Assessing the effects of scoring and non-scoring parameters on win probability and point total in the National Basketball Association: A Bayesian statistics data analysis

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Introduction:

The game of basketball has changed immensely since the formation of the National Basketball Association (NBA). The manner and benefit of these changes can be fiercely debated, but at a structural level, several rule changes and differences in game-play styles have led to higher scoring games. When Dr. James Naismith wrote the 13 rules of basketball, players were not allowed to dribble or move with the ball, the only legal body parts used to control the ball were the arms or hands and throwing the ball into the peach basket counted as 1 point. The final score of the first game played in 1891 was 1-0. The first season of the now NBA (then Basketball Association of America) saw an average score per game of 67.8. Quite clearly the game of basketball is fundamentally different today than it was in 1891, and many of these differences present as higher scoring games.

The game of basketball is a living culture that develops and changes with time. In 1979, the three-point line was invented to reward players with more points who were more skilled at shooting outside shots. The three-point shot is a statistically a lower percentage shot, so it is worth more points than higher probability closer-range shots. Further, the three-point line has been moved back in the history of the NBA as more players have gotten better at converting three-point shots. Importantly, the number of three-pointers attempted per game is higher now than ever. Unsurprisingly, the three-point line was not utilized much when it was first introduced.

In 2018, the freedom of movement rule was introduced as a way to better standardize foul calls. The rule states referees should call fouls if a player's freedom of movement is impeded. Related foul calls, such as charges and blocks can often times be subjective and tough split-second judgments to make due to the plethora of criteria to consider. In decades such as the 1980s and 1990s, players like Isiah Thomas or Michael Jordan would often get near-assaulted when driving to the basket, and the incidences of harder fouls were prevalent. The freedom of movement rule incentivizes players to get to the basket because they are provided some protection against hard fouls (hard fouls are now met with more repercussions and fines). Players driving to the basket with more frequency has hence increased the number of average free-throw attempts per game. Free-throws are, on average for most players, high percentage shots. Indeed, they are 'free' shots, and taken while the game clock is paused, thus have the ability to drastically increase point totals per minute of gameplay. Lastly, the freedom of movement rule has changed the game by deemphasizing hard defense, effectively upping points score per game.

Recent decades of basketball have also seen the rise of 'star players' who have taken away from a more team-first focused style of play. In the early seasons of the NBA, there were of course great players who stood out among the rest, but for many teams the scoring was more balanced. Now, scoring distributions are more skewed with the increase of star players on teams who handle the ball at a much higher rate. These players can be flashy, tend to 'take over' games, and are expected to be top scorers on teams (think Larry Bird, Magic Johnson, Michael Jordan, Kobe Bryant and Lebron James). With basketball becoming so much more engrained in American culture, star players are featured in advertisements, make millions of dollars, and have become idols in the face of the sport. With the increase in star players, the game pace has seemed to parallelly increase. Star players want to control the game, and many of them take a large number of close-range shots, that often lead to being fouled – again leading to an increase in free-throw attempts. A statistic that often represents star players is whether they record a double-double (being in double digits for two of: points, assists or rebounds) or a triple double (being in double digits for all three of those categories).

Similarly, this flashier style of play has dynamically changed basketball positioning and defense. Teams tend to play "position-less" basketball, where most every player on the floor is a scoring threat. This has led to an increase in average points because teams want to run with the ball and score as much as possible, deemphasizing defense in some cases. Further, teams are cultivating less traditional line-ups in the sense that they want five scorers on the floor at almost all times. Indeed, Lebron James (6-foot 9 forward) started numerous games in the 2021-2022 season at both point guard and center. The position name in those cases matters less than just having the Laker's star be on the floor and handling the ball for a large percentage of the game.

