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Team Travel Effects and the College Football Betting Market

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Abstract

This research examines whether the college football betting line and over/under accurately assimilate travel effects on visiting teams, including time zones traversed; direction and distance traveled; and temperature, elevation, and aridity changes. We investigate the market's accuracy at predicting winners, point differentials, and points scored and examine its market efficiency, that is, whether travel affects the chance the home team covers the spread or the chance that an "over" bet wins. The betting market is found to be an inaccurate and inefficient processor of travel effects, most consistently for late-season games involving an underdog with a 1-hr time deficit versus its opponent.

Keywords

college football, sports betting, travel, prediction, efficiency

Introduction

There is a considerable literature on betting market efficiency in American football. Paul, Weinbach, and Weinbach (2003), Kuester and Sanders (2011), Nichols (2012), and Sinkey and Logan (2012) provide excellent reviews of prior work on the National Football League (NFL) and/or college football as well as the associated

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literature in sports such as the National Basketball Association (NBA) and college basketball. There is a related body of research that focuses on the fundamentally different question of whether betting markets in football are predictive of game outcomes. Kain and Logan (2014) and Sinkey and Logan (2012) provide comprehensive literature background and discussion on that subject as well as its distinction vis-à-vis market efficiency.

Much of the prior work on the college football market has focused on market efficiency, which involves determining whether various betting strategies can generate statistically significant returns against the spread as well as returns that are economically profitable, that is, ones that exceed the transaction costs paid to the betting house (i.e., the vigorish). Paul et al. (2003), Kuester and Sanders (2011), and Sinkey and Logan (2012) have discovered various inefficiencies in the college football betting market associated with whether a team is playing at home, whether it is a favorite or an underdog, and whether a home team is facing an opponent from a less arid region. Other research has assessed the college football betting line's accuracy at predicting victory margins. Examples include Dare and MacDonald (1996), who in their analysis of the betting line found that their results were too inconsistent to conclude that it was biased. Kain and Logan (2014) investigated the predictive capacity of the college football betting line as well as the over/under (the sum of the points scored across both teams). They found that the line accurately predicts the victory margin but that the over/under poorly forecasts the point total.

However, very little existing literature on college or pro football has addressed the impact of travel-related factors as they relate to the betting market's efficiency or its predictiveness in estimating game outcomes. Borghesi (2007a), Kuester and Sanders (2011), and Nichols (2012) are notable exceptions.

Borghesi (2007a) examined the impact of temperature and travel distance in the NFL. He operationalized the home team's temperature advantage as the difference in mean temperature between the host team's locale and the locale of the visiting team, for the 5 days immediately preceding a game. Using a probit analysis of 5,748 NFL games from 1981 to 2004, and controlling for any bettor bias associated with home favorite and home underdog effects suggested by prior work, Borghesi found that home teams cover the spread significantly more often than bettors expect when they have an edge in cold acclimatization. Furthermore, this advantage increases as the temperature difference increases. Conversely, home teams with warmer weather than the one to which their visitors are acclimatized to do not cover the spread significantly more. Visiting team travel distance also was found to have no relationship to whether the home team covered the spread. The latter two findings suggested that the market efficiently processes any influences of warm weather and travel distance. Borghesi points out that his cold-weather results are consistent with medical and military research that indicates that human physical and cognitive performance are adversely affected by low temperatures and that performance improves with acclimatization.

Nichols (2012) extended the examination of travel in the NFL by analyzing the impact of number of time zones crossed by the visitor and the direction of visiting team travel (i.e., easterly or westerly), in addition to travel distance and Borghesi's measures of the home team's temperature advantages. As further extensions of Borghesi (2007a), Nichols examined the impact of travel on whether the home team won the game, and the point differential between the two teams, in addition to whether the home team covered the spread.

Using ordinary least squares, probit, and seemingly unrelated regressions on 5,453 NFL games from 1981 to 2004, Nichols (2012) found that neither the betting line nor the home team's favorite versus underdog status sufficiently accounted for the impact of travel distance and number of time zones crossed by the visitor. Visiting teams traveling greater distances to the east suffered (curvilinear) detrimental effects on their chance of winning. Home team point differentials were significantly greater than the betting market projections when the visitor crossed one or two time zones to the east. Home teams also covered the spread significantly more often when the visiting team traveled easterly one time zone, and this was the only travel factor significantly related to whether the home team covered. Noting that prior research on the NBA (e.g., Ashman, Bowman, & Lambrinos, 2010) and in general physiology (e.g., Reilly & Edwards, 2007) shows similar findings, Nichols concludes that this is likely due to the impact of fatigue associated with the loss of time. Nichols did not confirm Borghesi's findings in regard to cold weather's advantageous effect on the home team covering the spread, but the cold-temperature factor was found to impact the home team's victory margin. Nichols also finds that none of the significant effects discovered were sufficient to be economically profitable.

Kuester and Sanders (2011) is the only prior work to examine travel effects in college football. Those authors examined the impact of aridity, as measured by average annual rainfall in a team's locale, on 4,345 Football Bowl Subdivision (FBS) game outcomes from 2000-2006. Using a 32-inch annual rainfall to bifurcate between arid and humid regions, the authors employ simple binomial hypothesis testing to compare how well home teams do against the spread when hosting teams from their own or the other type of region. They find that home teams in arid regions win against the spread a significantly greater portion of the time when the visitor is from a humid region (based on a subsample of $n = 399$), and that this edge is sufficient to generate economic returns. Conversely, home teams playing visitors from their own region, or home teams in humid zones hosting visitors from an arid climate, were not found to have statistically significant advantages not already accounted for by the betting line.

The review of the extant literature indicates that no prior work on the efficiency or predictiveness of the betting market has investigated whether the college football betting line or over/under accurately represents the impact on visiting teams of travel factors such as distance, direction of travel, time zones crossed, elevation change, and temperature change. Previous research on college football also has not investigated the differences in these factors for betting favorites versus betting underdogs. Moreover, no earlier work on college football has examined whether the market's processing of any travel impacts is mitigated by the point in the season in which the game is played. As noted by Borghesi (2008), it seems likely that the learning curve regarding team quality experienced by the betting public would allow for improved market knowledge, and thus more accurate lines and over/under totals, later in the season. This appears particularly true, given the observation of Sinkey and Logan (2012) that many college teams are not in major media markets and/or receive much less attention versus the comparatively few traditional powers, and thus the increasing sample sizes deeper in the season might result in different effects. Thus, the market's assessment of travel effects might be expected to differ as the season progresses.

Research Questions

In order to explore the travel-related issues outlined previously, this research investigates six research questions for college football, the first three of which are similar to those that Nichols (2012) examined for the NFL:

1. Does the closing betting line accurately account for the impact of visiting team travel on whether a team wins a college football game?
2. Does the closing betting line accurately account for the impact of visiting team travel on the point differential (victory margin) in a college football game?
3. Does the closing betting line reflect market inefficiency: Do the factors associated with visiting team travel impact whether a team covers the spread in a college football game?
4. Does the closing over/under accurately account for the impact of visiting team travel on the point total in a college football game?
5. Does the combination of the betting line and the over/under accurately account for the impact of visiting team travel on the points scored by the home team and by the visiting team in a college football game? and
6. Does the closing over/under reflect market inefficiency: do the factors associated with visiting team travel impact whether the point total exceeds the over/under in a college football game?

Questions 1, 2, 4, and 5 address the predictive accuracy of the betting line and over/under, whereas Questions 3 and 6 assess whether the line and over/under are market efficient. As well described by Kain and Logan (2014), these are quite different issues. As those authors explain, in an effort to minimize their own risk and thereby maximize their own profit, betting houses try to set the line or the over/under such that it yields equal bet amounts on both sides. In doing so, they respond to the collective perceptions of their bettors. If those views are erroneous—in the current context, if bettor perceptions of the impact of travel are flawed—then even though the market may be efficient for its participants (see the discussion mentioned subsequently), the midpoint of the bets placed will be flawed, and the betting line or over/under will not be an accurate predictor.

Moreover, and as argued by many (e.g., Borghesi, 2007a; Dare & Holland, 2004; Kain & Logan, 2014; Nichols, 2012; Sinkey & Logan, 2012), neither bettors nor betting houses are necessarily concerned by who wins a game or by the victory margin of the winner, nor are they worried about how much the point total is above or below the over/under. A bettor's outcome is based solely on the point at which a given team covers the spread (where the point differential equals the betting line); whether he or she wins or loses is irrespective necessarily of who wins the game outright or by the margin by which a given team covers (or fails to cover) the spread. A similar statement could be made about the over/under vis-à-vis the point total in a game. As proven by Kain and Logan (2014), the betting house's profit maximization rests solely on setting the line at its risk minimization point: the "wager-weighted median" of all possible point differentials. In sum, all market participants care essentially about the same point—bettors only about being on the correct side of it, and betting houses only about whether it results in 50% of the amounts bet on each side of it. Thus, market efficiency is appropriately tested only by examining the relationship between the betting line and whether a team covers the spread (or similarly, by examining the relationship between the over/under and whether the point total is on a particular side of it). If the market is efficient—that is, if the market fully processes all available information, including information about team travel—there should be no factors travel-related or otherwise that are related to whether a team covers the spread. This would include the betting line itself, as it is essentially netted out in the process of making the binary determination of whether a team covered.

However, even though the betting line cannot be expected to be an accurate predictor of game winners or victory margins, there is evidence that it nevertheless is comparatively a very strong one. For example, the betting line's accuracy at predicting college football game winners consistently exceeds that of the large majority of the so-called computer rankings, including those recently used by the Bowl Championship Series (BCS; Beck, 2013). When examining victory margins, Fair and Oster (2007) showed that nine noted computer ranking systems added no predictive information over and above the betting line in 1998-2001. Song, Boulier, and Stekler (2007) found that the NFL betting line in 2000-2001 was superior at predicting games when compared to both mathematical systems and expert opinions.

Because of its relative strength as a predictor of game results, the predictive capacity of the betting line is of keen interest to many *outside* the betting market. In the academic community, and as noted by Kain and Logan (2014), the predictiveness of the line is used as a control measure when examining the predictive accuracy of other methods (Fair & Oster, 2007; Song, Boulier, & Stekler, 2007), or in the assessment of other factors. In the athletics community, the presumptive predictiveness of the line and/or the over/under is also used by media in game buildup and publicity and used by the media, coaches, and fans in setting game expectations and determining whether given games are upsets. Indeed, Paul, Weinbach, and Coate

(2007) show that team performance vis-à-vis the betting line has a highly significant positive effect on both the media and coaches polls, the latter of which has formed one third of the BCS formula that determined participants in the national championship game through 2013 (BCSfootball.org, 2013). Given that present or former coaches, athletics administrators, and media members make up a large portion of the selection committee for the College Football Playoff (Uthman, 2013) starting in 2014, team performance vis-à-vis the betting line might be expected to influence their decisions as well. Although perhaps unspoken, it seems likely that lines are used implicitly by athletics personnel—coaches, athletic directors, and even players themselves—in setting performance expectations and the ultimate performance evaluations that follow.

In sum, investigating the question of bias in the line and the over/under as predictive measures is of interest to many outside the gambling community, in addition to the obvious financial interest that examining their market efficiencies holds for participants inside the industry.

Furthermore, any research into travel effects on college football game outcomes should arguably be of concern to the sport's governing body, for which assessing team strengths for the sake of determining a champion is not a simple matter. Whereas many sports have a playoff qualification system based simply on a team's wins and losses, the greatly different scheduling strengths of college football teams, combined with the relatively small sample of games vis-à-vis the number of teams, essentially precludes the simple use of the win–loss record to qualify teams. The four-team playoff in major college football (Smith, 2012) does and likely will continue to require metrics and ranking systems that more effectively estimate team strengths (Hayes, 2013). However, no current system for this purpose is known to account for any sort of travel effects. Given the aforementioned predictive performance of existing systems versus the betting line, this should be of concern. As the line is already a superior predictor of game outcomes, any research that shows that it might be nevertheless flawed in its accounting of travel effects should interest and inform those developing mathematical ranking methods for future use.

