

On the optimal realignment of a contest: The case of college football

Stefan Szymanski* Jason A. Winfree†

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*Professor, Program in Sport Management, University of Michigan

†Assistant Professor, Department of Agricultural Economics and Rural Sociology, University of Idaho

Abstract

This paper examines the relationship between demand and scheduling in college football. We first derive two different metrics for team quality, and then use those metrics to see how they impact attendance. We find that there is a positive interaction between the quality of the teams. Then various simulations are run to see how attendance would change under different scheduling scenarios. If teams are put into conferences based on the team quality measures, overall college football attendance increases about 5% even though there are fewer rivalry games. This is true if one year or ten year quality measures are used. We conclude that the current conference alignments are inefficient in the sense that they do not deliver what fans appear to want, namely to see the best play against the best.

1 The Question

The production of team sports involves a form of matching. In most professional leagues the membership is fixed and there is no choice in the selection of matches (the most common form a of a league is a round robin where every team plays every other team twice, once at home and once away). College football is rather different. Teams belong to conferences and are usually required to schedule a certain number of games against conference rivals, but they are also free to schedule additional games against opposition of their choice. Moreover, the membership of conferences has always been fluid, and is going through a period of rapid change at the moment. According to Wikipedia 93 schools have jumped to a new conference (full membership) since 2010.¹

This paper develops with the aim of identifying an optimally matched conference structure. Our notion of optimal matching is very simple, not unlike Becker's (1973) theory of marriage. Each team has a productivity (team quality), Z_i , which they bring to any match. The productivity of a match is the sum of individual productivities plus the interaction of the two: $\alpha_i Z_i + \beta_i Z_j + \gamma_i Z_i Z_j$. This productivity then determines demand: the number of people who are willing to pay to watch the game.

One interpretation of the interaction term is that it represents the demand for competitive balance ($\gamma_i > 0$), which has long been considered by economists to be an important determinant of the demand for team sports (see e.g. Borland and McDonald (2003)). This element alone suggests that positive assortative matching is optimal - attendance is maximized globally when teams of similar quality play against each other. However, even if this is not true, positive assortative matching may still be optimal for individual teams ($\beta_i > 0$ and $\gamma_i = 0$). Under this assumption, if the home team retains all the gate money it will be revenue maximizing to play the best opponents.

We develop a simple empirical model to analyze the issue. Based on a sample of college football games we estimate attendance as a function of various observables in-

¹http://en.wikipedia.org/wiki/List_of_schools_changing_conference_in_the_2010%E2%80%932013_NCAA_conference_realignment uploaded 6/6/2013

cluding the quality of the teams. We then identify the attendance maximizing conference structure and calculate the expected attendance conditional on this structure. Our results show that optimal scheduling would increase attendance by roughly 5%. This is in itself substantial. However, we conjecture that TV audiences are even more sensitive to quality, so that the revenue benefits to the NCAA would be even greater.²

The next section gives some background on the economics of scheduling in college football. Section 3 describes our data and methodology, then we consider the results of the estimation in Section 4. Section 5 describes the simulated conference structure, and section 6 concludes.

2 Background

2.1 Matching Model

College football resembles a marriage market in the sense that each game played requires that both sides agree to play, and both have many alternatives from whom to choose. Surprisingly little has been written in the academic literature on this problem. In most team sports this problem is trivial because competition is organized on a league basis and opponents are dictated by the system adopted. For instance, the NFL has formula which requires each team to play two games against each of their divisional rivals, divisional rivals have fourteen out of sixteen games against common opponents, while the remaining two are decided by the standings of the previous season. College football, while also being built around league play, gives far more latitude to teams to decide who they play. For example, in the Big 10 teams currently have to play 8 conference games in the season, five against members of their own division, two against teams from the other division (on a rotating basis) and one that it plays every year. However, teams play a 12 game season and are at liberty to play any four teams that will agree to play with them. Moreover,

²Mongeon and Winfree (2012) find that in the National Basketball Association, television audiences are 4.5 times more sensitive to winning than live audiences.

while most popular sports leagues are stable over time, college football is subject to realignment, markedly so in recent years. Colleges are seeking out the best collection of competitors that they can find.

Matching theory suggests there should be few problems in finding optimal matches. Even in the absence of a pricing mechanism there are well known theorems, e.g. Gale and Shapley (1962), which suggest that optimal matches are feasible. Their model of a marriage market works via the "deferred acceptance mechanism" - one gender makes offers to as many partners as they wish and the other rejects all offers but one which is held, and then a second round of offers is made conditional on (deferred) acceptances received, and the process repeats until no new offers are received. This mechanism has the nice property that at equilibrium no one fails to make a match with someone that (a) they would prefer and (b) would also prefer switch their match. This is consistent with positive assortative matching, where each agent has a type, and matches are made between similar types. Becker (1973) shows that positive assortative mating is an equilibrium in a marriage market which ensures that aggregate output from matches is maximized. The idea of positive assortative matching has been applied to explaining the distribution of wages (Sattinger 1993) and economic development (Kremer 1993). In general, frictions may exist which prevent efficient assortative matching, while incomplete information and moral hazard may lead to inefficient matching (see e.g. Legros and Newman (2002)). For example, Fr chet te et al. (2007) show that when college football bowl games were scheduled later in the season with more information, efficiencies were gained as evidenced by higher television ratings.

One difficulty in identifying optimal matches for college football teams is that the objectives of each college are not clear. We will assume that an optimal schedule is one that maximizes total output which we will measure by total attendance. This will also imply that the schedule maximizes the total attendance of each team, subject to playing a schedule of 6 or 7 home games. However, decision makers within the college may have different objectives. Coaches will want a schedule which maximizes the probability

of reach the best possible Bowl game, Athletic Directors may want to maximize the resources provided the department, which might depend on meeting the demands of particular constituencies (e.g. the preferences of boosters) and University Presidents may have strategic goals which go beyond sport and relate to student recruitment, college profile and donors. This list of decision makers is not necessarily exhaustive.

