Statistical Predictors of March Madness: An Examination of the NCAA Men's Basketball Championship

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1. Introduction

1.1 History of the Tournament

The NCAA Men's Division I Basketball Championship, known as "March Madness," is one of the most popular sporting events in the United States. The championship is a single-elimination tournament that takes place at various locations throughout the United States each spring. The current format features 68 teams at the beginning of the tournament, but it has not always been such a large field. Since its origins as an eight-team tournament in 1939, the NCAA has changed and expanded the basketball championship many times. The largest changes include 1975, when the field grew to 32 teams and at-large teams[1] began to be placed into the tournament; 1985, when the field was expanded to 64 teams; and most recently in 2011, when the tournament was changed to feature 68 teams (with four play-in games occurring before the first round).

1.2 Qualifying and Selection

In the current format, 68 teams participate in the single-elimination championship tournament. Of these 68 teams that qualify for the championship tournament, 31 earn automatic bids by winning their respective conferences that year. The remaining 37 teams are given at-large bids by the Selection Committee, a special committee appointed by the NCAA. This committee is also responsible for dividing the field into four regions with 16 teams each and assigning seeding within each region. The Committee is responsible for making each region as close as possible in terms of overall quality of teams. This means, for instance, that the 7-

[1] "At-large teams" are teams that did not automatically qualify for the tournament by winning their conference tournament, but were invited by the selection committee based on their merit.

seeded team in one region should be very close in quality to the 7-seeded team from any of the other three regions. The names of the regions vary each year, and are typically based on the general geographic location of the host site of each region's semifinal and final matchups. For example, in 2012, the four regions were the South (Atlanta), East (Boston), West (Phoenix, AZ), and Midwest (St. Louis).

1.3 Current Format and Rules

The current 68-team format closely resembles the 64-team tournament that was introduced in 1985. The notable exception is the so-called "First Four" round of play-in games[2]. In this round, four games are played amongst the lowest four at-large qualifying teams and the lowest four automatic bid (i.e. conference champion) teams, as determined by the Selection Committee. These teams are not necessarily playing for a 16 seed; in 2012 for instance, the "First Four" consisted of matchups for a 12 seed, a 14 seed, and two 16 seeds. Nor is there necessarily one play-in game per region; in 2012 the Midwest region featured two play-in games and the East featured none. After this "First Four" round is complete, there are 64 teams remaining and the rest of the field begins play.

The tournament is typically played over the course of three weekends in March and April. The tournament is a single-elimination tournament, thus all games played eliminate the losing team. Over the first two weekends, the four regions of sixteen teams are entirely separated from each other, and four regional champions emerge after four rounds of games have been completed. These four teams then

[2] This play-in round is often referred to as the first round and the round of 64 is then referred to as the second round; however, to avoid confusion between data that are from years before 2011, the round of 64 will be referred to as the "first round" in this paper.

advance to the third weekend, the “Final Four” weekend, where they play in the fifth and sixth rounds to determine a single national champion. To better explain the layout of the tournament, the 2012 tournament field is presented in Figure 1, below.

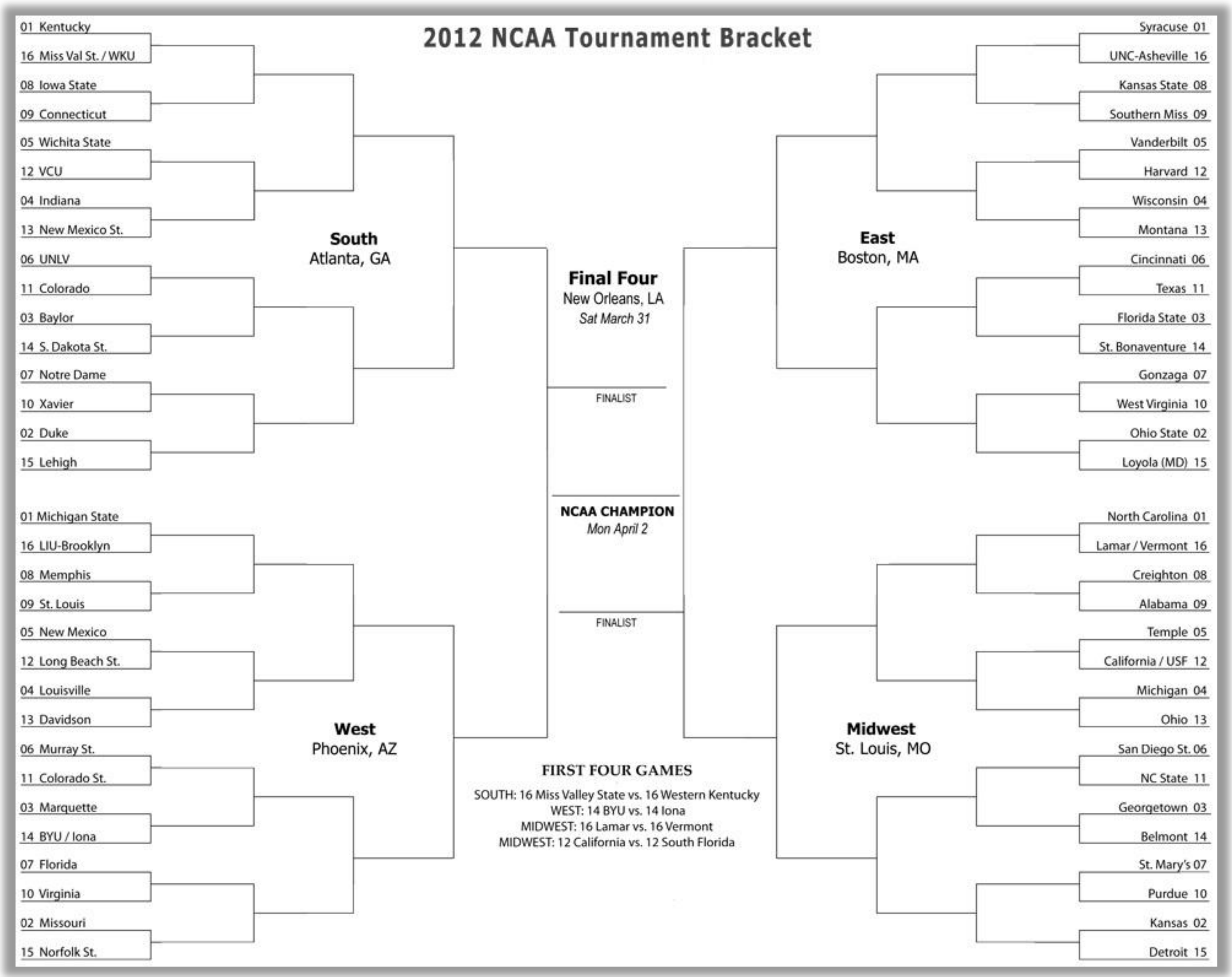

Figure 1 – The 2012 tournament bracket before play began. The bracket shows the potential path of each team, culminating in the Final Four round and Championship Game in the center.

The 64-team format always follows the example shown in Figure 1. Note how the first round consists of the 1st seed playing against the 16th seed, the 2nd seed playing the 15th seed, and so on. In the second round, the winner of the 1 vs. 16 matchup plays the winner of the 8 vs. 9 matchup, the 2 vs. 15 winner plays the 7 vs. 10 winner, and so on. Also notice how the winner of the West region plays the winner of the South region, no matter which teams win from these regions.

1.4 Bracketology

For years, it has been popular to attempt to predict the correct outcomes of all the games before the tournament starts by filling out a bracket, despite the odds being 2^{63} : 1 against randomly picking the entire bracket correctly (for a sixty-four team field).[3] In 2011, President Obama referred to filling out a bracket as a national pastime and revealed his own bracket predictions on an ESPN segment. Putting money on one's ability to predict tournament winners is also a popular aspect to March Madness; an estimated $7 billion is wagered annually on the outcomes of tournament games, typically in the form of private friend pools or office pools (Rushin, 2009). The objective of my research will be to design a model that is successfully predictive of outcomes of matchups in the March Madness basketball tournament.

1.5 Literature Review

Due to the popularity of the tournament and the size of the (somewhat illegitimate) market involved in wagering on it, there has been significant research done on March Madness before.

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[3] A typical bracket does not make you choose the outcomes of the "first four" games, you only pick winners from the round of 64 onwards.

