A Boxing-like Round-by-Round Analysis of American College Basketball

Paul Britton*, Carl R. Yerger†

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Abstract

In the last two decades, basketball coaches have increasingly relied on statistical analysis to determine coaching strategies for their teams. Davidson College (USA) men's basketball coach Bob McKillop divides each game into ten "rounds", with a round ending at each media timeout and at halftime, and gives his team several "round" goals for every game. In this article we investigate how winning rounds affects the outcome of a basketball game and investigate whether certain rounds are more important than others. We also look at whether the results of multiple rounds give more information than just looking at the results of one round at a time and whether there are other easy-to-measure factors that can produce a predictive model. Finally, we investigate whether there are any differences related to Davidson's round record compared to other teams as Davidson's players are coached to think about this strategy.

1 INTRODUCTION

In the game of basketball, coaches have tried thousands of strategies in an attempt to coax the best possible result from their players. They have designed offenses and defenses around specific attributes of the game such as rebounding, shooting percentage, and even time of possession. Several studies have analyzed the most important statistics for predicting a game's outcome. Notably, Dean Oliver identified the "Four Factors of Basketball Success" in a 2004 paper, which consist of shooting percentage, turnovers, offensive rebounding, and free throw percentage [1]. However, as in many other sports, basic statistics in basketball can never completely explain the outcome of any one game.

It is important to note that in this and subsequent sections when we say field goal percentage, we are actually referring to Oliver's "effective field goal" percentage statistic. This is calculated by summing the number of successful two-point shots and 1.5 times the number of successful three-point shots and dividing this total by the number of shots taken. The reason for this change from a straight percentage is that making a three-point shot is worth 1.5 times as many points as making a two-point shot. Another interesting observation is that

*Department of Mathematics and Computer Science, Davidson College, Davidson, NC 28035, pabritton42@gmail.com

†Department of Mathematics and Computer Science, Davidson College, Davidson, NC 28035, cayerger@davidson.edu

if we double the effective field goal percentage and divide by 100, this quantity gives the expected points per shot of a particular team.

At Davidson College (USA), coach Bob McKillop has a more unique teaching point, not based on any specific statistic, but simply the game's media timeouts. In college basketball, media timeouts occur roughly every four minutes of gameplay. After the 16:00, 12:00, 8:00 and 4:00 marks of each half, any subsequent stoppages of play (fouls or out-of-bounds turnovers, but not team-called timeouts) trigger a media timeout, which is a longer break in the game [2]. This results in eight media timeouts each game, plus halftime, effectively dividing the game into ten segments, four minutes long on average. During each of these timeouts, coach McKillop tells his team how they performed over the last segment, which he calls a "round" due to its resemblance to a round in boxing. McKillop feels that breaking the game into these rounds helps his team maintain focus, as each section is important, and that his players are motivated by the feedback during timeouts. After each game, he uses rounds in several metrics to grade the team's performance, including winning rounds five and ten, and winning seven rounds overall.

Our study was motivated by the concept of rounds as a coarse evaluation of team performance in a college game. "In football," McKillop [3] notes, "teams seem to have a unique ability to focus on one possession rather than worry about the whole game." seeks to capture this narrowed focus by discussing rounds with his team at each media timeout. However, it is undeniable that coaches use different strategies at different points in games, from the opening few possessions, to substitution rotations, to endgame strategy. It is also true that media timeouts happen every game at similar times, and thus generate consistent game segments to analyze. As a result, when Coach McKillop mentioned his round concept to us, we wanted to use his framework to test a wide range of hypotheses.

In speaking with McKillop [4], he emphasized the impact he feels momentum, or in his words, "Big Mo," has on a game. "When a team leaves the court at halftime, the coach is either happy or pissed off," McKillop says. As a result, the teams have very different experiences at halftime, which can affect their performance in the second half. In-game momentum has been challenged in several studies, such as [5], [6], [7], and [8]. Studies have almost universally found momentum's effects to be minimal. In these studies and for the purposes of this paper, we define momentum as the increase in likelihood of a positive (resp. negative) outcome given that the previous outcome for a player or team was positive (resp. negative). For example, Ezekowitz [9] showed that teams rallying in regulation to force overtime are actually slightly less likely to win an overtime game, in fact showing a slight reverse momentum effect. Another recent study by Fry and Shukairy [10] finds little empirical evidence for momentum in NFL games and also provides a literature review on other momentum studies.

To our knowledge, the concept of game rounds has not been tested in any formal setting to this point. Among other things, we want to test how rounds could be used as a predictor for game outcomes; specifically, if the coach's goal of winning 7 rounds is a strong predictor of a victory. We also looked at a number of other metrics that McKillop uses, such as round significance versus other rounds, the significance of scoring first, and the significance of field goal percentage to predicting game outcomes. After seeing that this analysis was fruitful, we investigated other ways to incorporate the concept of rounds into a more comprehensive study of college basketball data, and this forms the bulk of our paper.