However, we do not believe that these objectives are widely at variance with output maximisation as we have defined it. First, the rating schemes which determine the allocation of teams to Bowl games tend to favour those teams that play stronger schedules, all else equal, and so deliberately choosing a weak schedule can be counter-productive (Keener (1993)). Second, there are studies which have shown that successful athletic programs, especially in the revenue sports, tend to align with broader academic goals such as recruitment and donations.³

2.2 Matching and the uncertainty of outcome hypothesis

With the exception of Fréchette (2007), the sports literature has not focused on the matching issue for the reasons given above. However, it has focused on a related concept - the uncertainty of outcome hypothesis (the original article in this literature is Rottenberg (1956)). In our terms, this asserts that a match will be more attractive (larger attendance) if the strength of the two sides is closely matched than if they are unevenly matched. This question has generated a large literature which has been surprisingly inconclusive. Thus a survey by McDonald and Borland (2003) found:

Of 18 studies identified, only about three provide strong evidence of an effect on attendance. Other studies provide mixed evidence that suggests a negative effect on attendance of increasing home win probability only when that win probability is above about two thirds. The majority of studies find either that there is no significant relation

³Fort and Winfree (2013, p33) point out that research has found a positive correlation between college athletic success and alumni giving (Rhoads and Gerking (2000)), student applications (e.g. Pope and Pope (2009)) and budget allocations by legislators (Humphreys (2006)).

between difference in team performance and attendance, or more directly contradictory, that attendance is monotonically increasing in the probability of a home-team win.

We have reviewed 15 studies published since then and the results are shown in Table 1. There is some variability in the focus of these studies, but generally they test for the effect on demand of the quality of the home team, the quality of the away team, and the expected difference in performance of the two teams. Quality is typically measured either by the recent winning records of the teams or by the pre-match betting odds on the teams. Almost all of the studies find that demand is increasing in the quality of the home team. When tested for, it is generally found that demand is also increasing in the quality of the away team (in the words of Coates and Humphreys (2010) "fans want to see good teams play"). The results for the competitive balance measures are generally more ambiguous, in the line with the earlier research. Several studies suggest that the optimal winning percentage/probability of winning for the home team is in the region of 66%. Seen from our perspective the ambiguity is perhaps not surprising. If demand is increasing in qualities of the teams taken separately and in their interaction as well, then picking up the latter effect is likely to be difficult econometrically.

Measures of differences in team quality, whether based on win/loss records or betting odds fail to generate a consistent pattern, are sometimes perversely signed, and often entail quadratic terms with impossible implications. For example, a finding that demand is decreasing in both the absolute difference in win loss records and its square would normally be taken as confirmation of the uncertainty of outcome hypothesis. However, the implication of this is that a very weak home team playing against a very strong home team could face negative demand.

In our model we view the value of the match as dependent on both the qualities of the home and away teams taken separately and the product of the two qualities. Thus at worst a highly unbalanced match could contribute nothing to demand other than the quality of the strong team.

3 Data and Methodology

3.1 Team Quality Measures

Our first step is to measure team quality. Football Bowl Subdivision games were used to create team quality variables. Our sample consists of 14,924 games played between 1990 and 2010. However, since lagged variables were used, the games from 1990 were not used so the estimation had 14,278 observations.

We identify quality in two different ways: Method 1: We estimate the expected margin of victory for each game based on a weighted average of past performance measured by win percentage and the strength of schedule for each team. A team's strength of schedule is the average winning percentage of a team's opponents up to the date of the game. Therefore, this non-linear estimation takes into account where the game is played (home, away, or neutral), the winning percentage of each team for the current and previous year, and the strength of schedule for each team for the current and previous year. The weighting between the current and previous year depends on how many games the teams have played in the current season.

The equation is given by,

$$\begin{aligned}
 MOV = & \beta_1 + \beta_2 Neutral + \beta_3 \left(1 - \frac{1}{N_H^{\beta_{11}}}\right) win\%_{h,t,N_H} + \beta_4 \left(\frac{1}{N_H^{\beta_{11}}}\right) win\%_{h,t-1,\bar{N}} + \\
 & \beta_5 \left(1 - \frac{1}{N_H^{\beta_{11}}}\right) SOS_{h,t,N_H} + \beta_6 \left(\frac{1}{N_H^{\beta_{11}}}\right) SOS_{h,t-1,\bar{N}} + \beta_7 \left(1 - \frac{1}{N_A^{\beta_{11}}}\right) win\%_{a,t,N_A} + \\
 & \beta_8 \left(\frac{1}{N_A^{\beta_{11}}}\right) win\%_{a,t-1,\bar{N}} + \beta_9 \left(1 - \frac{1}{N_A^{\beta_{11}}}\right) SOS_{a,t,N_A} + \beta_{10} \left(\frac{1}{N_A^{\beta_{11}}}\right) SOS_{a,t-1,\bar{N}}
 \end{aligned} \tag{1}$$

where MOV is the margin of victory for the home team, $Neutral$ is equal to one if the game is on a neutral field, N_H is the n^{th} game of the season for the home team, N_A is the n^{th} game of the away team, $win\%$ is the winning percentage, SOS is the strength of

schedule⁴, h represents the home team, a represents the away team, t is the season, and \bar{N} denotes that the winning percentage or strength of schedule is calculated at the end of the previous season. Table 2 gives the parameter estimates and t-statistics, the model correctly predicts 73% of games.