One factor that has been studied extensively for its value as a predictor of success is a team's seed in the tournament, as assigned by the Selection Committee on Selection Sunday. It has been found that seeding is a significant predictor for the earlier rounds, but has less value in predicting outcomes of the final three rounds of the tournament (Jacobson and King 2009). Boulier and Stekler (1999) also looked at tournament seeds by using a probit analysis to determine the probability of teams winning a given matchup based solely on seed and found that it was a good predictor, especially in early rounds. Other models examined by Jacobson and King (2009) used average win margins, Vegas lines, season wins and losses, and press rankings to attempt to predict winners. These models have mostly been found to be predictive in the early rounds, but less helpful for later rounds. My goal is to build a model that uses more data for each team and can predict outcomes of the later round games, where well studied factors such as seeding seem to matter less. The ultimate goal is to be able to predict teams that will not only make it to the final rounds, but also succeed when they get there.

2. Methods

2.1 Data Sample

The data that I have used for my research are historical statistics compiled for teams from the NCAA tournament from the years 1986 - 2010. The data collected are made up of 74 variables for each matchup, listed in Appendix I, Figure B. About half of the variables for each matchup refer to the given team[4], and half

[4] The higher seed in the matchup is designated 'team'; the lower seed is designated 'opponent.' If a game is in the final two rounds, it is possible that the seeds are equal, in which case the school name that is first alphabetically is designated as 'team.'

refer to the opponent (denoted as "opp_variable name"), with a few referring to the matchup itself.

In all, I have data on the teams and outcomes from 1575 matchups over the twenty-five year period that I am examining.[5] It is important to note that I have created the dataset so that it represents each matchup of teams rather than each individual team isolated from their opponent. The dependent variable that I have compiled for analysis is margin of victory for the higher seed in any given matchup, with a negative number therefore representing a win by the lower seed. I also have a dummy variable called "win" that takes a value of 1 if the margin of victory is greater than zero. I obtained all the data for matchups and final scores from databasesports.com and sportsreference.com. A spread sheet version of the dataset can be found here.[6]

2.2 Data Analysis Overview

I will run a probit regression and an ordinary least squares (OLS) linear regression. The independent variables will consist of a combination of the variables that describe the teams in each matchup, and the dependent variable will be a dummy for a win in the probit model, and the margin of victory in the OLS linear regression.

3. Results

I have created two models to test with my data. One model uses variables that are only present in the dataset from 1997 onwards, such as offensive efficiency

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[5] A large portion of these data were obtained from Emily Toutkoushian, a graduate of Ohio State University, who compiled a March Madness dataset in 2011 for her own research at OSU into predicting March Madness.
[6] https://docs.google.com/spreadsheet/ccc?key=0Aq4oJhIoBJm1dFp3U3JyVFp4aDNRTlpCcXRNQjFUSnc

and defensive efficiency, as well as variables that are present in the entire dataset, from 1986 onwards. The other model contains only variables that are present throughout the entire time period and thus can be estimated and tested across the entire sample.

3.1 Model One

Model One uses some variables that are only present in the dataset from 1997 onwards, meaning for this model we can only utilize about half of the total range of years. My second will use data from the entire time period, but I felt that some of the variables only present in recent data were important to consider, hence I have created Model One. The variables to be used as input in Model One are as follows:

- seed
- win percent
- wins in last ten
- Sagarin rank
- ppg
- ppg allowed
- offensive efficiency*
- defensive efficiency*
- true shooting percentage*
- assists per game*
- coach final fours*
- percent of wins away
- opp_seed
- opp_win percent
- opp_wins in last ten
- opp_Sagarin ranking
- opp_ppg
- opp_ppg allowed
- opp_offensive efficiency*
- opp_defensive efficiency*
- opp_true shooting percentage*
- opp_assists per game*
- opp_coach final fours*
- opp_percent of wins away

** refers to variables only collected from 1997 onwards*

I have decided upon these variables as they are intuitively important inputs that I consider when I am choosing my own bracket. Summary statistics describing these variables are presented in Appendix I, Figure A.

3.1.1 Probit Analysis

The probit model will use the binary variable "win" as its output variable. The variable "win margin" will be used in the OLS linear regression, to be presented later. The results of the probit analysis are presented in Figure 2, below.

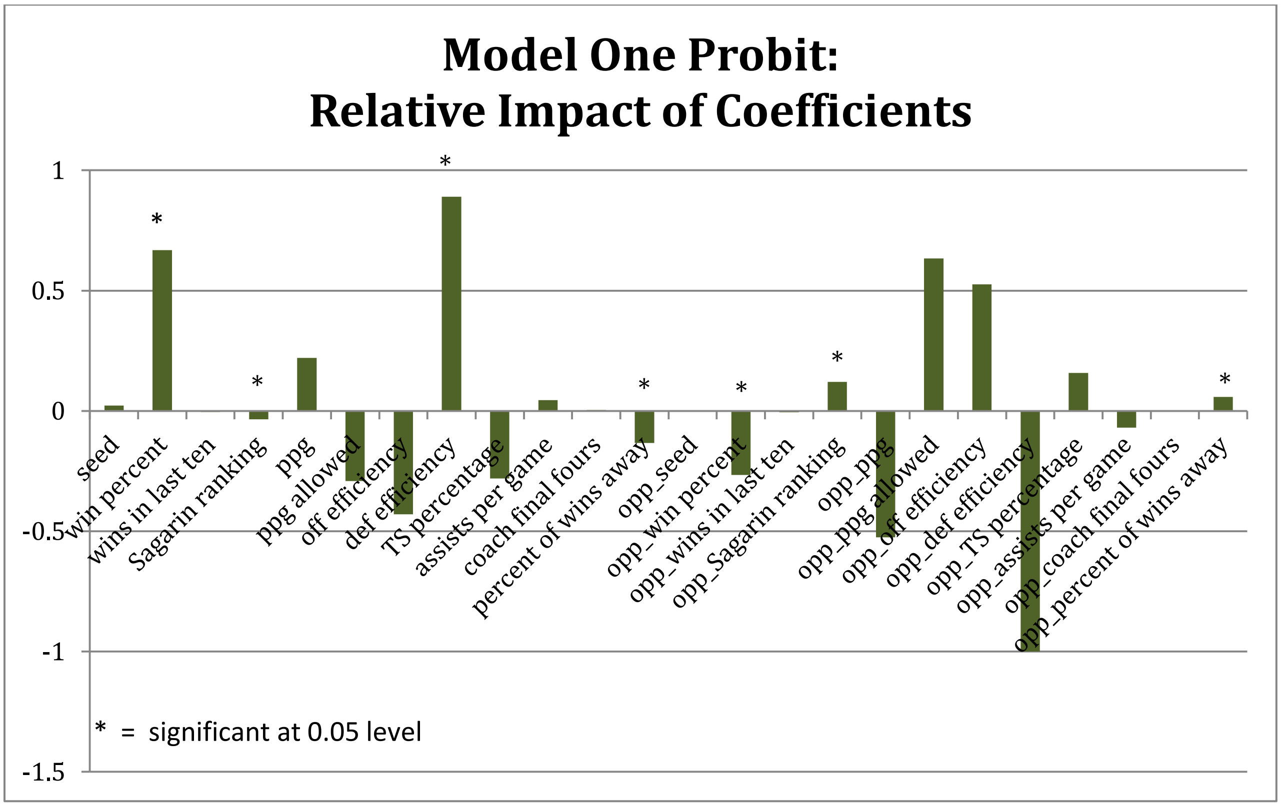
Figure 2 – Results of the Probit Regression for Model One[7]. Output variable is probability of "win" = 1, which is a dummy for a win by the team in a matchup, and loss by opponent.

variable	coefficient	std error	t	P > |t|
seed	0.0564	0.03650	1.54	0.123
win percent	7.5930	1.37463	5.52	0.000
winsinlast10	-0.0055	0.04918	-0.11	0.910
Sagarin rank	-0.0211	0.00480	-4.40	0.000
ppg	0.0250	0.04476	0.56	0.576
ppg allowed	-0.0385	0.05453	-0.71	0.480
efficiency	-0.0349	0.04017	-0.87	0.385
def efficiency	0.0847	0.04291	1.97	0.048
true shooting	-0.0451	0.03558	-1.27	0.205
assist per game	0.0259	0.03712	0.70	0.486
coach final fours	0.0333	0.02823	1.18	0.238
percent of wins away	-3.9675	0.81712	-4.86	0.000
opp_seed	0.0012	0.02562	0.05	0.964
opp_win percent	-3.3694	1.26071	-2.67	0.008
opp_winsi~10	-0.0069	0.04688	-0.15	0.884
opp_Sagain rank	0.0182	0.00307	5.94	0.000
opp_ppg	-0.0625	0.12825	-0.49	0.626
opp_ppg allowed	0.0829	0.14422	0.58	0.565
opp_efficiency	0.0440	0.08975	0.49	0.624
opp_def efficiency	-0.0932	0.10184	-0.92	0.360
opp_true shooting	0.0258	0.03643	0.71	0.478
opp_assists per game	-0.0427	0.04001	-1.07	0.286
opp_coach final fours	0.0604	0.05252	1.15	0.250
opp_percent wins away	1.5966	0.76063	2.10	0.036
_cons	-1.7195	2.68778	-0.64	0.522

[7] *Pseudo R^2 = 0.2528,* represents a measure of goodness of fit for the probit model.

