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Abstract

This article presents a method to measure the impact of the home field advantage for intra-conference college football. The method models longitudinal data across several years while utilizing a unique home field parameter for each individual team. Additionally, two novel yet intuitive measures of home field advantage are proposed. As a case study of the method and the definitions of home field advantage, teams with the best and worst home field advantages within their respective conferences are determined.

KEYWORDS: WinBUGS, Gibbs sampler, Linear Model, chi-square fit, MCMC, DIC

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1. INTRODUCTION

The question “Who has the best home field advantage?” has long circulated among sports enthusiasts. Home field advantage is an idea that is common to many sports, although the size of the effect appears to differ between sports. For example, the prediction rule "home team wins" works with different success rates depending on the sport (Stern, 1997).

It is well known that home teams in college football enjoy an advantage over their visiting opponent (Harville, 2003; Stern, 2004). Some teams, however, may have a better home field advantage than others. Understanding how home field advantage varies from team to team is an important concept to fans, faculty, staff, and students of a university (Stratton, 2002). The ability of home fans to influence their team’s performance in the game is difficult to measure. The impact that fans have on the game might be independent of the talent on the field. For example, the team with the worst talent in the nation might increase their level of play when playing in front of their home fans, whereas a more talented team might play with equal consistency both at home and on the road. Accordingly, it is not important that the team win more than half of their games at home, only that the home field provides the team a better chance of winning compared to their play on the road. Therefore the definition of home field advantage measures the score difference of the home team versus a team of equal ability.

This definition is a traditional view of home field advantage used in most home field advantage models (Harville, 2003; Glickman and Stern, 1998). This approach, referred to here as the *first definition*, called *home field advantage*, is convenient because it is directly estimated from the models. The limitation of this definition is its restrictiveness to a comparison of the home team versus a road team of the exact same ability - a virtual clone of themselves.

A broader view of home field advantage incorporates the home team’s ability compared to the ability of all of their opponents. Therefore, a *second definition* of home field advantage, called *home field winning probability*, is to simply measure the probability that the team wins at home against a randomly selected opponent. This definition combines the team’s ability together with their home field advantage estimated from the first definition of home field advantage. This non-conventional approach provides what many fans desire – the probability of a particular team winning at home against a randomly selected opponent. It is also a reasonable measure for combining a team’s strength and its home field advantage.

Some may have reservations about this definition because the measure might be nearly indistinguishable from the probability a team wins on a neutral field against a randomly selected opponent. An improvement might be to examine the ratio of this measure and the probability a team wins on neutral field against a randomly selected opponent. This type of measure will indicate a level of improvement of playing on one's home field over a neutral field. This *third definition* of home field advantage we refer to as the *home impact*. This article presents the impact the home field has on the outcome of college football games, using all three definitions.

Many fans utilize a team's home record to assess its home field advantage. Empirical evidence, such as wins and losses at home and on the road, and the difference in the scores between teams allow determination of an individual team's home field advantage

This paper focuses on identifying the team that has the best home field advantage in a particular conference. The exploration of home field advantage within conference is interesting because these teams generally play intra-conference home games four times a year. An interesting source for highly competitive college football conferences comes from members of the Bowl Championship Series (BCS). The BCS, formed in 1996 (Stern, 2004), uses a formula for matching major conference teams into four season finale major bowl games - one being the national championship game. This paper considers home field advantage for three BCS member conferences from the inception of the BCS to the 2004 season. The introductory details of our statistical model utilize the Big 12 conference, but the methodology developed can be applied to any of the other conferences in college football. In addition to reporting home field results for the Big 12, we explore the Big 10 and the Pac 10 conferences (Table 1).

A past approach includes Harville's (2003) linear model that assumes each team possess the same home field advantage. Using least squares and modifications of least squares, the model provides a single measure of home field advantage.

Another approach uses a separate home field parameter for each team. Glickman and Stern (1998) model the longitudinal difference in National Football League (NFL) scores on six and a half years of data. Using a fully Bayesian analysis, they model current team strength conditional on past team strength with "a between-season regression parameter" that reflects the degree of shrinkage or expansion.

Our longitudinal alternative to Glickman and Stern also utilizes a separate home field parameter for each team, but models year to year variation in the team effect using piecewise linear functions with three knots across nine seasons. Our model provides a slope parameter between knots interpreted as to the direction of the team's longitudinal effect. If the team's cumulative slope between a pair of knots is positive, then that the team's effect is increasing between knots; likewise if the slope is negative, it is decreasing. Besides a good fit to college football data, ours is an attractive model since the slope between a pair of knots covers two seasons of a strong recruiting class.

While our model is a simpler alternative to Glickman and Stern's (i.e. less parameters), it suffers in predicting score differences for future seasons because of extrapolation. However, as shown by the goodness of fit, our model is a reasonable alternative for estimating longitudinal team ability and home field advantage for college football teams.

Our Bayesian approach quantifies the probability of both a team winning against an equally talented team at home (first definition of home field advantage); winning at home against a randomly selected team within their conference (second definition of home field advantage); and the ratio of the probability of winning at home against a randomly selected team within their conference divided by the probability of winning on a neutral field against a randomly selected team within their conference (third definition of home field advantage). Big 12 conference data are introduced in Section 2. A repeated measures normal model and a report of the prior distributions for model parameters are shown in Section 3. In Section 4, a discussion of the multifaceted computational issues related to the Bayesian application is provided. The resulting posterior distributions, their relation to parameter estimates, and a discussion of the implications is provided in Section 5. Conference home field results are presented in Section 5 and concluding remarks in Section 6.

	Big 12		Big 10		Pac 10
BU	Baylor	IL	Illinois	AZ	Arizona
CU	Colorado	IU	Indiana	ASU	Arizona State
ISU	Iowa State	IA	Iowa	CAL	California
KSU	Kansas State	MI	Michigan	OU	Oregon
KU	Kansas	MSU	Michigan State	OSU	Oregon State
MU	Missouri	MN	Minnesota	SU	Stanford
NU	Nebraska	NU	Northwestern	UCLA	Univ California LA
OSU	Oklahoma State	OSU	Ohio State	USC	Southern California
OU	Oklahoma	PSU	Penn. State	WA	Washington
A&M	Texas A&M	PU	Purdue	WSU	Washington State.
TT	Texas Tech	UW	Wisconsin		
UT	Texas				

Table 1. Three conferences and their respective teams analyzed in this paper.

2. CONFERENCE DATA: BIG 12

The longitudinal data used are from regular season Big 12 conference football games for the years 1996-2004. With few exceptions, each team played four conference home games every year. The annual game between UT and OU is played on a neutral field, in Dallas, Texas and the 1998 NU and OSU game was played in Kansas City, Missouri. These neutral field games are included in the analysis in order to estimate regular season team ability in conference play. Championship games are not included in the analysis.

The average margin of victory for each team home conference competition is shown in Table 2A. A positive score indicates that the team scored more total points than their opponents in home games. To understand the patterns for teams when they are visiting their opponent, consider the data in Table 2B. For these data, the results are reversed so that positive values indicate that the visiting team score more total points than their opponents. There are a few patterns to notice in the data. First, with the exception of BU, all teams have at least one year of positive average margin of victory. Second, the average margin of victory varies considerably from year to year. Part of the variation can be explained by the fact that there are at most four games per average.

Another source of variation is due to strength of schedule. To understand the scheduling issue, consider the structure of the Big 12 Conference. The conference has two six-team divisions, the North and the South. Every team within a division plays each other once a year, alternating home and away from year to year. They each play three additional inter-division games, in a two-year series, alternating home and away. Thus, each year each team plays five games within their division and three games in the other division.