Data

The dates, participants, and scores for all games played between two FBS teams between 2004 and 2011, inclusive, were collected from Wolfe (2012).[1] Games played on neutral fields during that same time frame were identified from Howell (2012) for 2004 through 2010 and from Wolfe (2012) for 2011. As the research questions focused on the impact of travel on visiting teams, all games played on neutral sites (i.e., all games not played at a home team's usual site) were eliminated from the analysis.

In addition to neutral site games, a variety of other games were also excluded from the data. Games played by Western Kentucky during its transition to the FBS in 2007 were omitted due to the unavailability of betting lines for those games (i.e., see the prior footnote about lines not being posted for non-FBS teams). Hawaii was the lone team in the data that encountered travel that traversed more than three time zones as a visitor or as a host. Due to concerns over the potential impact of a relatively small number of extreme observations associated with a single team, all Hawaii games (home or away) were omitted. Finally, all Tulane games in 2005 were also excluded: due to the impact of Hurricane Katrina, Tulane encountered the outlier scenario of having to play all their games that season away from their usual home site. This process yielded a total of 5,093 usable observations.

Beyond the game score and site information, several data sources were used to construct control variables and the variables representing the hypothesized travel-related factors. The time zone of each FBS team was collected from Google Maps. (Since the state of Arizona does not participate in daylight saving time [DST], Arizona and Arizona State were essentially in the Pacific time zone for games played during DST. Similarly, since their counties in Indiana did not participate in DST prior to 2006, Ball State, Indiana, Notre Dame, and Purdue were effectively in the Central time zone for games played during DST in 2004 and 2005.) The elevation above sea level of the center of the home field of each FBS team was collected from Google Earth. The average annual rainfall in each school's location (or when unavailable, from a location in close proximity) was collected from weather.com and usclimatedata.com. Finally, the closing betting line (point spread) for each game was collected from Beck (2012), and the over/under for each game was collected from GoldSheet.com (2013). In a small number of cases in which the betting line was not reported by Beck, the closing betting line for the game was collected from GoldSheet.com (2013). Missing over/under from GoldSheet.com (2013) were collected from Covers.com (2013). A total of 32 games for which betting lines were available had no posted over/under in either source, which reduced the effective sample size for all analyses of over/under and team point totals to 5,061.

Variables

Table 1 contains descriptions and summary statistics for all variables in the full sample ($n = 5{,}093$), and games in which over/under were available ($n = 5{,}061$). Games were modeled from the perspective of the home team; that is, unless otherwise noted, variable values were computed as the simple difference between the home team's value of the respective variable and that of the visiting team.

Identically to Nichols (2012), three dependent variables were constructed to investigate each of the first three research questions, respectively: HomeWin, ScoreDiff, and HomeCovered. Four additional dependent variables were constructed to investigate the fourth, fifth, and sixth research questions, that is, TotalPts, HomePts, AwayPts, and OverBetWins. The home team was deemed to have covered the spread if the home team's score minus the betting line was greater

Table 1. Descriptive Statistics for all Variables.

Variable	Description	Full Sample (n = 5,093) Mean	*SD*
HomeWin	1 if home team won the game, 0 otherwise	0.5979	0.4904
ScoreDiff	Home team's score—visiting team' score	5.3778	20.8819
HomeCovered	1 if home team covered spread, 0 otherwise	0.4942	0.5000
Line	Closing betting line	5.2416	13.8061
HomeFavored	1 if home team favored to win, 0 otherwise	0.6442	0.4788
HomeUnderdog	1 if visiting team favored to win, 0 otherwise	0.3469	0.4760
AridEdge	1 if annual home rainfall ≤32" but >32" at visitor, 0 otherwise	0.0833	0.2763
Distance	Straight-line miles traveled by visiting team	508.9531	404.5791
Distance2	Distance squared	422,685.44	706,246.37
HigherElev	(Home elev. − visiting elev.) if home at higher elev., 0 otherwise	462.3383	1044.5300
LowerElev	(Visitor elev. − home elev.) if home at lower elev., 0 otherwise	477.9415	1091.6400
East1zone	1 if visitor traveled one time zone east, 0 otherwise	0.1569	0.3637
East2zones	1 if visitor traveled two time zones east, 0 otherwise	0.0249	0.1559
East3zones	1 if visitor traveled three time zones east, 0 otherwise	0.0079	0.0883
West1zone	1 if visitor traveled one time zone west, 0 otherwise	0.1518	0.3588
West2zones	1 if visitor traveled two time zones west, 0 otherwise	0.0200	0.1401
West3zones	1 if visitor traveled three time zones west, 0 otherwise	0.0069	0.0826
GameDate	No. of days beyond September 1 that game was played	45.5254	26.1598
Dome	1 if game played in domed stadium, 0 otherwise	0.0283	0.1658
Dome_LateNortherly	Dome × Northerly Latitude Difference × Days After October 17	1.2860	17.3163
Outside_LateNortherly	(1 − Dome) × Northerly Latitude Difference × Days After October 17	18.4926	56.0703
Dome_EarlySoutherly	Dome × Southerly Latitude Difference × Days Before October 17	0.4655	9.6761
Outside_EarlySoutherly	(1 − Dome) × Southerly Latitude Difference × Days Before October 17	22.8307	68.2546

(continued)

Table 1. (continued)

Variable	Description	Full Sample ($n = 5{,}093$)	
		Mean	*SD*
	Games with over/under ($n = 5{,}061$)		
TotalPts	Home team's score + visiting team's score	52.4489	17.7892
OverUnder	Closing over/under	52.1032	7.5068
OverBetWins (no pushes)	1 if TotalPts exceeds OverUnder, 0 otherwise	0.4891	0.4999
HomePts	Home team's score	28.8963	14.0860
AwayPts	Visiting team's score	23.5527	13.3112
PredictedHome	PredictedAway + Line	28.6654	7.9053
PredictedAway	(OverUnder – Line)/2	23.4379	7.7673

than the visiting team's score (the signs of all betting lines—which are normally reported as negative for the favored team—were coded as positive if the home team was favored, and negative if it was not). The choice of OverBetWins as a measure of the market efficiency of the over/under is consistent with the approach taken by Borghesi (2008) in his analysis of point totals in the NFL. In computing OverBetWins, any over/under pushes—games where TotalPts equaled the over/under—were left as missing values, meaning such games were omitted in models of this outcome.

The betting line was employed as the control variable when investigating the first three research questions. The over/under was used as the control variable when investigating the fourth and sixth research questions. For the investigation of the fifth research question, the control variables PredictedAway and PredictedHome were constructed from the over/under and betting line as estimates of the betting market's predicted scores for the visiting and home teams, respectively.

Since variable values were constructed from the standpoint of the home team, the intercept in each model reported subsequently accounts for a general home field advantage on the part of the home team associated with factors other than travel (e.g., crowd noise, referee bias toward the home team (Moskowitz & Wertheim, 2011), etc.), and/or the collective effects of any omitted factor. A significant intercept term would itself be evidence of market inefficiency or prediction bias, since the betting line should account for any general home field advantage as well as the effects of omitted factors.

Following the recommendation of Dare and Holland (2004), and consistent with the approaches of Borghesi (2007a) and Nichols (2012), binary variables HomeFavored and HomeUnderdog were constructed to represent whether the home team was a betting favorite or a betting underdog, respectively. These factors accounted for any gambling market biases associated with a home underdog effect that has been found in the NFL (Borghesi, 2007b) and NBA (Paul & Weinbach, 2005), as well as home underdog and home favorite biases found in college football (Paul, Weinbach, & Weinbach, 2003; Sinkey & Logan, 2012).

As an extension to Nichols (2012) and in an attempt to reduce further the unexplained variability in the models subsequently, a set of controls representing temporal factors were introduced that were similar to those used by Sinkey and Logan (2012). This included seven binary indicator variables not shown in Table 1 (denoted as Y20XX) to control for any fixed effect differences that might exist across the 8 years in the sample, using the most recent year of 2011 used as the omitted category. In addition, GameDate was constructed to control for any simple linear temporal effects associated with the point in the season at which a game is played. (Sinkey & Logan, 2012 included controls for the week of the season in which the game was played. However, given that many mid-week games are now played, that would have required a subjective judgment on the week in which some games should be placed.)

All the temporal factors were introduced as controls for the investigation of travel effects. However, statistical significance for any of these factors would also represent gambling market inefficiency or prediction bias, albeit not necessarily travel related.

The remaining variables represented various travel factors hypothesized to influence game results. Because the effects of time zone travel might be neither linear nor consistent in easterly and westerly directions (Nichols, 2012), six time zone factors were employed, representing travel of one, two, or three time zones easterly and westerly, with the omitted category being cases in which the visiting and home teams were in the same zone.[2] The straight-line distance (in miles) traveled by the visiting team was computed using zip codes to identify the longitude and latitude for the two teams in each game and then applying trigonometric methods accounting for the curvature of the earth. Consistent with Nichols (2012), and to account for any curvilinear effects of travel distance, the square of this distance was also included as a predictor.

As a measure of the impact of temperature differential on game outcomes, Nichols (2012) and Borghesi (2007a) computed the mean temperature in each team's locale for the 5 days preceding a given game and then used the difference in these two means as a predictor. While sound methodologically, one issue with using such an approach on an ongoing basis—whether for research or application purposes—is the sizable data collection problem that it presents (particularly in college football, with upward of 128 teams instead of 32). As a more easily implemented alternative, this research used the difference in latitude between the home and visiting team, the direction of travel, whether the game was played outdoors, and a measure for how late in the season the game was played, to construct a proxy for the impact of temperature encountered by the visitor. Variable construction was as follows:

Earliness = number of days prior to October 17 (inclusive) that the game was played, 0 otherwise.[3]
Lateness = number of days after October 17 (inclusive) that the game was played, 0 otherwise.
Southerly = (visiting team latitude – home team latitude) if home team at lower latitude, 0 otherwise.
Northerly = (home team latitude – visiting team latitude) if home team at higher latitude, 0 otherwise.
EarlySoutherly = Earliness × Southerly.
LateNortherly = Lateness × Northerly.

EarlySoutherly and LateNortherly essentially represented the latitude difference adjusted for the point in the season in which the game was played (Borghesi, 2007b employed a somewhat analogous time-based proxy for the effects of comparatively cold weather on visiting teams in the NFL: he used games played in 10 northern cities after Week 14, involving visitors from more moderate climates). Finally, given that playing indoors would mitigate impacts associated with weather conditions, a binary factor was constructed to account for 144 games played in domed stadiums. This included all the home games of Idaho, Syracuse, and Tulane throughout the data as well as the home games of Minnesota before 2009. This indicator and its complement were then multiplied by EarlySoutherly and LateNortherly to create the four temperature factors shown in Table 1.

As a further extension of Nichols (2012) and Borghesi (2007a), the change in elevation encountered by the visitor was included as well. Since the impact associated with a visitor traveling to a higher elevation versus traveling to a lower elevation was hypothesized potentially to be different, the predictors HigherElev and LowerElev were used to model the two types of elevation change.

To test for the impact of aridity that was found to be significant in Kuester and Sanders (2011), the binary indicator variable AridEdge was constructed. To be deemed arid, annual rainfall had to be within 32" according to both weather.com and usclimatedata.com (as results differed somewhat across the two sources). The 27 teams designated as being in arid locales were Air Force, Arizona, Arizona St., Boise St., Brigham Young, California, Colorado, Colorado St., Fresno St., Idaho, Minnesota, Nebraska, Nevada, New Mexico, New Mexico St., San Diego St., San José St., Southern Cal, Stanford, Texas Tech, UCLA, UNLV, Utah, Utah St., UTEP, Washington St., and Wyoming. Hawaii is also arid but is not listed since its home games were omitted from the data.