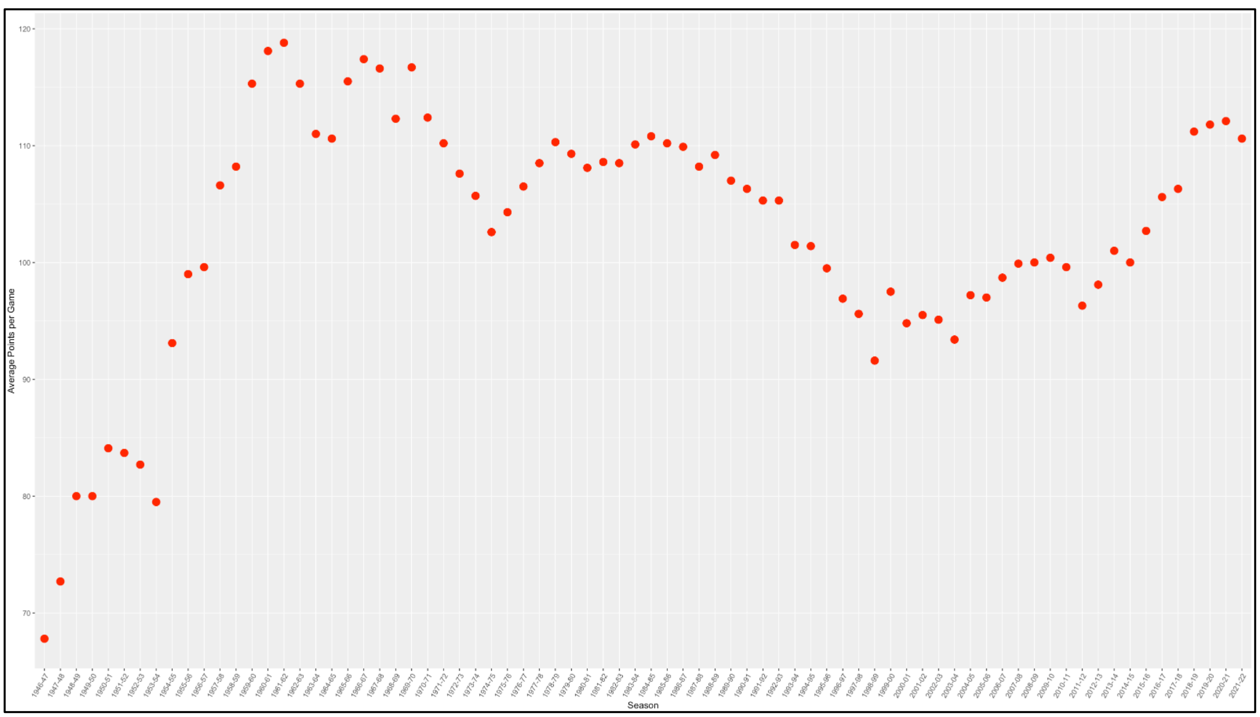

Figure 1. Average points per NBA season.

In this analysis, I focus on non-scoring and scoring metrics to analyze point total and win percentage in the 2021-2022 NBA season. Non-scoring metrics include home court advantage, turnovers, assists, offensive rebounds, steals, free throw attempts and dribbling percentage, and scoring metrics include players' plus minuses and double doubles. I am interested specifically in these parameters because metrics such as three-pointers made or offensive efficiency will certainly increase point totals and have a higher likelihood of increasing wins, but it is important to consider other less obvious intangibles that lead to team wins and higher point totals.

I predict that home court advantage may increase point total or likelihood of wins because of fan noise and not having to travel. Offensive rebounds and steals effectively increase the number of possessions a team has, thus increasing the chances they have to score points. Similarly, free-throw attempts increase the chances a team has to score without running game clock, and turnovers decrease the number of possessions a team has to score. Dribbling percentage might decrease the number of shots a team takes by lowering the pace, but this could be dependent on what player (position) is doing the most dribbling. A player recording a double double is a somewhat proxy for the existence of a star player. If a double double is recorded, that player had a significant amount of points, but I hypothesize that won't necessarily translate to a win. Lastly, plus minus is a newer metric that is calculated for each player on the court. For the minutes they played, the plus minus indicates how many net points were scored or given up on their team.

Methods:

Data.
I downloaded open-source NBA data from https://www.advancedsportsanalytics.com/nba-raw-data. To not overwhelm these models, I only downloaded data starting January 1 2022 running through April 10 2022. The data file includes 1,230 games and each game has a unique game ID. Each game has multiple rows to allow for both team-level variables and player-level variables. Team level variables are coded such as: "Team_Points" or "Team_FT_percentage" and are overall totals for the reference team per game. On that same line would be a team-level *opponent* variable, such as "Opponent_Points." The player-level variables contain parameters such as "minutes_played," or "assists" and are available for all players from that team who were in the line-up that game. The variable "player" denotes what player the player-level variables correspond to. Because there are two teams per game, both teams are the reference team for one game ID. Thus, the average game ID has 24 rows: 1 row per player for 2 teams (12 players per team). Further, for one game ID (e.g. Brooklyn vs Indiana April 10. 2022 where Brooklyn won 134-126), the "Team_Points" when Brooklyn is the reference team is equal to 134, which equals the "Opponent_Points" when Indiana is the reference team.