2 METHODOLOGY

In order to analyze round data in a meaningful fashion, we needed to accumulate a large sample of game data noting the scores at each media timeout. Although Coach McKillop can only test his methodology on the court in the Southern Conference (SoCon), we wanted to test his ideas in several different contexts, so we collected data for both the SoCon and the Atlantic Coast Conference (ACC). The reason we chose these two conferences is that the ACC is a traditional power-conference, where multiple teams usually qualify for the NCAA Basketball Tournament. On the other hand, only the automatic qualifier from the SoCon typically reaches the NCAA tournament. After testing several sources of game information, we used the website Statsheet.com for the required play-by-play data [11]. However, it is important to note that not all games had consistent media timeout data. When a timeout was omitted from the play-by-play of a particular game, its location could be determined by recording the first stoppage in play after each four-minute interval in the play-by-play data. In our analysis, there were no instances when a media timeout was not taken (which may be the case if there were no stoppages of play in the last eight minutes of a basketball game). For overtime games, we only analyzed data on the ten rounds in regulation and the final result. As a result, every game in our study contained exactly ten rounds.

We collected two seasons of data for each conference, including conference tournament games. We recorded the score at each media timeout, as well as the score margin for the last minute of each half, and the team to score first in each game. After collecting the raw data, we generated tables for each season and conference recording each round win, round margin, and total rounds won. We also recorded a number of other metrics, including the home and away team, the winner of each half, and team field goal percentage. Each of these statistics is connected with at least one of the metrics McKillop uses to evaluate team performance after each game.

Once the data had been collected and accumulated in an appropriate form, we ran a number of tests on the variables. We recorded team wins and losses as a binary variable where a home team win was counted as 1, and did the same with each round win or loss. A round tie was recorded as .5, but a game tied at the end of regulation was noted separately as an "OT" game, with the eventual winner entered into the binary data.

Because the game winner is a binary variable, any regression with the winner as the dependent variable should be modeled with a logistic model rather than a linear model. It is now commonplace to use a logistic regression for a binary random variable, as the logistic model carries several advantages explained in more detail in previous papers [12], [13]. While the model is in common use, there is still no standard method for testing relative significance of independent binary variables, as discussed in [14]. Further we controlled for year and conference by employing a generalized linear mixed model. This allows us to control for biases based on a particular conference or a particular year. However, both these random effects were predicted to affect the intercept by less than 10^{-6} with negligible variance (also less than 10^{-6}), so we can conclude that the model is unaffected by these two random effects.

We ran separate analyses for each individual season, each conference, the entire data set, and close games, to look at the significance of different independent variables in the overall game outcome. All of the regression analysis was performed with R, an open source

Category	Number of Observations
Total Games	453
SoCon 2009-2010	120
SoCon 2010-2011	119
ACC 2009-2010	107
ACC 2010-2011	107

Table 1: Summary Statistics

statistics program [15]. Menard suggests several methods for determining significance, but we chose to generate our significance scores as the ratio of each regression coefficient and its standard deviation (the R default). Other methods listed in Menard's paper were relevant in determining whether a variable was significant or not, but they were also inconclusive in evaluating the relative degrees of significance. Further, Menard states that "if the only interest is in the rank order of the magnitude of the influences of the predictors on the dependent variable, it makes little difference which of the five methods of standardization one uses." [14] We also ran linear least-squares regression models comparing total rounds won to game margin, and individual round margins to game margin. To better understand how combinations of round wins affect the game outcome, we examined interaction variables via an analysis of residual deviance. We summarized our results by developing a best-possible model using rounds, combinations of rounds, other game characteristics and significant portions of Oliver's Four Factors.

After compiling all of the data in a usable form, we analyzed the results in the context of coach McKillop's performance metrics for his team. In addition to the tests described above, we performed more basic calculations that will be explained in additional detail in subsequent sections.

3 RESULTS AND ANALYSIS

3.1 INTRODUCTION

Overall, we sampled 453 games from the Southern Conference and the Atlantic Coast Conference, using only inter-conference games from the 2009-2010 and 2010-2011 seasons. Two SoCon games from 2010-2011 did not have play-by-play data available for the entire game, so those games were omitted from further analysis. Table 1 gives summary statistics for the number of games recorded for each season in each conference. There are more games in the Southern Conference seasons because each team played 18 regular-season games compared to 16 in the ACC. We first tested the predictive validity of rounds won on the overall game outcome.

Coach McKillop's goal of winning 7 rounds (or generating a round score of 7 including ties) was strongly predictive of a team win, as only one team lost a game when they won 7 rounds in all sampled games. This effect was equally strong in both conferences, with Southern Conference teams that won more rounds winning 90.3% of the time and ACC teams winning 88.24% of the time. Table 2 gives information on the likelihood of winning

Either team wins X rounds	Observations (out of 451)	Wins by Round Winner	Regulation Losses by Round Winner	Overtime Losses by Round Winner	Win (%)
Exactly 5.0	68	NA	NA	NA	NA
Exactly 5.5	109	85	23	1	78.0
Exactly 6	114	100	11	3	87.7
Exactly 6.5	59	57	2	0	96.6
Exactly 7	53	52	1	0	98.1
7.5 or more	48	48	0	0	100

