variable is either a 0 or a 1. Problems occur when using OLS with a dependent dummy variable because the estimated probability of a win can turn out to be less than 0 or greater than 1 (which is not possible for probabilities). This could result with an inaccurate best-fit line. A logit model avoids this problem by limiting estimated probabilities to be between 0 and 1. Logit also fixes the heteroscedasticity problem of OLS regression with a dependent dummy.

Model A contains six independent variables: LN ATTENDANCE, HOME FG%, HOME FT%, FOUL RATIO, AWAY WIN% OF VISITORS, and DAYS REST. Model B uses those same variables except for HOME FT% and FOUL RATIO. Attendance could have an effect through these two variables; therefore the two models are used to show the effect attendance has before and after controlling for them. Table 1 lists all of these variables with descriptions and their expected sign.

Table 1: Variables List

Variable	Description	Expected Effect
WIN	Dependent dummy indicating a home win	
LN ATTENDANCE	Natural log of attendance for home games	Positive
HOME FG%	Field goal percentage at home	Positive
HOME FT%	Free throw percentage at home	Positive
FOUL RATIO	Ratio of fouls called on visiting team over fouls called on home team	Positive
AWAY WIN% OF VISITORS	Control variable of the visiting team's win percentage on the road	Negative
DAYS REST	Number of days of rest the home team has before each competition	Positive

LN ATTENDANCE is expected to be positive, meaning the more fans in the arena, the greater the probability of the home team winning. HOME FG% and HOME FT% are also expected to be positive, meaning higher percentages give greater chances of the home team winning.

FOUL RATIO is a made up metric that measures the fouls called on the away team over the fouls called on the home team. This variable determines if there is a referee bias that leads to a home court advantage. If there is a referee bias, this coefficient will be positive and greater than one. This means that the referee calls more fouls on the visitors than he does on the home team, and thus creates a home court advantage. Therefore, this coefficient is expected to be greater than one and have a positive effect on producing a win.

AWAY WIN% OF VISITORS is a control variable that measures how good the visiting team is. It measures the visiting team's winning percentage on the road. This control coefficient is expected to be negative, meaning the higher the away team's winning percentage, the less of a chance the home team has of winning the game.

DAYS REST measures how many days of rest the home team has before each individual game. Again, this variable is missing for the first games of each year. The coefficient is expected to be positive, with more rest giving teams a greater chance of winning. Finally, an error term is included in both models.

Model A

$$\ln\left(\frac{Probability\ of\ a\ Win}{1-Probability\ of\ a\ Win}\right) = \beta_1 + \beta_2(\text{LN ATTENDANCE}) + \beta_3(\text{HOME FG\%}) + \beta_4(\text{HOME FT\%}) + \beta_5(\text{FOUL RATIO}) + \beta_6(\text{AWAY WIN\% OF VISITORS}) + \beta_7(\text{DAYS REST}) + e$$

Model B

$$\ln\left(\frac{Probability\ of\ a\ Win}{1-Probability\ of\ a\ Win}\right) = \beta_1 + \beta_2(\text{LN ATTENDANCE}) + \beta_3(\text{HOME FG\%}) + \beta_4(\text{AWAY WIN\% OF VISITORS}) + \beta_5(\text{DAYS REST}) + e$$

V. Descriptive Statistics

Table 2 lists descriptive statistics for each variable in the models. Looking at AWAY WIN% OF VISITORS and WIN, it is easy to see that some home court advantage is happening. On average, between the years 2008-2011, home teams won 60.5% of the games during the regular season. There is a wide range in the data for AWAY WIN% OF VISITORS, showing that there are some very good teams and some very bad teams. The minimum value of AWAY WIN% OF VISITORS is .073, while the maximum ranged up to .707. There is also a lot of variation in ATTENDENCE with data ranging from 8,866 people to 23,129 people.

On average home teams shoot 46.7% from the field and 76.5% from the free throw line. By way of comparison, visiting teams shoot 45.5% from the field and 76.3%

from the free throw line. FOUL RATIO has a mean of over 1, suggesting a referee bias. This means that on average, the referees call more fouls on the visiting team than they do on the home team. Finally, DAYS REST shows that the average NBA team has 1.25 days of rest between games. The most days of rest are 11 over the all-star break, and the fewest is 0, with teams often playing games on back-to-back nights.