As shown in Table 1, the full sample statistics indicate that home teams won by an average of 5.38 points, which was closely approximated but underestimated by the average betting line of 5.24 points. Despite the slightly greater average winning margin, home teams covered less than 50% of the time. When betting line pushes were removed, the results suggest that the betting line has been efficient, that is, home teams covered 50.36% of the time ($n = 4{,}998$), which is not significantly different from 50% using likelihood ratio tests and a significance level of .05.[4]

In the slightly smaller sample of games with available over/under, the two teams combined to score an average of 52.45 points, closely approached but again underestimated by the average over/under of 52.10 points. The betting market's predicted number of points scored by home teams (28.67) and visiting teams (23.44) both underestimated the respective actual averages of 28.9 and 23.55. Despite this, an "over" bet in each game would have won only 48.9% of the time ($n = 4{,}993$, when omitting over/under pushes). A likelihood ratio test suggests that the over/under betting market is efficient, as this percentage is insignificantly different from 50%. As a comparative, Borghesi (2008) found nearly the same rate (48.92%) in his nearly identically sized full sample of 5,008 NFL games from 1984 to 2004.

Visiting teams encountered an average travel distance of 509 miles, and an average elevation change of 970 feet if going lower and 914 feet if going higher (the means for LowerElev and HigherElev in Table 1 are influenced by the numerous zero values for each of those variables). About 8% of the games involved a visiting team traveling to a relatively arid region versus its own location; the number of games involving such travel ($n = 424$) closely approximated the size of the comparable subsample in Kuester and Sanders ($n = 399$).

Moreover, 1,876 (or 37%) of the 5,093 games analyzed involved the visiting team crossing at least one time zone. Of those games, the large majority ($n = 1{,}572$) involved a one-time-zone change. Only 4.5% of the games (or $n = 229$) involved a differential of two time zones, and only 1.47% of the games (or $n = 75$) involved travel crossing three zones. Of the latter group, only a relatively small number of teams were involved; in 20 of the 75 such games, Notre Dame was either the visitor or the host. Moreover, only three different teams provided Notre Dame's opposition in 16 of those 20 games (Stanford, Southern Cal, and Washington). Across the full 8-year sample, only 36 different teams hosted at least one visitor from three zones away (but 19 did it only once), and only 33 different teams traveled three zones away (15 did so only once). Thus, it's possible that the results associated with this group are skewed not only by a relatively small sample size but by a small number of associated teams.

Analysis

Three models were estimated for each of the seven dependent variables. The first estimation for each dependent variable included all observations in the sample. In order to better assess the impact of any temporal effects on the impact of travel, two more estimations were done. These addressed concerns raised by Borghesi (2007b) that past analyses using a full season as the time frame were possibly flawed, at least in the NFL. Borghesi found that certain biases—for example, in favor of NFL home underdogs—existed only in the last 4 weeks of the season plus the playoffs and were nonexistent otherwise. To account for any such time-varying effects, the second estimation was fit to all games played in the first half of the season (games played prior to October 17) and the third estimation was fit to all games played in the second half of the season (games played on or after October 17).[5]

The time frame of the third estimation is fairly comparable to the one in which Borghesi found market bias in the NFL (the final four regular-season weeks plus the full playoffs). Moreover, examining the season by halves is identical to the methodology used in the seminal home field advantage research of Schwartz and Barsky (1977), when assessing the collective fatigue effect of travel exacerbated by the increasing physical toll on teams over the course of a season. Bifurcating the sample also closely approximates the approach that has been used by the BCS in the past and which is being used currently by the College Football Playoff selection committee (McMurphy, 2014), which reported (or does report) weekly rankings roughly only for the season's latter half, thus making the current findings of more direct relevance to the sport's past and current championship entities. Finally, the nature of the data itself supports treating each half separately, as there are statistically significant differences at the 0.01 level or better between the early season and late-season values for the betting line (6.35 vs. 4.12), the over/under (51.53 vs. 52.68), the score difference (6.33 vs. 4.41), predicted home team points (28.93 vs. 28.40), predicted visiting team points (22.60 vs. 24.28), the total points scored (51.64 vs. 53.26), visiting team points (22.68 vs. 24.43), whether the home team won (.6153 vs. .5802), whether the home team was favored (.6733 vs. .6147), and whether the home team was an underdog (.3201 vs. .3743). Of all game outcome and betting market factors, only home team points scored (28.96 vs. 28.83), whether the home team covered (.4895 vs. .4990), and whether an "over" bet wins (.4864 vs. .4918) were insignificantly different across the two subsamples.

Unless otherwise noted subsequently, all estimations were modeled using the following functional form, which is similar to those of Nichols (2012) and where i represents a given game in the sample, Y_i is one of the seven dependent variables described previously, and MarketControl_i is the respective betting market control factor hypothesized to be related to the dependent variable:

$$\begin{aligned}
Y_i = {} & \beta_0 + \beta_1\text{MarketControl}_i + \beta_2\text{HomeFavored}_i + \beta_3\text{HomeUnderdog}_i \\
& + \beta_4 Y2004_i, + \beta_5 Y2005_i + \beta_6 Y2006_i + \beta_7 Y2007_i + \beta_8 Y2008_i + \beta_9 Y2009_i \\
& + \beta_{10} Y2010_i + \beta_{11}\text{GameDate}_i + \beta_{12}\text{East1zone}_i + \beta_{13}\text{East2zones}_i \\
& + \beta_{14}\text{East3Zones}_i + \beta_{15}\text{West1zone}_i + \beta_{16}\text{West2zones}_i + \beta_{17}\text{West3zones}_i \\
& + \beta_{18}\text{Distance}_i + \beta_{19}\text{Distance2}_i + \beta_{20}\text{Outside_LateNortherly}_i \\
& + \beta_{21}\text{Outside_EarlySoutherly}_i + \beta_{22}\text{Dome_LateNortherly}_i \\
& + \beta_{23}\text{Dome_EarlySoutherly}_i + \beta_{24}\text{HigherElev}_i + \beta_{25}\text{LowerElev}_i \\
& + \beta_{26}\text{AridEdge}_i + \beta_{27}\text{Dome}_i + \varepsilon_i.
\end{aligned} \tag{1}$$

The models of HomeWin, ScoreDiff, and HomeCovered used the betting line as the market control. The models of TotalPts and OverBetWins used OverUnder as the market control, and the models of HomePts and AwayPts used PredictedHome and PredictedAway, respectively, as the respective market control. The models of HomeWin, HomeCovered, and OverBetWins were estimated using probit, whereas the models of the remaining dependent variables were estimated using robust regression with Tukey's biweight. As in Nichols (2012), all "pushes"—games in which the victory margin matched the betting line—were excluded from the ScoreDiff and HomeCovered model estimations. This reduced the sample size from 5,093 to 4,998 for these regressions. To maintain as much direct comparison as possible between the modeling of the line (here and in prior literature) and the modeling of the over/under, all betting line pushes were also omitted from the points scored models (note that all pushes in regard to the over/under, where the total points scored in the game exactly matched the over/under, were included in the data).

If the line is a linear and unbiased predictor of the home team's chance of winning, β_1 should be positive and statistically greater than zero in the model of HomeWin, whereas all other coefficients should be zero. (In comparable models of whether the home team wins, Nichols (2012) omitted the betting line and instead used HomeFavored and HomeUnderdog simply to control for team differences. This is due to his somewhat different initial research question, which focused on whether travel affects the home team's chance of winning, and not necessarily on whether the line is a biased predictor of that chance.) If the line is an unbiased predictor of point differentials, it should move identically with ScoreDiff, meaning that β_1 should equal 1, whereas all other coefficients should equal zero. All coefficients in the HomeCovered models—including β_1—should be zero under an assumption of market efficiency (any and all market information in the line should have been fully accounted for when it was netted out of the equation's left side). Similarly, all coefficients in the OverBetWins model estimations—including the coefficient of the over/under itself—should be zero if the over/under betting market is efficient. In the models of points scored, all coefficients other than β_1 should be zero if the market is efficient, whereas β_1 should equal 1.

Model runs were performed using SAS 9.2 (2008). In addition to the measures of model fit reported in the tables discussed subsequently, Hosmer and Lemeshow tests were performed to check for lack of fit for all probit estimations, and none exhibited statistically significant concerns. A two-tailed p value of .05 was used as the threshold for statistical significance in all tables and in the discussion mentioned subsequently, unless otherwise noted.

Results Regarding Whether the Home Team Wins

Results for each of the probit estimations of whether the home team wins are summarized in Table 2. Not surprisingly, in the probit fit to the full sample, the coefficient of the line was positive and highly significant ($p < .0001$), indicating a strong linear relationship between the size of the line and the home team's chance

Table 2. Probit Model of Whether the Home Team Wins (HomeWin).

	Full Sample (n = 5,093)			First Half of Season (n = 2,568)			Last Half of Season (n = 2,525)		
Max-rescaled R^2	.404			.4368			.3777		
Hosmer-Lemeshow GOF Test	10.3325 (p = .2425)			5.0291 (p = .7545)			3.1998 (p = .9212)		
Variable	Coeff	*SE*	*p*	Coeff	*SE*	*p*	Coeff	*SE*	*p*
Intercept	−0.0525	0.2102	.8027	0.0352	0.3337	.9160	0.1509	0.3180	.6352
Line	0.0738	0.0033	<.0001	0.0814	0.0048	<.0001	0.0668	0.0047	<.0001
HomeFavored	0.0425	0.1938	.8266	−0.1527	0.3171	.6302	0.1862	0.2470	.4509
HomeUnderdog	0.1747	0.1939	.3675	0.1279	0.3174	.6870	0.1802	0.2468	.4652
AridEdge	0.0095	0.0957	.9211	−0.0446	0.1401	.7501	0.0710	0.1332	.5940
Distance	−0.00016	0.00019	.4011	0.00000	0.00025	.9843	−0.00033	0.00031	.2824
Distance2	0.00000	0.00000	.7311	0.00000	0.00000	.8691	0.00000	0.00000	.5708
HigherElev	0.00003	0.00002	.2500	0.00005	0.00003	.1402	0.00001	0.00004	.8345
LowerElev	0.00003	0.00002	.1677	0.00002	0.00003	.4847	0.00004	0.00003	.1654
East1zone	0.1073	0.0625	.0859	0.0372	0.0887	.6745	0.1783	0.0887	.0444
East2zones	0.1419	0.1942	.4649	0.2097	0.2426	.3874	−0.0163	0.3457	.9625
East3zones	−0.1252	0.3546	.7241	−0.0268	0.4142	.9484	−0.9018	0.8831	.3072
West1zone	−0.0429	0.0616	.4863	0.0371	0.0890	.6766	−0.1214	0.0865	.1605
West2zones	−0.0167	0.1995	.9334	−0.0001	0.2475	.9996	−0.1026	0.3652	.7788
West3zones	0.0712	0.3642	.8450	0.0752	0.4464	.8662	0.0506	0.6604	.9389
Y2004	0.1378	0.0841	.1011	0.1487	0.1176	.2061	0.1218	0.1212	.3152
Y2005	−0.1257	0.0829	.1291	0.0082	0.1174	.9442	−0.2581	0.1177	.0283
Y2006	−0.0308	0.0810	.7035	−0.0080	0.1160	.9449	−0.0574	0.1138	.6142
Y2007	−0.0294	0.0806	.7157	0.0186	0.1158	.8724	−0.0861	0.1131	.4464
Y2008	−0.0300	0.0809	.7104	−0.0921	0.1184	.4368	−0.0019	0.1117	.9863
Y2009	−0.0035	0.0809	.9653	0.0163	0.1206	.8924	−0.0399	0.1109	.7188
Y2010	−0.0646	0.0810	.4251	0.0774	0.1170	.5080	−0.1848	0.1129	.1017
GameDate	−0.0009	0.0009	.3148	−0.0047	0.0023	.0457	−0.0033	0.0023	.1624
Dome	0.0279	0.1450	.8472	−0.0326	0.1911	.8644	0.0788	0.2281	.7297
Dome_LateNortherly	−0.0020	0.0014	.1612				−0.0021	0.0017	.2011
Outside_LateNortherly	0.0007	0.0004	.1001				0.0008	0.0004	.0791
Dome_EarlySoutherly	−0.0137	0.0062	.0277	−0.0129	0.0061	.0352			
Outside_EarlySoutherly	0.0002	0.0004	.5845	0.0001	0.0004	.7303	−0.0030	0.0612	.9604

Note. SE = standard error; GOF = goodness of fit.

of winning.[6] The only statistically significant travel effect was Dome_Early-Southerly; however, the subgroup size for such games was only $n = 18$, with 16 of those games involving Tulane as the host, making generalizing this finding tenuous. East1zone was weakly significant at the .10 level. Thus, we find some degree of evidence in the full sample that teams that travel one time zone to the east are at a competitive disadvantage that is underestimated by the line. This result coincides with Nichols (2012) who found that the visitor's chance of winning suffered when it traveled east (but with dampened effects for further travel), whereas those traveling west were not affected.