Displayed in Tables 3A and 3B is the number of games that each team won at home and on the road, respectively. As an example of the home field impact consider that NU won only 21 games on the road, but won 31 games at home from 1996 to 2004.

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A)

	Average Margin of Victory									
	Year									
Home	1996	1997	1998	1999	2000	2001	2002	2003	2004	Mean
BU	.00	-14.25	-17.25	-36.75	-28.00	-35.00	-28.00	-27.25	-13.75	-22.25
CU	11.25	4.25	6.50	13.00	-7.25	15.25	19.00	-3.75	-10.00	5.36
ISU	-6.75	-8.25	-13.75	-8.75	-1.25	.75	21.25	-38.50	-5.25	-6.72
KSU	-1.75	24.50	32.00	38.50	9.75	9.50	29.50	25.75	-2.50	18.36
KU	-18.25	-3.50	-11.25	13.00	-18.00	-29.50	-37.00	9.00	-2.75	-10.92
MU	-7.25	10.75	12.50	-10.75	-5.25	-11.25	-7.00	27.25	-5.75	.36
NU	38.50	45.50	11.50	30.50	29.50	16.00	7.75	11.25	13.25	22.64
OSU	-2.00	1.25	2.75	4.00	2.75	-13.25	13.25	-2.50	9.50	1.75
OU	-21.75	-21.25	-6.75	37.50	24.50	8.75	29.50	44.75	21.25	12.94
A&M	-.75	20.25	11.50	17.75	5.75	2.25	-2.50	4.00	3.75	6.89
TT	7.25	-2.25	3.50	11.25	5.25	2.75	23.50	9.00	22.75	9.22
UT	32.00	-3.50	9.00	11.75	32.25	29.25	21.00	-5.25	18.00	16.06
Mean	2.54	4.46	3.35	10.08	4.17	-.37	7.52	4.48	4.04	4.47

B)

	Average Margin of Victory									
	Year									
Visitor	1996	1997	1998	1999	2000	2001	2002	2003	2004	Mean
BU	-23.75	-13.50	-7.00	-34.75	-37.25	-20.00	-40.25	-34.00	-28.75	-26.58
CU	12.50	.25	-10.00	3.50	1.75	-2.00	7.50	-3.00	1.00	1.28
ISU	-12.75	-34.00	-24.50	-11.75	-4.25	3.75	-30.25	-31.50	-4.75	-16.67
KSU	10.50	6.25	26.00	5.50	12.50	2.25	33.00	16.50	-2.75	12.19
KU	-10.50	-23.00	-17.25	-31.00	-14.25	-25.25	-26.75	-18.50	-6.50	-19.22
MU	-20.25	-6.75	2.00	-32.75	-11.50	-7.00	-6.50	-14.25	-1.50	-10.94
NU	34.25	18.25	6.25	9.00	14.25	23.00	-13.50	-2.75	-29.50	6.58
OSU	-28.50	10.00	-8.00	-14.75	-30.75	-2.25	-6.75	-2.00	-1.50	-9.39
OU	-2.50	-13.75	-11.50	-3.25	17.75	11.50	8.25	37.75	13.75	6.44
A&M	.75	7.00	8.25	-11.75	6.50	-9.00	7.75	-41.75	8.25	-2.67
TT	4.75	7.50	-1.25	-17.50	-7.75	4.50	-20.50	3.00	-2.75	-3.33
UT	5.00	-11.75	-3.25	18.50	3.00	25.00	-2.25	36.75	6.50	8.61
Mean	-2.54	-4.46	-3.35	-10.08	-4.17	.37	-7.52	-4.48	-4.04	-4.47

Table 2. A) Each team's average difference in score at home across the nine years of the Big 12. B) Team's average difference in score as a visitor across the nine years of the Big 12.

A)

Sum

	Number of Games Won at Home									
	Year									
Home	1996	1997	1998	1999	2000	2001	2002	2003	2004	Total
BU	1	1	1	0	0	0	1	1	1	6
CU	4	1	3	3	1	4	4	2	2	24
ISU	1	1	1	0	2	2	4	0	2	13
KSU	3	4	4	4	3	2	3	4	1	28
KU	0	3	1	3	1	0	0	3	1	12
MU	2	3	3	1	1	1	1	4	1	17
NU	4	4	3	4	4	4	2	3	3	31
OSU	2	2	2	2	1	0	4	3	2	18
OU	1	1	2	4	4	3	4	4	4	27
A&M	1	4	4	4	2	3	1	2	3	24
TT	2	2	3	4	2	2	4	3	3	25
UT	4	2	4	3	4	3	4	3	4	31
Total	25	28	31	32	25	24	32	32	27	256

B)

Sum

	Number of Games Won on the Road									
	Year									
Visitor	1996	1997	1998	1999	2000	2001	2002	2003	2004	Total
BU	0	0	0	0	0	0	0	0	0	0
CU	3	2	1	2	2	3	3	1	2	19
ISU	0	0	0	1	3	2	0	0	2	8
KSU	3	3	4	3	3	1	3	2	1	23
KU	2	0	0	0	1	1	0	0	1	5
MU	1	2	2	0	1	2	1	0	2	11
NU	4	4	2	3	2	3	1	2	0	21
OSU	0	3	1	1	0	2	1	2	2	12
OU	2	1	1	1	4	3	2	4	4	22
A&M	3	2	3	1	3	1	2	0	2	17
TT	3	3	1	1	1	2	1	1	2	15
UT	2	0	2	3	3	4	2	4	3	23
Total	23	20	17	16	23	24	16	16	21	176

Table 3. A) Each team's number of games won at home across the nine years of the Big 12. B) Team's number of games won on the road across nine years of the Big 12. This does not include UT versus OU across all years and the 1998 NU versus OSU because these games were played on a neutral field.

3. MODEL AND PRIOR DISTRIBUTIONS

3.1. Model for Single Season with a Constant Home-Field Advantage

Consider an individual game for one year in which the difference in scores between the home and visiting teams is $y_{jj'}$ where *j* is the home team playing the road team *j'*. The difference score is modeled with the equation $y_{jj'} = B_j - B_{j'} + \lambda + e$, where the "team effects" $B_1, \ldots, B_K$ (*K* teams) and the "home field advantage," λ, are unknown parameters and *e* is the residual noise of the model. Harville shows that the individual parameters are not identifiable. However, a linear combination of the parameters in the form $\sum_{j=1}^{K} d_j B_j + c\lambda$ is identifiable, where $\sum_{j=1}^{K} d_j = 0$. Therefore, one can predict two teams' difference score by setting all of the *d*'s to zero except $d_j = 1$ and $d_{j'} = -1$. Notice also that λ, which is fixed across all teams, is identifiable when a team plays a clone of itself (*j=j'*). In this paper, we allow for each team to have their own home field advantage parameter, λ_j, allowing us to examine how the home advantage varies across teams.

3.2. Longitudinal Model for Several Seasons (Our Approach)

The longitudinal model for the Big 12 Conference data is on 432 games played across nine years. Let $n_{ijj'}$ represent the number of games in which teams *j* and *j'* are the home and visiting teams respectively at the *i*th season, and for *i*, *j* and *j'*, let $y_{ijj'k}$ represent the difference score for the game between the *j* and *j'* teams in the *k*th matchup of the *i*th season. Note that in the case of our analysis that $n_{ijj'} = 1$ since we do not include conference championship games. If championship games or intra-conference bowl match ups are included, then it is possible for $n_{ijj'} > 1$. For any game played on a neutral field, label one of the two opposing teams as the "home team." The variable $z_{ijj'k}$ is an indicator variable that equals 0 if the *ijj'k*th game is played on a neutral field and 1 otherwise.