To more easily compare coefficients to each other, I have scaled each coefficient relative to the values of variable it applies to, and presented this data in Figure 3[8]. The results give us an idea about the sign and relative of each coefficient in the model.

Figure 3 – Relative effect of coefficients on model one probit output.



By examining Figure 3, we can start to understand the effect that the different variables of the model have on outcomes of March Madness games. The effect of win percentage seems to have a large, positive, statistically significant effect on the outcome, which makes sense as a team that won more during the regular season is typically a better team, all else held equal. Opponent win percentage also

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[8] To do this I multiplied each cofficient by the mean value throughout the dataset of the variable it corresponds to. I then scaled each coefficient as a fraction of the largest one.

has an effect, not as large as a team's own win percentage, but in the opposite direction, which also makes intuitive sense.

Sagarin rankings also seem to have a statistically significant effect on the outcomes of games. A team's Sagaring rank has a negative effect on the outcome of "win," which makes sense as better ranked teams will have lower value for their Sagarin ranking.[9] We also see that an opponent's Sagarin ranking has a significant positive effect on the team's chances of a win, which also makes logical sense.

Sagarin rankings come from Jeff Sagarin, an American sports statistician well known for his ranking systems in sports such as basketball and football. His rankings have been featured in USA Today's sports section since 1985.

Other variables that seemed to have a large magnitude of effect on the probability of a win are points per game (ppg) and points per game allowed, as well as opponent's ppg and opponent's ppg allowed. The effects of these variables were not statistically significant, but the effects are in the expected direction for all four: positive for ppg, negative for ppg allowed, negative for opp_ppg, and positive for opp_ppg allowed.

Some unexpected effects that appear large, albeit not statistically significant, can be seen in the efficiency variables. Each of these is affecting the outcome in the opposite manner that would be expected. My thought here is that perhaps there is endogeneity between the ppg variables and the efficiency variables, causing the coefficients to be thrown off.

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[9] Sagarin ranking values work as follows: the "best team" is given the ranking of 1 and values go up form there. Thus a larger value for Sagarin ranking implies a worse team by Sagarin's method.

3.1.2 OLS Regression

My next step is to run an OLS linear regression using the same input variables but with the margin of victory of the higher seeded team as the output. As stated above, a statistical description of all variables used in this model can be found in Appendix I, Figure A.

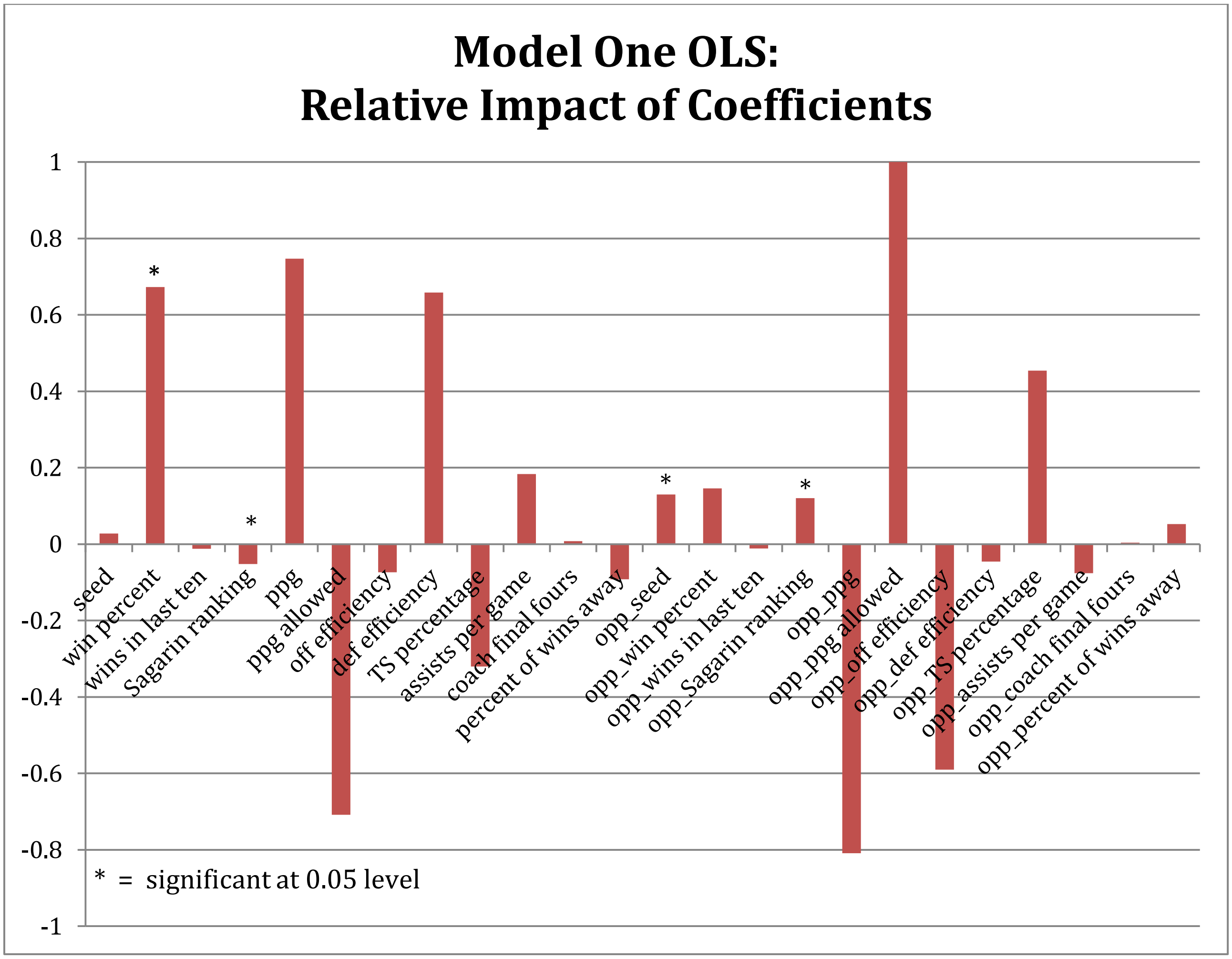
Figure 4 – OLS Regression Results. Output variable is the margin of victory for the higher seed.

variable	coefficient	std error	t	P > |t|
seed	0.2813	0.26930	1.04	0.296
win percent	30.1224	9.45998	3.18	0.002
winsinlast10	-0.0544	0.34613	-0.16	0.875
Sagarin rank	-0.1236	0.04078	-3.03	0.003
ppg	0.3350	0.30021	1.12	0.265
ppg allowed	-0.3686	0.37129	-0.99	0.321
efficiency	-0.0235	0.27601	-0.09	0.932
def efficiency	0.2468	0.29482	0.84	0.403
true shooting	-0.2030	0.24799	-0.82	0.413
assist per game	0.4161	0.25966	1.60	0.109
coach final fours	0.2509	0.18546	1.35	0.176
percent of wins away	-10.8274	5.53160	-1.96	0.051
opp_seed	0.4694	0.17110	2.74	0.006
opp_win percent	7.2705	8.35004	0.87	0.384
opp_winsi~10	-0.0541	0.32523	-0.17	0.868
opp_Sagain rank	0.0718	0.01327	5.41	0.000
opp_ppg	-0.3790	0.87352	-0.43	0.664
opp_ppg allowed	0.5159	0.96700	0.53	0.594
opp_efficiency	-0.1947	0.61369	-0.32	0.751
opp_def efficiency	-0.0168	0.67966	-0.02	0.980
opp_true shooting	0.2922	0.24672	1.18	0.237
opp_assists per game	-0.1813	0.27611	-0.66	0.512
opp_coach final fours	0.3786	0.40683	0.93	0.352
opp_percent wins away	5.6355	5.06110	1.11	0.266
_cons	-42.3040	18.98041	-2.23	0.026

Adj. $R^2 = 0.3362$

As above, I created a "Relative Impact" chart in order to better examine the impact of the coefficient for each input variable on the "margin of victory" output variable. This chart is shown in Figure 5, below.

