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RESEARCH ARTICLE

Predicting Winners and Evaluating Simple betting Strategies for BCS College Football Games

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Abstract

We investigate two sets of questions concerning Bowl Championship Series (BCS) college football games. The first set of questions pertains to predictors for the outcomes of these games. We evaluate whether the differences in rankings between teams and the point spread are good predictors for outcomes of BCS games, which involve top ranked teams in the NCAA Division I Football Bowl Subdivision. We use probit regressions with the differences in ranking, differences in the log rankings, and the point spread as the predictors of the outcomes of the games. The second set of questions pertains to betting market efficiency and testing if simple betting strategies are profitable. We investigate whether betting on the underdog is profitable when the spread is greater than 5 points and also if there are returns to betting the under. We use Z-values and likelihood ratio testing for these analyses.

Keywords: *Amateur sports, Rankings, Gambling, Betting, Market efficiency, Prediction markets.*

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Introduction

We investigate two sets of questions concerning Bowl Championship Series (BCS) college football games. The first set of questions pertains to good predictors for the outcomes of these games. We test whether ranking differences, using rankings from the Associated Press (AP) and the USA Today polls, are good predictors for Bowl Championship Series (BCS) game victories for the 1998-1999 through 2013-2014 college football seasons.[1] This testing also allows for a comparison of the rankings by these polls. We also test whether the point spread, or betting line, is a good predictor for BCS game victories. The second set of questions pertains to betting market efficiency and testing if simple betting strategies are profitable. We investigate whether betting on the underdog is profitable when the spread is greater than 5 points and also if there are returns to betting the under.

Interest in rankings of athletic competitors is growing. Lebovic and Sigelman [1] note that college football rankings, "…have by no means escaped the notice of social scientists and statisticians, who have probed the predictive accuracy of various ranking and rating schemes." Their work uses AP poll data to show weekly changes in rankings. These authors also provide a concise overview of works from the 1980s and 1990s on college football rankings. However, none of these works uses differences in rankings to predict college football victories. Differences in rankings have been found to be good predictors of winning other various sporting contests. Boulier et al [2] find ranking differences are useful predictors in NCAA basketball games and professional tennis matches. Rankings differences were also found to be useful predictors for Grand Slam tennis matches by del Corral and Prieto-Rodriguez [3].

[1] The USA Today poll is also known as the Amway Coaches poll.

There are a number of works regarding betting on football and the efficiency of betting markets. Paul and Weinbach [4, 5] investigate betting markets for National Football League (NFL), arena league, and college football games. Badarinarthi and Kochman [6], building on the work of Tryfos et al. [7], test profitable betting strategies using NFL betting data. Even and Noble [8] and Sauer et al. [9] investigate betting market efficiency for the NFL as well. Nevertheless, there does not appear to be any works focusing on BCS games.

A priori, we anticipate the point spread to serve as the best predictor for BCS game victories. This is due to the fact that the rankings are established following the last regular season or conference championship game for each team participating in a BCS game, and these rankings are given weeks prior to the bowl games actually being played.[2] However, the point spread reflects information available to bettors up to the start of the game. In this sense, the bettors are able to incorporate the rankings that are available along with additional information, e.g. player injuries or suspensions, coaching changes, etc., which would not have been available to pollsters at the time their rankings were announced. Due to the informational advantage available to bettors we expect the point spread to best predict victory.

We chose the BCS bowl games as the focus of the study for three primary reasons:

- Virtually all of the games involve two ranked teams.[3]
- These are the most watched college football games according to Nielson ratings.
- For a given year, the rankings prior to the bowl games better reflect that season's actual performance relative to preseason or earlier in the season rankings.

We find that rankings differences may be useful predictors for BCS bowl game victories. However, this finding pertains to the USA Today poll and the best predictive power with differences in log ranks, suggesting that quality differences grow at an increasing rate at higher rankings. Additionally, we find that while the percentage of bets on the underdog being profitable when the spread is greater than 5 points exceeds the break-even percentage, these bets are random and not profitable in a statistically significant sense. We also find that the percentages concerning betting the under exceed the break-even percentage, which supports the notion that bettors like to bet the over for games with higher expected totals, but that betting the under is not profitable in a statistically significant sense. However, for games with expected totals greater than or equal to 52 points there is statistically significant support of win percentages exceeding 50 percent regarding betting the under.

Data

The Associate Press poll consists of weekly voting from a panel of sports writers and broadcasters from around the country; currently the panel consists of 60 voters. The USA Today poll consists of weekly voting from a panel of head coaches at Bowl Subdivision schools; this panel currently consists of 62 head coaches. These polls provide rankings for the top 25 teams. The rankings data was collected from www.espn.com and *The New York Times*. The rankings data used in this analysis consists of the final rankings of the BCS teams *prior* to their bowl games, i.e. the rankings following the last regular season or conference championship game for each team participating in a BCS game. The point spreads and totals, i.e. over/under, data was collected from www.covers.com.