The main linear model is

$$y_{ijj'k} = \mathrm{B}_{ij} - \mathrm{B}_{ij'} + z_{ijj'k}\lambda_j + e_{ijj'k}, \qquad i = 1, \ldots, 9;$$
$$j \neq j' = 1, \ldots, 12; \quad k = 1, \ldots, n_{ijj'},$$

where the "team effects" for year $t_i = 1995 + i$, $\mathrm{B}_{i1},...,\mathrm{B}_{i12}$, and the "home field," λ_j, are unknown parameters and where the $e_{ijj'k} \sim N\left(0, \sigma_e^2\right)$. More specifically, B_{ij} is the "strength parameter" for team *j* for year t_i.

The strength parameter for each team is modeled using a linear spline as a function of time. Specifically, for each *j*=1,…,12 $\mathrm{B}_{ij} = \beta_{0j} + \beta_{1j}t_i + \beta_{2j}t2_i + \beta_{3j}t3_i + \beta_{4j}t4_i$ where:

- $t2_i = \max\left(t_i - 1997.5, 0\right)$,
- $t3_i = \max\left(t_i - 2000, 0\right)$ and
- $t4_i = \max\left(t_i - 2002.5, 0\right)$.

As mentioned in the introduction, the model provides a slope parameter between knots interpreted as to the direction of the team's longitudinal effect. If the team's cumulative slope between a pair of knots is positive, then that the team's effect is increasing between knots; likewise if the slope is negative, it is decreasing. The model is attractive since the slope between a pair of knots covers two seasons of a strong recruiting class.

The piecewise function will allow for team improvement or decline for four different times across the nine years of the Big 12 existence. The first linear association is between 1996 and 1997, the second is between 1998 and 2000, the third 2001 to 2002 and the final is between 2003 and 2004. The model allows for more flexibility than a simple linear model. This piecewise linear model is similar to the model that Berry and Wood (2004) applies to football field goal data.

For inferential purposes, a Bayesian approach is used to model the data, requiring prior distributions on all of the unknown model parameters.

3.3. Priors

All of the regression parameters are each assigned flat (constant) priors.

We assume the prior distributions are all semi-conjugate (Gelman et al., 2000). The variance parameter has an informative gamma distribution, specifically $1/\sigma_e^2 \sim IG\left(1.2, 80\right)$. This corresponds to a prior 90% credible interval for σ_e of 5 to 29. Considering that Gelman et al. (2000) obtained a point estimate for the standard deviation of about 14 in college football data difference scores, our prior is informative but relatively wide.

The second set of informative priors is for the set of parameters that explain home field advantage. For team *j*, $\lambda_j \sim N\left(2, 10^2\right)$ is a reasonable prior since Harville (2003) reported estimates of about four points. The 90% credible interval is -14.5 to 18.5. Therefore this set of priors is also informative but wide compared to previous work.

4. CALCULATION AND COMPUTATION

4.1. Computational Discussion

A Bayesian estimation of the model parameters is performed using Markov chain Monte Carlo (MCMC), implemented in WinBUGS (Gilks et al., 1994; Gilks et al., 1996; Congdon, 2001). Following a burn-in of 5,000 iterations, the posterior distributions were monitored over a further 10,000 iterations of the MCMC. The length of burn-in and monitoring was sufficient to achieve convergence as assessed by trace plots, autocorrelation for each identified parameter and a calculation of the square root of a weighted sum of within-sequence variance and between-sequence variance divided by within-sequence variance of three sampling chains with different starting values (*F*). If *F* value is close to 1 then the model has converged (Gelman et al., 2000).

4.2. Prediction and Probability Calculations

First, all of the conference teams' average differences are evaluated against a visiting reference team (*R*). This will allow a cross comparison for all teams relative to that reference team. Specifically, the posterior distribution of $\mu_{ijR} = \mathrm{B}_{ij} - \mathrm{B}_{iR} + \lambda_j$ is calculated, to evaluate home team *j* against the visiting reference team *R* at year t_i. It makes sense to choose as a reference team, the team with the most stability in wins over the life of the conference. In the Big 12, Texas Tech (TT) is chosen because of their consistency of performance.

To evaluate the home field advantage (*first definition*), the parameter $\mu_{ijj} = \mathrm{B}_{ij} - \mathrm{B}_{ij} + \lambda_j = \lambda_j$, which is the difference in scores for the j^{th} team playing itself at home, is investigated. In addition to the difference score, the predictive probability of winning at home, against a visiting clone of themselves, is calculated. This probability is the proportion of times $y_j^P \sim N\left(\lambda_j, \sigma_e^2\right)$ is greater than 0, calculated from the Markov chain Monte Carlo (MCMC).

Exploration of the *second definition* of home field advantage, home field winning probability, is estimated by the proportion of times $y_{ijj'k}^P \sim N\left(\mathrm{B}_{ij} - \mathrm{B}_{ij'} + \lambda_j, \sigma_e^2\right)$ is greater than 0 where *j'* (the visiting team's index) is drawn uniformly from the set of integers from 1 to *T*, where *T* is the number of teams in the conference (*T*=12, 11, and 10 for Big 12, Big 10, and Pac 10). The *third definition* of home field advantage, home impact, is the ratio of the probability measure and the probability a team wins on neutral field against a randomly selected opponent (proportion of times $y_{ijj'k}^{P_2} \sim N\left(\mathrm{B}_{ij} - \mathrm{B}_{ij'}, \sigma_e^2\right)$ is greater than 0), averaged across all years. These measures are also calculated from the Markov chain Monte Carlo (MCMC).

Several models are examined before choosing the final model. The specifics of the Big 12 are presented. The relative fit of each of the models is assessed using deviance information criterion (DIC, Spiegelhalter et al., 2002). Here are the four variations of the main model:

M1. Set the regression parameters $\beta_{0j} = \beta_{1j} = \beta_{2j} = \beta_{3j} = \beta_{4j} \equiv 0$. This model relies solely on the home field advantage parameter for describing the variation from team to team. A team's home field advantage would completely determine (up to random variation) the probability of winning a conference game.

M2. Set the regression parameters $\beta_{1j} = \beta_{2j} = \beta_{3j} = \beta_{4j} \equiv 0$. This model has a team parameter and home field parameters. In addition to home field advantage, each team would have an ability parameter that would remain constant from year to year.

M3. Set the regression parameters $\beta_{2j} = \beta_{3j} = \beta_{4j} \equiv 0$. This model has a team linear trend across time and home field parameters. In addition to home field advantage, each team would have an ability parameter that is allowed to change *linearly* from year to year.

M4. This is the full model described in Section 3.1. This model has the advantage for a team's ability to change in *a non-linear* fashion.

We assess the adequacy of the fit of the final model, the model with the lowest DIC, using a Bayesian chi-square test for goodness of fit (Johnson, 2004). This produces a p-value at each of the iterations of the MCMC. For a sample of size 432 (Big 12), twelve equal probability bins for a_u were selected (Johnson, 2004). See Johnson (2004) for further details of the algorithm for calculating the chi-squared test statistic. If the 5%-tile of the p-value of the chi-square test statistic is above 0.01 and the 95%-tile is below 0.99, the model is considered adequate. Models not fitting this criterion "must therefore be attributed to either dependence between the sampled values of the chi-squared statistic, or lack of fit" (Johnson, 2004).. Therefore chi-squared values in this range lead to a properly specified conditionally independent model. Note that this chi-squared test statistic is different than that proposed by Gelman et al. (1996).

5. RESULTS

For presentation purposes we focus on modeling the Big 12 data and give specific results for model parameters, model selection, model fit, and provide a discussion of the results regarding home field advantage. We also give results for the Big 10 and Pac 10 conferences. The reader can replicate our approach for a conference team of their choice by downloading data from http://www.goldsheet.com and using team websites.