The results for the fits of the HomeWin model to only those games played in each half of the season yield insight into the impact of the East1zone factor vis-à-vis the betting line. In the initial half of the season, crossing one time zone to the east was not significant, nor were any of the travel effects other than the Dome_Early-Southerly finding noted previously. Conversely, the results for the latter half of the season indicated that East1zone was significant and was the only travel factor that was significant (although Outside_LateNortherly was weakly significant). Thus, the betting line appears to be inaccurate in assessing the impact of that factor only late in the year. The finding of a temporal element to the line's prediction bias vis-à-vis easterly travel crossing one time zone has not necessarily been identified in previous literature. It also points to the possibility of a time-varying impact of time zone travel that is misunderstood by the gambling public.

This incongruous behavior of the betting market from the early season to the late season mirrors the Borghesi (2007b) findings in regard to the home underdog bias in the NFL, which he found to exist only in the late season. It also suggests that the theories proffered by Borghesi as to its cause may apply. Borghesi posits that bettors may tend to make more irrational bets later in the season in an effort to make up for prior losses. Whereas more informed arbitrageurs would theoretically be able to correct for the presence of such "noise traders," this group's limited capital keeps it from doing so, and the less informed then dominate the market. It seems possible that this effect could be manifested in the current results.

The nature of college football schedules might also contribute to this phenomenon. Many of the biggest games that are regularly played on home fields take place at or near the end of the year. This would include many traditional rivalries, for which the betting public might wager on their favorite teams more readily than their actual win prospects would reasonably allow. The contemporaneous nature of such games, combined with the massive college football fan base of 75–80 million (Silver, 2011), might yield an influx of overly loyal bettors that more rational gamblers cannot offset. Regardless, and similarly to Borghesi's conclusion, the current results suggest that the use of the full season as the frame of study when researching market behavior appears inappropriate.

The observed late-season effects could alternately or additionally be the result of physiological impacts on teams and players that are simply not understood sufficiently by the gambling public (or perhaps the public at large, as revealed in or by the gambling public). The market might be underestimating a general fatigue or injury factor that exacerbates the more specific effects of time zone travel as the season progresses. In a highly physical contact sport such as football, it's obvious that players' bodies take increasing wear and tear—including occasionally significant injury—through which players often continue to participate. Until season's end, players also generally have few breaks from the physical toll of the game. This load, when combined with time zone travel that necessitates a time and rest deficit vis-à-vis the opponent (Nichols, 2012), may interact to create effects that are more averse later in the season.

Given that the latter half of the season is where travel effects appear to have the most impact, two additional estimations were done in which the HomeWin model was estimated for all home favorites and pick-ems (n = 1,580), and then again for all home underdogs (n = 945), using only the second half of the season data (Nichols, 2012 took a similar approach, although he reported separate results for home favorites/pick-ems and home underdogs for his full sample). This was done in order to determine if the observed travel effects are consistent across the spectrum of betting lines. It's also prompted in part by the analysis of Paul et al. (2003) who examined home underdogs separately and found different betting line behavior for (and within) that subgroup. Finally, it's also consistent with the way in which the betting market reports team performance results, which are often presented separately for when the team is a favorite versus an underdog.

The results indicated that the East1zone factor is significantly related to whether a home favorite (or pick-em) wins the game (coefficient of 0.2844, with $p = .0139$) but contrastingly is not remotely close to being significant for home underdogs ($p = .8386$).[7] The Outside_LateNortherly effect is also inconsistent for home favorites vis-à-vis home underdogs, but in the opposite manner, that is, it's significant for home underdogs ($p = .0281$) but insignificant for home favorites ($p = .7629$). The significant and positive coefficient of Outside_LateNortherly for home dogs is consistent with the findings of Borghesi (2007a, 2007b) and Nichols (2012) regarding general cold-acclimatization detriments for visiting teams. The finding that late-season cold-weather effects are associated with home underdogs in college football aligns well with the conclusions of Borghesi (2007b) regarding the cause of the late-season home-underdog effect in the NFL.

West1zone was also significant ($p = .0483$) for home underdogs, albeit with a negative coefficient of –.2791 (i.e., in favor of the visiting team's prospects of winning), but it was insignificant for home favorites/pick-ems ($p = .8550$). However, this West1zone finding is consistent with the significant and positive East1zone finding for home favorites/pick-ems in a key way: both imply that underdogs lose more readily than expected late in the year when they have a 1-hr time deficit versus their opponent. Road dogs have lost an hour of their own time when they've traveled east, and home dogs are playing a visitor that has gained an hour when it has traveled west. This hour of difference is perhaps assumed to have minimal effect by game-day and team-travel planners (e.g., athletic directors, and coaches) as well as the gambling public. Early in the season, teams may be both fresh and motivated enough such that the time difference doesn't matter. However, late in the year, when both teams are more physically fatigued, and when an underdog may be less motivated and more apt to "play out the string"—that is, it may very well expect to lose itself—this time differential may take enough of a toll to impact who wins. Regardless of the cause, the East1zone and West1zone observations suggest that the betting line is an inconsistent and biased processor of available information when used as a predictor of who wins.

That visiting underdogs suffer time zone effects late in the season, while late-season visiting favorites do not, seems to run counter to the theory put forward by Ashman, Bowman, and Lambrinos (2010) in their study of the NBA, where visiting favorites do worse than expected. Ashman et al. posit that when a poor NBA home team is playing a favored visitor, the extra attention from the media and peers that comes with playing a good team causes the home team to exert greater effort and play above expectations. The authors further point to the Paul and Weinbach (2005) supposition that players on a visiting team may not put forth their best efforts if they are heavily favored to win.

It seems plausible though that a different season length and postseason structure might explain the opposite effect found in this research for college football. The nature of the NBA playoffs and extensive length of the NBA season may encourage favored visitors to rest or protect against injury when playing on the road, particularly if a postseason bid has been essentially (or actually) secured. However, the nature of the relatively short college football season is very different. Far more so than in most sports, every game matters. Home teams that are favored have likely had reasonably if not very successful seasons already, and may exert unexpectedly strong effort in order to seal conference titles or bowl positions, sufficient to overcome the fatigue affecting the players on both teams. For the same reasons, visiting favorites may do the same. In contrast, the home or visiting underdog late in the season may succumb more to fatigue, as there may be little to play for, and this may be particularly true for visitors who lose time when traveling.

The HomeWin model results for home underdogs in the season's second half also reveal similar aridity advantages to those found by Kuester and Sanders (2011). Home underdogs enjoy a statistically significant aridity advantage over their visitors from less arid regions in the last half of the season (coefficient of .4063, $p = .0486$), suggesting that such teams win the game "straight up" more frequently than would otherwise be expected, given the size of the betting line and other travel effects (there were 87 games in which a home underdog had a presumed aridity advantage in the last half of a season, so this finding is based on a somewhat small observation group).

Results Regarding the Score Difference

Results for the robust regression estimations of the model of the score difference are shown in Table 3. The full sample estimation results yield similar findings to the full

Table 3. Robust Regression Model (Using Tukey's Biweight) of Point Differentials (ScoreDiff).

	Full Sample (n = 4,998)			First Half of Season (n = 2,517)			Last Half of Season (n = 2,481)		
R^2	.4020			.4229			.3831		
Variable	Coeff	*SE*	*p*	Coeff	*SE*	*p*	Coeff	*SE*	*p*
Intercept	0.4815	2.5429	.8498	−2.3626	4.0208	.5568	3.9204	3.7868	.3005
Line	1.0639	0.0257	<.0001	1.0865	0.0350	<.0001	1.0329	0.0382	<.0001
HomeFavored	−0.8298	2.3839	.7278	1.2824	3.8591	.7396	−1.7733	3.0525	.5613
HomeUnderdog	0.6072	2.3863	.7991	3.4416	3.8633	.3730	−1.1454	3.0550	.7077
AridEdge	0.4107	1.0418	.6934	1.0499	1.4819	.4787	−0.2196	1.4838	.8823
Distance	−0.00310	0.00200	.1237	−0.00170	0.00260	.5133	−0.00310	0.00340	.3508
Distance2	0.00000	0.00000	.1098	0.00000	0.00000	.2420	0.00000	0.00000	.6333
HigherElev	0.00010	0.00030	.5701	0.00010	0.00040	.8493	0.00020	0.00040	.5696
LowerElev	0.00030	0.00020	.1792	0.00040	0.00030	.2634	0.00030	0.00030	.3377
East1zone	1.2302	0.6751	.0684	0.0980	0.9402	.9170	2.3021	0.9758	.0183
East2zones	−0.8833	1.9779	.6552	−2.7753	2.4318	.2538	3.0155	3.5593	.3969
East3zones	−8.5041	3.7231	.0224	−9.0170	4.2737	.0349	−11.8665	8.9304	.1839
West1zone	0.3574	0.6807	.5996	0.5071	0.9570	.5962	0.0812	0.9759	.9336
West2zones	−0.8727	2.1616	.6864	−2.3508	2.6644	.3776	1.4565	3.8505	.7052
West3zones	−3.4585	3.8657	.3710	−6.2754	4.6892	.1808	2.4749	6.9692	.7225
Y2004	2.2990	0.8976	.0104	3.2191	1.2352	.0092	1.2003	1.3154	.3615
Y2005	−0.1208	0.8991	.8931	1.2546	1.2477	.3146	−1.6754	1.3016	.1980
Y2006	−0.4330	0.8810	.6231	−0.1045	1.2385	.9328	−0.9519	1.2596	.4498
Y2007	−0.0975	0.8779	.9116	0.9498	1.2261	.4386	−1.3159	1.2641	.2979
Y2008	−0.2038	0.8797	.8168	−0.8927	1.2625	.4795	0.1162	1.2354	.9251
Y2009	−0.9983	0.8808	.2571	−0.0790	1.2900	.9512	−2.1420	1.2263	.0807
Y2010	−0.4512	0.8823	.6091	1.0869	1.2482	.3838	−1.9483	1.2516	.1195
GameDate	−0.0030	0.0101	.7680	−0.0371	0.0246	.1318	−0.0174	0.0262	.5061
Dome	−0.5587	1.5885	.7251	−0.0273	2.0505	.9894	−1.7652	2.5424	.4875
Dome_LateNortherly	−0.0218	0.0144	.1305				−0.0147	0.0168	.3811
Outside_LateNortherly	0.0074	0.0044	.0941				0.0084	0.0048	.0811
Dome_EarlySoutherly	−0.0609	0.0241	.0117	−0.0662	0.0249	.0080			
Outside_EarlySoutherly	−0.0007	0.0037	.8435	−0.0021	0.0040	.5908	0.1574	0.6892	.8194

Note. SE = standard error.

sample estimation of whether the home team wins: East1zone is significant at the .10 level and Dome_EarlySoutherly is significant at the .05 level (with a negative coefficient). While Outside_LateNortherly was weakly significant, its *p* value was only slightly lower than its *p* value in the HomeWin model. East3zones was significant but with a negative coefficient, suggesting lower victory margins for home teams when visitors travel fully cross-country. However, as noted previously, the relatively small sample size of games and teams involved in three-zone travel might be influencing this finding.[8]

The results for the two halves of the data were also similar to those from the half-season estimations of whether the home team wins: East1zone was insignificant and Dome_EarlySoutherly was significant (and negative) in the early season estimation, and East1zone was significant and Outside_LateNortherly was weakly significant in the season's latter half (the significance of East3zones also differed between the early season and late season subsamples).[9] This underscores the existence of an apparently temporal element to travel's impact on visiting team performance and/or the associated expectations of the betting public.