	game_id	game_date	OT	H_A	Team_Abbrev	Team_Score	Team_pace	Team_efg_pct	Team_tov_pct	Team_orb_pct	Team_ft_rate	Team_off_rtg	Opponent_Abbrev	Opponent_Score	Opponent_pace	Opponent_off_rtg	player	player_id	starter	mp	fg	fga	fg_pct	fg3
1	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Tyrese Haliburton	halibty01	1	39:28:00	7	14	0.500	2
2	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Buddy Hield	hieldbu01	1	35:53:00	8	23	0.348	5
3	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Oshae Brissett	brissos01	1	35:47:00	10	20	0.500	5
4	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Isaiah Jackson	jacksis01	1	32:01:00	3	4	0.750	0
5	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	T.J. McConnell	mccontj01	1	30:52:00	5	15	0.333	3
6	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Terry Taylor	taylote01	0	23:37	4	7	0.571	0
7	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Duane Washington Jr.	washidu02	0	18:42	7	11	0.636	4
8	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Lance Stephenson	stephla01	0	17:15	3	8	0.375	0
9	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Gabe York	yorkga01	0	6:25	0	2	0.000	0
10	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Goga Bitadze	bitadgo01	0	0:00	0	0	0.000	0
11	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Malcolm Brogdon	brogdma01	0	0:00	0	0	0.000	0
12	202204100BRK	4/10/22	0	A	IND	126	103.9	0.543	5.9	20.8	0.125	121.3	BRK	134	103.9	129.0	Jalen Smith	smithja04	0	0:00	0	0	0.000	0
13	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Kevin Durant	duranke01	1	40:41:00	5	17	0.294	0
14	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Kyrie Irving	irvinky01	1	39:52:00	15	20	0.750	4
15	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Kessler Edwards	edwarke02	1	39:17:00	4	7	0.571	0
16	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Bruce Brown	brownbr01	1	37:47:00	8	13	0.615	1
17	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Andre Drummond	drumman01	1	19:52	9	9	1.000	0
18	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Patty Mills	millspa02	0	30:23:00	3	6	0.500	2
19	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Nic Claxton	claxtni01	0	23:22	6	6	1.000	0
20	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Cam Thomas	thomaca02	0	8:46	2	3	0.667	1
21	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Blake Griffin	griffbl01	0	0:00	0	0	0.000	0
22	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Seth Curry	curryse01	0	0:00	0	0	0.000	0
23	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	David Duke Jr.	dukeda01	0	0:00	0	0	0.000	0
24	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	Day'Ron Sharpe	sharpda01	0	0:00	0	0	0.000	0
25	202204100BRK	4/10/22	0	H	BRK	134	103.9	0.691	17.9	29.6	0.272	129.0	IND	126	103.9	121.3	LaMarcus Aldridge	aldrila01	0	0:00	0	0	0.000	0

Figure 2. Data frame example showing all rows for one game ID.

Analyses.

I conducted two sets of analyses with these data. For the first, I subsetted the data to only include one row per game ID to perform team-level analyses on the effects of non-scoring metrics on winning. I disregarded player-level variables and kept team score, free throw attempts, assists, offensive rebound percentage, steals, turnovers, and these same statistics for the opponent in this game ID. I selected the home team to be the reference team for each game ID. I created a variable for assists to turnover ratio and denoting whether or not the home team won the game. Lastly, I merged in the reference team's division in the NBA and their color palates for graphing.

With this data frame I conducted several team-level analyses in a Bayesian framework. Specifically, I used Monte Carlo Markov Chains (MCMC) to estimate posterior probability distributions of team winning probability and team points scored per game. MCMCs take into account specified prior values and estimate samples from the joint distribution based on the given data. It is able to sample directly from the posterior and gets around the assumption of a Gaussian data distribution. The command ulam() in the Rethinking package allows you to specify the desired formula and prior distributions for the data in your analysis. It produces samples from the posterior distribution in the form of 2,000 samples from 4 chains. In MCMC framework, each 1,000-sample chain uses half the samples as 'warmups' to adapt to the data.