For reference we place the name and the definition for each home field advantage definitions:

Name	Definition	Notation for home team j
1. Home field advantage	1. Score difference (& probability) of home team playing a "clone of themselves" at home.	1. λ_j and $P\left(y_j^P > 0 \mid \lambda_j, \sigma_e^2\right)$
2. Home field winning probability	2. Probability home team winning against a randomly selected team at home.	2. $P\left(y_{ijj'k}^P > 0 \mid \mathrm{B}_{ij} - \mathrm{B}_{ij'} + \lambda_j, \sigma_e^2\right)$ for a randomly selected opponent j'.
3. Home Impact	3. Probability home team winning against a randomly selected team at home *divided* by probability home team winning against a randomly selected team on a neutral field (*Home Impact*), averaged across all years.	3. $\sum_{i=1}^{9} \frac{\left\{P\left(y_{ijj'k}^P > 0 \mid \mathrm{B}_{ij} - \mathrm{B}_{ij'} + \lambda_j, \sigma_e^2\right)\right\}}{\left\{P\left(y_{ijj'k}^P > 0 \mid \mathrm{B}_{ij} - \mathrm{B}_{ij'}, \sigma_e^2\right)\right\}} / 9$ for randomly selected opponent j'.

5.1. Estimation of Model Parameters in Big 12

Inspection of the trace plots, autocorrelation plots and the diagnostics statistics for all model parameters including the variance parameter and the regression parameters, using various starting values, indicated quick convergence to the stationary distribution. The diagnostic test statistics for all model parameters were 1.01 when rounded to two significant digits.

When comparing the four models, model M4 has the lowest DIC since DIC=3899 (M1), 3807 (M2), 3808 (M3), and 3720 (M4). It is interesting that M2 and M3 are rather close. This suggests that a naïve single linear relationship would not outperform flat team strength across time. The lower M4 suggests that a non-linear trend is beneficial. The model with the lowest DIC indicates the best goodness of fit even after adjusting for the number of parameters. The DIC compares these sets of models relative to one another but does not tell us if the model actually fits well to our particular dataset.

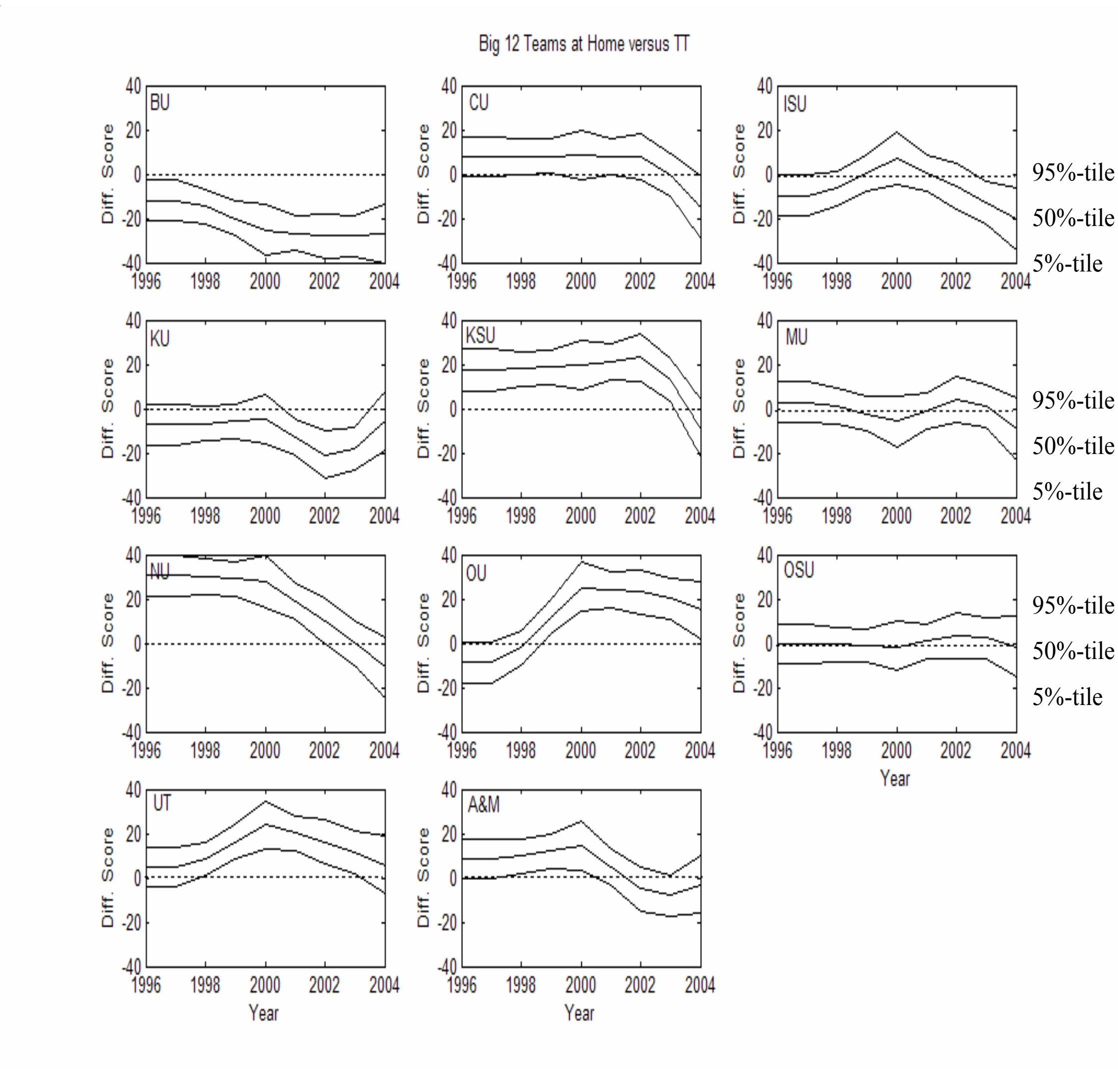
To see if this particular model fits our dataset, a 90% credible interval of 4.1-18.5 and a median of 9.4 for the chi-square test statistic, corresponds to 90% interval of 0.0324-0.9291 and median of 0.4128 pvalues. This is a reasonable fit. Therefore the chi-squared values in this range indicate a properly specified conditionally independent model.

The posterior distribution of the parameter, σ_e, has a 90% credible interval of 15.8-17.8. This says that the variation from game to game, relative to what is expected, is greater than two touchdowns. Therefore, a loss by a team favored to win by 34 or more points would be quite rare.

Figure 1 shows the distribution of the expected difference scores ($\mathrm{B}_{ij} - \mathrm{B}_{i12} + \lambda_j$), at home, across time relative to team 12 (TT, even if the team did not play TT in that particular season). For example, BU has a median -10 and a 90% credible interval of -20 to -2 for expected difference ($\mathrm{B}_{1,1} - \mathrm{B}_{1,12} + \lambda_1$) score against TT in 1996.

The fact that the comparison adjusts for strength of schedule is a key concept of the model. If a particular team has a difficult/weak schedule one can still estimate the strongest team in the Big 12 for that particular year. The strongest team is defined to be the team with the best chances of winning a game against a randomly selected opponent in the Big 12. Interestingly, from the 90% intervals in Figure 1, in 2004 three teams were significantly lower than TT: BU, CU, and ISU. Seven teams have intervals overlapping 0 in 2004 (KU, KSU, MU, NU, OSU, UT and A&M), whereas OU has an interval that is completely above 0. Examination of longitudinal trends shows that the team effects for BU, MU, OSU and KU are relatively stable compared to the team effect of TT; ISU, UT and A&M are stable with a peak; KSU, NU and CU appear to be getting weak and OU has shown the largest improvement in the Big 12.