Although Nichols (2012) did not investigate the temporal issue, results from his full sample examination of NFL point differentials are similar to the current findings for college football. He found that the betting line did not accurately account for cold weather, whereas playing in relatively warm weather had no significant effect not already included in the line. Like the current results, he also found no effect of travel distance on point differentials in the presence of the line and variables accounting for the number of time zones traveled. Nichols did find that both easterly and westerly travel were significant vis-à-vis the NFL line, whereas only easterly travel is found to be significant in the current analysis. However, his results showing the insignificance of three-zone travel do differ from the current findings.

The lack of significance for travel distance in all estimations thus far is noteworthy, as any effect is apparently and presumably subsumed by the time zone factors. Stated otherwise, travel distance seems impactful only if it involves a loss of time for the visitor. Otherwise, with rather efficient means of travel available to many or most teams, often including charter plane service, the impact on performance appears to be minimal or at least sufficiently addressed by the traveling institution—or simply accurately estimated by the betting market.

The ScoreDiff model results are also of note in regard to the coefficient of the line itself. If the line is an unbiased estimator of the point differential, its coefficient should be no different from 1.00 in all estimations. However, the line's coefficient is significantly different from 1.00 in the full sample and in the early season estimation.[10] Both results suggest additional bias in the line not associated with factors included in the model. That the line's coefficient is statistically indifferent from 1.00 in the season's latter half provides support for the hypothesis that the betting market becomes more knowledgeable as a season progresses.

Given the differentiated findings for HomeWin in regard to the home team's favorite status in the season's latter half, the ScoreDiff second-half model was also estimated separately for home favorites/pick-ems ($n = 1{,}558$) and home underdogs ($n = 923$). The results are similar to those for HomeWin: the betting line underestimates the effect of easterly time zone travel on visiting underdogs (i.e., when the home team is a favorite or pick-em), and crossing one time zone east costs such visitors just over a field goal ($p = .0092$) over and above the score difference that would be expected, given the betting line and other travel effects. Moreover, crossing two time zones to the east is also weakly significant ($p = .0556$); its coefficient indicates that such travel costs visitors an estimated 8.53 points or well over a touchdown.[11] (However, there were only 26 games in the subsample that involved crossing two time zones to the east, so this finding is based on a small group of observations. Contrastingly, there were 262 late-season home-favorite-and-pick-em games that involved a visitor traveling just one zone to the east.) The ScoreDiff model fits for home underdogs reverse the finding for East2zones, as its coefficient flips to a weakly significant but negative value of -11.65 points.[12] The East1zone effect that was significant for home favorites/pick-ems is insignificant for home underdogs ($p = .8144$). These findings point to a considerable bias in the college football betting line's predictive accuracy.

Results Regarding Whether the Home Team Covered the Spread

Results for all estimations of the model of whether the home team covered the spread are shown in Table 4. The fit to the full sample reveals some commonalities to those found in the full sample for the HomeWin and ScoreDiff models: easterly travel crossing one time zone was again significant at the .10 level. Moreover, East3zones was weakly significant (with a negative coefficient), similar to its effect on ScoreDiff.[13] However, despite it being weakly related to whether the home team wins, Outside_LateNortherly was not close at all to being significantly related to whether a team covered the spread, indicating that either it has no effect or the betting market efficiently accounts for whatever effect it has. The difference in findings could be the result of the betting market more accurately processing information when it is directly relevant to their financial outcomes. It also could be due to the limitations of the current proxy for actual temperature that is being employed herein.

A factor not found to be significantly related to HomeWin and ScoreDiff was significantly related to HomeCovered: Dome_LateNortherly (with a subgroup size of $n = 54$). Its negative coefficient implies that visiting teams traveling northerly cover the spread more frequently than expected when playing indoors. When viewed in conjunction with the significant and negative coefficient for the 18 Dome_EarlySoutherly games in the models of HomeWin and ScoreDiff, these findings imply a possible visiting team advantage when playing in temperatures more closely approximating their own climates at the time of the game than those

Table 4. Probit Model of Whether the Home Team Covered the Spread (HomeCovered).

	Full Sample (n = 4,998)			First Half of Season (n = 2,517)			Last Half of Season (n = 2,481)		
Max-rescaled R^2	.0124			.016			.0211		
Hosmer-Lemeshow GOF Test	10.3602 (p = .2406)			6.2744 (p = .6165)			12.2451 (p = .1406)		
Variable	Coeff	*SE*	*p*	Coeff	*SE*	*p*	Coeff	*SE*	*P*
Intercept	−0.1439	0.2042	.4808	−0.0675	0.3233	.8346	0.0559	0.3032	.8538
Line	0.0057	0.0021	.0056	0.0064	0.0028	.0232	0.0050	0.0031	.0993
HomeFavored	0.0408	0.1915	.8312	−0.0739	0.3104	.8117	0.1142	0.2448	.6407
HomeUnderdog	0.2450	0.1917	.2011	0.2068	0.3107	.5057	0.2519	0.2450	.3039
AridEdge	0.0422	0.0835	.6130	0.1221	0.1193	.3062	−0.0165	0.1187	.8893
Distance	−0.00014	0.00016	.3850	−0.00008	0.00021	.6974	−0.00013	0.00027	.6174
Distance2	0.00000	0.00000	.2094	0.00000	0.00000	.2308	0.00000	0.00000	.8923
HigherElev	0.00001	0.00002	.5839	0.00000	0.00003	.8826	0.00002	0.00003	.5926
LowerElev	0.00003	0.00002	.0780	0.00003	0.00003	.2132	0.00003	0.00003	.2019
East1zone	0.1049	0.0541	.0525	0.0018	0.0756	.9809	0.2135	0.0782	.0063
East2zones	−0.1380	0.1588	.3846	−0.2998	0.1961	.1263	0.2006	0.2856	.4824
East3zones	−0.5322	0.3013	.0773	−0.6874	0.3470	.0476	−0.5646	0.7596	.4573
West1zone	−0.0140	0.0545	.7969	−0.0463	0.0770	.5476	0.0104	0.0779	.8936
West2zones	−0.1290	0.1736	.4577	−0.3465	0.2149	.1068	0.2507	0.3097	.4182
West3zones	−0.1957	0.3103	.5283	−0.5161	0.3784	.1726	0.4352	0.5611	.4380
Y2004	0.1498	0.0720	.0375	0.1751	0.0994	.0782	0.1245	0.1053	.2369
Y2005	−0.0104	0.0720	.8854	0.0525	0.1002	.6004	−0.0824	0.1039	.4276
Y2006	0.0100	0.0705	.8869	0.0549	0.0995	.5813	−0.0455	0.1006	.6512
Y2007	0.0152	0.0703	.8288	0.0921	0.0985	.3501	−0.0754	0.1009	.4551
Y2008	−0.0134	0.0704	.8490	−0.0879	0.1016	.3873	0.0333	0.0987	.7355
Y2009	−0.0547	0.0705	.4381	−0.0131	0.1037	.8993	−0.1329	0.0980	.1750
Y2010	−0.0510	0.0707	.4707	0.0666	0.1003	.5066	−0.1621	0.1000	.1050
GameDate	−0.0002	0.0008	.8375	−0.0023	0.0020	.2383	−0.0029	0.0021	.1695
Dome	0.0272	0.1287	.8326	0.0132	0.1655	.9367	0.0311	0.2083	.8814
Dome_LateNortherly	−0.0031	0.0014	.0231				−0.0029	0.0016	.0697
Outside_LateNortherly	0.0002	0.0004	.5245				0.0004	0.0004	.3244
Dome_EarlySoutherly	−0.0034	0.0021	.1127	−0.0036	0.0022	.1053			
Outside_EarlySoutherly	0.0000	0.0003	.8918	−0.0001	0.0003	.7651	0.0800	0.0600	.1826

Note. SE = standard error; GOF = goodness of fit.

of their hosts—a potential effect that is not recognized by the gambling public nor identified in previous literature.

The first-half and second-half estimations of the HomeCovered model largely emulate the behavior of the first-half and second-half estimations of the models of HomeWin and ScoreDiff. East3zones is the only significant travel factor (albeit weakly so) in the first half,[14] whereas the results in the second-half estimation point to the market's inefficient processing of easterly travel crossing one time zone. For the second-half model of HomeCovered, East1zone is significant at the .01 level. Although Nichols (2012) did not separately examine early and late season subsamples, the current East1zone result directly mirrors Nichols' findings for his full sample: he found that the only travel factor to significantly impact whether the home team covered the spread was the visitor traversing one time zone to the east.

As in the ScoreDiff model, the line's coefficient again illustrates further bias not associated with the factors in the model. Under an efficient market hypothesis, the coefficient should be no different from zero in all estimations of the HomeCovered model. However, Table 4 indicates that its coefficient is significantly different from zero in the full sample and early season fits ($p < .01$ and $p < .05$, respectively) but only weakly significantly different from zero in the late-season fit. Again, these results suggest that the market processes information about teams much more readily as additional data are gained.

Separate latter-half fits of the HomeCovered model for home favorites/pick-ems ($n = 1{,}558$) and home underdogs ($n = 923$) underscored a finding that the market is also inefficient. For visiting underdogs, the late-season time zone effects are similar to those found for ScoreDiff. Crossing one zone to the east is significantly related to whether the home team covers the spread (coefficient of 0.2377, $p = .0134$). Although easterly travel crossing two zones was also found to be related to covering (coefficient of 0.7425, $p = .0411$), that result was again based on a relatively small number of observations ($n = 26$, as noted previously).[15] Nevertheless, the East1zone results for visiting underdogs provided evidence of inefficiency in the gambling market.

Given this evidence for inefficiency, an additional test was performed to determine if the late-season East1zone effect was sufficient to generate economic returns, that is, returns beyond those necessary to cover transaction costs. As noted by many (e.g., Nichols, 2012), a betting strategy must win more than 52.38% of the time to generate a profit. A simple strategy was analyzed, that is, betting on a favored home team in the latter half of the season, when hosting a visiting team traveling one time zone to the east. Omitting any pushes, there were 262 such opportunities within the current sample, and the strategy would have won on 152 occasions (58.02%), significantly greater than 52.38%, with $p < .05$ using a likelihood ratio test. The percentage of winning bets in each of the 8 years would have ranged between 50% and 66.7% and would have exceeded the 52.38% profitability threshold in 7 of the 8 years, suggesting a persistent effect not isolated to given years within the sample. These findings suggest that the East1zone effect has been an economically exploitable market anomaly. As to the amount of profit potential involved, a bettor employing this strategy would have received a 10.76% return on the initial funds invested, after paying the vigorish.[16]

The betting strategy was also tested out of sample during the latter halves of the 2012 and 2013 seasons. Out of sample, the approach would have won only 34 (45.9%) of 74 times, which is obviously not statistically significantly greater than 52.38%. However, the winning percentage in the out-of-sample games is statistically significantly different from neither the in-sample proportion (using a test for the difference in the two proportions) nor the profitability threshold of 52.38% (using a likelihood ratio test) and thus not sufficient to conclude a change in market behavior vis-à-vis the 2004-2011 time period.