There were 72 BCS games played from the 1998 -1999 through 2013-2014 seasons, with 1998-1999 being the introduction of the BCS. From the 1998-1999 through 2005-2006 seasons there were 4 BCS games per season. This changed to 5 BCS games per season in 2006-2007. Thus, the data used in the analysis below reflects all BCS games to date.

[2] In some cases there is more than a month between a team's last regular season game and their BCS game.
[3] The two exceptions being the 2011 Fiesta Bowl involving a team from the University of Connecticut, which was unranked in the USA Today poll, and the 2013 Rose Bowl involving a team from Stanford University, which was unranked in the AP Poll.

Table 1:Descriptive statistics

	AP	USA Today	Point spread
Higher ranked/favored team wins	46	40	44
Number of games	72	72	71
Predicted win percentage	63.89%	55.56%	61.97%
Mean rank difference/mean point spread	-4.68	-4.44	-7.09
Standard deviation	4.72	4.29	4.19

Table 1 presents an overview of the number of wins and winning percentages for higher ranked teams by poll and for favored teams by point spread. The winning percentages of the AP poll and point spread are similar and exceed 60 percent, while the higher ranked teams according to the USA Today poll won just under 56 percent. In the 6 fewer wins by higher ranked teams with the USA Today poll, the differences in ranks were just 1 position in 4 instances and 2 positions in the remaining 2 instances. These "upsets" could be viewed as not particularly surprising given the closeness in rankings by the teams playing in these matchups.

Methodology and Results

Predicting BCS Wins Using Rank Differences and Point Spreads

We use two approaches for the differences in rankings. We use the difference s_1-s_2, where s_1 is the ranking of the higher ranked team and s_2 is the ranking of the lower ranked team, in a manner similar to Boulier et al [2]. We also use the difference between the natural logarithms of the rankings, i.e. log (s_1)-log (s_2), similar to that of del Corral et al [3].

The first approach provides a simple linear difference between the ranks. The second approach provides a nonlinear measure that allows for greater differences between teams as they move up the rankings. This method suggests that a one position difference in rankings is more substantial for higher ranked teams than for lower ranked teams.

The dependent variable takes a value of 1 if the higher ranked or favored team wins in the probit models to follow. The independent variables for the differences in rankings are negative values; a higher ranked team has a lower number than a lower ranked team.[4] The point spread independent variable is non-positive; the spread is reported as a negative number for the favored team or as zero if the point spread does not indicate a favorite.[5]

Table 2 presents the estimated coefficients of the probit equations for the linear differences in ranking by each poll and the point spread.

The signs of the coefficients are as expected. Negative values indicate that higher ranked and favored teams are more likely to win. However, only the *Rank difference* coefficient from the USA Today poll model indicates a statistically significant result at the usual levels.

Table 3 presents the estimated coefficients of the probit equations for the log differences in ranking by each poll and, for the sake of comparison, the point spread once again.[6]

The negative and significant coefficients on the rankings differences for the USA Today poll models indicate that the probability of winning a BCS bowl game is a function of the difference in rankings of the teams. Note that the Brier scores for the log difference models indicate that these are the best fitting of the results presented in tables 3 and 4. This suggests that there are quality differences at higher ranks relative to lower ranked teams.

[4] For example, a team ranked #3 is higher ranked than a team ranked #7.

[5] A point spread of zero only occurred in one instance, the 2001 Rose bowl.

[6] We also used the squared rankings differences, s_1^2-s_2^2, as the independent variable in models that are available upon request. This difference in rankings indicates that lower ranked teams would have greater quality differences than higher ranked teams. This would not be expected and the results from these models were not statistically significant. This also resulted in the worst fitting Brier scores relative to the models presented in tables 3 and 4.

Table 2: Probit results for poll differences and point spread

	AP Top 25			USA Today	Point Spread	
	Coeff.	St. dev.	Coeff.	St. dev.	Coeff.	St. dev.
Constant	0.204	0.217	-0.248	0.224	0.170	0.297
Rank difference/point spread	-0.030	0.034	-0.088**	0.041	-0.019	0.036
Brier Score	0.2297		0.2308		0.2347	
N	71		71		71	
LR Test	0.78		5.23		0.28	
Pseudo R^2	0.008		0.054		0.003	
Log likelihood	-46.249		-46.254		-47.023	

Notes: * is significance at 10 percent, ** is significance at 5 percent, and *** is significance at 1 percent.