Figure 1. Big 12. Posterior distribution of the expected difference in score between the home team and TT as the visiting team across the 1996 to 2004 seasons, using 90% credible interval and 50%-tile. TT is chosen because of its consistency of performance across the existence of the Big 12 conference.



5.2. Home Field Advantage in the Big 12

Figure 2 shows the 90% credible intervals for the home field parameter (λ_j) across the 12 universities in the Big 12 ranked by the predictive probability of winning at home ($P\left(y^P_{ijj'k} > 0 \mid \mathrm{B}_{ij} - \mathrm{B}_{ij'} + \lambda_j, \sigma^2_e\right)$) along the bottom axis. All of the schools show potential for a home field advantage because none have intervals significantly below zero. However, the intervals for NU, TT, ISU, and OSU are completely above zero.

The median values give the estimated probability of winning at home against an equally talented team (their clone). All estimates are greater than 50% except for BU. NU has the largest expected advantage with an estimated 71% winning percentage against an equally talented foe.

The estimate of the second definition of home field advantage, home field winning probability, is displayed in Figure 3. This measure combines, conceptually, the information from Figures 1 and 2. Both the team's ability and their home field parameter are combined, generating patterns very similar to the patterns in Figure 1. In this case, the interpretation is the probability of winning at home rather than the expected difference in score. One of the more interesting findings is the fact that CU, despite its low home field parameter, has almost a uniformly higher probability of winning at home than BU, ISU, KU, MU and OSU. According to the model, this is evidence of talent on the team rather than better home field advantage. BU has both the lowest talent level and weakest home field advantage in the Big 12. Thus, it is the only school whose hypothetical home winning probability was always under 50%. It is interesting that team trends are consistent with the 1996 NU and 2000 OU national championship teams.

To summarize the third definition of home field advantage, home impact, we rank the programs from highest to lowest based on their average ratio. The third definition, home impact, preserved the rankings from 8-12, relative to the first definition (Figure 2). The rankings 1-7 were in different order. Under the third definition of home field advantage, ISU is the top program in the Big 12 (Table 4).

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Figure 2. 90% credible interval and median of the home field advantage of each team in the Big 12 (posterior predictive probability of the team beating a clone of themselves at home).

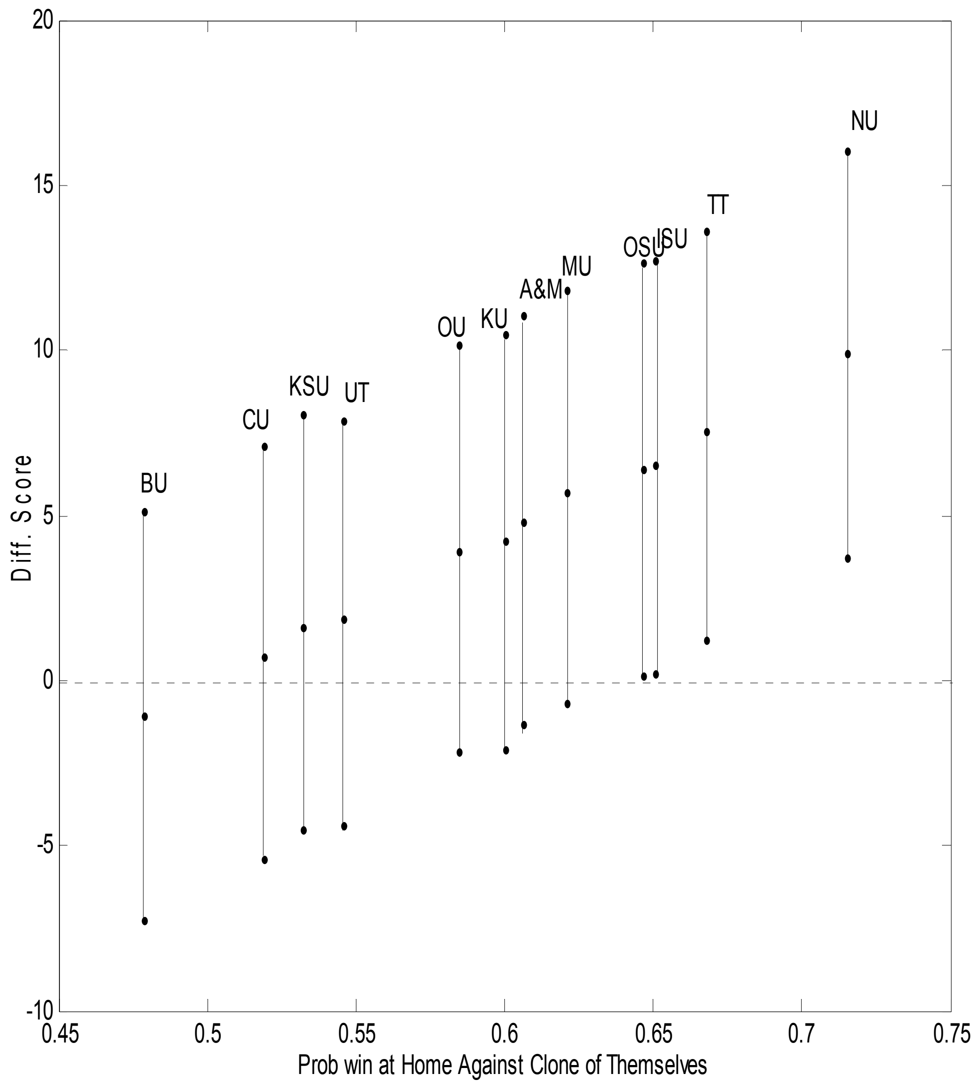
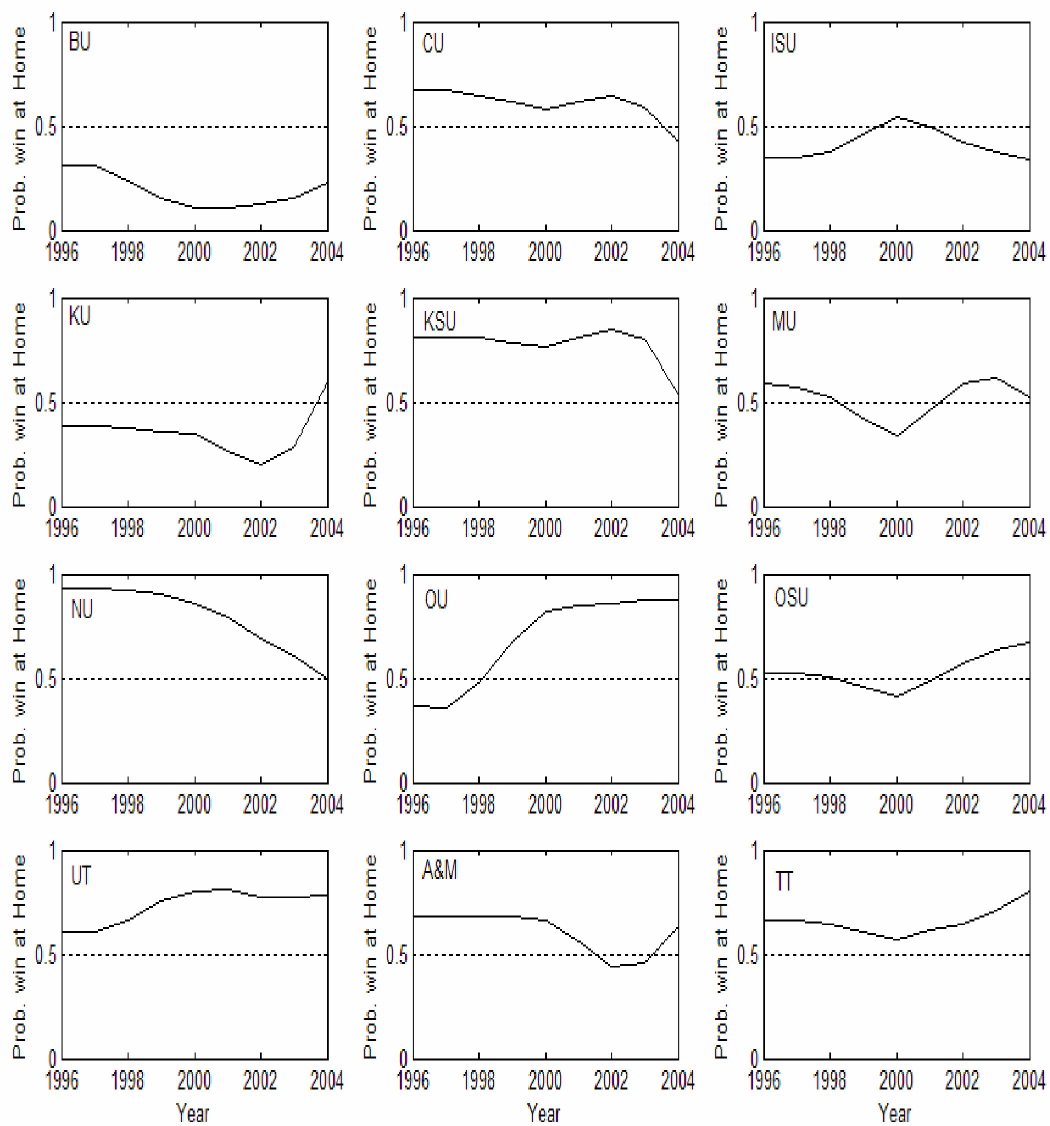