Results Regarding Total Points Scored

Results for the robust regression estimations of the TotalPts model are summarized in Table 5. In the presence of the other factors in the model, the coefficient of the over/under was not statistically significantly different from 1.00, suggesting an apparently accurate market estimation of the total points scored in a game.[17] However, other findings in the three fits of the TotalPts model indicate that the over/under is not an accurate predictor of travel effects on road teams.

In games involving visitors traveling two time zones to the east (a subgroup of $n = 123$), the two teams combine to score a statistically significant 4.81 more points than expected. When visiting teams travel one time zone to the west, the point total is a significant 1.49 points higher than expected. Moreover, the point total is significantly less than the betting market anticipates when a visitor travels southerly in outdoor games early in the season. The TotalPts model estimation fit to each half of the season indicates that the East2zones effect is significant only in the early part of the season—although its coefficient is very similar across both cuts of the data—and the West1zone effect is significant only in the second half of the season. Although the coefficient of the over/under is statistically no different from 1.00 in either subsample,[18] the findings indicate that the over/under is an inaccurate assimilator of travel effects on visiting teams.

However, when the TotalPts model is fit separately for home favorites/pick-ems and then for home underdogs in each half of the season, no evidence of inaccuracy in the over/under is revealed for games in which the home team is favored or pick-em in either half of the season. However, there are significant effects when the home team is the underdog. One of these is difficult to generalize: the two teams combine to score significantly more points (13.6, $p = .0250$) when a favored visitor has crossed two zones easterly in the season's early stages, but the subgroup size for such games is only 11. However, the West1zone effect on total scoring in late-season games when the visitor is favored is a statistically significant ($p = .0024$) 4.88 increase (based on a subgroup size of 160) versus what is anticipated by the

Table 5. Robust Regression Model (Using Tukey's Biweight) of Total Points Scored in a Game (TotalPts).

	Full Sample (n = 4,966)			First Half of Season (n = 2,485)			Last Half of Season (n = 2,481)		
R^2	.1496			.1337			.1682		
Variable	Coeff	*SE*	*p*	Coeff	*SE*	*p*	Coeff	*SE*	*p*
Intercept	6.9058	3.1516	.0284	7.2178	4.8624	.1377	4.6744	4.6189	.3115
OverUnder	0.9478	0.0327	<.0001	0.9065	0.0491	<.0001	0.9825	0.0445	<.0001
HomeFavored	−4.8386	2.4629	.0495	−1.7937	3.9542	.6501	−7.1721	3.1862	.0244
HomeUnderdog	−5.4324	2.4753	.0282	−3.2292	3.9686	.4158	−6.9120	3.2068	.0311
AridEdge	0.1674	1.0937	.8783	2.1725	1.5455	.1598	−1.9202	1.5722	.2220
Distance	0.00130	0.00210	.5204	0.00040	0.00270	.8790	0.00440	0.00350	.2131
Distance2	0.00000	0.00000	.3468	0.00000	0.00000	.7142	0.00000	0.00000	.1857
HigherElev	−0.00010	0.00030	.7675	−0.00040	0.00040	.2628	0.00030	0.00040	.5004
LowerElev	0.00000	0.00020	.9122	−0.00030	0.00030	.3787	0.00020	0.00030	.5836
East1zone	0.7345	0.7061	.2983	0.8040	0.9767	.4104	0.4848	1.0309	.6382
East2zones	4.8077	2.0672	.0200	4.9487	2.5180	.0494	4.7162	3.7556	.2092
East3zones	0.6459	3.8938	.8683	−0.3029	4.4280	.9455	1.2375	9.4369	.8957
West1zone	1.4924	0.7123	.0361	0.4229	0.9942	.6706	2.6639	1.0304	.0097
West2zones	1.7392	2.2605	.4417	0.0679	2.7600	.9804	5.1757	4.0718	.2037
West3zones	4.1116	4.0609	.3113	3.5085	4.8880	.4729	4.3665	7.3651	.5533
Y2004	0.1051	0.9556	.9124	−1.5961	1.3177	.2258	2.1059	1.3973	.1318
Y2005	0.4020	0.9411	.6693	0.2743	1.2918	.8318	0.4671	1.3805	.7351
Y2006	−0.7578	0.9473	.4237	−1.5654	1.3150	.2339	0.0344	1.3760	.9800
Y2007	1.1380	0.9155	.2139	1.8586	1.2658	.1420	0.1694	1.3357	.8991
Y2008	0.6187	0.9205	.5015	−0.4938	1.3059	.7054	1.7740	1.3107	.1759
Y2009	0.2481	0.9215	.7877	−0.5564	1.3347	.6768	1.0161	1.3001	.4345
Y2010	0.5316	0.9206	.5636	0.0136	1.2883	.9916	0.9702	1.3232	.4634
GameDate	−0.0016	0.0106	.8771	0.0023	0.0254	.9274	0.0133	0.0277	.6319
Dome	2.0916	1.6530	.2057	1.5710	2.1130	.4572	2.4973	2.6774	.3510
Dome_LateNortherly	−0.0036	0.0150	.8110				−0.0066	0.0178	.7091
Outside_LateNortherly	0.0030	0.0046	.5131				0.0006	0.0051	.9065
Dome_EarlySoutherly	−0.0037	0.0252	.8843	0.0025	0.0257	.9218			
Outside_EarlySoutherly	−0.0088	0.0039	.0244	−0.0093	0.0041	.0237	−0.3509	0.7282	.6299

betting market. Thus, the positive West1zone effect on points scored in the late-season holds only when the road team is favored.

Taken collectively, these findings point to inaccuracy in the market's estimation of the over/under, most pointedly in games in which the visiting team is favored. This general conclusion regarding error in the over/under's predictiveness is consistent with the findings of Kain and Logan (2014) for college football (as well as for college basketball, the NFL, and the NBA), which represents the only previous literature on the predictive accuracy of the over/under in the sport. This research extends Kain and Logan (2014) by identifying travel effects as at least one source for the market's prediction error.

Results Regarding Home and Visitor Points

The combination of the over/under and the betting line reveals further insight into the sources of market error in estimating travel effects on visiting teams. Tables 6 and 7 contain the estimations of the market's predicted number of points for the home team (HomePts) and the visiting team (AwayPts), respectively, across the full sample as well as for the first and second halves of the season.

The market is an inaccurate overall predictor of the number of points scored by the home team, as the coefficient of PredictedHome is statistically significantly different from 1.00 across the full season,[19] and suggests that the market's prediction needs to be increased by an average of 6.55%. However, this inaccuracy holds for the season's first half only, when the market's estimate of home team points has a nearly 9% error.[20] The statistical insignificance of PredictedHome's coefficient (vs. a value of 1.00) in the season's latter half provides further support for the theory that the market better integrates knowledge and adapts as the season progresses.[21] Conversely, in the presence of the other factors in the AwayPts model, there is no bias in the market's estimate of the visiting team's score, as the coefficient of PredictedAway in Table 7 is not significantly different from 1.00 for the full season or either of the two half-season subsamples.[22]

However, the findings associated with visitor travel reveal market errors in projecting the impact on both home and visiting team scoring. When the visiting team travels one time zone to the east, the home team scores a statistically significant 1.20 points more than expected, whereas the market's estimate of the visiting team's score is unbiased. More specifically, this positive effect of East1zone on home team scoring is significant only in the season's second half, when the home team scores a significant 1.53 points more than expected. This finding suggests that the East1zone effect observed earlier in the second-half estimations of the HomeWin, ScoreDiff, and HomeCovered models is the result of the market underestimating the number of points scored by the home team when visitors travel one-zone east. This also implies that the travel effect on visiting teams in such situations is on their respective defensive squads, not on their offenses.[23]

Table 6. Robust Regression Model (Using Tukey's Biweight) of Home Team Points (HomePts).

	Full Sample (n = 4,966)			First Half of Season (n = 2,485)			Last Half of Season (n = 2,481)		
R^2	.3093			.3317			.2927		
Variable	Coeff	*SE*	*p*	Coeff	*SE*	*p*	Coeff	*SE*	*p*
Intercept	1.0447	2.0458	.6096	−1.8416	3.1835	.5629	3.0244	3.0142	.3157
PredictedHome	1.0655	0.0289	<.0001	1.0894	0.0406	<.0001	1.0401	0.0414	<.0001
HomeFavored	−3.3800	1.7670	.0558	−0.9183	2.8582	.7480	−5.2825	2.2576	.0193
HomeUnderdog	−3.0880	1.7696	.0810	−0.6475	2.8591	.8208	−4.9156	2.2646	.0300
AridEdge	−0.3078	0.7785	.6925	1.1651	1.1071	.2926	−1.7844	1.1058	.1066
Distance	−0.00100	0.00150	.4852	−0.00110	0.00200	.5903	0.00090	0.00250	.7320
Distance2	0.00000	0.00000	.6612	0.00000	0.00000	.5062	0.00000	0.00000	.4766
HigherElev	0.00000	0.00020	.8364	−0.00020	0.00030	.5564	0.00030	0.00030	.3568
LowerElev	0.00010	0.00020	.5888	0.00000	0.00020	.8661	0.00020	0.00020	.3839
East1zone	1.1969	0.5034	.0174	0.7825	0.7015	.2646	1.5313	0.7256	.0348
East2zones	2.0617	1.4742	.1619	1.0475	1.8107	.5629	4.2109	2.6447	.1113
East3zones	−3.2786	2.7767	.2377	−3.9796	3.1845	.2114	−5.2758	6.6419	.4270
West1zone	1.1545	0.5079	.0230	0.7936	0.7142	.2665	1.4662	0.7258	.0434
West2zones	1.0493	1.6116	.5150	−0.9568	1.9846	.6297	4.4159	2.8654	.1233
West3zones	0.9085	2.8955	.7537	−0.8852	3.5148	.8012	4.3930	5.1829	.3967
Y2004	1.2848	0.6797	.0587	1.0376	0.9434	.2714	1.6200	0.9829	.0993
Y2005	0.1918	0.6697	.7746	1.0155	0.9267	.2731	−0.7273	0.9700	.4534
Y2006	−0.1106	0.6625	.8674	−0.1568	0.9268	.8656	−0.1514	0.9505	.8735
Y2007	0.6949	0.6529	.2872	1.7744	0.9097	.0511	−0.5171	0.9400	.5823
Y2008	0.2279	0.6553	.7280	−0.6643	0.9377	.4787	0.9487	0.9212	.3031
Y2009	−0.1910	0.6557	.7709	0.0027	0.9579	.9977	−0.5058	0.9130	.5796
Y2010	−0.0853	0.6563	.8966	0.4259	0.9261	.6456	−0.5879	0.9310	.5277
GameDate	−0.0010	0.0075	.8952	−0.0156	0.0183	.3922	0.0053	0.0195	.7847
Dome	0.6818	1.1791	.5631	0.6681	1.5208	.6604	0.4503	1.8822	.8109
Dome_LateNortherly	−0.0144	0.0107	.1790				−0.0134	0.0125	.2850
Outside_LateNortherly	0.0051	0.0033	.1180				0.0044	0.0036	.2177
Dome_EarlySoutherly	−0.0356	0.0179	.0475	−0.0354	0.0185	.0558			
Outside_EarlySoutherly	−0.0045	0.0028	.1049	−0.0055	0.0030	.0643	0.0202	0.5125	.9685

Table 7. Robust Regression Model (Using Tukey's Biweight) of Away Team Points (AwayPts).