This model was then used to create a quality metric for every team for each game. A team's quality value was computed using the parameter estimates from equation (1) in addition to their winning percentages for this year and the previous year, as well as the strength of schedule for both years. Home team parameter estimates were used and a value of .5 was used for the visiting team's winning percentage and strength of schedule so that the metric for team i during season t for the N_i^{th} game is given by,

$$\begin{aligned}
MOV_{i,t,N_H}^* = & \beta_1 + \beta_2 + \beta_3 \left(1 - \frac{1}{N_H^{\beta_{11}}}\right) win\%_{i,t,N_H} + \beta_4 \left(\frac{1}{N_H^{\beta_{11}}}\right) win\%_{i,t-1,\bar{N}} + \\
& \beta_5 \left(1 - \frac{1}{N_H^{\beta_{11}}}\right) SOS_{i,t,N_H} + \beta_6 \left(\frac{1}{N_H^{\beta_{11}}}\right) SOS_{i,t-1,\bar{N}} + \beta_7 \left(1 - \frac{1}{N_H^{\beta_{11}}}\right) .5 + \quad (2) \\
& \beta_8 \left(\frac{1}{N_H^{\beta_{11}}}\right) .5 + \beta_9 \left(1 - \frac{1}{N_H^{\beta_{11}}}\right) .5 + \beta_{10} \left(\frac{1}{N_H^{\beta_{11}}}\right) .5
\end{aligned}$$

MOV_{i,t,N_H}^* was then used as a quality metric for the home team, MOV_H , and the away team, MOV_A . A constant was then added to ensure that $MOV_H > 0$ and $MOV_A > 0$.

Method 2: We also construct an *ELO* rating for each team. *ELO* ratings are widely used in competitions where the organizers want to match competitors of similar ability, most notably in chess. An *ELO* rating is built up by playing games, where the result of each game generates an addition or subtraction depending on win or loss, where the size of the adjustment is calibrated according to the pre-match expectation of the outcome, which is based on the *ELO* ratings going into the game. For each competitor the initial value is arbitrary, but once enough games have been played *ELO* ratings provide a

⁴*SOS* is equal to the average winning percentage of the opponents that the team has played up until that game.

consistent measure of relative performance. Thus for each game the expectation of a win for team i against team j is

$$E_{ij} = \frac{1}{1 + 10^{(ELO_i - ELO_j)/400}} \quad (3)$$

And the rating is updated according to

$$ELO'_i = ELO_i + K(R_{ij} - E_{ij}) \quad (4)$$

Where R is the result (win = 1, loss = 0) and K is a scaling factor. There is some controversy over the appropriate value of the scaling factor, but we chose the commonly used value of 50. However, we do not believe this significantly affects the estimation of our demand model. To construct the ELO ratings we used results dating back 20 years so that even our earliest demand observations are based on around ten years of results.

3.2 Attendance Estimation

We collected attendance data from various sources for 4839 college football games played between 2001 and 2010. However, we do not have attendance for all Football Bowl Subdivision games over this time period. Attendance data is more readily available for recent games. For example, we have 245 observations in 2001, but 729 in 2010.⁵

We now use our alternative measures of quality to estimate demand. Our hypothesis is that attendance is a function of both home and away team quality. As well as team quality we assume that demand is a function of year and stadium fixed effects and monthly dummies. We also allow for the effect of rivalry games. Clearly the definition of a rivalry game is somewhat arbitrary, but we want to capture the possibility that certain games may add to demand even if the quality of the teams is poor. We suspect that Michigan v Ohio State would sell out no matter who played for the teams. To capture rivalry

⁵This does not include Notre Dame because all of their games were censored due to sell outs according to our criteria, explained later in the paper.

effects we invited six colleagues to choose from a list of all match-ups from the last 20 years (2769) and to indicate they thought were true rivalry games. Only about 15% of these games have been played more than 15 times, whereas one might expect true rivalry games would be played almost every year. We decided to designate match-ups as rivalry games if two thirds or more (at least 4 of 6) of our assessors thought that they were. This generated a total of 31 rivalry games, which are listed in Table 3. Table 4 has summary statistics of the data used to estimate attendance.

Although we do not have data on prices, these are likely to be captured by the combination of stadium fixed effect and year dummies. A number of stadiums sell out on a regular basis and so we use Tobit as well as OLS to estimate demand. Ideally we would like to know the exact stadium capacity at each game, since this can vary significantly for a number of reasons. There are differences in how teams report attendance and stadium capacity can vary for each team from year to year or even game to game.

In order for a game to be denoted as censored (sold-out), it met three criteria. First, the attendance had to be least 98% of the maximum attendance value for that stadium. Second, there had to be at least two games that were 98% or more of the maximum attendance value for the stadium. Third, at least one-tenth of the games in the stadium in the sample had to be at least 98% of the maximum value of the stadium.⁶ This resulted in 16.3% of games being denoted as a sell-out, after Notre Dame was thrown out of the sample since all of their games qualified as a sell-out.

4 Results

The demand estimation results are presented in Table 5. Using both measures (*MOV* and *ELO*), we ran an OLS on the full sample, and OLS using only teams without censored observations, a Censored Least Absolute Deviation (CLAD) model as described in Powell

⁶If less than 10% of games were greater than 98% of the maximum, the censoring issue was not deemed to be severe at that stadium and there is a greater probability that the games are uncensored and randomly within 2% of the maximum.

(1984), and a Tobit model. Both our *MOV* and our *ELO* measures of quality show that the strength of the home team and the strength of the away team add significantly to demand, as one might expect. The interaction of the home and away quality measures, which can be interpreted as the effect of competitive balance on demand, is insignificant in the full sample OLS and CLAD estimations but significant and with the expected sign in the sub-sample OLS and Tobit estimations. One interpretation of this is that the teams with capacity constraints are generally the stronger teams who have big rivals but also have a habit of scheduling very weak teams from time to time. If capacity constraints are not allowed for, then it might appear that playing minnows does not reduce demand, but once capacity constraints are included the effect of the competitive imbalance becomes apparent. Our rivalry measure is also strongly significant and adds significantly to demand.