Table 2: Rounds Needed to Win

the basketball game based on the number of rounds won. For example, winning even one more round than a team's opponents (5.5-4.5) still gave that team a 78.0% chance of a game victory. The fact that a team wins the game almost nine out of ten times when winning a majority of the rounds can be a meaningful in-game coaching remark when a team is down just one or two rounds (but many points) early in the game. As the discrepancy in round score increased, so did the winning percentage, with fewer than one in every 50 teams winning the game after losing at least 6.5 rounds. On the other hand, when exactly five rounds are won by each team, the home team won 64.7% of the games in our study. (In particular, the home team won 44 of 68 games and the home team had two overtime losses. We add an N/A to the table since there really is no round winner.) This is consistent with the observation that amongst all games in our data set 63.7% of the games were won by the home team.

3.2 RELATIVE ROUND IMPORTANCE

To test the possibility of some rounds being more significant to the outcome than other rounds, we used a logistic regression model on the set of all games from both conferences. Tests of one season at a time showed some possibility of differences in the significance of particular rounds, but this possibility disappeared when more games were added to the data set as the z values of individual rounds were more clustered. Our logistic regression was modeled with the following formula, where the x_i's are ternary variables that are 1 if the home team wins round i, .5 if round i is a tie, and 0 if the home team loses round i:

$$F(z) = \frac{1}{1+e^{-z}}; z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \cdots + \beta_{10} x_{10} + conf + year$$

Our $F(z)$ values can only vary between zero and one, which fits the binary nature of our dependent variable, as teams can only win or lose a basketball game. Notice that we have included the random effects of conference and year in this model, but we can safely exclude these factors because their variance is extremely small, less than 10^{-6}. (We also analyze these factors later via residual deviance testing, which also strongly supports excluding these factors.)

Following the conventions in R, in this and subsequent tables, * denotes a variable significant at the .05 level, ** denotes a variable significant at the .01 level and *** denotes a variable significant at the .001 level.

Coefficients	**Estimate**	**Std. Error**	***z* value**	**Odds Ratio**	**Significance**
Intercept	-10.3463	1.0750	-9.624	NA	***
Round 1	2.8708	0.3753	7.649	17.6511	***
Round 2	1.6091	0.3402	4.730	4.9983	***
Round 3	1.8319	0.3417	5.362	6.2457	***
Round 4	2.7482	0.3938	6.979	15.6145	***
Round 5	2.1097	0.3551	5.942	8.2458	***
Round 6	1.6616	0.3453	4.812	5.2677	***
Round 7	2.1839	0.3450	6.330	8.8809	***
Round 8	2.4298	0.3866	6.286	11.3566	***
Round 9	1.9331	0.3421	5.650	6.9109	***
Round 10	2.1161	0.3616	5.852	8.2987	***

Table 3: Combined Results

As noted earlier, there is no standard method for comparing significance of logistic regression coefficients. The R software generates a Z-score by the same method we decided on for our linear regression: by taking the ratio of the estimated beta values to the corresponding standard errors. Menard [14] notes that this is an appropriate method for comparing the relative significance of the β values.

The data in Table 3 shows that every round is significant to at least the .01 level in ACC data, and to the .001 level in Southern Conference data. In both the Southern Conference and ACC results, the first round had the highest β value in the regression. However, there was not a large difference between the Z-values of the first round and the next highest round for either conference. For brevity considerations we only include the combined results in tabular form.

We computed odds ratios for each of the individual rounds. One observation to note is that the odds ratios for the Southern Conference seem larger than those for the ACC. When testing for the hypothesis that the average coefficient for a round in the SoCon is the same as the average coefficient for a round in the ACC, we obtain that a 95% confidence interval that the difference in means is $.6857 \pm .5555$. This assumes a common variance of .5661 for each SoCon coefficient and a common variance of .5097 for each ACC coefficient.

To test the effects of momentum in a game, we focused on results from rounds close to halftime. Coach McKillop believes that performing well in the last round and last minute before halftime gives his teams a mental edge coming into the second half, and that ”momentum” will carry over into the second half. We tested this by looking at winners of round 5 (the last round before halftime) and winners of the last minute before halftime, then testing correlation between those winners and round 6 winners.

In all metrics based on halftime rounds, there was no evidence for better performance in round 6 after a win in round 5 before halftime. In total, there were 372 games where both rounds 5 and 6 were won outright. Out of those games, however, only 174 times did the same team win both rounds, showing a negative correlation between performance in rounds 5 and 6. This result is evidence against McKillop's momentum hypothesis and not so surprising given the regression effect. Teams that won both rounds 5 and 6 did go on to win the game 124 times (out of 174), showing a positive correlation; however, wins in rounds 5 and 6 give that team a two-round lead, putting them on pace to win 6 rounds overall. As shown earlier, teams that win 6 rounds exactly win games 87.7% of the time, much higher than 124 out of 174, a 71.3% rate. Winning the last minute of the first half was also negatively correlated with winning round 6.