	Full Sample (n = 4,966)			First Half of Season (n = 2,485)			Last Half of Season (n = 2,481)		
R^2	.2930			.2900			.2985		
Variable	Coeff	*SE*	*p*	Coeff	*SE*	*p*	Coeff	*SE*	*p*
Intercept	1.9591	1.9532	.3158	3.5721	2.9769	.2302	−0.6813	2.9530	.8175
PredictedAway	0.9638	0.0292	<.0001	0.9430	0.0412	<.0001	0.9785	0.0418	<.0001
HomeFavored	−2.0275	1.6904	.2304	−2.4903	2.6822	.3532	−1.8271	2.2025	.4068
HomeUnderdog	−1.7515	1.6971	.3020	−2.4250	2.6928	.3678	−1.2855	2.2105	.5609
AridEdge	0.2563	0.7446	.7307	1.2496	1.0410	.2300	−0.7878	1.0768	.4644
Distance	0.00190	0.00140	.1830	0.00100	0.00180	.5869	0.00330	0.00240	.1727
Distance2	0.00000	0.00000	.1358	0.00000	0.00000	.3089	0.00000	0.00000	.3123
HigherElev	−0.00010	0.00020	.4747	−0.00030	0.00020	.1724	0.00010	0.00030	.7230
LowerElev	−0.00010	0.00020	.7050	−0.00020	0.00020	.3623	0.00000	0.00020	.8594
East1zone	−0.4404	0.4823	.3611	0.1305	0.6599	.8432	−1.0941	0.7079	.1222
East2zones	2.3472	1.4120	.0964	3.6703	1.7019	.0310	0.0835	2.5813	.9742
East3zones	4.7827	2.6591	.0721	5.0886	2.9931	.0891	5.4897	6.4787	.3968
West1zone	0.4436	0.4861	.3615	−0.2231	0.6716	.7398	1.1799	0.7075	.0954
West2zones	0.3572	1.5434	.8170	−0.0952	1.8660	.9593	1.4542	2.7936	.6027
West3zones	3.4174	2.7730	.2178	4.8337	3.3040	.1435	−0.0204	5.0568	.9968
Y2004	−1.0885	0.6491	.0936	−2.3093	0.8861	.0092	0.3152	0.9542	.7412
Y2005	0.3330	0.6411	.6034	−0.3156	0.8711	.7171	1.0661	0.9455	.2595
Y2006	−0.1147	0.6364	.8569	−0.6593	0.8744	.4508	0.5524	0.9287	.5520
Y2007	0.8014	0.6252	.1999	0.5220	0.8552	.5416	1.1355	0.9172	.2157
Y2008	0.1759	0.6270	.7791	0.0683	0.8808	.9382	0.4891	0.8971	.5856
Y2009	0.5997	0.6282	.3397	−0.2482	0.9004	.7829	1.5783	0.8914	.0766
Y2010	0.6990	0.6284	.2660	−0.3773	0.8704	.6647	1.7746	0.9082	.0507
GameDate	0.0025	0.0072	.7336	0.0199	0.0173	.2494	0.0142	0.0190	.4551
Dome	1.8912	1.1317	.0947	0.8892	1.4297	.5340	3.1726	1.8476	.0860
Dome_LateNortherly	0.0094	0.0103	.3592				0.0015	0.0122	.9053
Outside_LateNortherly	−0.0017	0.0031	.5816				−0.0039	0.0035	.2597
Dome_EarlySoutherly	0.0240	0.0172	.1624	0.0319	0.0174	.0667			
Outside_EarlySoutherly	−0.0045	0.0027	.0948	−0.0042	0.0028	.1311	−0.2533	0.5000	.6124

The earlier observation regarding the 2.66 increase in total points scored in games requiring the visitor to travel one-zone westward in the season's second half (see Table 5) appears to be the result of both teams scoring more than expected: West1zone is positive and significantly related to home team points in the late season, and is positive and weakly related to visitor scoring.

In contrast, the previously noted East2zones effect on total points in the season's first half appears primarily to be associated with increased visitor scoring. Visitors score a statistically significant average of 3.67 points more than expected when traveling east two zones in the early season, whereas home team scoring is not significantly affected.[24] These results imply that the market is anticipating more substantial time zone effects on the visitor—particularly its offense—than ultimately arise, and/or that visiting teams in these circumstances are taking appropriate precautions to mitigate the effects of 2 hr of lost time. The insignificance of this travel factor in determining whether the home team wins, its victory margin, or whether it covers the spread implies that this scoring increase by the road team is not sufficient to significantly impact those outcomes. Obviously, visitors can score more points without necessarily winning the game or impacting who covers, and the earlier results for East2zones in the HomeWin and HomeCovered models support this conclusion. Table 3 indicates that the coefficient of East2zones in the ScoreDiff model fit to the season's first half represents a -2.78 point effect on the home team's victory margin (albeit with a p value of .2538), implying that home teams score enough extra points themselves—about a point more (see East2zones' first half coefficient for home scoring in Table 6)—in such games to make the effect of the visitor's increased scoring on the victory margin statistically insignificant. Regardless, the collective findings associated with East2zones suggest the presence of betting market error.

Breaking out home and away team scoring by favorite status suggests that the aforementioned positive effects of East1zone for home favorites/pick-ems in the season's latter half appear twofold: the home team scores a weakly significant 1.70 points more (p = .0634) and gives up significantly less points (1.83, p = .0324), implying negative travel effects on a visiting underdog's offense *and* defense. Neither of these effects is significant when the visitor is favored in the late-season. A home underdog and its favored visitor *both* score more points—1.98 (p = .0683) and 3.24 (p = .0050), respectively—when the visitor has traveled one zone westward late in the season. These results were large enough to generate a strongly significant (p = .0024) West1zone effect on total points scored in second halves when the home team is the underdog. The difference is also sufficiently large to impact the previously noted significant (p = .0483) and negative West1zone effect on a home underdog's chance of winning in the second half. The combination of findings suggest that underdog teams perform worse than expected, regardless of whether they're playing home or away, late in the season. Moreover, all of these findings point to predictive error on the part of the betting public when estimating team travel effects.

Results Regarding the Over/Under's Market Efficiency

Table 8 contains the results for the OverBetWins model for the full sample as well as the season's two halves, which indicate that the over/under market is inefficient in regard to the East2zones effect.[25] Although this factor is significant and positive in the full sample, the results indicate that that an "over" bet is more apt to win only in the season's first half. This is not surprising, given the previously discussed significant and unexpectedly higher early season scoring by visitors in this travel scenario. However, a simple strategy of betting the "over" in the early season, when visitors have traveled two zones east, would have won 51 of 87 times (omitting over/under pushes), which is not significantly larger than the 52.38% minimum threshold for economic profitability using a likelihood ratio test. These findings suggest a statistically significant market inefficiency that is nevertheless insufficient to be economically exploitable.

Breaking the analysis of each half into separate estimations for home favorites/pick-ems and home underdogs indicates that the positive East2zones effect on total scoring in the season's first half is significant ($p = .0487$) when the home team is favored or pick-em—an "over" bet would have won 43 (57.33%) of 75 times–but is not significant when the home team is an underdog. However, the subsample of first-half/home underdog/East2zones games is only $n = 11$ (or $n = 12$ if including betting line pushes), and the strategy of betting the over would have won 8 of those 12 times. Thus, it doesn't appear that any market inefficiency in the early season is necessarily affected by which team is favored—at least as it regards East2zones.

However, the coefficient of the over/under itself is significantly different from zero ($p = .0495$) in home underdog games in the early season, whereas it is not significant for home favorite/pick-em games ($p = .5070$). The first half/home underdog estimation also reveals market inefficiency in regard to East1zones: an "over" bet is significantly more likely to win when the visitor travels one zone east ($p = .0282$). Given the weakly significant ($p = .0586$) but positive coefficient of 3.47 for this factor in a first half/home underdog model of total points, this finding is not necessarily surprising. However, it further emphasizes a rather consistent theme of market error involving games for which visitors travel eastward one zone.[26]

Second-half estimations for home favorites/pick-ems and home underdogs again point to market error involving West1zones. The significance of westerly one-zone travel by visiting favorites late in the season ($p = .0312$) is consistent with its aforementioned large and strongly significant ($p = .0024$) positive effect of 4.88 on total points scored in such scenarios. Betting the "over" in such games would have won 93 (57.41%) of 162 times, which is only weakly significantly better than the 52.38% economic profitability threshold, but would have exceeded that threshold in each of the 8 years studied. Out of sample, the same strategy would have won 17 (50%) of 34 times during 2012-2013, which while not profitable, is not significantly different from the in-sample proportion or the 52.38% economic threshold.

Table 8. Probit Model of Whether an "Over" Bet Wins (OverBetWins).

	Full Sample (n = 4,898)			First Half of Season (n = 2,449)			Last Half of Season (n = 2,449)		
Max-rescaled R^2	.0068			.0173			.0156		
Hosmer-Lemeshow GOF Test	6.5286 (p = .5871)			4.4302 (p = .8164)			10.7725 (p = .2149)		
Variable	Coeff	SE	p	Coeff	SE	p	Coeff	SE	p
Intercept	0.5542	0.2463	.0244	0.5454	0.3808	.1521	0.3297	0.3597	.3594
OverUnder	−0.0032	0.0025	.2111	−0.0067	0.0039	.0837	−0.0004	0.0034	.9133
HomeFavored	−0.3802	0.1936	.0496	−0.0929	0.3088	.7634	−0.5940	0.2546	.0197
HomeUnderdog	−0.4259	0.1946	.0286	−0.1836	0.3099	.5537	−0.5903	0.2561	.0212
AridEdge	0.0615	0.0843	.4655	0.1924	0.1212	.1123	−0.0716	0.1195	.5491
Distance	0.00004	0.00016	.8183	−0.00013	0.00021	.5386	0.00046	0.00027	.0913
Distance2	0.00000	0.00000	.4832	0.00000	0.00000	.8619	0.00000	0.00000	.0823
HigherElev	−0.00002	0.00002	.4279	−0.00005	0.00003	.0710	0.00002	0.00003	.4353
LowerElev	−0.00001	0.00002	.7773	−0.00004	0.00003	.1079	0.00003	0.00003	.2823
East1zone	0.0376	0.0545	.4900	0.0659	0.0766	.3892	−0.0125	0.0784	.8731
East2zones	0.3789	0.1600	.0179	0.4467	0.1982	.0242	0.3341	0.2874	.2451
East3zones	−0.0191	0.3021	.9495	−0.1008	0.3488	.7725	−0.0825	0.7635	.9139
West1zone	0.0820	0.0549	.1355	0.0136	0.0779	.8613	0.1480	0.0784	.0591
West2zones	0.1808	0.1742	.2993	0.1121	0.2159	.6035	0.3501	0.3112	.2606
West3zones	0.2670	0.3132	.3940	0.1413	0.3827	.7119	0.3735	0.5619	.5062
Y2004	−0.0233	0.0740	.7531	−0.1408	0.1039	.1752	0.1124	0.1065	.2910
Y2005	−0.0148	0.0728	.8385	0.0002	0.1016	.9985	−0.0355	0.1049	.7347
Y2006	−0.0779	0.0733	.2874	−0.1144	0.1038	.2703	−0.0456	0.1042	.6619
Y2007	−0.0183	0.0707	.7954	0.0888	0.0997	.3728	−0.1456	0.1012	.1504
Y2008	−0.0040	0.0711	.9550	−0.0377	0.1028	.7140	0.0256	0.0992	.7966
Y2009	−0.0568	0.0711	.4246	−0.0640	0.1050	.5418	−0.0293	0.0985	.7657
Y2010	0.0045	0.0712	0.9494	0.0515	0.1016	.6125	−0.0480	0.1004	.6328
GameDate	−0.0002	0.0008	.8532	−0.0004	0.0020	.8495	0.0021	0.0021	.3127
Dome	0.0459	0.1276	.7192	0.0476	0.1650	.7731	0.0303	0.2046	.8824
Dome_LateNortherly	−0.0006	0.0012	.6039				−0.0007	0.0014	.5931
Outside_LateNortherly	0.0003	0.0004	.3787				0.0000	0.0004	.9794
Dome_EarlySoutherly	0.0015	0.0020	.4585	0.0016	0.0020	.4203			
Outside_EarlySoutherly	−0.0006	0.0003	.0528	−0.0006	0.0003	.0677	−0.0897	0.0635	.1578

Conclusions

The research reported here finds evidence that the college football betting line and the over/under are market inefficient, economically exploitable, and biased when used as predictors. The inefficiency and predictive bias relate most persistently to travel crossing one time zone in the latter half of the season. Visiting teams traveling in an easterly direction and crossing one zone are found to suffer deleterious effects that are underestimated by the size of the betting line. However, this appears to be true only when the visiting team is already a betting underdog: the market's betting line underestimates the home favorite's prospects of winning, its victory margin, and whether it covers the point spread. In addition, the market significantly underestimates the total points that will be scored when visiting favorites travel westerly one zone, largely due to the visiting team scoring more than expected. Such travel effects are found exclusively in the last half of the season, by which time one might expect the betting line to be comparatively well honed versus the earlier part of the season.