5 Schedule Simulations

5.1 Random Schedule

Based on this analysis we are able to construct simulated schedules for the 2010 season and estimated the demand that would be associated with these alternative schedules. First, we compared the actual schedule to a random schedule. 100 simulations were run where each week the visiting teams were randomly assigned one of the home teams. The results in Table 10 are the averages from the 100 simulations, and we discuss these below.

5.2 Stratified Schedules

Next, we simulated what a stratified schedule based on the quality measures for the teams. We report four schedules (conference realignments) based on (a) each quality measure (*MOV* and *ELO*) and (b) one year's quality measures (2010) or a ten year average quality measure.

For each schedule we ranked the teams from 1 to 118. We then put the top 13 teams in the first conference, the next 13 teams in the next conference, and so on. We then gave each team a 12 game schedule, 6 home games and 6 road games with the other 12 teams in the conference. Each team's schedule is balanced in the sense that if they play the best team at home, they play the next best team on the road, the next team at home, and so on. This balanced scheduling process generates a slightly smaller number of games than are currently played in a season.

Recall that demand in our model is determined by quality, which is in turn determined by performance results. For the simulation we need to update quality throughout the season. We did this by assuming that each team's quality measure is updated throughout the season in the way that the measures actually did change in 2010. For example, for a team's third road game, their quality measure was the same as that team's quality measure when they played their third game in 2010. If a team did not have 6 home games, or 6 road games, their last home/road quality measure was used. Unfortunately, with 118 teams, there is one team left over after teams have been assigned to 9 conferences. In the simulation, this team plays a generic Football Championship Subdivision team for each game.

The four proposed conferences are shown in Tables 6-9. Tables 6 and 7 are based only on quality as measured in 2010, tables 8 and 9 are based on average quality measured between 2001 and 2010. Tables 6 and 8 are calculated on the basis of the *MOV* measure, tables 7 and 9 on the basis of the *ELO* measure.

These schedules are optimal in the sense that the best teams (based on the relevant quality measure) are playing the best teams, which increases demand for college football. However, this does cause a decrease in rivalry games, which is a major complaint about conference realignment. Another factor that can decrease overall attendance is that each team has 6 home games and 6 road games. Currently, teams with high demand typically have more home games than road games, thereby increasing aggregate attendance.

Table 10 shows the results from the various schedules. The first row in Table 10 shows

that our stratified schedule does have fewer games, due to the fact that this schedule is balanced. Thus, while the second row shows the estimated total attendance for the 2010 season, the effect on demand is shown in the per game comparisons. The third row shows the highest team average. For example, for the 2010 season, if we put teams in conferences based on the quality measure of only one year and use the *MOV* quality variable, the average estimated attendance for Ohio St. was 113,611, the highest among all 117 teams. The final row shows the average attendance for each game.

The average attendance of the random schedules are .47% and .38% *lower* than the actual schedule using the *MOV* and *ELO* variables respectively. The average attendance using the one-year stratified schedule is 5.02% and 5.64% *higher* compared to the actual schedule. Again, these numbers would be higher except that many rivalry games are lost and all teams have the same number of home games. If we use the 10-year stratified schedule, attendance would increase 5.43% and 5.91% respectively. One reason for the slight increase compared to the one-year stratified schedule is that more rivalry games are intact.

Our results show that basing conference schedules on team quality is likely to increase attendance significantly relative to the current scheduling arrangements, which generates about the same attendance as would be generated by a completely random schedule.

6 Conclusions

It is commonplace in sports competition to match contestants of similar ability. In a league format, players of similar ability are usually classed together although there may be some opportunities to move between classes (in knock-out competition organizers usually prefer to seed players so that the best do not meet in the early rounds). Arguably this matching occurs because people like to see the best play against the best.

Sports economics has tended to focus on the competitive balance hypothesis that demand increases when opponents are equally balanced. This entails the proposition

that the best playing against the best (as well as the worst playing against the worst) is more attractive than contests among teams of unequal abilities.

In many contexts it has proved hard to demonstrate clear support for the competitive balance hypothesis, perhaps because leagues often tend to be relatively well balanced. It may be that the disparities in some college football games are great enough to reveal the competitive balance effect. Indeed, we know that strong teams often choose to play against a very weak opponents, and our analysis shows that this comes at a cost in terms attractiveness to fans. Our findings suggest that a conference restructuring that created competitively balanced conferences would significantly add to demand even if this required discarding several traditional rivalry games.

The competitive balance hypothesis has been used as an argument in favour of re-distribution among teams that are already members of a league. In the college football context, where teams have discretion to choose who they play during the season, the implications are rather different. It is not surprising that teams have incentives to pick very weak opponents, all else equal. There are benefits in terms preparing players for stronger opponents ahead, and also in terms of creating an aura of invincibility (even if this is not always entirely credible).

Were the NCAA free to design the entire conference system from scratch, then we suppose they would pick a structure along the lines we have identified. More interestingly, will realignments driven by individual choice lead ultimately to what we identify as the optimal structure? There are reasons to think that they will, given that strong teams potentially gain revenues when they commit to playing more games against other strong teams, and there are clear benefits to be seen to be playing at the highest level. We believe that conference realignments are evidence of this process at work. That said this process could take decades or more complete.

Finally, we draw a parallel between this problem and the issues facing European soccer competition. In Europe teams are traditionally organized in national leagues, but the most attractive competition format is generally thought to be UEFA Champions League,

where teams from different countries play each other. The problem with this system is that the top teams in different countries (e.g. Barcelona, Bayern Munich, Manchester United or AC Milan) seldom get to play each other. For many years now there have been discussions about the creation of a European Superleague and although this has not materialized existing competitions have been reformed to enable the top clubs from different countries to play each other more often than in the past. In our view, that is because fans typically want to see the best play against the best.