Figure 5 – Relative effect of coefficients, scaled for variable values



From this figure, we can see that win percent, Sagarin rank, and opponent Sagarin rank all have statistically significant effects in the expected direction, similar to the probit regression. A new variable that has a statistically significant effect in the OLS model is the opponent seed variable, with the positive effect meaning the greater value an opponent's seed (i.e. worse seed), the greater the expected margin of victory in a matchup, all else held equal. This is the effect that one would intuitively expect from this input variable.

In another similarity to the probit model, the four "point per game" input variables[10] all have effects of a large magnitude in the expected directions, but are not statistically significant. The efficiency variables are still having effects that are counterintuitive, although of smaller magnitude in this model when compared to the probit model.

3.2 Model Two

Model Two contains only variables that are present across all 25 years of the dataset, allowing us to use the entire dataset in our regressions. I once again chose input variables that I believe intuitively to be important to success of teams in March Madness. The input variables to be used in Model Two are as follows:

- seed
- win percent
- wins in last ten
- percent of wins away
- Sagarin rank
- Ppg
- ppg allowed
- opp_seed
- opp_win percent
- opp_wins in last ten
- opp_percent of wins away
- opp_Sagarin rank
- opp_ppg
- opp_ppg allowed

[10] The four are ppg, ppg allowed, opp_ppg, and opp_ppg allowed.

3.2.1 Probit Model Regression

Once again, a binary output variable is needed for the probit regression, and this variable will once again be the dummy variable "win." The results of this probit analysis are presented below, in Figure 6.

Figure 6 – Results from the Probit Regression for Model Two

Probit Results				
variable	**coefficient**	**std error**	**z**	**P > |z|**
seed	0.0667	0.02832	2.35	0.019
win percentage	7.39	0.949	7.79	0.000
win in last ten	-0.0459	0.03633	-1.26	0.206
percent of wins away	-3.83	0.570	-6.72	0.000
Sagarin rank	-0.0218	0.00372	-5.85	0.000
ppg	-0.0521	0.01445	-3.61	0.000
ppg allowed	0.0619	0.01621	3.82	0.000
opp_seed	-0.0198	0.01826	-1.09	0.277
opp_win percentage	-3.93	0.909	-4.32	0.000
opp_win in last ten	-0.0188	0.03389	-0.56	0.579
opp_percent of wins away	1.81	0.520	3.48	0.001
opp_Sagarin rank	0.0171	0.00223	7.66	0.000
opp_ppg	0.0390	0.01824	2.14	0.033
opp_ppg allowed	-0.0482	0.01943	-2.48	0.013
constant	-1.54	1.045	-1.47	0.141

Pseudo R^2 = 0.221[11]

Figure 7 below presents a visual representation of the relative impacts that each coefficient has on the output of the regression. These effects were again calculated by scaling the estimated coefficient for each variable by the values of the variable.

[11] Once again, Pseudo R^2 is a measure of goodness of fit for the probit model.

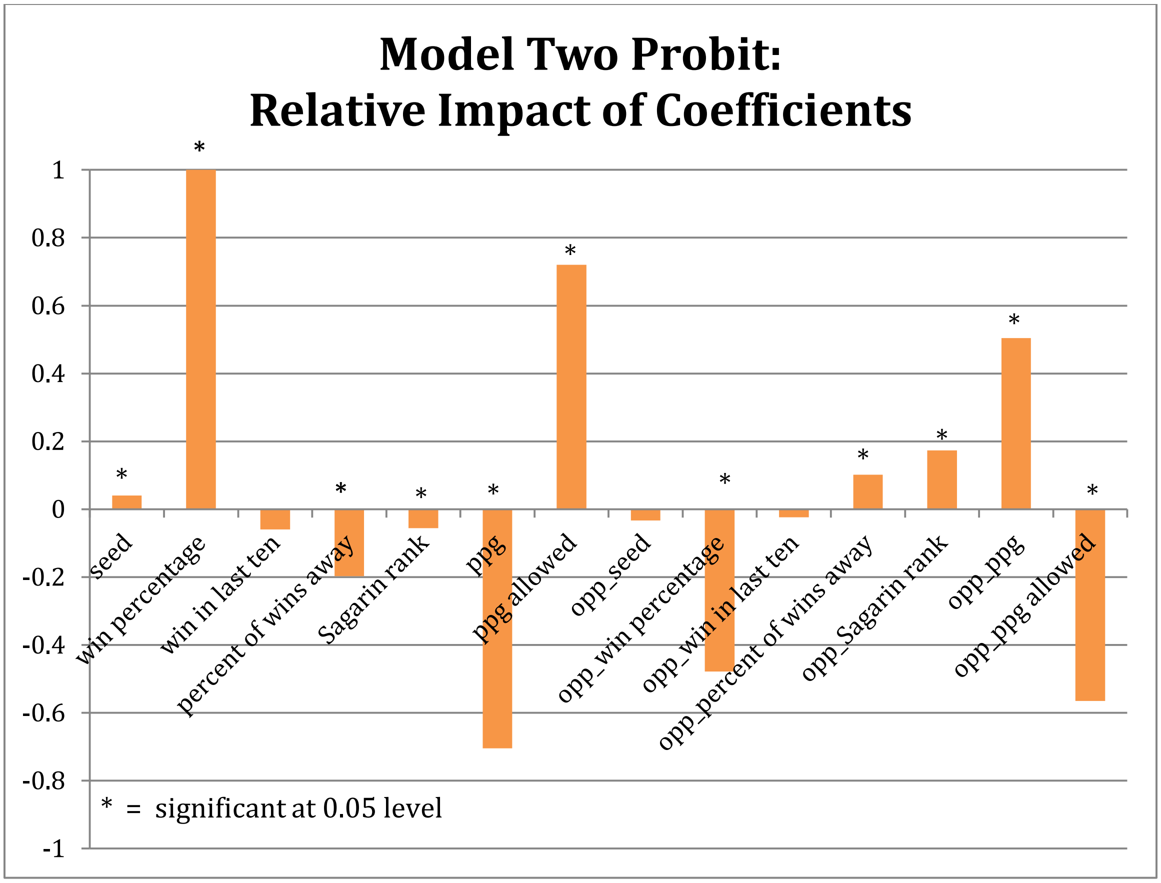


Figure 7 – Relative impacts of coefficients, scaled for input variables values.

From Figure 7, we can examine the average effects that each variable in Model Two had on the probit output. We can see that win percentage and opponent win percentage have large, statistically significant effects in the direction that is expected: positive for a given team's win percentage and negative for an opponents win percentage. Sagarin rank and opponents Sagarin rank also have statistically significant effects with the expected sign. The number of statistically significant coefficients has increased from Model One, and this could possibly be sue to the larger sample size employed by Model Two.

One strange observation is that the points per games variables seem to have significant effects in the directions opposite that which would be expected. That is to say, having outscored your opponents throughout the regular season seems to hurt a team's chances of winning, while playing an opponent who has outscored their opponents throughout the season seems to help a team's chances of winning. These results do not make sense intuitively and my first thought is some sort of endogeneity with other variables in the model. The percent of wins away variable seems to affect the output in the following manner: the higher percentage of wins that come away from a team's home court, the lower their chances of winning a tournament matchup, which seems counterintuitive to the mainstream thought.

3.2.2 OLS Linear Regression

The output variable in this regression will be the variable of margin of victory. The results of the OLS regression for Model Two are presented below, in Figure 8.