Figure 3. Displayed is the predictive probability of the team winning at home across all Big 12 teams from 1996 to 2004 seasons. The dashed line represents a 0.5 probability of winning at home.



Rank	Big 12 School	Home Impact
1	ISU	1.37
2	OSU	1.28
3	MU	1.25
4	TT	1.25
5	KU	1.24
6	NU	1.23
7	A&M	1.15
8	OU	1.11
9	UT	1.04
10	KSU	1.03
11	CU	1.02
12	BU	0.92

Table 4. Big 12 schools ranked by their "Home Impact."

5.3. Home Field Advantage in the Big 10 and the Pac 10

Figure 4 shows the 90% credible intervals for the home field parameter across the 11 universities in the Big 10 ranked by the predictive probability of winning at home. Figure 5 shows the probability of winning at home under the second definition of home field advantage.

According to the home field probability, MSU enjoys the best home field advantage within the Big 10. The school with the worst home field in the Big 10 is IL. Their probability of winning at home is less than 0.5 - suffering the same phenomenon as BU (Big 12). As for the probability of winning at home across all schools, it is interesting to note that IA has had a recent increase to a level higher than that of the 2002 OSU national championship team.

The Pac 10 (Figures 6 and 7) results are surprising in that the discrepancy between the home field advantage for ASU and AZ is so great. ASU enjoys the best home field advantage in the Pac 10 with OSU as close second. AZ has the worst home field advantage in the Pac 10 – less than 0.4! This very unusual pattern suggests that AZ is much better off playing away from their home stadium. Also interesting is the fact that CAL has a very high probability of winning at home and is competitive with the 2003 and 2004 USC national championship teams.

Again, to summarize the third definition of home field advantage, home impact, we rank the programs from highest to lowest based on their average ratio (Table 5). The third definition kept the top ranked programs in the top half, relative to the first definition, and kept the bottom in the bottom half for both conferences. It is reassuring that no drastic changes in the rankings occurred as a result of the definition of home field advantage.

Figure 4. The 90% credible interval and median of the home field advantage of each team in the Big 10 (predictive probability of the team beating a clone of themselves at home).

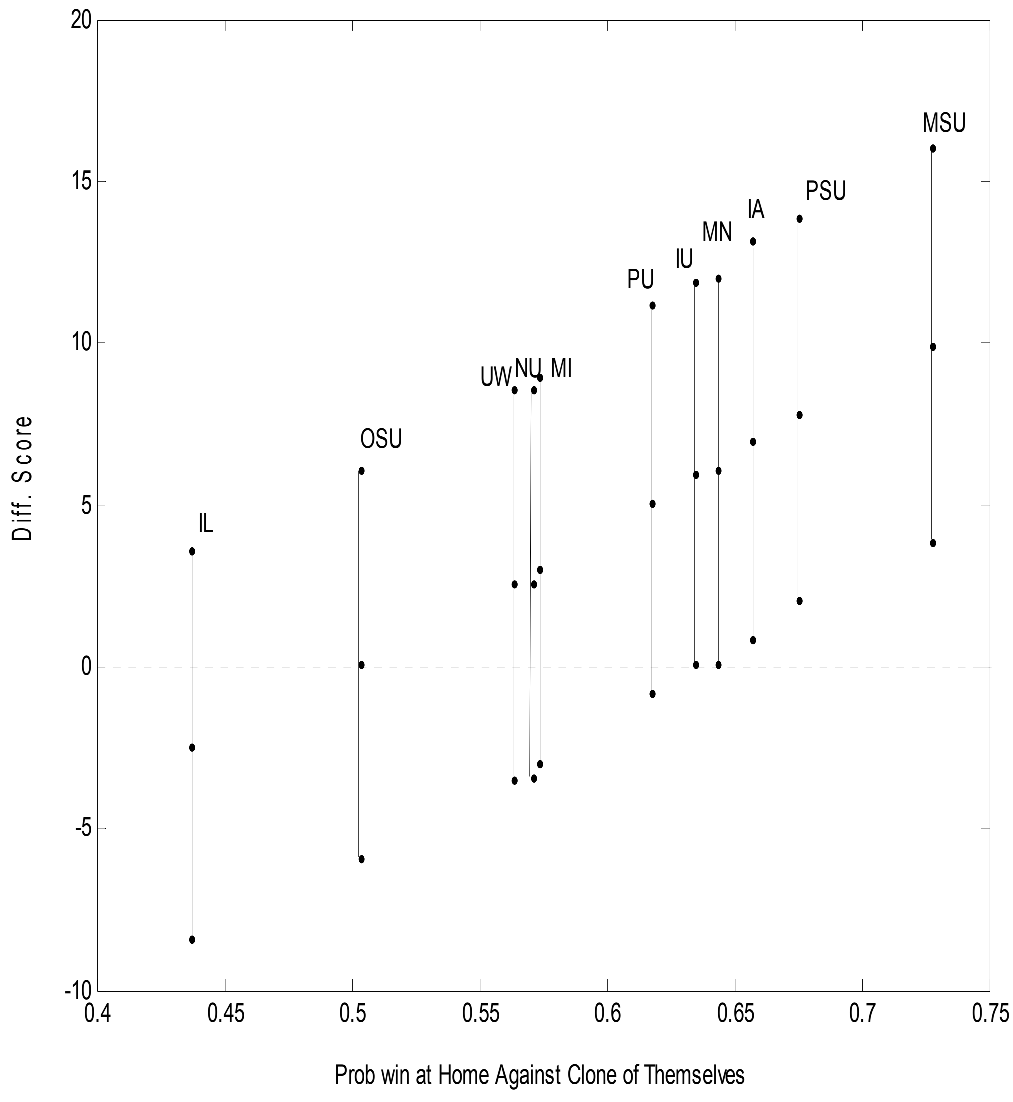


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Figure 5. Longitudinal predictive probability the team winning at home against randomly selected Big 10 team.