References

- Becker, Gary S. "A Theory of Marriage: Part I" *Journal of Political Economy*, 81(4), (1973), 813-847.
- Benz, Men-Andri, Leif Brandes, and Egon Franck, "Do Soccer Associations Really Spend on a Good Thing? Empirical Evidence on Heterogeneity in the Consumer Response to Match Uncertainty of Outcome" *Contemporary Economic Policy*, 27(2), (2009), 216-235.
- Borland, Jeff and Robert Macdonald, "The Demand for Sports" *Oxford Review Of Economic Policy*, 19(4), (2003), 478-502.
- Buraimo, Babatunde, David Forrest, and Robert Simmons, "Insights for clubs from modelling match attendance in football" *Journal of the Operational Research Society* 60, (2009), 147-155.
- Buraimo, Babatunde and Robert Simmons, "Do Sports Fans Really Value Uncertainty of Outcome? Evidence from the English Premier League" *International Journal of Sports Finance*, 3 (3), (2008), 146-155.
- Coates, Dennis and Brad R. Humphreys "Week to week attendance and competitive balance in the National Football League" *International Journal of Sport Finance*, 5, (2010), 239-252.
- Coates, Dennis and Brad R. Humphreys, "Game Attendance and Outcome Uncertainty in the National Hockey League" *Journal of Sports Economics* 13(4), (2012), 364-377.
- Davis, Michael C. "Analyzing the Relationship Between Team Success and MLB Attendance with GARCH Effects" *Journal of Sports Economics*, 10(1), (2009), 44-58.
- DeSchraver, Timothy D. and Paul E. Jensen, "Determinants of Spectator Attendance at NCAA Division II Football Contests" *Journal of Sport Management*, 16, (2002), 311-330.

- Forrest, D., J. Beaumont, J. Goddard, and R. Simmons, "Home advantage and the debate about competitive balance in professional sports leagues" *Journal of Sports Sciences*, 23(4), (2005), 439-45.
- Forrest, David, and Robert Simmons, "New issues in attendance demand: The case of English League Football" *Journal of Sports Economics*, 7(3), (2006), 247-266.
- Fort, Rodney and Jason Winfree, "15 Sports Myths and Why They're Wrong" Stanford University Press. (2013).
- Fréchette, Guillaume R., Alvin E. Roth and M. Utku Ünver "Unraveling yields inefficient matchings: evidence from post-season college football bowls" *RAND Journal of Economics*, 38(4), (2007), 967-982.
- Gale, D. and L. S. Shapley "College Admissions and the Stability of Marriage" *American Mathematical Monthly*, 69, (1962), 9-15.
- Groza, Mark D. "NCAA Conference Realignment and Football Game Day Attendance" *Managerial and Decision Economics*, 31(8), (2010), 517-529.
- Humphreys, Brad R. "The Relationship Between Big-Time College Football and State Appropriations for Higher Education" *International Journal of Sport Finance*, (1), (2006), 119-128.
- Keener, James P. "The Perron-Frobenius Theorem and the Ranking of Football Teams" *SIAM Review*, 35(1), (1993), 80-93.
- Kremer, Michael, "The O-Ring Theory of Economic Development", *Quarterly Journal of Economics*, 108, (1993), 551-575.
- Legros, Patrick and Andrew F. Newman "Monotone Matching in Perfect and Imperfect Worlds" *Review of Economic Studies*, 69(4), (2002), 925-942.
- Lemke, Robert J., Matthew Leonard, and Kelebogile Tlhokwane, "Estimating attendance at

- major league baseball games for the 2007 season" *Journal of Sports Economics*, 11(3), (2009), 316-348.
- Meehan Jr., James W., Randy A. Nelson and Thomas V. Richardson "Competitive balance and game attendance in major league baseball" *Journal of Sports Economics*, 8(6), (2007), 563-580.
- Mongeon, Kevin and Winfree, Jason, "Comparison of television and gate demand in the National Basketball Association" *Sport Management Review*, 15(1), (2012), 72-79.
- Paul, Rodney, Brad R. Humphreys and Andrew Weinbach "Uncertainty of Outcome and Attendance in College Football: Evidence from Four Conferences" *The Economic and Labour Relations Review* 23(2), (2012), 69-82.
- Powell, James L. "Least absolute deviations estimation for the censored regression model" *Journal of Econometrics*, 25(3), (1984), 303-325.
- Pope, Devin G. and Jaren C. Pope, "The impact of college sports success on the quantity and quality of student applications" *Southern Economic Journal*, 75(3), (2009), 750-780.
- Price, Donald I. and Kabir C. Sen, K., "The demand for game day attendance in college football: An analysis of the 1997 division 1-A season" *Managerial and Decision Economics*, 24, (2003), 35-46.
- Rascher, Daniel A. and John Solmes, "Do fans want close contests? A test of the uncertainty of outcome hypothesis in the National Basketball Association" *International Journal of Sport Finance*, 2, (2007), 130-141.
- Rhoads, Thomas A. and Shelby Gerking, "Educational contributions, academic quality, and athletic success" *Contemporary Economic Policy*, 18(2), (2000), 248 -258.
- Sattinger, Michael, "Assignment Models of the Distribution of Earnings" *The Journal of Economic Literature*, 31(2), (1993), 831-880.