Figure 8 – Results from OLS regression for Model Two

OLS Results				
variable	**coefficient**	**std error**	**t**	**P > |t|**
seed	0.156348	0.215345	0.73	0.468
win percentage	30.44454	6.941815	4.39	0.000
win in last ten	-0.24395	0.267238	-0.91	0.361
percent of wins away	-14.0896	4.079614	-3.45	0.001
Sagarin rank	-0.12991	0.031335	-4.15	0.000
ppg	0.196113	0.109627	1.79	0.074
ppg allowed	-0.14389	0.121059	-1.19	0.235
opp_seed	0.277245	0.126024	2.20	0.028
opp_win percentage	2.061132	6.134739	0.34	0.737
opp_win in last ten	-0.22487	0.242445	-0.93	0.354
opp_percent of wins away	4.641649	3.578983	1.30	0.195
opp_Sagarin rank	0.086361	0.010208	8.46	0.000
opp_ppg	-0.28903	0.131985	-2.19	0.029
opp_ppg allowed	0.315573	0.139416	2.26	0.024
consant	-23.5521	7.596111	3.10	0.002

Adj $R^2 = 0.3186$

As with previous regressions, I found it easiest to interpret the results by creating a chart showing the relative impact that each coefficient has on the margin of victory, scaled for values of the variables. This information is contained in Figure 9 below.

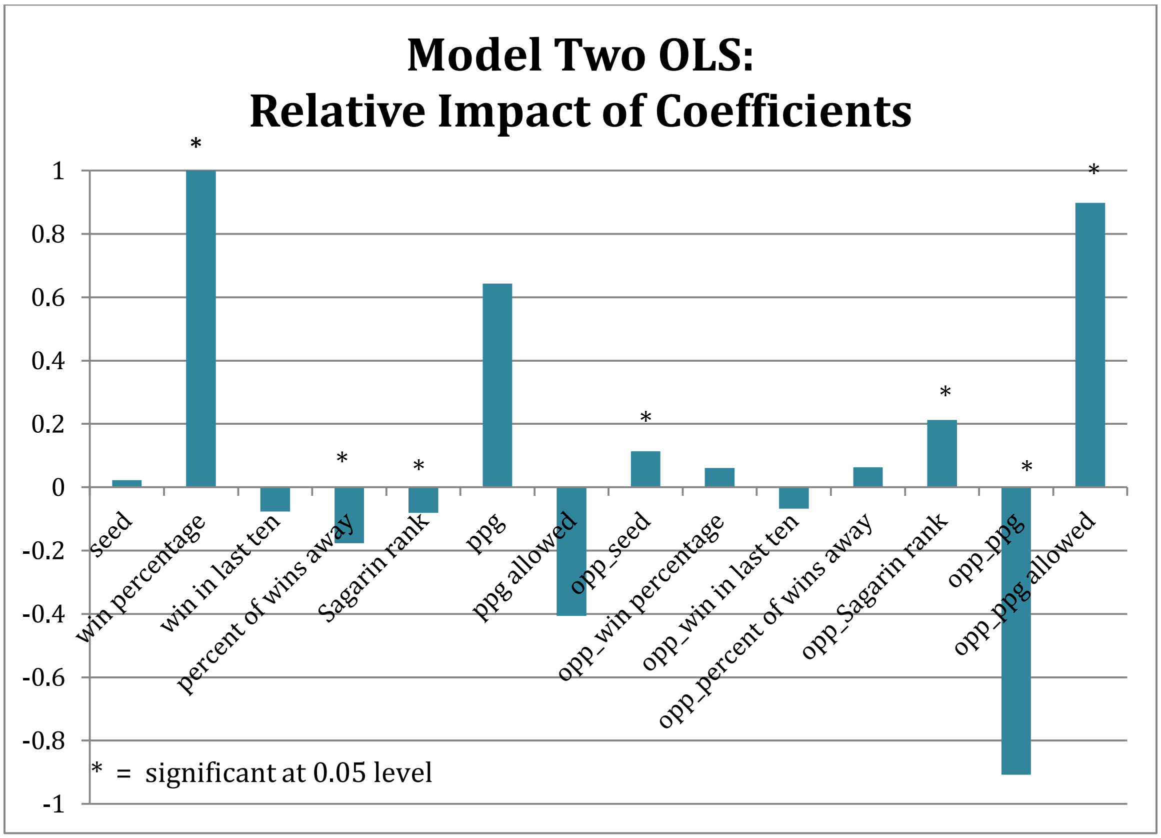


Figure 9 – Relative impacts of coefficients for each variable, scaled for values of the variable

Examining Figure 9, we can observe the effect of the Model Two variables in the OLS regression on margin of victory. We can immediately see that win percentage of a team has a large, statistically significant effect in the expected direction; however, an opponent's winning percentage does not seem to have a great effect as in previous regressions.

The Sagarin ranking of a team still has a statistically significant effect of the expected sign, and the team scoring variables (ppg, ppg allowed, opponent ppg and opponent's ppg allowed) each have effects in the expected directions, but they are not statistically significant. We also see the positive effect of an opponent's seed, which is expected as opponents with large seed values (e.g. 16 seed) represent teams and would be expected to fare worse in a given matchup.

3.3 Predictive Abilities of Models for 2012 Tournament

To test the predictive abilities of the models constructed, I used them to attempt to predict results from this year's March Madness tournament before play began, and then examined their performance after the tournament was played. The results are on the following pages. I used ESPN's scoring method of brackets to evaluate the success of my models[12]. One model, the OLS Regression on Model One, performed poorly and finished in the 37th percentile nationally based on ESPN's bracket database. The other three models all performed well, finishing at least in the 84th percentile, while the best, the Model Two OLS Regression finished with a 68.3% accuracy of picks and scored in the 91st percentile of brackets. One thing that all three successful brackets had in common was that they picked the number-one-overall seed Kentucky to win the tournament, which it did. In bracket scoring, picking the correct champion is very important, and these three models may have performed artificially well because they were able to do this.[13]

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[12] ESPN gives 10 points for a correct first round pick, 20 points, for a correct second round pick, 40 points for a correct third round pick, and so on, up until 320 points for a correct national champion.
[13] Likewise, my unsuccessful model may have done poorly because it picked St. Louis, an 8 seed from the West region, to win the championship. This seems poor to me, but may have been based on St. Louis' scoring defense which held opponents to a very low amount of points over the season.