Table 2: Descriptive Statistics

Variable	Mean	Std. Deviation	Min	Max
ATTENDENCE	17,305.2	2,840	8,866	23,129
HOME FG %	.467	.057	.279	.675
AWAY FG %	.455	.055	.289	.658
HOME FT %	.765	.096	.364	1
AWAY FT %	.763	.099	.357	1
FOUL RATIO	1.08	.280	.379	3
AWAY WIN% OF VISITORS	.397	.167	.073	.707
DAYS REST	1.25	.980	0	11
WIN	.605	.489	0	1

Table A1, in Appendix A, lists more descriptive statistics pertaining to each individual NBA team between 2008-2011. It shows each team's record at home and on the road, as well as each team's field goal percentage at home and on the road, and the plus/minus statistic of average points scored at home and on the road. This table shows an overwhelming support of the home court advantage thesis. More insight on this table is given in Appendix A.

VI. Results

Table 3 shows the initial results of both models. A distinct home court advantage is found in the NBA. All coefficients except for DAYS REST are significant at the 1% level and have the correct signs. However, while these coefficients can indicate

Table 3: Model Results

Variable	Model A		Model B	
	Coefficient	Std. Error	Coefficient	Std. Error
LN ATTENDANCE	0.816***	0.224	1.02***	0.212
HOME FG%	22.1***	0.903	19.5***	0.830
HOME FT%	2.88***	0.427		
FOUL RATIO	2.66***	0.170		
AWAY WIN% OF VISITORS	-1.92***	0.248	-2.04***	0.234
DAYS REST	-0.022	0.041	-0.0047	0.039
Sample Size	3642			
Pseudo R^2	0.2468			

***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

significance, their values are log odds and difficult to interpret. Tables B1 and B2 in Appendix B show the calculations of predicted probabilities at various values for the explanatory variables. Table 4 summarizes the most important results from those calculations.

Beginning with Model A and Table 4 below, with all variables at their mean values, the predicted probability of the home team winning the game is 66.6%. The probability column then shows the predicted probability of the home team winning the game when increasing each variable by one standard deviation, in turn, and the change in probability column shows the difference in the probability between the results of the

Table 4: Probability Results

Variable	Model A Probability: .666		Model B Probability: .643	
	Probability	Change in Probability	Probability	Change in Probability
LN ATTENDANCE	.693	.027	.678	.035
HOME FG%	.875	.209	.846	.203
HOME FT%	.724	.058		
FOUL RATIO	.808	.142		
AWAY WIN% OF VISITORS	.591	-.075	.562	-.081
DAYS REST	.656	-.010	.641	-.002

original variables and the results of the standard deviation increased variables. Therefore, Table 4 shows that increasing LN ATTENDANCE by one standard deviation increases the probability of the home team winning by 2.7%.

It is important to recognize that this effect of attendance does not include the effect fans have through the FOUL RATIO and HOME FT% because those variables are held constant in the model. As previously stated, attendance could have an effect through a referee bias and through the free throw percentage because fans can influence the referee's decisions as well as affect free throws. To see how much these variables add to the effect, Model B is created to remove the variables through which attendance can have an effect. The results of Model B show that a one standard deviation increase in LN ATTENDANCE increases the probability the home team wins by 3.5%. This means that part of the effect that attendance has comes through FOUL RATIO and HOME FT%. The rest of the coefficients in Model B are similar to those in Model A so the rest of the analysis will be concerned just with the results of Model A.

Increasing the HOME FG% by one standard deviation increases the probability of the home team winning by 20.9 %, the largest effect. HOME FT% also has a positive effect on producing a win. By increasing HOME FT% by one standard deviation, the probability of the home team winning the game increases by 5.8%. FOUL RATIO shows that a referee bias is evident in the NBA, and it creates a greater home court advantage. By increasing FOUL RATIO by one standard deviation, the probability of the home team winning the game increases by 14.2%.