3.3 TESTING OTHER COACHING GOALS

In our complete sample, winning any round was positively correlated with winning the game. Our regression model showed that this correlation was significant for every round at better than a .001 level of significance. Two other factors, scoring first and shooting a higher field goal percentage (treated as a binary variable), were investigated and tested against individual rounds to determine their relative significance. When we tested scoring first as an independent variable against each round, it did not come out as significant, with a p-value greater than .1. Field goal percentage, on the other hand, was highly significant, and had a higher Z-value, 6.67, than any individual round in our sample (individual rounds had Z-values between 3.3 and 5.9 for this analysis).

When testing these regressions, one of our considerations was the overlap between scoring first and the outcome of the first round. Since the round one significance might mask the effect of scoring first, we also ran a regression excluding round one with just scoring first and the other nine rounds as variables. While the α value of scoring first did improve with this adjustment, it was still greater than .1 and the least significant of any round in the regression. This result was in line with expectations, as one basket should not be as strong a predictor of success as any four-minute period of the game.

While manually recording the data in our spreadsheets, we noticed that teams with large leads would often play the end of the game with substitute players who would not ordinarily play many minutes. As a result, the final two or three rounds in such games were often closer than the first seven rounds due to different players competing for the winning team. In close games, however, the teams would play similar rotations throughout, and games would often come down to the last few minutes to be decided. We wondered if the irregular substitutions in blowout games might have been skewing our results; specifically, would rounds nine and ten be more significant if teams only played their best players?

To test this hypothesis, we narrowed our pool of games to games where the final margin of victory was eight points or fewer, giving us a sample of 200 games. We then ran the same logistic regression from our larger sample on just the close games. The Z-scores decreased for all rounds, but this can be attributed to the smaller sample size and not any feature of the close game data. In the larger sample, the ninth and tenth round had the seventh and sixth largest Z-scores, respectively. In the close game analysis, those two rounds had the eighth and third largest Z-scores, suggesting no improvement for the ninth round but a slight jump for the tenth round.

3.4 MARGIN OF VICTORY ANALYSIS

In addition to our logistic regression analysis, we ran a regression with total rounds won as the independent variable and margin of victory as the dependent variable. Because margin of victory is not a binary variable like winning and losing, linear regression was the most appropriate regression for this test. For our linear regression, we used the following formula:

$$z = \beta_0 + \beta_1 x_1.$$

Here, z is our margin of victory dependent variable, and β_1 is the coefficient generated from the independent variable, x_1, of rounds won. Using the data from both conferences, we found β_0 to be 7.3866, indicating a round win is worth slightly more than seven points. Despite a high number of data points from both conferences, the correlation coefficient R^2 was still very high, .6687. This indicates that there is a strong correlation between round performance and overall margin of victory. These results held across both conferences, with β_0 at 7.36 in the ACC and 7.41 in the Southern Conference, and both R^2 values between .63 and .7.

4 OTHER ROUND FRAMEWORKS AND ANALYSES

When looking at game rounds in a number of different contexts, it is clear that they are significant predictors of team success, both individually and in sum. However, Coach McKillop's breakdown of the individual rounds (into round wins and round losses) is not the only possible breakdown of the game into rounds. We now examine several possible extensions of the round framework, by examining the round scores in more detail (with "Knockdown Rounds"), investigating whether there exists a "Davidson Effect," looking at the game from a model-building standpoint, and comparing round significance to other variables in an effort to develop a "best possible model" for the college game.

4.1 KNOCKDOWN ROUNDS

To get a more accurate characterization, it would be helpful to break down the rounds into more subcategories than simply a win, loss, or tie. However, breaking down each round into margin of victory (the smallest possible denominator) would give a trivial result.

To aim for this better characterization, we extended the comparison between boxing rounds and basketball rounds. In boxing, a round winner typically wins a round by a score of 10-9, which we imitate in our model with a 1-0 score. However, if a boxer does unusually well in a round, it is possible to win by a score of 10-8, meaning his opponent would have to win two normal rounds to catch up in the eyes of the judges. This frequently happens when a boxer knocks his opponent down during a round. In our model, we decided to create "Knockdown" rounds where a team wins a round by a significant margin. Since the average round margin of victory was slightly over 3.5, our definition of a knockdown round was a round won by more than twice that margin, or more than seven points. To make this worth twice a normal round, we assigned winning a knockdown round a value of 1.5 points, and losing a value of -.5 points, keeping our two teams' combined round total at ten for every game. Further, the notion of a knockdown round is still easy to communicate to players during the limited time constraints of a time out.