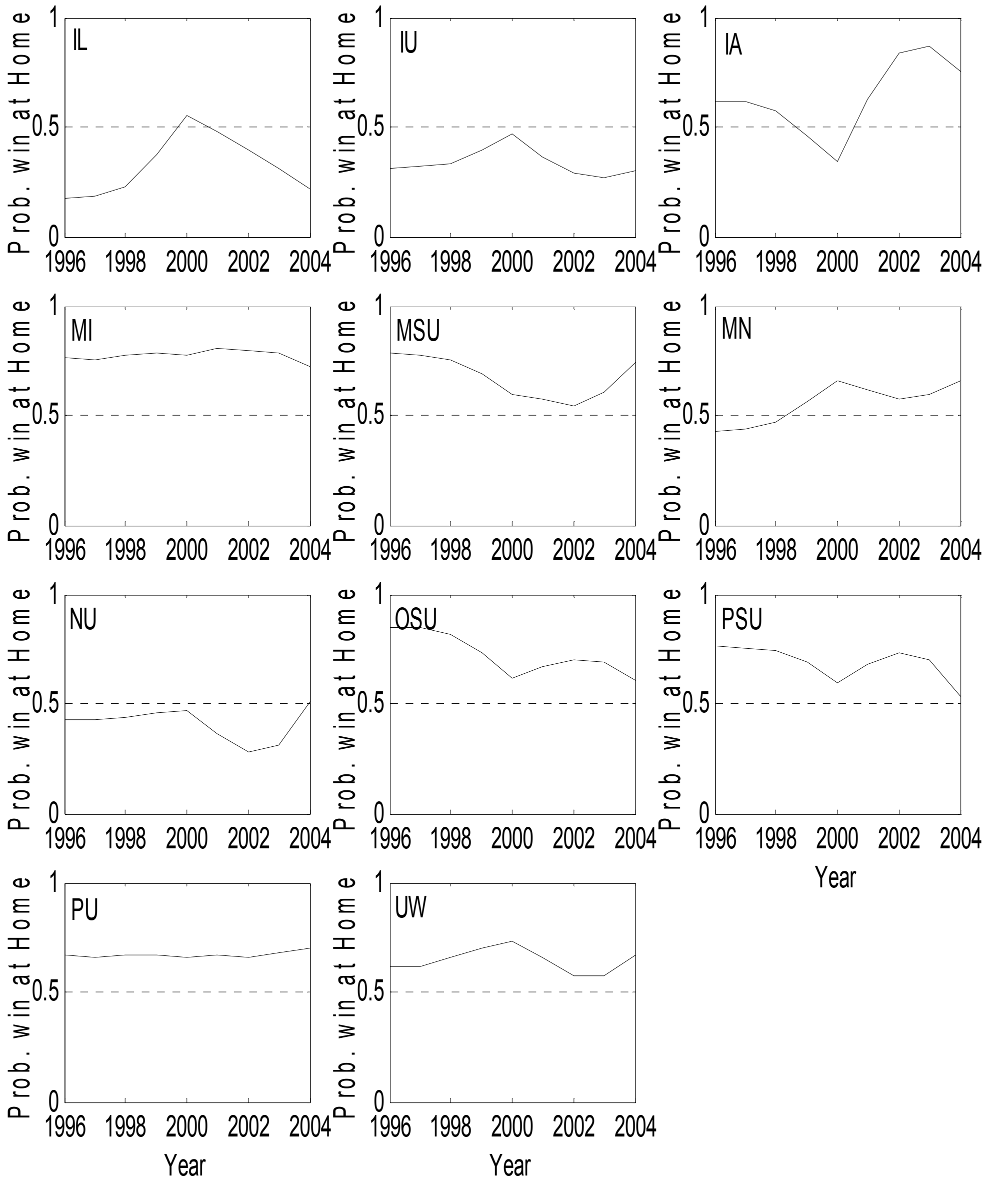


Figure 6. The 90% credible interval and median of the home field advantage of each team in the Pac 10 (predictive probability of the team beating a clone of themselves at home).