A commonality to both findings is that the market fails to properly account for the effects of 1-hr deficits encountered by underdog teams in the late season, when physical fatigue is a greater factor and motivation is perhaps diminished for teams not expected to win. When a visiting underdog travels easterly one zone, it loses an hour vis-à-vis its opponent. Since a visiting favorite gains an hour by traveling one-zone westward, the home underdog has a 1-hr deficit by comparison but is at least in its own time and place. The visiting underdog in the first scenario loses more often than expected, loses by more points (or wins by fewer) than expected, and loses against the spread more than expected. The home underdog in the second scenario gives up more points and loses more often than expected, although it scores enough extra points itself to maintain expected point differentials and to cover the spread as expected—and to help inflate the total points scored beyond what the market's over/under expects.

Tests of the economic profitability of betting on these one-zone underdog effects in the late-season indicate that the impact of each has been sufficient to generate returns that exceed the 52.38% minimum profitability threshold, most significantly for easterly travel on visiting underdogs. Although neither strategy is found to be profitable in the out-of-sample years of 2012 and 2013, the winning percentages out of sample are found not to be significantly different from the in-sample proportions or the economic profitability threshold.

This research also finds some evidence that the college football betting line errs when predicting the impact on visitors of traveling to colder climates, particularly in home underdog scenarios, supporting similar findings in earlier work on the NFL betting market. However, this weather effect does not impact the chances of covering the spread, implying that the market is efficient in that regard. Although the evidence for a cold-weather effect was not as consistent as that found for travel crossing one zone, this is possibly due to the current use of a proxy for actual temperature differences. Interestingly, acclimatization may be a factor even when teams are playing in domed stadiums. Visitors perform slightly better than expected when playing inside, when the inside temperature may be more similar to the current one in their location than the current one in the host's location.

The aridity advantage for a team hosting a visitor from a wetter climate, which was suggested in earlier work to be inefficiently processed by the college football line, is found here only to be related to the chance that a home underdog wins a late-season game, over and above expectations based on the size of the line. However, its significance in those circumstances again is further evidence that the betting line is a biased predictor. Since most of the games in the current data were played after those in the Kuester and Sanders (2011) data (which covered 2000-2006), the lack of significance for aridity when modeling whether home teams cover the spread could also be the result of the market recognizing this anomaly and responding efficiently.

This findings regarding the inaccuracy and/or inefficiency of the over/under are consistent with the conclusions of Kain and Logan (2014) and Weinbach and Paul (2009) for college football as well as the NFL findings of Borghesi (2008) but extend the prior literature by identifying travel effects as one source of market error. Moreover, the research reported here also builds on the extant literature by isolating the impacts on home and visiting team scoring.

A primary contribution of this research over and above past work in other sports is that it introduces a temporal component to the examination of travel effects. It appears that travel is more impactful as the season progresses, and/or that the market less accurately estimates its effects later in the year. This inconsistency in the market's accuracy from the early season to the late season and market error that is most pervasive in the late-season is consistent with findings from the NFL (Borghesi, 2007b). It may have similar causes such as market irrationality associated with bettors trying to make up for early season losses, or greater available capital of less informed versus more informed bettors. However, overly loyal bettors in college football, combined with the presence of rivalry games in the late season, may also contribute to this phenomenon. Regardless, the current results emphasize that using full seasons as the frame of study when researching market behavior appears inappropriate.

The late-season effects observed here could be the result of physiological impacts on teams and players that are misunderstood and underestimated. Mounting physical fatigue and injuries over the course of a season may aggravate the effects of time zone travel as the season progresses, such that even a 1-hr time and rest deficit vis-à-vis the opponent is sufficient to affect games.

Late-season detrimental effects on visiting underdogs—but not on visiting favorites—are inconsistent with previous literature on the NBA. However, college football's much shorter season length and much different postseason structure imply that every game matters, particularly to favored teams regardless of whether they are playing home or away. Favorites may have successful seasons going and thereby exert extra effort sufficient to overcome the physical issues affecting both teams. In contrast, home or road dogs late in the season may be more inclined to yield to both physical and emotional fatigue. This may be particularly true for road dogs who also lose time when traveling.

The lack of significance for some travel factors such as distance or elevation change should not necessarily be interpreted as implying that such factors do not influence game outcomes; their insignificance is likely better interpreted as simply representing efficient market responses to these factors. The line or over/under has likely accounted for many such influences, and thus these factors are commonly not significant in the presence of the line (or over/under) in each model reported here. This is perhaps particularly true of easily understood factors such as distance or elevation change, of which the betting public is probably cognizant, particularly when the differences between the two teams are relatively sizable. It also likely accounts to some extent for the lack of significance of factors representing travel crossing two or three time zones; bettors presume an effect in these relatively extreme cases, and adjust the line or over/under accordingly. In contrast, it seems plausible that bettors presume that one-zone travel has minimal effects and don't correspondingly adjust the line, and/or don't recognize the increase in those effects on underdogs late in the season.

Finally, it seems possible that the reason that one-zone travel to the east is significant, while crossing multiple zones largely is not, is due to erroneous presumptions made by team administrative personnel. Coaches perhaps consider the loss of time associated with cross-country travel significant enough to warrant changes in game and travel preparation (such as arriving earlier than normal), whereas one time zone travel is assumed to be de minimis and therefore not worthy of alternate approaches. If true, such presumptions—in light of the evidence here and in earlier research—appear flawed. Even outside the implications this research has for the betting market, this finding is of substantial practical significance for the sport at large.

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Notes

1. Football Bowl Subdivision (FBS) refers to the group of major college football teams within the National Collegiate Athletic Association (NCAA) in the United States. Prior to December 2006, this group was called NCAA Division I-A (Weiberg, 2006). The current analysis was restricted to games played by FBS teams, as betting markets focus almost solely on games involving such teams. Lines and/or over/under totals are

frequently not even posted for games involving teams from lower divisions (Covers.com, 2013; GoldSheet.com, 2013).

2. To use in later checks for robustness, two more general time-zone variables were also computed, representing easterly travel across any number of time zones (EastTravel) and westerly travel across any number of time zones (WestTravel).
3. October 17 represented the average date for the 5,093 games in the sample and that date was thus used as a measure of a season's midpoint.
4. As done in Weinbach and Paul (2009), the likelihood ratio test of Even and Noble (1992) was used as the test of market efficiency. The log-likelihood ratio test statistic, which follows a χ^2 distribution with one degree of freedom, is $2\{n[\ln(q)-\ln(t)] + (N-n)[\ln(1-q) - \ln(t)]\}$, where N is the number of observations, n is the observed number of successes for the strategy being tested, q is the observed proportion of successes, and t is the target threshold: for example, $t = .50$ when testing whether the market is efficient.
5. Because the latter-half data included the midpoint date of October 17, there were some observations with nonzero Outside_EarlySoutherly or Dome_EarlySoutherly values in the late-season subsample. To control for these, Outside_EarlySoutherly or Dome_EarlySoutherly were included as predictors even in the late-season estimations of all models.
6. The marginal effect of a one-point change in the line on the chance of the home team winning is approximately 2.7 percentage points.
7. In the interest of space, the full results for home favorite/pick-ems and home underdogs are not reported but are available by request.
8. When the ScoreDiff model was fit while pooling all easterly travel into a single binary representing easterly travel crossing any number of zones (EastTravel), and similarly pooling all westerly travel under one binary (WestTravel), EastTravel was positive with a p value of .1039. When modeling HomeWin in this manner, EastTravel was positive with a p value of .0913.
9. Similar findings were generated when the ScoreDiff model was fit to each of the half-season subsamples using EastTravel and WestTravel: easterly travel was insignificant in the season's first half, but positive and significant at the .10 level in the season's second half.
10. The 95% confidence interval for the line's coefficient is [1.0137, 1.1142] in the full-season estimation, and [1.018, 1.1551] in the early season estimation.
11. For the last-half subsample of home favorites and pick-ems, when the model is estimated using EastTravel and WestTravel, EastTravel was significant at the .01 level with a coefficient of 3.22 points.
12. For the last-half subsample of home underdogs, when the model is estimated using EastTravel and WestTravel, EastTravel was not significant.
13. When HomeCovered was modeled using EastTravel and WestTravel, EastTravel was positive and significant at the .10 level.
14. When the model was fit using EastTravel and WestTravel, EastTravel was not significant in the early-season, but was significant with $p = .009$ in the late season.
15. When estimated using EastTravel and WestTravel, EastTravel was positive and significant at the .05 level.

16. For example, US$10 bet on each of the 262 games would have cost (262)(US$10)(1.10) = US$2,882 after paying a 10% vigorish. A total of 152 wins would have returned (152)(US$21) = US$3192, a 10.76% increase over the original US$2,882 investment.
17. The 95% confidence interval for the coefficient of the over/under is [0.8837, 1.0119] in the full sample.
18. The 95% confidence interval for the coefficient of the over/under is [0.8104, 1.0027] in the season's first half, and [.8954, 1.0697] in the season's second half.
19. The 95% confidence interval for the coefficient of PredictedHome is [1.0089, 1.1221] in the full season estimation.
20. The 95% confidence interval for the coefficient of PredictedHome is [1.0098, 1.1690] in the season's first half.
21. The 95% confidence interval for the coefficient of PredictedHome is [0.959, 1.1212] in the season's second half.
22. The 95% confidence interval for the coefficient of PredictedAway is [0.9066, 1.021] in the full season, [0.8623, 1.0236] in the season's first half, [.8966, 1.0604] in the season's second half.
23. As will be discussed later, this preliminary finding will be altered once the analysis is broken out for home favorites/pick-ems and home underdogs.
24. Visiting underdogs score 3.26 points more than expected ($p = .0771$), and favored visitors score nearly 8 points more than expected ($p = .0754$), after traversing two zones easterly in the early season. Home teams do not score significantly differently in the early-season, whether favored ($p = .8393$) or not ($p = .2367$).
25. The finding of inefficiency in the college football over/under market is consistent with the general conclusions of Weinbach and Paul (2009), who found that an "under" bet was more apt to win in nationally televised games on major networks, sufficient to generate economically profitable returns.
26. In first half/home underdog games in which the visitor has traveled one-zone east, an "over" bet would have won 60 of 112 times in sample (53.57%), which is not significantly larger than the minimum profitability threshold of 52.38%.

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