AWAY WIN% OF VISITORS is the final significant variable. This variable shows that the better the visiting team is on the road, the less of a chance the home team has at winning. Specifically, for an increase in this variable by one standard deviation, the home team's chances of winning the game decreases by 7.5%. The final variable, DAYS REST, is not significant at all, nor does it yield the expected effect, and therefore will not be discussed further.

VII. Conclusion

Initial descriptive statistics show a home advantage. Home records are consistently better than away records with home teams winning 60.5% of the games between 2008-2011. Field goal percentages at home are also consistently better than away field goal percentages. The plus/minus statistic also show a home court advantage with teams scoring more and allowing fewer points at home than they do on the road. This all agrees with the theory that teams will not shirk in front of their home fans.

Regression results also show a home court advantage through the selected variables. All variables except for DAYS REST are significant at the 1% level. Therefore, through a logit regression analysis a home court advantage is found through attendance, field goal percentage, free throw percentage, and a referee bias. In agreement with theory and most of the previous literature, attendance is a factor in creating a home court advantage. The more fans a team has in the stadium, the greater chance that team has of winning the game. Specifically, with a one standard deviation increase in LN ATTENDANCE, the home team's chances of winning the game increase by 2.7% while controlling for other factors through which attendance can have an affect. This gives team executives a greater incentive to fill their stadiums. Not only will they increase their revenue, but they will also increase their team's chance of winning the game, because more people equals a greater chance of winning. This also could imply executives should lower ticket prices to fill more seats. However, sufficient data on ticket pricing to do a full analysis on this theory is not included in the dataset. It is also worth mentioning again that LN ATTENDANCE is significant despite controlling for performance-based variables, through which attendance can have a factor. The results of Model B show that attendance has an effect through referee bias and through the free throw percentage because the fans influence referees and players.

In agreement with theory, FOUL RATIO also suggests a home court advantage for NBA teams. For a one standard deviation increase in FOUL RATIO, the home team's chances of winning the game increases by 14.2%. This means that there is a referee bias towards home teams, which can be explained by fan influence. The referee does not want to make the home fans boo him, so his calls are more favorable toward the home team. Referee biases could lead teams to change the way they play. If they know there is a referee bias, home teams could be more likely to attack the basket on offense and try to draw fouls. On the defensive side of the ball, teams could be more aggressive because they know that referees would be less willing to call a foul. This result agrees with both Page and Page (2010) and Moskowitz and Wertheim (2011). This referee bias could also be troubling news for the NBA. Ideally, the NBA wants unbiased referees and this study shows that referees show favor to the home team when making decisions. At the same time, this study speaks out to fans. They really can affect the outcome of winning the game.

Future research could include analyzing individual teams instead of a combined NBA model. This could yield interesting results as it could show if there is a greater home court advantage for some teams than others. More travel factor variables could be added into the model. Visiting teams undergo the inconvenience of some travel; therefore a variable such as a measurement of distance traveled or even game start time could influence the effect of home court advantage. For example, compare the start times for games on the east coast and the west coast. A 9 p.m. Eastern game start time in Boston for a Celtics/Clippers game has a relatively low impact for both teams. However, a 9 p.m. Pacific game start time for those same teams in Los Angeles would greatly affect the Celtics because that same start time in Boston would be midnight or later. This factor might be a better variable than days of rest. Finally, applying this model to sports such as baseball, soccer, or football could yield interesting comparisons to the effect of home court advantage between different sports.

Appendix A

Again, Table A1 below lists descriptive statistics for every team for the three-year span followed in this study. Every team has a better record at home than on the road except for the 2009-10 Boston Celtics, the 2008-09 Minnesota Timberwolves, the 2009-10 Philadelphia 76ers, and the 2010-11 Sacramento Kings. And, the differences in home and away records for these four teams are very small. In support of home court advantage, there are some drastic differences between home and away games in other team's records. The 2008-09 Atlanta Hawks won 31 games at home, but had a sub-.500 record of 16-25 on the road. The Denver Nuggets had a record of 34-7 at home in 2009-10, but they had a sub-.500 record of 19-22 on the road. The 2010-11 Washington Wizards won 20 games at home, just under a .500 record, but they won measly three games on the road.