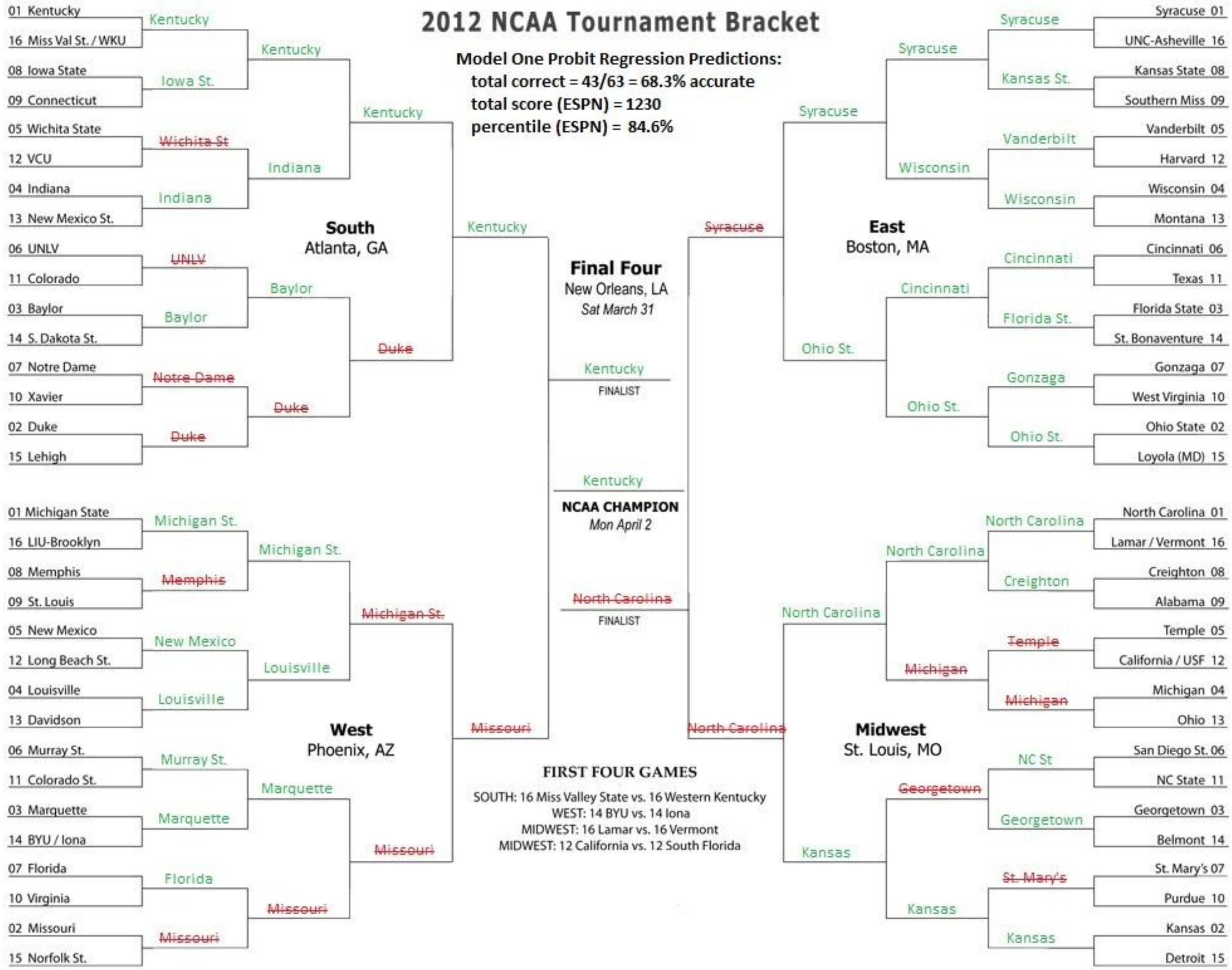


Figure 10 – Model One Probit Regression Predictions

68.3% of winners picked correctly

84.6th percentile on ESPN.com

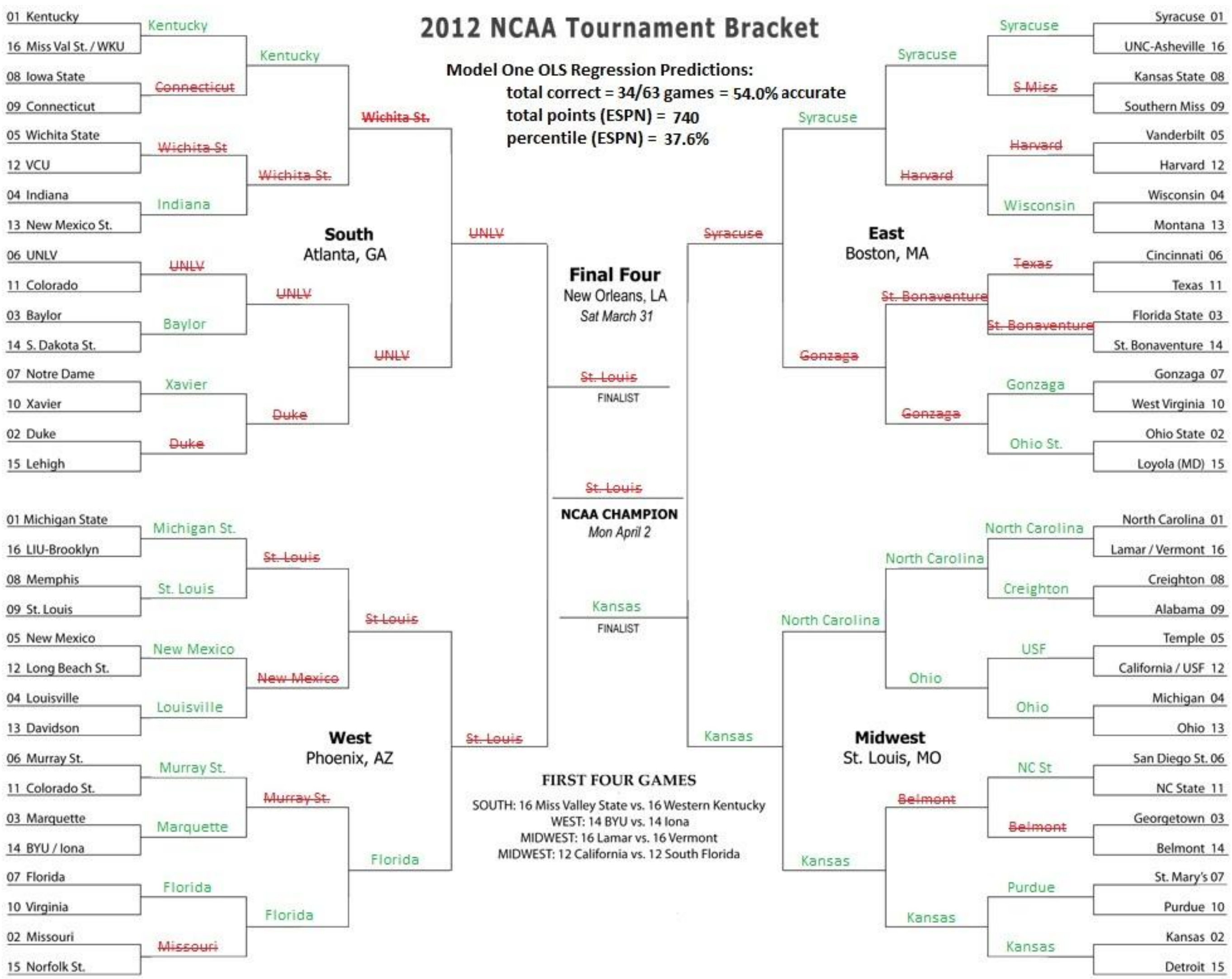


Figure 11 – Model One OLS Regression Predictions

54.0% winners picked correctly

37.6th percentile on ESPN.com

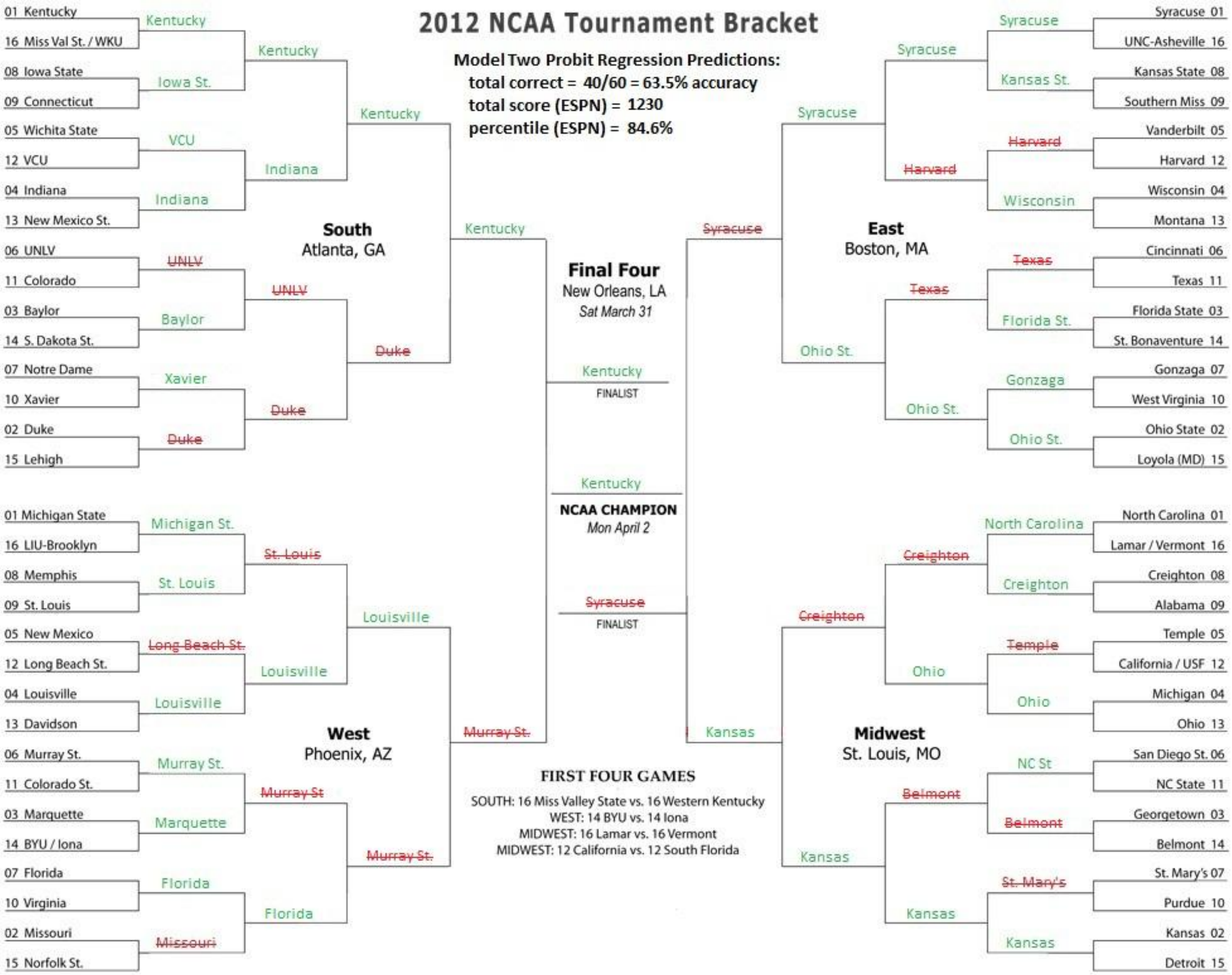


Figure 12 – Model Two Probit Regression Predictions

63.5% winners picked correctly

84.6th percentile ESPN.com

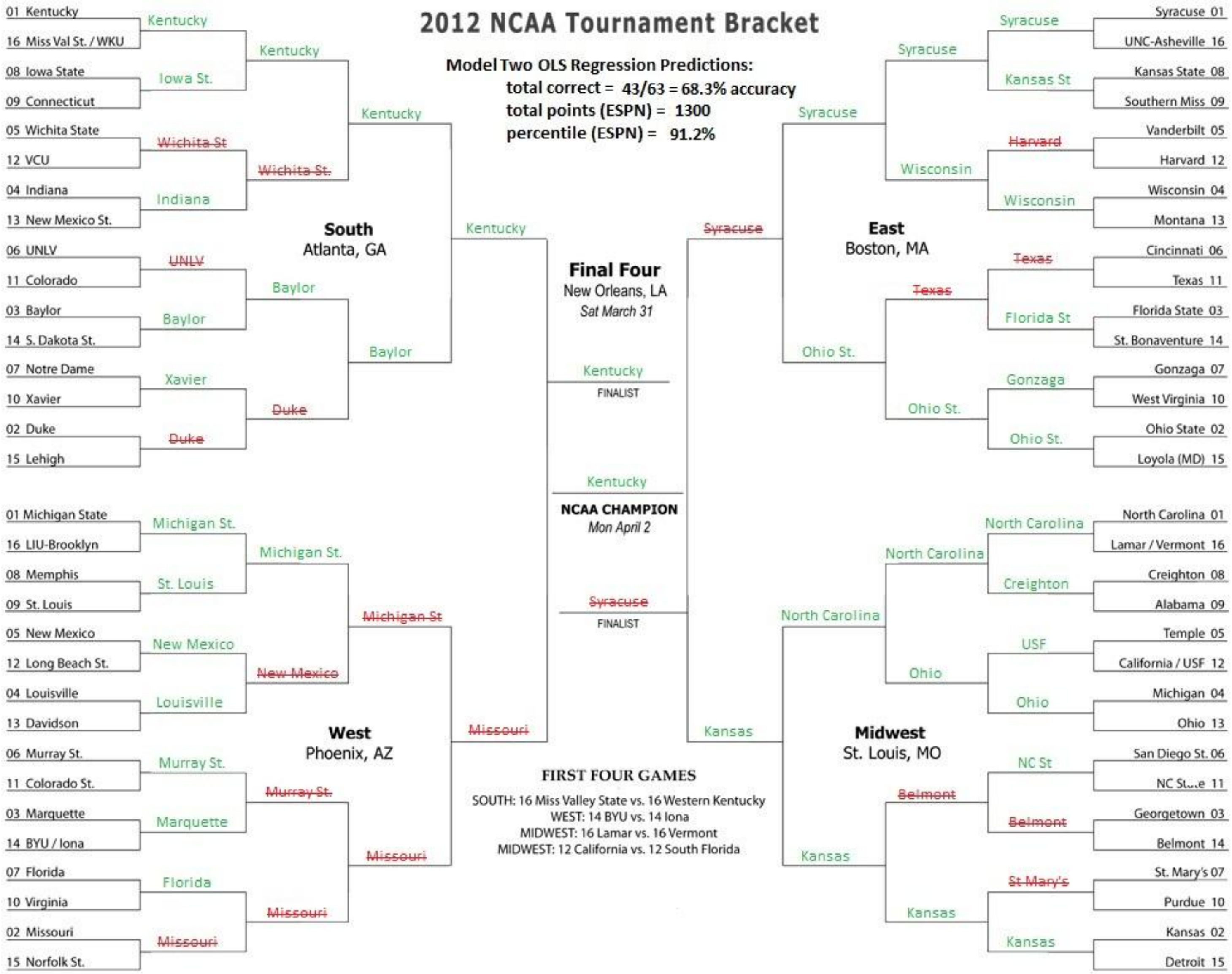


Figure 13 – Model Two OLS Regression Predictions

68.3% winners picked correctly

91.2nd percentile ESPN.com