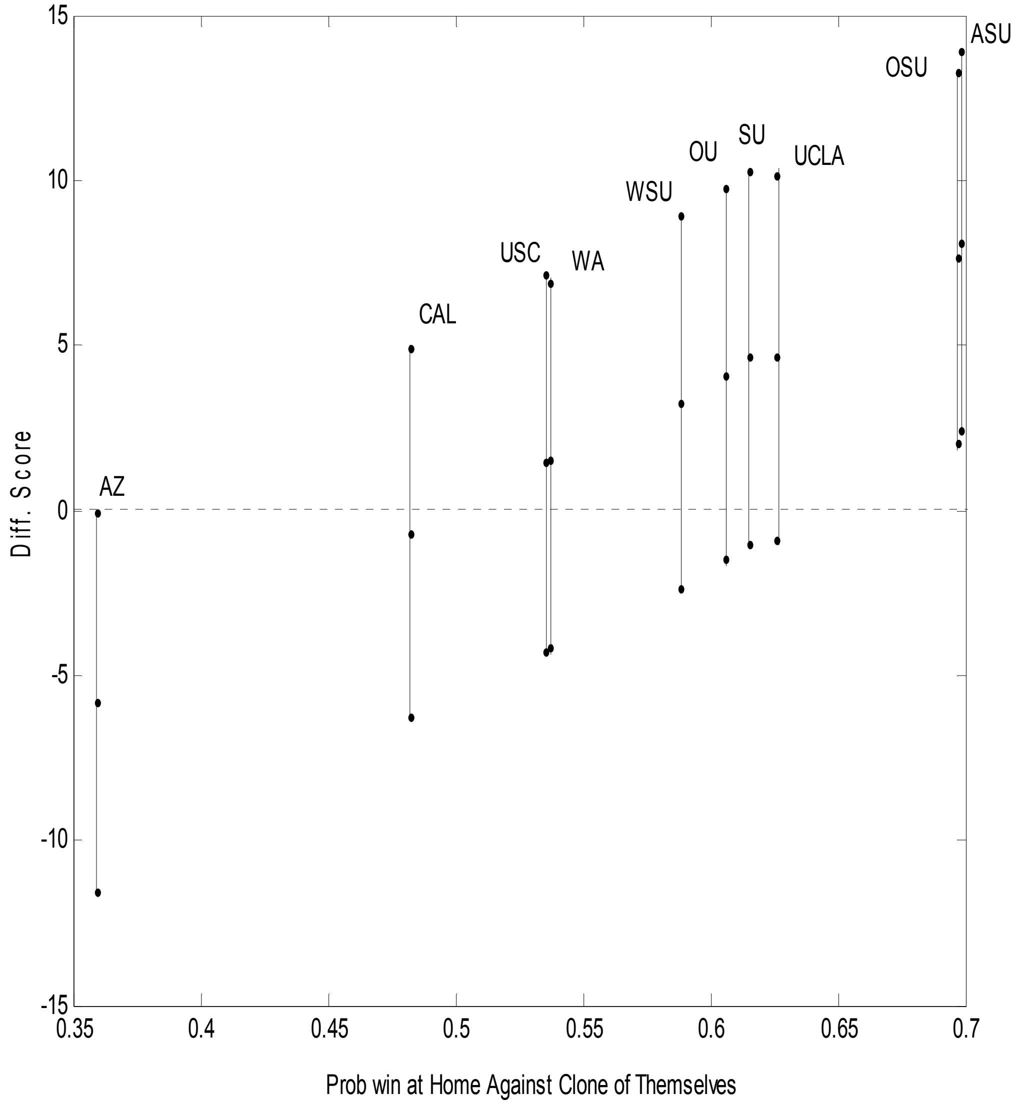
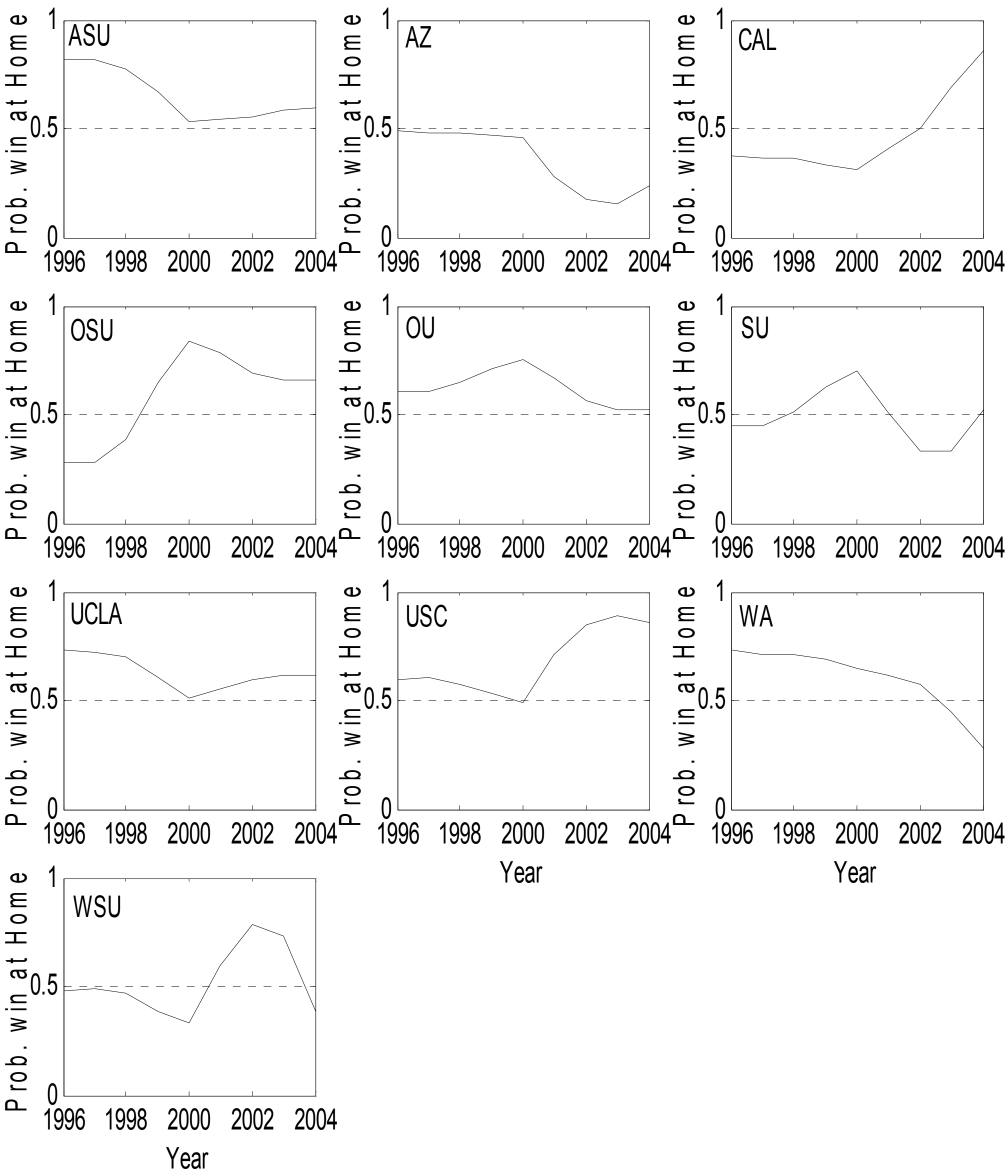


Figure 7. Longitudinal predictive probability of the team winning at home against randomly selected Pac 10 team.



Rank	Big 10 School	Home Impact	Rank	Pac 10 School	Home Impact
1	IU	1.46	1	OSU	1.45
2	MSU	1.43	2	ASU	1.39
3	IA	1.31	3	SU	1.27
4	PSU	1.30	4	UCLA	1.19
5	MN	1.30	5	OU	1.17
6	PU	1.18	6	WSU	1.16
7	NU	1.14	7	WA	1.06
8	UW	1.08	8	USC	1.06
9	MI	1.07	9	CAL	0.97
10	OSU	1.00	10	UA	0.73
11	IL	0.87			

Table 5. Big 10 and Pac 10 schools ranked by their "Home Impact."

6. DISCUSSION & CONCLUSION

This paper presents a methodology for evaluating a team's home field advantage for college football. The model in this paper includes separate parameters for each team, for the Big 12, Big 10, and Pac 10 conferences, based on data from 1996 to 2004. We define two additional home field advantage definitions. The three definitions of home field advantage will please fans caring simply about either: a) *home field advantage*, b) *home field winning probability*; or c) the ratio of the probability their team will win at home and the probability their team will win on a neutral field (*home impact*).

In this paper, a normal distribution model using difference scores is considered. Under the first definition, results indicate that NU has the best home field advantage in the Big 12; MSU in the Big 10; and ASU in the Pac 10. The worst home field advantages were BU, IL, and AZ in the Big 12, Big 10, and Pac 10 respectively. Under the third definition, results indicate that ISU has the best home field advantage in the Big 12; IU in the Big 10; and OSU in the Pac 10. The worst home field advantages in the third definition were the same as the first definition. The model analyzed conference games from 1996-2004 using a piecewise linear model.

There is a limitation to the model worth mentioning. Due to an NCAA rule, the model may penalize talented programs. The rule is that a team can "suit up" 90 players on the road. Therefore, if the team which is winning by a wide margin is at home, the coach can go even deeper into his bench, curbing the size of the final potential margin. However, the Big 12 data indicates that this may not be an issue. Among all regular season games in the Big 12, the home team beat the road team by 14 or more points 35% of the time, whereas the visiting team beat the home team by 14 or more points 22% of the time.

If this rule is an issue, a binary model might be appropriate. In a binary model, rather than a normal distribution on the difference scores, a binomial distribution would be a reasonable alternative. However, if the rule is not an issue, a binary model would take away important information that the difference score provides.

Another possible limitation to the model is the fact that the rules for the Bowl Championship Series (BCS) may affect how a team plays at home. For example, the influence of point differentials on BCS rankings has declined. However, this may be a non-issue since two human polls are currently components of the BCS ranking system. Human polls will always indirectly include point differences when ranking teams.

A third possible challenge to the model is the assumption of the stability of the home field advantage across 1996-2004. Specifically, the model accounts for changes in overall team ability, longitudinally across time, but does not allow any changes in the home field advantage. We believe that this is a reasonable assumption for conference football teams. Since there are only four conference home games a year, the fan base is likely to be very stable. One should exercise caution when applying the model to another sport, such as basketball, where the fan composition may be less stable.

There are possibilities for future work for modeling home field advantage. We mentioned in the discussion and rejected the notion of home field advantage changing over time. However, one might consider a model in which home field advantage is a multiple of team strength. In addition, one might consider changes when stadiums are remodeled.

Keeping the possible model shortcomings in mind, final results, from the first definition (classic definition: *home field advantage*), indicate that the teams in the Big 12, Big 10, and Pac 10 with the best home field advantage respectively are NU, MSU, and ASU, placing an exclamation point on what many Nebraska, Michigan, and Arizona residents will say is a well-known fact.

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