Table 1: Previous Studies

Paper	sport	Price?	<i>UO</i> Hmeasure	Sign	Significant
DeSchriver & Jensen (2002)	College football	Yes (+, sig)	<i>Homewpcbyseasonquarter</i>	+	Yes, mostly in Q4
Price & Sen (2003)	College football	Yes (-, sig)	<i>Homewpc</i> <i>Awaywpc</i> <i>Dif f wpc</i> ²	+	Yes
				+	Yes
				-	No
Paul, Humphreys & Weinbach (2012)	College football	No	<i>Homewin%</i> , <i>pointsspread</i> , <i>under/over</i>	+	Yes
				+	Yes
				+	Yes
Groza (2010)	College football	No	<i>HomeWpc</i> <i>Sagarinrating</i> <i>Dif fsag</i> ²	+	Yes
				+	Yes
				-	Yes
Coates & Humphreys (2010)	NFL	No	<i>Homewpc</i> <i>Awaywpc</i> <i> Pointsspread </i> <i> Pointsspread</i> ² <i> Pointsspread * homeunderdog </i>	+	Yes
				+	Yes
				+	Yes
				-	Yes
				-	Yes
Meehan Nelson & Richardson (2007)	MLB	Yes (+, sig)	<i>Homewpc</i> <i>HomeGBdivleader</i> <i>AwayGBdivleader</i> <i>Wpcdif f absolute</i> <i>Wpcdif f+</i> <i>Wpcdif f-</i>	+	Yes
				-	Yes
				-	Yes
				-	Yes
				-	Yes
				+	Yes
Lemke, Leonard & Tlhokwane (2009)	MLB	Yes (+, sig)	<i>Homewinprob</i> <i>Homewinprob</i> ² <i>Playoff chances</i>	-	Marg
				+	Marg
				various	Marg
Davis (2009)	NL	No	<i>Homewpc > .5</i>	+	yes
Coates & Humphreys (2011)	NHL	No	<i>Probhomewin</i> <i>Homewpc</i> <i>Awaywpc</i>	+	Yes, if > .584
				-	No
				+	Yes
Rascher & Solmes (2007)	NBA	Yes(-, NS)	<i>(i)Wpchome</i> <i>Wpchome</i> ² <i>Wpcaway</i> <i>Wpcaway</i> ² <i>Dif finwpc</i> <i>Dif finwpc</i> ² <i>(ii)Homewinprob</i> <i>Homewinprob</i> ²	+	No
				+	No
				+	No
				+	No
				-	No
				-	No
				+	Yes
				-	Yes
Simmons & Buraimo (2008)	EPL	No	<i>Homeptspergame</i> <i>Awayptspergame</i> <i>Theilmeasure</i> <i>Probhomewin</i> <i>Probhomewin</i> ²	+	Yes
				+	Yes
				-	Yes
				-	Yes
				+	Yes
Forrest et al. (2005)	Eng. Foot. Lea. (3 division)	No	<i>Homepointspergame</i> <i>Awaypointspergame</i> <i>Probratio</i> <i>Probratio</i> ²	+	Yes
				-	No
				-	Yes
				+	Yes
Forrest & Simmons (2006)	FLC	No	<i>Homepoints</i> <i>Awaypoints</i> <i>Hometeamhome form</i> <i>Points/gamedifferenceadjusted</i>	+	Yes
				+	Yes
				+	Yes
				?	No
Buraimo, Forrest, & Simmons (2009)	FLC	No	<i>Homeptspergame</i> <i>Awayptspergame</i>	+	Yes
				+	Yes
Benz et al (2009)	Bundesliga	Yes (-, NS)	<i>Dif finleaguepos</i> <i>Dif finptspergame</i> <i>Theil</i> <i>Relativewinprob</i> <i>Probhomewin</i> <i>Probhomewin</i> ²	-	No
				-	No
				-	No
				-	No
				+	No
				+	No

Table 2: Estimation of Margin of Victory

Variable	Estimate	t-statistic
β_1	6.575	4.17
β_2	-3.331	-5.59
β_3	48.663	26.86
β_4	39.167	29.85
β_5	26.409	10.64
β_6	71.260	23.86
β_7	-54.304	-28.09
β_8	-39.496	-29.21
β_9	-29.737	-14.31
β_{10}	-70.739	-24.08
β_{11}	0.345	19.32
N	14278	
R^2	.37	
% of games predicted correctly	.73	

Table 3: List of Rivalry Games

Air Force	Army
Air Force	Navy
Alabama	Auburn
Alabama	LSU
Arizona	Arizona State
Army	Navy
California	Stanford
Duke	North Carolina
Florida	Georgia
Florida	Florida State
Florida State	Miami
Georgia	Georgia Tech
Indiana	Purdue
Iowa	Iowa State
Kansas	Kansas State
Kansas	Missouri
Michigan	Michigan State
Michigan	Notre Dame
Michigan	Ohio State
Mississippi State	Ole Miss
Notre Dame	Stanford
Notre Dame	USC
Oklahoma	Oklahoma State
Oklahoma	Texas
Oregon	Oregon State
Pittsburgh	West Virginia
Texas	Texas A&M
UCLA	USC
Utah	Utah State
Virginia	Virginia Tech
Washington	Washington State

Table 4: Summary Statistics for Attendance Estimation

Variable	Mean	Standard Deviation	Maximum	Minimum
Attendance	53092	26835	113090	1535
MOVH	26.822	9.227	49.088	0.068
MOVA	47.026	10.200	71.732	0
ELOH	1.092	0.229	1.620	0.452
ELOA	0.962	0.281	1.590	0.304
Sep	0.355	0.478	1	0
Oct	0.315	0.465	1	0
Nov	0.285	0.451	1	0
Dec	0.018	0.131	1	0
Rival	0.044	0.206	1	0
2001	0.051	0.219	1	0
2002	0.063	0.243	1	0
2003	0.059	0.236	1	0
2004	0.061	0.240	1	0
2005	0.070	0.255	1	0
2006	0.095	0.294	1	0
2007	0.111	0.315	1	0
2008	0.143	0.350	1	0
2009	0.151	0.358	1	0
2010	0.151	0.358	1	0