Finally, the home and away plus/minus statistic is a great indicator of home court advantage. A positive number indicates more points scored than points given up, while a negative number signifies more points given up than scored. For example, the 2008-09 Chicago Bulls outscored their opponents at home by an average of 4.1 points per game. But, on the road, they were outscored on average by 4.7 points. Even more drastic differences than this can be found. The 2010-11 Denver Nuggets outscored opponents by 10.6 points on average at home. But, on the road, they were outscored by an average of 1.0 points per game. Only five times in Table A1 do teams have a better plus/minus statistic on the road than at home. And these differences, like the home and away records, are very small.

Table A1: Individual Team Descriptive Statistics

Team	Year	Home Record	Away Record	Home FG%	Away FG%	Home Points +/-	Away Points +/-
Atlanta Hawks	2008-09	31-10	16-25	47.0%	44.7%	5.7	-2.5
	2009-10	34-7	19-22	47.2%	46.4%	8.5	0.8
	2010-11	24-17	20-21	46.5%	45.9%	-0.9	-0.8
Boston Celtics	2008-09	35-6	27-14	49.7%	47.4%	10.1	4.9
	2009-10	24-17	26-15	48.9%	47.6%	3.4	3.9
	2010-11	33-8	23-18	50.3%	46.9%	8.2	2.6
Charlotte Bobcats	2008-09	23-18	12-29	45.4%	45.6%	2.2	-4.7
	2009-10	31-10	13-28	46.1%	44.5%	6.6	-3.6
	2010-11	21-20	13-28	46.0%	44.3%	-0.6	-7.4
Chicago Bulls	2008-09	28-13	13-28	46.0%	45.3%	4.1	-4.7
	2009-10	24-17	17-24	45.2%	45.1%	0.7	-3.9
	2010-11	36-5	26-15	46.4%	45.9%	10.2	4.4
Cleveland Cavaliers	2008-09	39-2	27-14	47.8%	45.9%	14.4	3.5
	2009-10	35-6	26-15	49.7%	47.4%	8.9	4.2
	2010-11	12-29	7-34	43.4%	43.5%	-5.7	-12.3
Dallas Mavericks	2008-09	32-9	18-23	47.9%	44.5%	6.5	-2.5
	2009-10	28-13	27-14	46.1%	46.8%	2.2	3.2
	2010-11	29-12	28-13	48.2%	46.7%	6.2	2.2
Denver Nuggets	2008-09	33-8	21-20	47.5%	46.5%	7.1	-0.3
	2009-10	34-7	19-22	47.7%	45.9%	9.0	-0.8
	2010-11	33-8	17-24	48.8%	46.3%	10.6	-1.0
Detroit Pistons	2008-09	21-20	18-23	46.2%	44.7%	0.2	-1.2
	2009-10	17-24	10-31	43.8%	45.2%	-3.3	-6.9
	2010-11	21-20	9-32	47.6%	44.3%	-0.5	-6.7
Golden State Warriors	2008-09	21-20	8-33	47.5%	44.1%	1.4	-8.9
	2009-10	18-23	8-33	47.3%	46.5%	0.8	-8.0
	2010-11	26-15	10-31	47.3%	45.0%	2.7	-7.4
Houston Rockets	2008-09	33-8	20-21	45.6%	45.0%	8.8	-0.8
	2009-10	23-18	19-22	45.6%	43.8%	1.5	-2.3
	2010-11	25-16	18-23	45.1%	45.8%	4.7	-0.3
Indiana Pacers	2008-09	25-16	11-30	45.5%	45.5%	2.5	-4.8
	2009-10	23-18	9-32	44.9%	43.6%	1.9	-7.9
	2010-11	24-17	13-28	45.2%	43.3%	3.5	-5.6
Los Angeles Clippers	2008-09	11-30	8-33	44.2%	44.1%	-7.6	-10.0
	2009-10	21-20	8-33	46.2%	44.8%	-2.8	-10.0
	2010-11	23-18	9-32	46.4%	45.0%	1.2	-7.4
Los Angeles Lakers	2008-09	36-5	29-12	47.5%	47.3%	10.1	5.2
	2009-10	34-7	23-18	45.9%	45.6%	8.5	0.9
	2010-11	30-11	27-14	46.6%	45.9%	8.7	3.6
Memphis Grizzlies	2008-09	16-25	8-33	45.9%	44.9%	-3.3	-7.7
	2009-10	23-18	17-24	46.2%	47.5%	0.0	-3.1