First, I used logistic MCMC in the R Rethinking Package to predict whether the game was a win or loss for the home team. The predictor variables were assists to turnover ratio, free throw attempts, offensive rebound percentage, and number of steals. I included random effects of individual intercepts for each team in this analysis. I did not include random intercepts for each game ID because each game was only included in this analysis once. The random intercepts per team allow the team record (winning probability) to vary by team. This is important because the Houston Rockets had the worst winning percentage in the league in the 2021-2022 season (24%) while the Phoenix Suns had the best winning percentage in the league (78%). Further, I had no reason to specify random slopes because I am investigating the general relationship between assists to turnover ratio, free throw attempts, offensive rebound percentage and steals on wins, and assuming the effect of, for example, number of steals on winning, is the same for even the Houston Rockets and Phoenix Suns.

Finally, I conducted this same analysis but instead of using logistic regression to predict winning probability for the home team, I predicted total number of points scored for the home team. I ran this analysis to see if these non-scoring metrics predict number of points scored as I hypothesized in the Introduction. Indeed, it is possible for a team to perform very well on the metrics included in these analyses (i.e. score a lot of points) but not win the game. I used the same priors for this analysis as I did above, because they allowed the model to effectively explore the distribution in the first analysis.

	Team	game_id	H_A	Team_Abbrev	Team_Score	Team_Ft_Attempts	Team_Assts	Team_orb_pct	Team_Steal	Team_tov	Team_asst_to_tov	Opponent_Abbrev	Opponent_Score	Opponent_tov_pct	Opponent_orb_pct	Team_ID	Game_ID	Team_W	Conf	primary	secondary	tertiary	division
1	Atlanta Hawks	202204020ATL	H	ATL	122	49	18	19.2	10	6	3.000000	BRK	115	10.8	18.5	1	1161	1	East	#e13a3e	#c4d600	#061922	Southeast
2	Atlanta Hawks	202204060ATL	H	ATL	118	19	26	15.6	11	6	4.333333	WAS	103	13.4	15.8	1	1190	1	East	#e13a3e	#c4d600	#061922	Southeast
3	Atlanta Hawks	202112220ATL	H	ATL	98	29	21	28.9	4	14	1.500000	ORL	104	9.5	18.2	1	463	0	East	#e13a3e	#c4d600	#061922	Southeast
4	Atlanta Hawks	202202030ATL	H	ATL	124	22	25	15.4	6	15	1.666667	PHO	115	9.4	14.6	1	775	1	East	#e13a3e	#c4d600	#061922	Southeast
5	Atlanta Hawks	202110210ATL	H	ATL	113	9	31	13.0	8	13	2.384615	DAL	87	13.2	16.9	1	14	1	East	#e13a3e	#c4d600	#061922	Southeast
6	Atlanta Hawks	202203310ATL	H	ATL	131	28	27	27.3	7	8	3.375000	CLE	107	12.0	29.4	1	1146	1	East	#e13a3e	#c4d600	#061922	Southeast

Figure 3. Data frame example showing each game ID has only one row.

For the second set of analyses, I assessed the effect of player-level metrics on total points per team per game. Using the full NBA dataset (with on average 24 rows per game ID), I pared the data down to include the game ID, player IDs, each player's plus minus, whether that player recorded a double double, how much that player dribbled during the game and whether the team was home or away.

First, I ran a simple Bayesian MCMC that used whether the team was home or away to predict total points. I allowed for random intercepts for both team ID and game ID, because each team might perform differently at home vs being away, and because each game was included twice in the analysis (once for each team in the game ID), thus violating the assumption of non-independence.

Finally, I ran an MCMC assessing the effect of individual players' plus minuses, instances of a double double and dribbling percentages on team points per game. For this model, I once again allowed random intercepts for game ID (not team ID this time) and player ID. I did not include team ID as a random effect because I am controlling for random effects at the player level. The random effect for team ID controls for factors such as location of and pace of the game (i.e. factors that would influence point totals and performance for both teams in the game). Lastly, I did not include random slopes for each variable because I am assuming the occurrence of a double double or positive plus minus has an effect similar in magnitude across players and teams on points (20 points, 10 rebounds for Steph Curry contributes equivalently to the final score as 20 points, 10 rebounds does for DeAndre Ayton). Percent of time spent dribbling could affect team scores differently based on who is dribbling (i.e. if Demarcus Cousins [6'10 center] spent 60% of the time dribbling the ball the game might look a lot slower paced than if Ja Morant [6'3" point guard] spent 60% of the time dribbling the ball), but these nuances are beyond the scope of this preliminary analysis.