Table 5: Attendance Estimation (year and stadium fixed effects not shown)^{7,8}

	OLS	OLS sub	CLAD	Tobit	OLS	OLS sub	CLAD	Tobit
MOV_H	283 (6.64)	115 (1.91)	252 (4.01)	191 (5.56)				
MOV_A	114 (4.61)	33.4 (1.04)	73.2 (2.02)	60.1 (2.43)				
$MOV_H * MOV_A$	0.891 (1.04)	5.24 (4.23)	1.84 (1.41)	4.1 (3.00)				
ELO_H					21264 (13.79)	16456 (7.51)	18908 (12.05)	19714 (7.90)
ELO_A					7263 (4.78)	251 (0.12)	4039 (2.20)	2679 (1.23)
$ELO_H * ELO_A$					-816 (-0.60)	7074 (3.56)	1960 (1.18)	4733 (2.18)
Sep	-119 (-0.24)	-1104 (-1.53)	157 (0.32)	264 (0.48)	-479 (-1.00)	-1606 (-2.27)	-337 (-0.74)	-149 (-0.19)
Oct	-265 (-0.54)	-1781 (-2.45)	102 (0.22)	36.1 (0.06)	-1304 (-2.68)	-3003 (-4.19)	-1151 (-2.49)	-1230 (-1.40)
Nov	-947 (-1.93)	-3017 (-4.15)	-806 (-1.67)	-657 (-1.46)	-2328 (-4.77)	-4599 (-6.39)	-2445 (-5.11)	-2336 (-2.85)
Dec	599 (0.79)	-714 (-0.65)	-449 (-0.51)	739 (0.80)	-892 (-1.19)	-2390 (-2.22)	-1340 (-1.14)	-1046 (-0.87)
Rivals	4600 (11.71)	6707 (11.23)	6600 (6.14)	6114 (9.58)	4345 (11.20)	6097 (10.38)	5796 (4.77)	5689 (8.53)
R^2	0.963	0.933			0.964	0.935		
Log Likelihood				41197				41114
N	4839	2771	4839	4839	4839	2771	4839	4839

⁷“OLS sub” refers to OLS estimates using only teams that have no censored observations.⁸Standard errors for the CLAD estimation was calculated using a bootstrap with 200 replications.

Table 6: Conference alignment from MOV variable for 2010 season⁹

Conference 1	Conference 2	Conference 3
Texas	Arizona	Arkansas
Alabama	Oregon State	Utah
Cincinnati	LSU	UCLA
Boise State	BYU	Oklahoma State
Florida	Penn State	Bowling Green
Pittsburgh	Georgia Tech	Clemson
Wisconsin	Navy	Minnesota
Ohio State	Nebraska	Central Michigan
Iowa	North Carolina	Auburn
Oregon	Miami	Georgia
TCU	Missouri	Florida State
Virginia Tech	West Virginia	Kentucky
USC	Oklahoma	SMU
Conference 4	Conference 5	Conference 6
Washington	Syracuse	Middle Tennessee
Troy	Rutgers	Idaho
<i>Mississippi State</i>	<i>Stanford</i>	Northern Illinois
Marshall	Boston College	Louisiana Lafayette
Texas Tech	Fresno State	Utah State
South Carolina	South Florida	Ohio
Tennessee	UCF	Iowa State
East Carolina	Nevada	Louisiana Monroe
Purdue	<i>Notre Dame</i>	Texas A&M
Air Force	<i>California</i>	Temple
<i>Ole Miss</i>	Southern Miss	Florida Atlantic
Northwestern	Michigan State	Louisville
Houston	Wyoming	Baylor
Conference 7	Conference 8	Conference 9
<i>Kansas</i>	San Jose State	Western Michigan
Tulsa	NC State	Toledo
UNLV	Memphis	Duke
<i>Kansas State</i>	Arizona State	North Texas
Wake Forest	Louisiana Tech	Tulane
Colorado State	Washington State	Vanderbilt
Miami (OH)	Illinois	UTEP
UAB	Virginia	Rice
Hawaii	Army	Kent State
Michigan	Indiana	Maryland
Buffalo	San Diego State	New Mexico State
Colorado	Florida International	Western Kentucky
Arkansas State	New Mexico	Ball State

⁹Teams in italics maintained a rivalry game with this conference alignment. Stanford maintained 2 rivalry games. Eastern Michigan was the last ranked team and played Football Championship Subdivision teams in the simulation.

Table 7: Conference alignment from ELO variable for 2010 season¹⁰

Conference 1	Conference 2	Conference 3
<i>Florida</i>	TCU	Boston College
<i>Texas</i>	Georgia Tech	Clemson
<i>Alabama</i>	Utah	Auburn
Ohio State	BYU	Pittsburgh
USC	Texas Tech	Miami
Oregon	Iowa	Arkansas
Penn State	Oregon State	Arizona
Boise State	Nebraska	Missouri
Virginia Tech	West Virginia	Ole Miss
<i>Oklahoma</i>	Wisconsin	Tennessee
<i>Georgia</i>	Florida State	Stanford
Cincinnati	California	South Carolina
<i>LSU</i>	Oklahoma State	Rutgers
Conference 4	Conference 5	Conference 6
North Carolina	NC State	Maryland
Michigan State	Mississippi State	Troy
Northwestern	Air Force	Washington
Kentucky	Texas A&M	Hawaii
UCLA	Michigan	Colorado
South Florida	Purdue	UCF
Kansas	Kansas State	Illinois
Wake Forest	Houston	Iowa State
Notre Dame	Fresno State	Middle Tennessee
Navy	Virginia	Wyoming
East Carolina	Nevada	Southern Miss
Central Michigan	Minnesota	Baylor
Arizona State	Louisville	Tulsa
Conference 7	Conference 8	Conference 9
Vanderbilt	Rice	UTEP
Indiana	SMU	San Jose State
Syracuse	Northern Illinois	Arkansas State
Bowling Green	Colorado State	Utah State
Washington State	UAB	Memphis
Temple	Idaho	Kent State
UNLV	Louisiana Lafayette	Army
Ohio	New Mexico	Florida International
Marshall	Louisiana Monroe	Tulane
Duke	Buffalo	New Mexico State
Louisiana Tech	Ball State	Miami (OH)
Florida Atlantic	San Diego State	Eastern Michigan
Western Michigan	Toledo	North Texas

¹⁰Teams in italics maintained a rivalry game with this conference alignment. Western Kentucky was the last ranked team and played Football Championship Subdivision teams in the simulation.