As we expected, rescoring the rounds based on a "knockdown" criteria increased the win percentages for round winners by a substantial margin. The win percentages for teams that have won a specific number of knockdown rounds are shown in Table 4. In our initial test,

Either team wins X rounds	Observations (out of 451)	Wins by Round Winner	Regulation Losses by Round Winner	Overtime Losses by Round Winner	Win (%)
Exactly 5.0	51	NA	NA	NA	NA
Exactly 5.5	102	82	17	3	80.4
Exactly 6	102	97	3	2	95.1
Exactly 6.5	75	74	1	0	98.7
7 or more	121	121	0	0	100

Table 4: Knockdown Round Analysis

winning 6 or more rounds led to victory 93.8% of the time, but when scoring by knockdown rounds, the percentage increases to 97.99%. Additionally, McKillop's "win seven rounds" criteria becomes a perfect statistic for ensuring team success, although there was only one counterexample in the initial scoring system. A 5.5-4.5 advantage was also a better predictor of success, as 80.4% of teams won the game when they maintained a one-round advantage. Similar to results in Section 3, when exactly five rounds are won by each team, the home team won 62.79% of the games in our study. (In particular, the home team won 32 of 51 games and the home team had two overtime losses. Again, we add an N/A to the table since there really is no round winner.) This is consistent with the observation that amongst all games in our data set 63.7% of the games were won by the home team.

Testing our logistic regression in this new framework, the rounds again perform much better than before as seen in Table 5. In our initial regression, the range of Z-values was from 4.8 to 7.6, whereas the range for knockdown scoring is from 6.0 to 7.8. The knockdown rounds seem to have improved the performance of the more poorly scoring rounds to a greater degree than the rounds that already had higher β_0 values. Even the least correlated round to game outcomes, round six, has a Z-value over 6.0 in the knockdown framework. In the linear regression comparing victory margin to round score, which is displayed as Figure 1, the knockdown component improves the correlation coefficient from .669 to .807, while leaving the β_0 value almost unchanged.

4.2 INTERACTION VARIABLES

One possible way to search for a momentum effect, is to investigate whether winning multiple consecutive rounds could have a higher level of significance than winning each of those rounds individually. Interaction variables are additional model parameters representing the intersection of multiple rounds. We investigated interaction values representing the intersection of two consecutive rounds, making a total of nine in our ten-round model. These variables are positive when a team wins both rounds, negative when a team loses both rounds, and zero otherwise (a win-tie or loss-tie combination should not provide additional momentum for either team). To test for the significance of these variables, we used the residual deviance testing method, where the variables were added one at a time from the model and the resulting residual deviance was compared with the original model. For each test, this difference follows a Chi-squared distribution with 1 df, allowing for a simple test of interaction variable significance. We display the results of these tests in Tables 6 and 7.

Coefficients	**Estimate**	**Std. Error**	**z value**	**Odds Ratio**	**Significance**
Intercept	-15.6232	1.7315	-9.023	NA	***
Round 1	3.8873	0.4972	7.819	48.7790	***
Round 2	2.8289	0.4401	6.428	16.9268	***
Round 3	2.9063	0.4612	6.302	18.2890	***
Round 4	3.8804	0.5172	7.503	48.4436	***
Round 5	3.0084	0.4439	6.778	20.2550	***
Round 6	2.7270	0.4535	6.013	15.2870	***
Round 7	3.0075	0.4466	6.734	20.2367	***
Round 8	3.5747	0.5241	6.820	35.6839	***
Round 9	2.4768	0.4058	6.103	11.9031	***
Round 10	3.3303	0.4898	6.800	27.9467	***

Table 5: Knockdown Round Logistic Regression

Interaction	**TEST**	**1**	**2**	**3**	**4**
Round Deviance	302.35	302.22	300.04	301.97	301.69
Round Difference	.00	.13	2.31	.38	.66
Significance	—	None	None	None	None

Table 6: Interaction Variable Significance, Rounds 1-5

Interaction	**5**	**6**	**7**	**8**	**9**
Round Deviance	299.14	302.34	297.24	301.22	302.12
Round Difference	3.21	.01	5.11	1.13	.23
Significance	$< .10$	None	$< .025$	None	None