Table 3: Probit results for log differences in polls and point spread

	AP Top 25		USA	Today	Point Spread	
	Coeff.	St. dev.	Coeff.	St. dev.	Coeff.	St. dev.
Constant	-0.020	0.304	-0.598*	0.328	0.170	0.297
Rank difference/point spread	-0.508	0.374	-1.030**	0.42	-0.019	0.036
Brier Score	0.2261		0.2261		0.2347	
N	71		71		71	
LR Test	1.91		6.55		0.28	
Pseudo R^2	0.021		0.067		0.003	
Log likelihood	-45.683		-45.594		-47.023	

Notes: * is significance at 10 percent, ** is significance at 5 percent, and *** is significance at 1 percent.

Evaluating Simple Betting Strategies for BCS Games

We begin our analysis with the betting data by verifying that there are no observed biases in the betting market for these games. In their overview of professional sports betting, Steckler et al [10] note, "The overwhelming majority of the evidence of the betting market is efficient, in the sense that, on average, there is no profitable betting strategy against the spread." We use the traditional method for determining whether a forecast is unbiased with the results of that regression presented in Table 4 below.[7]

Table 4: Regression results for efficiency of point spreads

	Coeff.	St. dev.
Constant	1.496	2.369
Point spread	0.917***	0.288
N	71	
F Test	0.002	
Pseudo R^2	0.128	

Notes: * is significance at 10 percent, ** is significance at 5 percent, and *** is significance at 1 percent.

We then conduct the joint test of the null hypothesis that the coefficients of *Constant* = 0 and *Point spread* = 1. The resulting F-test statistic is 0.58 with a p-value of 0.563, so the null is not rejected at any meaningful level. Therefore, the results indicate that the point spread, or forecast, is unbiased as on average the scoring difference does not vary significantly from the point spread.

Table 5: Regression results for efficiency of over-under

	Coeff.	St. dev.
Constant	20.652	12.736
Over-Under	0.628***	0.231
N	72	
F Test	7.42	
Pseudo R^2	0.096	

Notes: * is significance at 10 percent, ** is significance at 5 percent, and *** is significance at 1 percent.

Table 5 presents results concerning market efficiency using the market totals, i.e. over/under, data. The joint test of the coefficients *Constant* = 0 and *Over-Under* = 1

[7] The earliest appearance of this testing for football-betting markets appears to be Pankoff (1968) with National Football League (NFL) games.

has an F-test statistic of 1.32 with a p-value of 0.274, so the null is not rejected at any usually accepted level. These results suggest that the forecast is unbiased as the average total scoring does not vary significantly from the over/under.

We now investigate whether betting on the underdog is profitable when the spread is greater than 5 points. We pick this simple rule as this is the core of Badarinthi and Kochman's [6] testing of the findings of Tryfos et al. [7], i.e. that profitable rules, "…called for betting on the underdog when the point spread was greater than five points" for NFL games.[8] We do not test whether there is any variation in spreads among bookmakers in different cities, or taking advantage of a syndicate, as we do not have that data available.

Of the 72 BCS bowl games, there were 44 involving a point spread of greater than 5 points. The underdog covered the spread in 25 cases and there were no ties. This results in a win-to-bet ratio of 56.82 percent. This would appear to be profitable as it exceeds the 52.38 percent breakeven mark.[9] However, it is of use to test if this rule satisfies either non randomness or profitability at commonly accepted statistically significant levels. We use the Z-value measures proposed in Badarinathi and Kochman [6]:

Nonrandomness: $Z_1=[W-0.5(B)]x[B(p)(1-p)]^{-1/2}$
Profitability: $Z_2=$

$$\frac{\frac{W}{B}-\frac{(1.1)L}{B}}{\{1/B[\left(\frac{W}{B}+\frac{(1.21)L}{B}\right)-\left(\frac{W}{B}-\frac{(1.1)L}{B}\right)^2]\}^{1/2}}$$

where: W = winning bets, (= 25)
L = losing bets, (= 19)
B = total bets, (= 44)
p = probability of winning, (= 0.5)

The Z-values are Z_1 = 0.905 and Z_2 = 0.594. Neither test results in statistical significance at even the 10 percent level. These results suggest that the strategy's success was random and was not, statistically speaking, profitable.

We are also interested in determining if bettors exhibit a preference for scoring by investigating the totals, or over/under, market. Paul and Weinbach [5] test betting the under against the null of a fair bet and a second test against the null of betting the under not being profitable. We use a similar testing approach, which involves log-likelihood ratio tests as initially developed by Even and Noble [8]. As there are a limited number of BCS games we focus on two sets of the games: (1) the complete set of BCS games and (2) a subset of the games where the over/under is at least 52 points. We selected this 52-point total as Paul and Weinbach [5] report this being the lowest total with a statistically significant result in their findings on NCAA football games for 1999 to 2003. The test statistics are listed below and the results are presented in table 6.