Descriptives.

Table 1 shows the mean and standard deviations for team-level variables used in the first set of analyses.

	Mean	Standard Deviation	Min	Max
Points	111.48	12.45	77.0	153.0
Free throw attempts	22.19	7.73	6.0	72.0
Assists	25.33	5.92	11.0	72.0
Turnovers	13.09	4.04	4.0	36.0
Steals	7.70	2.95	0.0	24.0
Offensive rebound percentage	23.39	7.24	2.90	48.9

Table 1. Mean, standard deviation, minimum and maximum for team-level variables used across all 1,230 games.

Results:

Non-scoring metrics on team winning probability.

The first MCMC I ran using assist to turnover ratio, free throw attempts, offensive rebound percentage and steals to predict home team win probability with random effects to allow each team to have a unique intercept. I specified normal priors based on the averages of the predictor variables in the model. For assists to turnover ratio, the priors were m=3, sigma=1, for free throw attempts the priors were m=20, sigma=5, for offensive rebound percentage the priors were m=0, sigma=1.5, and for number of steals the priors were m=6, sigma=3. These all reflect what I presumed to be around league averages for those variables. A prior simulation using extract.prior() shows the priors for this model were acceptable (Figure 4) and exhibit a normal distribution. Further, the effective sample size for each Monte Carlo Markov Chain parameter was greater than 2,450 with Rhats equal to 1 for every parameter, indicating the model effectively explored the sample space.

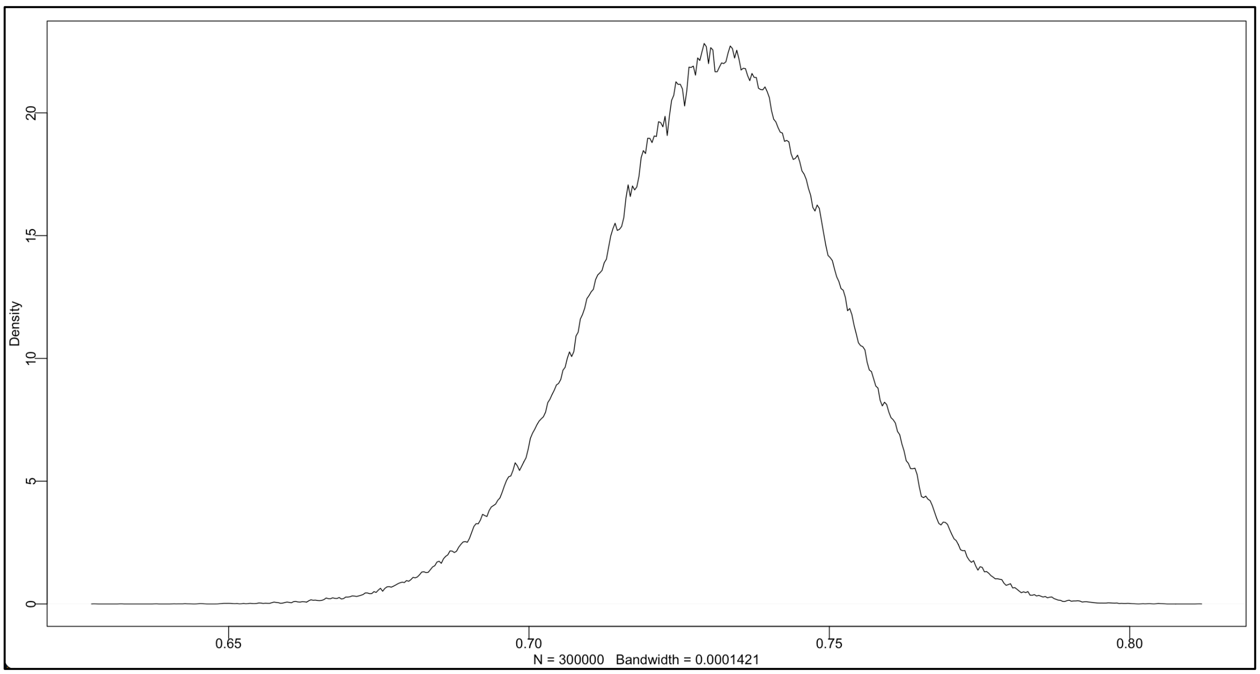

Figure 4. Prior simulation for the logistic MCMC where all non-scoring metrics predicting win probability.