Table 7: Interaction Variable Significance, Rounds 5-10

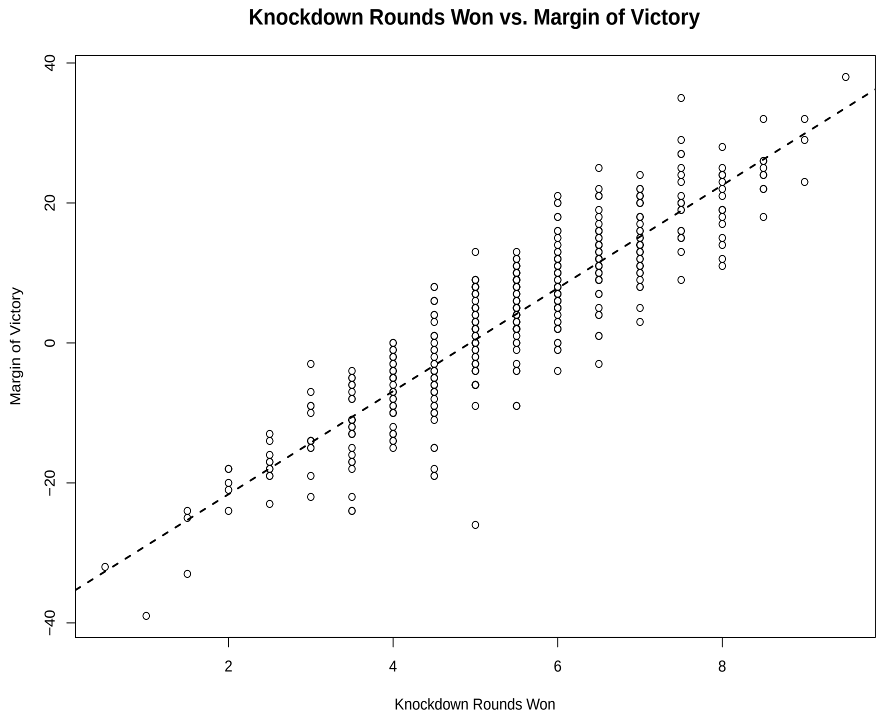

Figure 1: Knockdown Round Linear Regression

This test reveals that interaction variables do not generally add any momentum effect for a team, but the variable between rounds 7 and 8 was significant at the $p < .025$ level using the Chi-squared test. While the significance level was fairly strong, we were initially concerned that it was an artifact of testing many different variables at the same time. However, when we ran the same test using the sample of close games, we saw the same level of significance and a Chi-squared statistic of 4.71. In contrast, the interaction between rounds 5 and 6 was significant at the $p < .1$ level in the sample of all games, but was not significant in the close game sample. It seems like the round 7 - round 8 interaction significance is not a fluke. One possible suggestion for this significance is as follows. At halftime, both teams (and possibly more emphatically the team that loses Round 5) make adjustments. In Round 6, the players play with those initial adjustments, but how each team responds to the second-half adjustments of the other team really happens in Rounds 7 and 8, after the coaches and players have a chance to "sit down in their corner after a round" and adjust their strategies to counter the second-half adjustments.

4.3 MODEL BUILDING AND VALIDATION

The residual deviance test is not limited in use to interaction variables, but can be used to test for the importance of any factor in building a model of a college basketball game. After examining the effects of rounds in great depth, we wondered what factors should be included to build an accurate model of game outcome using only coarse indicators (i.e., without use of any scoring categories). To accomplish this goal, we ran a number of residual deviance tests on various indicators from the games in our sample to see what indicators were more or less significant in predicting the victor of any given game.

In addition to testing each interaction variable, we looked at some of the other statistics we had previously gathered on each game; conference, year, and scoring first. We also looked at two other sets of statistics: the number of runs in each game and Dean Oliver's Four Factors. These results appear in Tables 8 and 9. A *run* is defined as any number of consecutive rounds where the same team wins - e.g., a game where one team wins every round would only have one run. Ties were counted as streak breakers, so a game with ten tie rounds would have ten runs instead of only one. Once the number of runs had been calculated, we divided the games hierarchically based on the number of runs, and tested if the model performed any better for high-run games or low-run games. Oliver's Four Factors - effective field goal percentage, offensive rebound percentage, turnover percentage, and free throw rate - are the four metrics that he has found predictive of game outcomes in his own analysis of the college game [1].

The average number of runs was 6.3. When runs are divided in two segments, these segments were games with six or fewer runs and games with seven or more runs. When the game is divided in three segments, the segments are five or fewer runs, six or seven runs, and eight or more runs. When there are four segments, runs were partitioned by four or fewer runs, five and six runs, seven runs, and eight or more runs, respectively. Of the first set of model variables, the runs, only dividing the game into three levels of runs seems to be a significant addition to the round model. The situation with two or four levels of runs was also investigated in Table 8. In addition we report in the table that the game year and conference alignment literally show no effect, and scoring first and the other two run alignments do not add much useful information either. However, when the set of games was divided into three classifications based on the number of runs in each game, the model was significantly more accurate at a $p < .05$ level. Like with the interaction variable from the previous test, this result held true in the sample of close games (Chi-square statistic 4.71).

Looking at Oliver's Four Factors, some interesting results arise in the residual deviance tests. Two of the factors, effective field goal percentage and free throw rate, rate as significant at the $p < .01$ level with the Chi-squared test, with effective field goal percentage significant at the $p < .001$ level. However, the other two statistics are not significant at any level over the entire sample of games. This is contradictory to what might be expected from the four factors which Oliver has shown paint a fairly clear picture of the outcome of any college game. When the round framework is used as a basis for building a model, not all of the four factors are useful additions to increase predictive validity. It should be noted that every round produces a significance at the $p < .001$ level when it is removed from the model under the residual deviance test.

Another interesting question is whether the home team winning a certain number of rounds is different from the away team winning a certain number of rounds. To test this, we include a binary variable that distinguishes between whether the home or away team scores a majority of the rounds. In particular, this variable is 1 if the home team scores more than 5 rounds and is zero otherwise. When this was included in the original model with just the ten individual rounds, the residual deviance decreased by 2.52, which is not significant at

Test Factor	Scoring First	Year	Conference	Runs - 2	Runs - 3	Runs - 4
Round Deviance	301.54	302.35	302.35	301.78	297.69	301.75
Round Difference	.81	.00	.00	.57	4.66	.60
Significance	None	None	None	None	$< .05$	None

Table 8: Residual Deviance Testing

Test Factor	Eff. FG%	Turnover %	Off. Reb. %	Free Throw Rate	Home Effect
Round Deviance	268.47	300.98	302.01	293.34	299.83
Round Difference	33.88	1.37	.34	9.01	2.52
Significance	$< .001$	None	None	$< .01$	None

Table 9: Additional Residual Deviance Testing

the 95% level.