	2010-11	30-11	16-25	49.2%	44.9%	7.2	-2.5
Miami Heat	2008-09	28-13	15-26	46.6%	44.7%	4.2	-3.7
	2009-10	24-17	23-18	45.6%	46.0%	3.4	1.1
	2010-11	30-11	28-13	47.9%	48.3%	9.1	5.8
Milwaukee Bucks	2008-09	22-19	12-29	45.5%	43.6%	2.9	-5.1
	2009-10	28-13	18-23	43.9%	43.3%	3.3	0.1
	2010-11	22-19	13-28	43.4%	42.6%	2.0	-3.7
Minnesota Timberwolves	2008-09	11-30	13-28	44.1%	44.2%	-5.8	-4.0
	2009-10	10-31	5-36	45.6%	44.2%	-5.6	-13.6
	2010-11	12-29	5-36	43.9%	44.2%	-3.3	-10.0
New Jersey Nets	2008-09	19-22	15-26	44.4%	45.1%	-0.9	-4.0
	2009-10	8-33	4-37	42.3%	43.5%	-7.2	-11.0
	2010-11	19-22	5-36	44.3%	43.6%	-3.2	-9.2
New Orleans Hornets	2008-09	28-13	21-20	46.3%	45.2%	4.6	-1.5
	2009-10	24-17	13-28	46.5%	46.4%	0.9	-5.8
	2010-11	28-13	18-23	47.0%	44.8%	3.6	-1.8
New York Knicks	2008-09	20-21	12-29	44.9%	44.1%	-1.0	-4.3
	2009-10	18-23	11-30	46.0%	44.9%	-0.7	-7.0
	2010-11	23-18	19-22	47.2%	44.3%	1.9	-0.3
Oklahoma City Thunder	2008-09	15-26	8-33	45.3%	44.1%	-3.7	-8.5
	2009-10	27-14	23-18	47.6%	44.8%	5.6	1.3
	2010-11	30-11	25-16	47.3%	45.5%	6.3	1.3
Orlando Magic	2008-09	32-9	27-14	45.8%	45.5%	9.9	3.5
	2009-10	34-7	25-16	48.3%	45.7%	11.6	3.3
	2010-11	29-12	23-18	46.6%	45.6%	9.0	1.9
Philadelphia 76ers	2008-09	24-17	17-24	46.0%	45.8%	4.0	-3.9
	2009-10	12-29	15-26	46.2%	45.8%	-4.8	-3.0
	2010-11	26-15	15-26	46.7%	45.5%	5.1	-2.1
Phoenix Suns	2008-09	28-13	18-23	52.0%	48.8%	6.3	-2.5
	2009-10	32-9	22-19	49.8%	48.6%	9.4	0.4
	2010-11	23-18	17-24	46.9%	47.1%	0.8	-2.6
Portland Trailblazers	2008-09	34-7	20-21	47.5%	45.4%	10.3	0.3
	2009-10	26-16	24-17	46.0%	46.2%	4.8	1.9
	2010-11	30-11	18-23	45.3%	44.1%	5.6	-2.6
Sacramento Kings	2008-09	11-30	6-35	44.6%	44.9%	-6.0	-11.5
	2009-10	18-23	7-34	46.3%	44.9%	-1.2	-7.5
	2010-11	11-30	13-28	44.4%	45.5%	-3.4	-7.2
San Antonio Spurs	2008-09	28-13	26-15	48.1%	45.0%	4.9	2.6
	2009-10	29-12	21-20	49.2%	45.4%	8.3	1.8
	2010-11	36-5	25-16	48.8%	46.2%	9.9	1.5
Toronto Raptors	2008-09	18-23	15-26	47.1%	44.5%	0.5	-6.1
	2009-10	25-16	15-26	48.1%	48.4%	1.3	-4.9
	2010-11	16-25	6-35	48.2%	45.0%	-2.6	-10.0
Utah Jazz	2008-09	33-8	15-26	48.6%	46.3%	9.5	-4.2
	2009-10	32-9	21-20	51.1%	47.1%	9.5	1.2