3.4 Historical Accuracy of Models

To briefly examine the historical accuracy of my models, I decided to examine their predictions versus the actual historical outcomes for margin of victory in a scatter plot. The Model One scatter plot is presented in Figure 14, below, and the Model Two scatter plot is presented in Figure 15, also below.

Figure 14 – Scatter plot for Model One. Point in the upper-right and lower-left quadrants represent correctly predicted matchups, and other points represent mis-predictions. Only represents matchups from 1997 onwards.

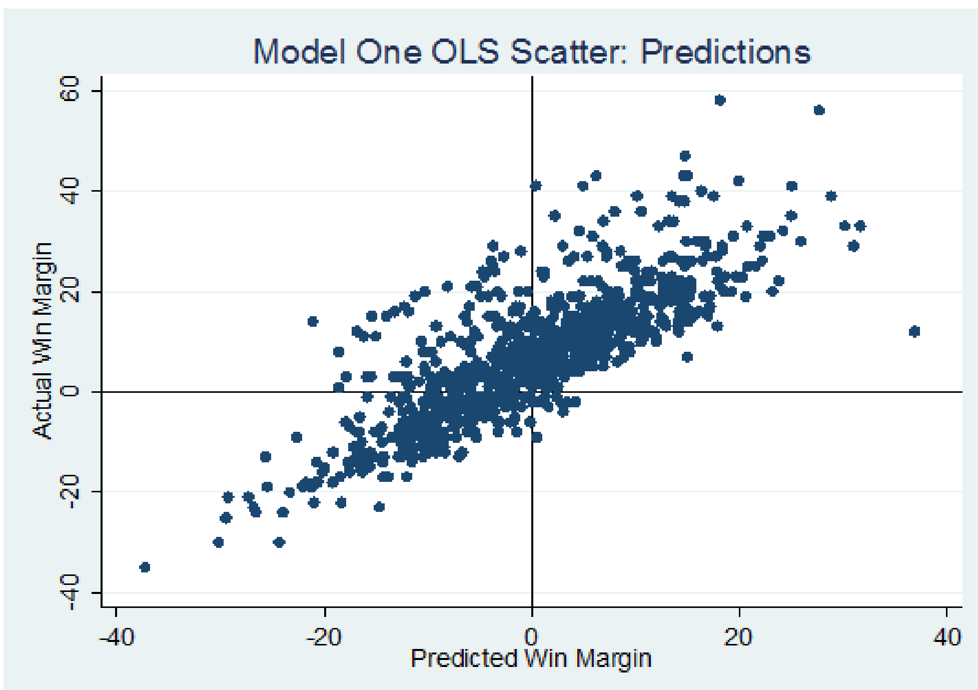
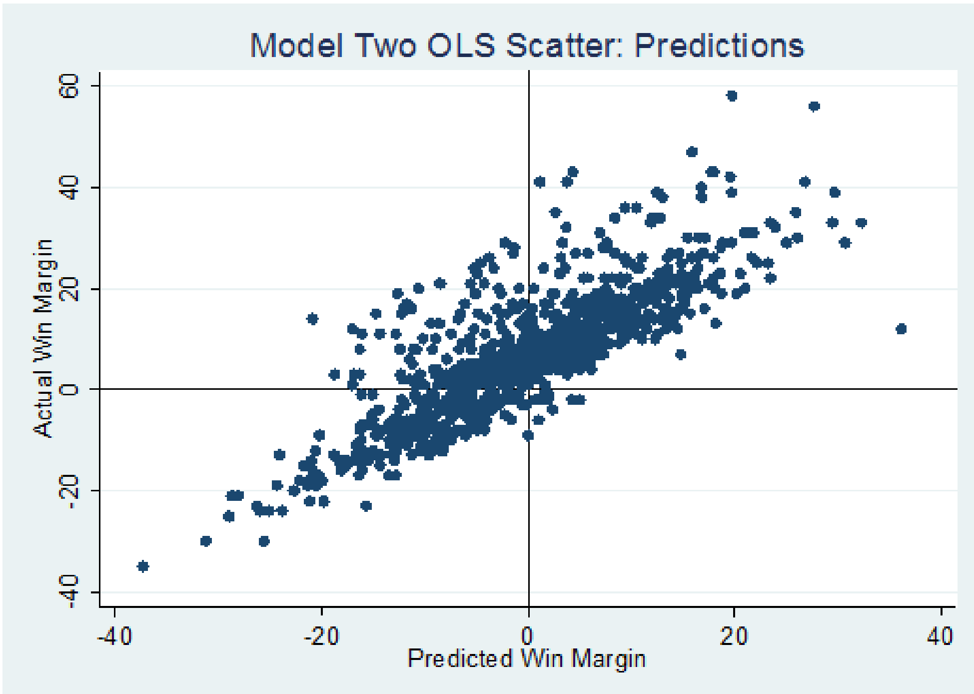