Thus it appears as though the most accurate model utilizes a number of disjoint factors. It is likely to include all ten individual rounds, one interaction variable, the relative number of runs compared to an average game, and the EFG% and free throw rate comparison between the two teams. We will ensure all variables are significant during our model selection process. This type of model should do an excellent job predicting game winners, and it does not utilize any scoring categories beyond the round winners. We will test our model later via cross-validation. For an even more accurate model, the rounds could be utilized in their knockdown framework instead of the standard framework, though we will focus our model selection efforts within the standard framework only.

Our first attempt at a model is given by

$$F(z) = \frac{1}{1+e^{-z}}; z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{14} x_{14},$$

where variables x_1 through x_{10} are binary random variables representing the home team winning rounds 1 through 10 respectively. The other four variables x_{11} to x_{14} are defined (in order) as follows: a binary variable with a 1 when the home team leads in field-goal percentage, another binary variable with a 1 when the home team leads in free throw percentage, our ternary random variable based on runs, the interaction variable previously described relating rounds 7 and 8, and the binary variable distinguishing between home and away rounds won. However, when observing this regression, we see that if the interaction variable (x_{13}) is included, the residual deviance when excluding x_7 or x_8 is not significant. Consequently, following the paradigm of backwards elimination, we will then exclude binary random variables x_7 and x_8. This leaves the following for our final model as shown in Table 10:

$$F(z) = \frac{1}{1+e^{-z}}; z = \beta_0 + \beta_1 x_1 + \cdots + \beta_6 x_6 + \beta_9 x_9 + \cdots + \beta_{14} x_{14}.$$

As a way to ensure the assumptions of the model were reasonable and to test the predictive nature of our model, we performed a 4-way cross-validation analysis on our data set and this model. The games were randomized and then chosen for the four cross-validation

Coefficients	**Estimate**	**Std. Error**	***z* value**	**Odds Ratio**	**Significance**
Intercept	-8.2939	0.9671	-8.519	NA	***
Round 1	2.9762	0.4264	6.980	19.6131	***
Round 2	1.2988	0.3753	3.461	3.6649	***
Round 3	1.7211	0.3809	4.519	5.5907	***
Round 4	2.6180	0.4239	6.176	13.7083	***
Round 5	1.8254	0.3828	4.769	6.2053	***
Round 6	1.5642	0.3834	4.080	4.7789	***
Round 9	1.8775	0.3715	5.054	6.5371	***
Round 10	1.9814	0.3800	5.214	7.2529	***
Eff. FG	1.6491	0.3287	5.017	5.2023	***
Free Throws	0.7584	0.3281	2.312	2.1349	*
Runs 3 Parts	-1.0189	0.4716	-2.160	NA	*
Interaction 7-8	2.3689	0.3539	6.693	10.6856	***

Table 10: The Final Model

groups. Out of 451 games, the cross-validated model correctly predicted the outcome of the game 391 times, a success rate of 86.7 percent. For comparison, note that in Section 3 we stated that teams winning a majority of the rounds win around 89 percent of games; however, in the cross-validation model we included games with a tie round score which were excluded in the analysis from Section 3. Out of the 451 games studied, 68 had a tie in the round score, so including these games (at a 50% success rate) brings the 89% success rate down to 83%. Thus, including the additional factors boosts the performance of our model.

4.4 THE DAVIDSON EFFECT

Another interesting question to ask is whether a team that employs the rounds framework as a coaching strategy affects how many and what rounds a team must win to win the game. To test for this, in Table 11, we included a binary random effect variable which is 1 if the game involves Davidson and 0 if not. We also included ten additional interaction variables between the Davidson binary variable and each of the ten rounds. Including these interaction variables will allow us to see how the rounds framework may act differently for a team that actively uses it as a coaching strategy.

It seems that the only round where there is a significant difference for Davidson is round 8. This difference is positive indicating that for Davidson, winning round 8 may be about twice as important as winning an arbitrary round for winning the game. According to McKillop, this round was a potential problem for Davidson when playing strong teams. He mentioned that round 8 is usually a time when bench players may be playing and the significant difference in talent depth between Davidson and the other school may be highlighted. This additional importance may also be due to McKillop's substitution strategy or the tendency of starters with foul trouble to be sat during this time period. As with the random effects of year and conference, Davidson's random effect also had an extremely small variance (less than 10^{-6}) and so we can confidently exclude the effect from our overall model.