Fair Bet:
$2(L^u – L^r) = 2\{n[\ln(\hat{q}) – \ln(0.5)]+(N-n)[\ln(1 - \hat{q}) – \ln(0.5)]\}$
No profit:
$2(L^u – L^r) = 2\{n[\ln(\hat{q}) – \ln(0.5238)]+(N-n)[\ln(1 - \hat{q}) – \ln(0.4762)]\}$
where: $\hat{q}$ = Under Win Percentage
N = number of games (i.e. sum of Unders and Overs)
n = number of Unders

Table 6: Likelihood ratio tests for betting the under

Bet Under with Total Greater Than or Equal to:	Unders	Overs	Under Win Percentage	Null Hypothesis: Fair bet	Null Hypothesis: No profit
52	26	14	0.65	3.656*	2.604
ALL	38	34	0.528	0.222	0.005

Notes: Test statistics have chi-square distribution with one degree of freedom. * is significance at 10 percent, ** is significance at 5 percent, and *** is significance at 1 percent.

In both cases the under win percentages exceed the breakeven threshold of 52.38 percent. Likelihood ratio testing of the sample of games with a total greater than or equal to 52 points finds statistically

[8] Osborne (2001) also investigates the 5 point spread difference in his study of NFL betting markets.
[9] The 52.38 percent breakeven mark results from the "eleven for ten" rule. For more information see Tryfos et al (1984) or Even and Noble (1992).

significant support of win percentages exceeding 50 percent, which is the null hypothesis for the fair bet. However, there is not statistically significant support at generally recognized levels for win percentages exceeding 52.38 percent, i.e. the breakeven or "no profit" null hypothesis.[10]

Regarding all BCS games the likelihood ratio tests do not reject either of the null hypotheses. Our results are similar to those of Paul and Weinbach [4], lending further support to the finding that bettors prefer to bet the over [11-12].

Conclusions

This study presents results concerning the usefulness of rankings differences and point spreads in predicting winners of BCS games and investigates betting market efficiency and the returns to simple betting strategies. Our results suggest the rankings of a subset of the coaches of the Bowl Subdivision Schools, i.e. those polled by USA Today, are useful in that the difference in these rankings better indicate the likelihood of a higher ranked team winning.

This is not the case for the rankings provided by sportswriters and broadcasters around the country, i.e. those polled for the AP poll. Additionally, we were surprised to find that the point spread was not useful in predicting the likelihood of the favored team winning. Our prior was that the difference in the point spread would best predict victory due to the informational advantage available to bettors. In regard to the betting markets, our simple betting strategies have win percentages exceeding the breakeven point for both betting on the underdog if the point spread is greater than 5 points and also for betting on the under for BCS games, particularly if the total is greater than or equal to 52 points. However, testing of the strategies does not indicate profitability at the generally accepted levels of statistical significance. Nevertheless, the null hypothesis of a fair bet can be rejected for the total points greater than or equal to 52 points as bettors prefer betting the over to the under for these games.

[10] The "fair bet" LR test statistic of 3.656 has a p-value of 0.06. The "no profit" LR test statistic of 2.604 has a p-value of 0.11.

References

1. Lebovic James H, Sigelman L (2001) The forecasting accuracy and determinants of football rankings. International Journal of Forecasting, 17(1):105-20.
2. Boulier Bryan L, Stekler HO (1999) Are sports seeding good predictors?: an evaluation. International Journal of Forecasting, 15(1):83-91.
3. Del Corral Julio, Prieto-Rodriguez Juan (2010) Are differences in ranks good predictors for Grand Slam tennis matches? International Journal of Forecasting, 26(3):551-63.
4. Paul Rodney J, Weinbach Andrew P (2005) Bettor preferences and market efficiency in football totals markets. Journal of Economics & Finance, 29(3):409-415.
5. Paul Rodney J, Weinbach Andrew P (2002) Market efficiency and a profitable betting rule: evidence from totals on professional football. Journal of Sports Economics, 3(3):256-63.
6. Badarinathi Ravija, KochmanLadd (1966) Football betting and the efficient market hypothesis. American Economist, 40(2):52-55.
7. Tryfos P, Casey S, Cook S, Leger G, Pylypiak B (1984) The profitability of wagering on NFL games. Management Science, 30(1):123.
8. Even William E, Noble, Nicholas R (1992) Testing efficiency in gambling markets. Applied Economics, 24(1):85-88.
9. Sauer Raymond D, Brajer Vic, Ferris Stephen P, Marr M Wayne (1988) Hold your bets: another look at the efficiency of the betting market for NFL games. Journal of Political Economy, 96(1):206-13
10. Stekler HO, Sendor David, Verlander Richard (2010) Issues in sports forecasting. International Journal of Forecasting, 26(3):606-21.
11. Osborne Evan (2001) Efficient markets? Don't bet on it. Journal of Sports Economics, 2(1):50-61.
12. Pankoff LD (1968) Market efficiency and football betting. Journal of Business, 41:203-14.