Figure 15 – Scatter plot for Model Two. Points in the upper-right and lower-left quadrants represent correctly predicted matchups, and other points represent mis-predictions.



In these two figures, points in the upper-right and lower-left quadrants represent successful predictions, while the other points represent incorrect predictions. From the two figures, we can see that most matchups were predicted correctly by our models, and matchups that were picked incorrectly tended to be predicted upsets that ended up with the favorite actually winning. It is important to note that these figures show that the models systematically tend to error in the upset direction rather than predicting favorites to win that end up losing. I believe this is a desirable attribute to a March Madness model.

4. Conclusion

Overall, it seems like it is very difficult to predict the winners of March Madness matchups. Even if an unbiased model for predicting outcomes of games could be constructed, I would expect that the error term is large enough to create a lot of outcomes that were not predicted. In light of this, I am pretty impressed with the performance of three of my four models. More review is needed to cross validate my models across my historical data; however, for the 2012 tournament, these three models performed quite successfully – all of them beat the bracket that I picked by hand myself this year.

The model that did not perform well, the OLS Regression for Model One, seemed to pick an unreasonable amount of upsets, including selecting a Final Four containing a six seed in UNLV and an eight seed in St. Louis. I am not sure why this model was so prone to picking upsets, but one possibility is that it heavily weighted the amount of points that opponents gave up during the regular season. For some small schools that play in less skilled conferences, games typically are lower scoring due to a generally lower level of offensive talent and slower paced games. This could result in schools that are defensive oriented and in small conferences, such as St. Louis, to be more favored by the model.

In the end, I believe that it is very difficult to consistently do well in picking brackets for March Madness. Rather than attempting to pick all 63 games correctly, the task that may be more useful to focus on in the future is picking the overall champion, as this is worth by far the most points of any matchup. This would be something slightly different to think about and would require a different type of model, but this is where I would direct a line of future research in this field.

4. Appendix I

Figure A – Summary Statistics of variables used in Model One

variable	*observations*	*mean*	*std dev*	*min*	*max*
seed	1575	3.48	2.346	1	12
win percent	1575	0.788	0.0882	0.516	0.971
wins in last ten	1575	7.56	1.487	3	10
Sagarin ranking	1575	14.9	14.45	1	207
ppg	1575	78.7	6.62	36.5	102.9
ppg allowed	1575	67.8	5.41	49	88.5
off efficiency	882	110.1	4.25	94	121.6
def efficiency	882	94.1	3.94	84.7	106.2
TS percentage	882	55.7	2.18	49.5	61.8
assists per game	882	15.6	1.82	11.2	20.7
coach final fours	1575	1.09	1.87	0	10
opp_seed	1575	9.79	1.869	1	16
opp_win percent	1575	0.709	0.0874	0.367	0.95
opp_wins in last ten	1575	7.25	1.601	3	10
opp_Sagarin ranking	1575	59.1	53.91	1	305
opp_ppg	1575	75.3	6.79	50.4	122.4
opp_ppg allowed	1575	68.4	6.36	48.3	108.1
opp_off efficiency	882	106.9	4.53	85.2	119.4
opp_def efficiency	882	96.1	3.84	83.1	110.2
opp_TS percentage	882	54.8	2.37	45.8	62
opp_assists per game	882	14.7	1.69	10.1	20.3
opp_coach final fours	1575	0.331	0.9055	0	9

Figure B – List of Variables in Complete Dataset

variable name	***description***	***var type***
year	year matchup was played	int
seed	seed of team	int
win margin	outcome of game (< 0 represents win by opponent)	int
win	dummy for if team wins (i.e. win margin > 0)	dummy
team	name of team	string
previous tournament	dummy for if team played in previous tournament	dummy
tournament two years back	dummy for if team played in tournament two years ago	dummy
win percent	win percentage of team's regular season record	float
wins in last 10	number of wins in last ten games	int
percent of wins away	percentage of total wins that occurred away from home court	float
coach tenure	number of years coach has been with school	int
total seasons coaching	number of years head coaching experience	int
coach final fours	number of final four appearances by coach	int
coach championships	number of national championships won by coach	int
coach NBA draft picks	number of NBA draft picks coached	int
automatic bid	dummy for if a team is an automatic bid	dummy
RPI	ratings percentage index	int
Sagarin ranking	Jeff Sagarin sports ranking system for NCAA (depends on strength of schedule and record)	float
SOS	strength of schedule	float
Total Games	total number of games played during season	int
ppg	points per game	float
ppg allowed	points per game allowed	float
Offensive Efficiency	offensive efficiency = (points / possessions) ● 100	float
Defensive Efficiency	= (points allowed / possessions) ● 100	float
Rbs Per Game	rebounds per game	float
Rbs Per Game Allowed	rebounds per game allowed	float
Steals Per Game	steals per game	float
Steals Per Game Allowed	steals allowed per game	float
Blocks Per Game	blocks per game	float
FG%	field goal shooting percentage	float
3-pt%	three point field goal shooting percentage	float
TS%	true shooting percentage (weights for three pointers and free throws)	float
free throw rate	free throws attempted per game	float
assists per game	assists per game	float
freshmen play time	minutes per game	float
sophomore play time	minutes per game	float
junior play time	minutes per game	float
senior play time	minutes per game	float

variable name	*description*	*var type*
opponent	name of opponent	string
opp_seed	seed of opponent	int
opp_previous tournament	dummy for if team played in previous tournament	dummy
opp_tournament two years back	dummy for if team played in tournament two years ago	dummy
opp_win%	win percentage of team's regular season record	float
opp_wins in last 10	number of wins in last ten games	int
opp_percent of wins away	percentage of total wins that occurred away from home court	float
opp_coach tenure	number of years coach has been with school	int
opp_total seasons coaching	number of years head coaching experience	int
opp_coach final fours	number of final four appearances by coach	int
opp_coach championships	number of national championships won by coach	int
opp_coach NBA draft picks	number of NBA draft picks coached	int
opp_automatic bid	dummy for if a team is an automatic bid	dummy
opp_RPI	ratings percentage index	int
opp_Sagarin ranking	Jeff Sagarin sports ranking system for NCAA (depends on strength of schedule and record)	float
opp_SOS	strength of schedule	float
opp_Total Games	total number of games played during season	int
opp_ppg	points per game	float
opp_ppg allowed	points per game allowed	float
Opp_ Offensive Efficiency	offensive efficiency = (points / possessions) ● 100	float
opp_Defensive Efficiency	= (points allowed / possessions) ● 100	float
opp_Rbs Per Game	rebounds per game	float
opp_Rbs Per Game Allowed	rebounds per game allowed	float
opp_Steals Per Game	steals per game	float
opp_Steals Per Game Allowed	steals allowed per game	float
opp_Blocks Per Game	blocks per game	float
opp_FG%	field goal shooting percentage	float
opp_3-pt%	three point field goal shooting percentage	float
opp_TS%	true shooting percentage (weights for three pointers and free throws)	float
opp_free throw rate	free throws attempted per game	float
opp_assists per game	assists per game	float
opp_freshmen play time	minutes per game	float
opp_soph play time	minutes per game	float
opp_junior play time	minutes per game	float
opp_senior play time	minutes per game	float
round	round of tournament	int

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