Coefficients	Estimate	Std. Error	z value	Odds Ratio	Significance
Intercept	-9.3026	1.1082	-8.394	NA	***
Round 1	3.4306	0.4946	6.936	30.8952	***
Round 2	1.3636	0.4083	3.340	3.9102	***
Round 3	1.9981	0.4266	4.684	7.3750	***
Round 4	2.8724	0.4790	5.997	17.6794	***
Round 5	2.1110	0.4287	4.924	8.2565	***
Round 6	1.7113	0.4292	3.987	5.53615	***
Round 9	2.1691	0.4187	5.180	8.7504	***
Round 10	2.1525	0.4231	5.088	8.6063	***
Eff. FG	1.8112	0.3493	5.185	6.11778	***
Free Throws	0.8137	0.3508	2.319	2.2562	*
Runs 3 Parts	-1.1031	0.4975	-2.217	NA	*
Interaction 7-8	2.5401	0.3948	6.434	12.6809	***
Dav. Int. R1	-1.2962	1.0179	-1.273	0.2800	
Dav. Int. R2	1.0876	1.0949	0.993	2.9671	
Dav. Int. R3	-0.4701	1.2091	-0.389	0.6249	
Dav. Int. R4	2.7139	1.5069	1.801	15.0880	
Dav. Int. R5	-2.7664	1.3957	-1.982	0.0629	*
Dav. Int. R6	-0.2077	1.2813	-0.162	0.8125	
Dav. Int. R7	-0.9742	1.2193	-0.799	0.3775	
Dav. Int. R8	3.1799	1.1163	2.849	24.0443	**
Dav. Int. R9	-1.1390	1.1550	-0.986	0.3201	
Dav. Int. R10	0.1360	1.1332	0.120	1.1457	

Table 11: The Davidson Effect

5 DISCUSSION

Looking at our data and the results of numerous regressions on round outcomes, we can make several statements about rounds as a team performance analysis technique. As we expected when we began the project, and as McKillop has expected for years, there is a correlation between winning more rounds and winning the game. This makes logical sense, because teams win rounds the same way they win games: by scoring more points than their opponents. As John Madden once said (and has been widely quoted) about football, "Usually the team that scores the most points wins the game," [16] and the same logic clearly applies to both normal round scoring and knockdown round scoring. What was less evident at the outset, however, was the predictive strength of winning even one more round than the opposing team. In the larger context of a game, an advantage over 10% of gameplay does not seem like a large sample on which to predict a game's outcome with any accuracy. In our data, however, a 5.5-4.5 advantage in round scoring still equates to a victory 78.9% of the time, and winning at least six rounds makes a team a 14 to 1 favorite to have won.

Rounds also showed their strength in the logistic regression when every round was shown to be significant at a p-value less than 10^{-5}. The strength of every round was higher in the combined sample than each individual conference, indicating the significance values are likely to be accurate across the entire college basketball landscape and are not just a feature of our data. One trend requiring further exploration is the higher p-value of the first round than all other rounds in both conferences. Until we settle on a method for comparing the significance of logistic variable coefficients, we cannot make a definitive statement on this trend as either a statistically significant difference or an inconsistency in our data set. Besides the first round, however, it is evident that each section is similarly correlated with the final result, which confirms previous studies on momentum in basketball.

The strength of these results lends credence to McKillop's focus on each round as a separate entity and shows that any round could be the deciding factor in a game. Of the items on his checklist for each game, winning seven rounds is certainly the only factor that nearly guarantees victory (100 out of 101 seven-round winners also won the game in our sample). This makes it an admirable goal for each game, even if it represents a far higher standard than the other items on the list. Winning rounds five and ten, while positively correlated with winning the game, are not better indicators of team success than winning any two arbitrary rounds. However, they are stronger predictors than scoring first in the game, which was not shown to be a significant when also regressed with rounds against winning.

The other pronounced trend that emerged in our logistic regression tests was the similarity of the results for the ACC and SoCon. Although the ordering of Z-scores by round was slightly different in each conference, the overall trend of similarity was present in both conferences. Both conferences also had similar field goal percentage results in terms of both raw percentage as well as significance. The one difference was the significance of scoring first, which was significant at the .1 level in the ACC but not at all in the SoCon. Given the relatively small sample of ACC data, and the low level of significance for scoring first in the overall results, this result could be a focal point for further research. Additionally, the set of 200 close games had similar traits to the overall data set in all different regression models.

This result is especially important in the context of comparing round significance scores. The previously noted concern of teams far ahead after 8 rounds putting inferior players into the game, thus skewing the results of the last few rounds and possibly the overall sample, proved to be unfounded.

6 CONCLUSION

Bob McKillop's "round" model of the college game gives some interesting insights into scoring trends and shows the value of each four-minute section of a game. While the first round had the highest Z-score in our logistic regression, all ten rounds were significant predictors of game outcome at a .00001 level of significance in the complete sample. Furthermore, our linear regression showed that rounds are an effective predictor of margin of victory, and the knockdown scoring added a layer of accuracy to the model. All of these trends generally held true in both conferences as well as in the smaller sample of close games (games decided by less than 8 points). Further exploration of rounds and logistic regression significance is needed to completely confirm the hypothesis that all rounds are equally important despite round 1 having the highest significance coefficient.

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