	2010-11	21-20	18-23	47.1%	45.9%	0.8	-4.5
Washington Wizards	2008-09	13-28	6-35	45.1%	44.8%	-4.7	-10.2
	2009-10	15-26	11-30	45.7%	44.1%	-2.8	-6.8
	2010-11	20-21	3-38	44.6%	43.9%	-2.0	-12.8

Appendix B

Tables B1 and B2, below, show the calculation behind the probabilities in Table 4. Looking at Table B1, the first column in each table multiplies each coefficient by the mean of each variable. The means for all variables are found in Table 2. Summing all the results of that action together yields log odds (0.690) of the home team winning the game. Taking the antilog of the log odds gives us the odds ratio (1.994) of a win. This odds ratio is changed into a probability by dividing the odds ratio by one plus the odds ratio. This probability (0.666, or 66.6%) is the probability the home team wins the game. The remaining columns in the tables show how the probability of a win changes by increasing a variable mean by one standard deviation. A one standard deviation increase in LN ATTENDANCE, for example, increases the probability of a win to 69.3%, an increase of 2.7%. Or a one standard deviation increase in HOME FG%, for example, increases the probability of a win to 87.5%, an increase of 20.9%. Table B2 is interpreted in the same manner as Table B1.

Table B1: Model A Probability Table

Variable	Average (Mean x Coeff)	Change LN ATT; Otherwise Average	Change HOME FG% Otherwise Average	Change HOME FT% Otherwise Average	Change FOUL RATIO Otherwise Average	Change AWAY WIN% Otherwise Average	Change DAYS REST Otherwise Average
LN ATTEND	7.963	8.087*	7.963	7.963	7.963	7.963	7.963
HOME FG%	10.316	10.316	11.575*	10.316	10.316	10.316	10.316
HOME FT%	2.203	2.203	2.203	2.480*	2.203	2.203	2.203
FOUL RATIO	2.873	2.873	2.873	2.873	3.618*	2.873	2.873
AWAY WIN%	-0.762	-0.762	-0.762	-0.762	-0.762	-1.083*	-0.762
DAYS REST	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.048*
CONSTANT	-21.9	-21.9	-21.9	-21.9	-21.9	-21.9	-21.9
Log Odds	0.690	0.814	1.949	0.997	1.435	0.340	0.645
Odds Ratio	1.994	2.257	7.024	2.629	4.120	1.447	1.906
Probability	0.666	0.693	0.875	0.724	0.808	0.591	0.656
Change in Prob		0.027	0.209	0.058	0.142	-0.075	-0.010

* Changed Variable by Std. Dev.

Table B2: Model B Probability Results

Variable	Average (Mean x Coeff)	Change LN ATT; Otherwise Average	Change HOME FG%; Otherwise Average	Change AWAY WIN%; Otherwise Average	Change DAYS REST; Otherwise Average
LN ATTEND	9.954	10.109*	9.954	9.954	9.954
HOME FG%	9.125	9.125	10.239*	9.125	9.125
AWAY WIN%	-0.810	-0.810	-0.810	-1.083*	-0.810
DAYS REST	-0.00059	-0.00059	-0.00059	-0.00059	-0.010*
CONSTANT	-17.68	-17.68	-17.68	-17.68	-17.68
Log Odds	0.589	0.744	1.702	0.248	0.579
Odds Ratio	1.802	2.104	5.487	1.281	1.784
Probability	0.643	0.678	0.846	0.562	0.641
Change in Prob		0.035	0.203	-0.081	-0.002

* Changed Variable by Std. Dev.

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