Table 8: Conference alignment from average MOV variable from 2001 to 2010 season¹¹

Conference 1	Conference 2	Conference 3
USC	Tennessee	Iowa
<i>Oklahoma</i>	<i>Auburn</i>	Louisville
<i>Texas</i>	Oregon State	UCLA
<i>Florida</i>	West Virginia	Oklahoma State
LSU	Michigan	South Carolina
Ohio State	<i>Alabama</i>	Arkansas
<i>Miami</i>	Boston College	Cincinnati
<i>Florida State</i>	Wisconsin	Clemson
<i>Georgia</i>	Texas Tech	Penn State
Virginia Tech	Notre Dame	Maryland
Boise State	Georgia Tech	Pittsburgh
Oregon	Nebraska	California
TCU	Utah	BYU
Conference 4	Conference 5	Conference 6
Fresno State	Bowling Green	Arizona
Texas A&M	Washington	Northern Illinois
Colorado	South Florida	NC State
Virginia	Colorado State	Kentucky
Southern Miss	Michigan State	Air Force
Purdue	Arizona State	Troy
Kansas State	North Carolina	Illinois
Minnesota	Syracuse	New Mexico
Wake Forest	Stanford	Kansas
Northwestern	Toledo	Nevada
Missouri	Marshall	Miami (OH)
Ole Miss	Hawaii	Houston
Washington State	East Carolina	Western Michigan
Conference 7	Conference 8	Conference 9
Rutgers	Ball State	Tulane
Tulsa	North Texas	Arkansas State
UCF	UTEP	Western Kentucky
Mississippi State	UNLV	SMU
Iowa State	Rice	Louisiana Lafayette
Central Michigan	Utah State	New Mexico State
Middle Tennessee	San Jose State	Idaho
Baylor	Vanderbilt	Kent State
Louisiana Tech	Indiana	Louisiana Monroe
UAB	Ohio	Duke
Memphis	San Diego State	Buffalo
Navy	Wyoming	Army
Florida Atlantic	Temple	Florida International

¹¹Teams in italics maintained a rivalry game with this conference alignment. Florida and Florida St. maintained 2 rivalry games. Eastern Michigan was the last ranked team and played Football Championship Subdivision teams in the simulation.

Table 9: Conference alignment from ELO variable from 2001 to 2010 season¹²

Conference 1	Conference 2	Conference 3
<i>Texas</i>	<i>Oregon</i>	Iowa
<i>Florida</i>	Nebraska	Arkansas
USC	Wisconsin	Kansas State
<i>Oklahoma</i>	Penn State	UCLA
<i>Ohio State</i>	<i>Oregon State</i>	Utah
<i>Georgia</i>	Boston College	Virginia
LSU	Texas Tech	California
<i>Miami</i>	Alabama	Maryland
<i>Florida State</i>	Georgia Tech	TCU
Virginia Tech	Boise State	Purdue
Tennessee	Clemson	Louisville
<i>Michigan</i>	West Virginia	Texas A&M
Auburn	Notre Dame	Arizona State
Conference 4	Conference 5	Conference 6
South Carolina	Arizona	Colorado State
Colorado	Minnesota	Marshall
BYU	Cincinnati	Mississippi State
NC State	North Carolina	Air Force
Michigan State	South Florida	Illinois
Pittsburgh	Fresno State	Toledo
Missouri	Northwestern	New Mexico
<i>Washington State</i>	Southern Miss	East Carolina
Oklahoma State	Kansas	Troy
Ole Miss	Hawaii	Bowling Green
<i>Washington</i>	Iowa State	Indiana
Stanford	Kentucky	Miami (OH)
Wake Forest	Syracuse	Houston
Conference 7	Conference 8	Conference 9
Rutgers	Baylor	Duke
Northern Illinois	Tulsa	SMU
Navy	UNLV	North Texas
UCF	Middle Tennessee	Utah State
Nevada	Rice	Florida International
Louisiana Tech	Tulane	Louisiana Lafayette
Memphis	Central Michigan	Arkansas State
Vanderbilt	San Jose State	New Mexico State
San Diego State	Ball State	Louisiana Monroe
Florida Atlantic	Ohio	Kent State
Wyoming	UTEP	Idaho
UAB	Western Kentucky	Army
Western Michigan	Temple	Eastern Michigan

¹²Teams in italics maintained a rivalry game with this conference alignment. Florida and Florida St. maintained 2 rivalry games. Buffalo was the last ranked team and played Football Championship Subdivision teams in the simulation.

Table 10: Unrestricted Attendance Estimation From Simulation Results

schedule	actual		random		stratified		10 year avg.	
	MOV	ELO	MOV	ELO	MOV	ELO	MOV	ELO
# of games	729	729	729	729	708	708	708	708
total att.	31,484,558	31,533,459	31,336,819	31,413,705	31,841,933	32,077,262	31,813,761	32,038,083
max team	113611 Ohio St.	113901 Ohio St.	112440 Ohio St.	112849 Ohio St.	116774 Ohio St.	117062 Ohio St.	115614 Ohio St.	117174 Ohio St.
min team	8884 Ball St	9636 Ball St	10093 Ball St	11071 E. Mich.	9272 Ball St	9663 E. Mich.	9401 Ball St	10101 E. Michigan
avg. att.	43119	43256	42986	43092	45359	45694	45319	45638
% from actual			-.47%	-.38%	5.02%	5.64%	5.43%	5.91%