All predictors in this model were significant with the exception of number of steals per game. The slope and 95% highest posterior density interval (HPDI; the narrowest interval containing 95% of the probability mass) for assists to turnover ratio was 0.32 [0.21, 0.41]; the slope and 95% HPDI for free throw attempts was -0.04 [-0.05, -0.02]; the slope and 95% HPDI for offensive rebound percentage was -0.02 [-0.03, -0.01] and the slope and 95% HPDI for number of steals was -0.01 [-0.04, 0.02]. These results indicate a higher assist to turnover ratio predicts a greater probability of winning, and that a higher number of free throw attempts and offensive rebound percentage predict a lower probability of winning. The assists to turnover ratio finding was expected, but the free throw attempt and offensive rebound percentage finding was not.

Sampling from the posterior of this model, we can compare each team's predicted win probability. For example, comparing the Sacramento Kings posterior winning probability to the Memphis Grizzly's posterior winning probability yields a mean difference of -0.13 [-0.34, 0.10], which is surprisingly not significant.

Non-scoring metrics on team point total.

Because teams may perform very well on the non-scoring metrics and still lose, we replicated the previous analysis (including the same priors) but used the non-scoring metrics to predict total team points per game, not wins and losses. Here, we found all parameters to significantly predict point total. The slope and 95% HPDI for assists to turnover ratio was 12.22 [11.44, 12.96]; the slope and 95% HPDI for free throw attempts was 1.34 [1.25, 1.43]; the slope and 95% HPDI for offensive rebound percentage was 1.51 [1.43, 1.60] and the slope and 95% HPDI for number of steals was 2.20 [1.96, 2.43]. These effect sizes are much more in line with my hypotheses and suggest higher scores on all of these metrics (more assists than turnovers, greater number of free throw attempts, higher offensive rebound percentage and greater number of steals) lead to more points scored on average.

The univariate relationship between each of these variables and team points per game is depicted in Figure 3, allowing each team to have its own slope. Although some teams do have slopes divergent from the other team slopes in their division, it does not seem the relationships differ greatly enough from team to team to warrant random slopes in our model.

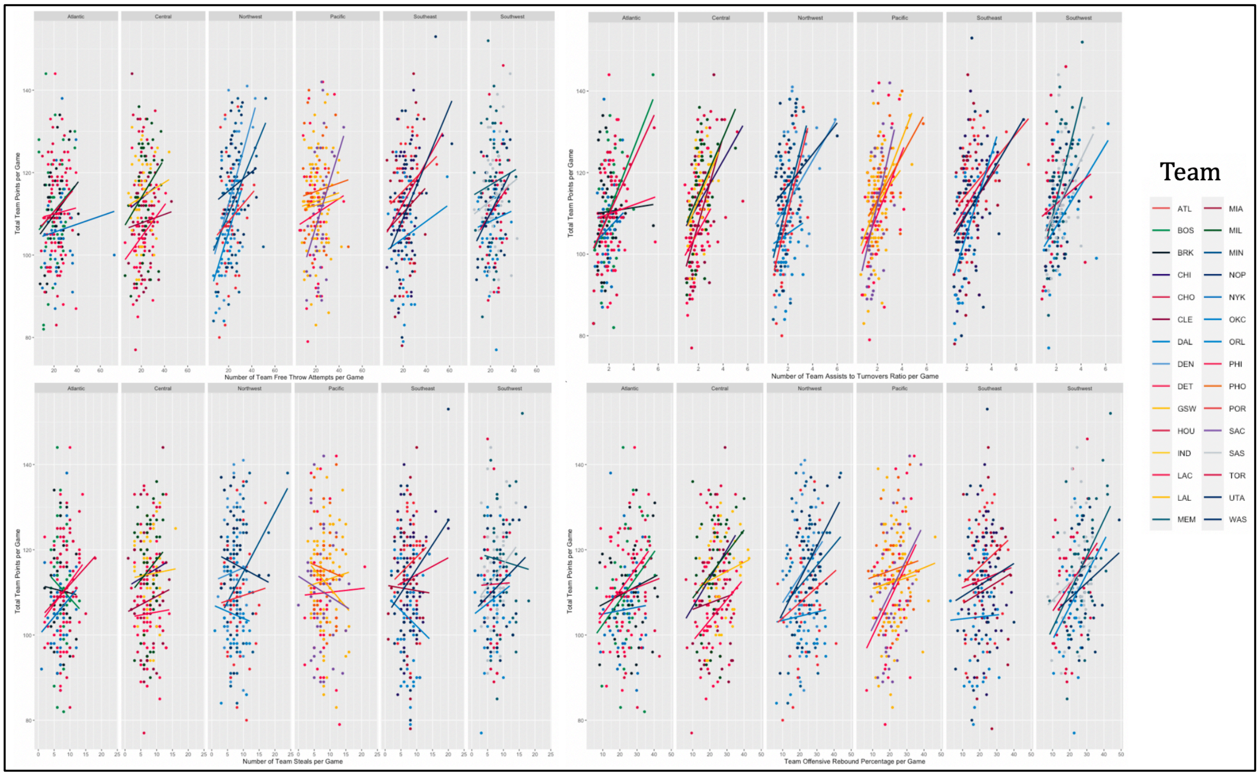

Figure 5. Linear bivariate relationships between number of free throws, assists to turnover ratio, steals and offensive rebound percentage and points per game. Each team has its own slope, although individual slopes were not allowed in the model.

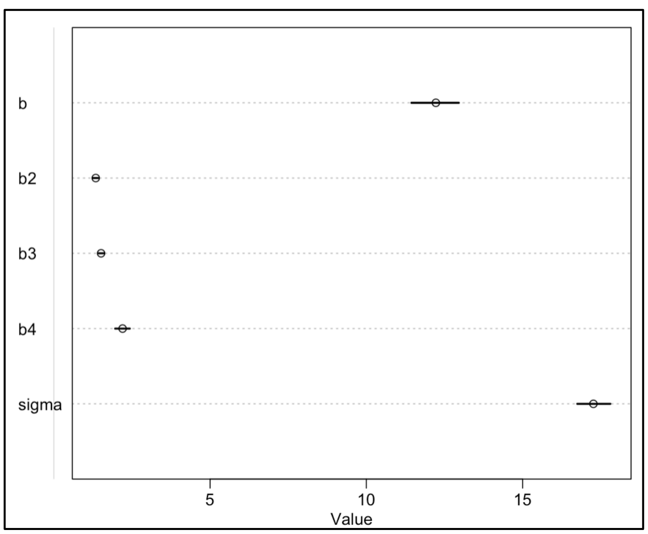

Figure 6. Effect sizes for the non-scoring metric parameters on team points per game. All parameters were significant. B= slope for assists to turnovers ratio; b2= slope for free throw attempt, b3= slope for offensive rebound percentage; b3= slope for number of steals; sigma= model residuals.

The last non-scoring metric I assed was home court advantage. I did not control for home court advantage in the previous analyses because it was implied in the data. The models were predicting win probability and point total for the *home* team, effectively controlling for location of the game. Here, I wanted to assess how much home court advantage influences points scored for each team. I ran a MCMC allowing for random intercepts for both game ID and team ID, to control for non-independence among location and whether certain teams have a better home crowd than others. The priors I chose for the home court advantage slope were m=7, sigma=3, and reflect the point differential I thought the home team might have over the away team. The slope and 95% HPDI for the effect of being the home team on point total was 109.39 [109.24, 109.55], while the slope and 95% HPDI for the effect of being the away team on point total was 107.72 [107.56, 107.89]. Computing a contrast between being the home vs away team, the average difference in point total is 1.67 points [1.44,1.89], which, although small, is a statistically significant difference. Figure 7 shows the posterior mean differences and posterior predicted mean differences after simulation of 10,000 games in team points for home court advantage vs not. While all 30 teams show variable distributions in these data, with a large posterior simulation the predicted differences are small and converge around 1.

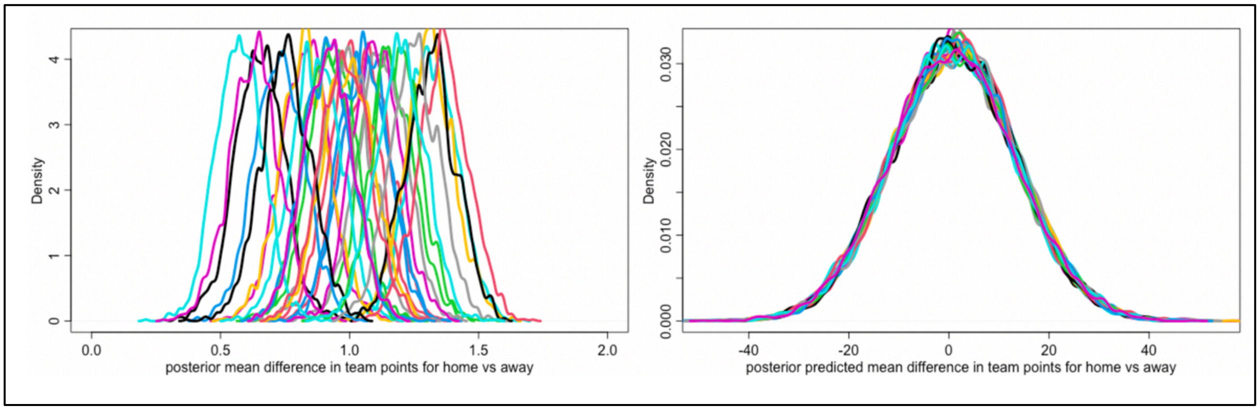

Figure 7. Posterior mean differences in team points being home vs away for all 30 teams and posterior predicted mean differences in team points being home vs away for all 30 teams after a simulation of 10,000 games.

Player scoring and non-scoring metrics on team point total.

Finally, I conducted an analysis that assessed the effects of individual players' plus minuses, occurrences of double doubles and dribble percentages had on team point total. Here, I allowed for random intercepts for both the game ID and player ID, as factors such as the pace of play and location of game are likely to influence the relationship of player performance on points and individual players are likely to have different mean points per games. The priors I used were m=0, sigma=3 for plus minus, double double occurrence and dribble percentage because I did not expect these to have large effect sizes on point total.

This model appeared to fit well as the effective sample sizes were greater than 2,245 and Rhats were 1.0 or 0.999 for all parameters. The slope and 95% HPDI for player plus minus was 0.42 [0.41, 0.43], the slope and 95% HPDI for dribble percentage was -0.02 [-0.02,-0.01], and the effect of the occurrence of a double double on team point total was 108.59 [108.13, 109.06] whereas the effect of no double double on team points was 108.79 [108.65, 108.94]. Given that the HPDIs for the occurrence and nonoccurrence of a double double overlap, there is no significant difference in the effect of a player's double double on team point total (difference mean= -0.20 [-0.64, 0.25]. Overall, these individual player metrics did not have much of an impact on team point total.

Discussion:

Average point total per game in the NBA has fluctuated since the foundation of the league but has been on a fairly steady increase in the last decade. It is easy to imagine metrics such as three-point shot percentage or offensive efficiency increasing the average point total per game, but here, I was interested mostly in non-scoring metrics to predict team winning probability and team points. The MCMC model that allowed assists to turnover ratio, free throw attempts, offensive rebound percentage and steals to predict team win probability was not very useful. All variables significantly predicted home team win, except steals, but the effect sizes were very small and not in all the directions we would expect.

However, quite interestingly, when we used that model to predict team points, all predictors were significant and in the directions we expected. As assists to turnover ratio increases 1, the average point total per home team is expected to increase 12.22. This implies with more possessions and fewer turnovers, point total increases significantly. As free throw attempts increase by 1, the average point total is expected to increase 1.34. This is corroborated by free throws being a very high percentage shot (and worth 1 point) for most players. As offensive rebound percentage is expected to increase 1, the average point total increases 1.51, and as number of steals increases 1, the average point total is expected to increase 2.20. Similarly, both of these findings make sense as an offensive rebound and steal are likely to lead to the make of a basket, often worth 2 points.

I also ran a model that used home court advantage to predict team points to see how valuable that really is. These data reveal there is a significant difference between point total per team when home vs away, but that the difference is quite small. Further, after a posterior simulation of 10,000 games, the difference in point total was still quite small and similar among all 30 teams.

Finally, I was interested in the influence of player-level metrics that were more scoring oriented (yet still not directly scoring-metrics) on team point total. Controlling for individual players and game pace by allowing each player to have their own intercept and each game to have its own intercept, I used the occurrence of a double double, plus minus and dribbling percentage to predict team points. The effect of a player's plus minus and dribbling percentage did significantly influence team point total, but effect sizes were very small. The occurrence of a player recording a double double or not did not significantly influence team point total.

In summary, these results show the utility of non-scoring metrics on team point total, but perhaps not winning probability. This could be due to all NBA teams having the ability to play at a very high level and their ability to win on any given night.