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COLLEGE FOOTBALL BETTORS AND THE WISDOM OF CROWDS

Apostantes de Fútbol Americano Universitario y la Sabiduría de las Multitudes

James D. Francisco, Evan C. Moore

Auburn University-Montgomery, USA

ABSTRACT: This article examines whether the "wisdom of crowds" theory applies to college football wagering markets. Employing regression analysis, likelihood ratio testing, and *Z* testing, we examine the movement of betting lines (which function as prices) in spreads and totals markets leading up to college football games using data from thirteen seasons. We find that 1) opening and closing lines on spreads and totals are generally efficient, and 2) the closing lines on totals and spreads are more accurate, providing evidence of the wisdom of crowds effect.

KEY WORDS: gambling; college football; financial markets

RESUMEN: *Este artículo examina si la teoría de la "sabiduría de las multitudes" se aplica a los mercados de apuestas del fútbol Americano universitario. Mediante el uso del análisis de regresión, prueba de razón de verosimilitud, y prueba Z, examinamos el movimiento de las líneas de apuestas (que funcionan como precios) en los mercados de márgenes y totales que conducen a los partidos de fútbol Americano universitario usando información de trece temporadas. Encontramos que 1) las líneas de apertura y cierre en los márgenes y totales son generalmente eficientes, y 2) las líneas de cierre en los márgenes y totales son más precisas, lo que demuestra el efecto de la teoría de la sabiduría de las multitudes.*

PALABRAS CLAVE: apostar; futbol Americano universitario; mercados financieros

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Contact information:

Corresponding author

James D. Francisco	Evan C. Moore
jfranci1@auburn.edu	emoore1@aum.edu
Auburn University-Montgomery	Auburn University-Montgomery
7440 Senators Drive	7440 Senators Drive
Clement Hall 320C	Clement Hall 320H
Montgomery, AL 36117	Montgomery, AL 36117
334-244-3815	334-244-3364

1. INTRODUCTION

Over $90 billion is bet on college and professional football (both legally and illegally) in the United States annually (American Gaming Association, 2016). In 2014 alone, more than 12 million individual bets were made on college football at the top offshore betting sites (Fuhrman, 2015). In this paper, we examine the nature of the line movements for both spreads and totals in college football betting markets. We pay special attention to the "wisdom of crowds" theory, and attempt to evaluate if the incorporation of changing information over the course of the week – quantitative and qualitative information about the previous performance of teams, personnel differences arising from injuries and suspensions, and myriad potential other factors – leads to an increase in the accuracy of the lines. If it does, we would expect the closing lines to be closer to the actual outcomes substantially more often than not.

The most common form of college football wagering is betting on "spreads" or "lines" which act as handicaps, and purport to reflect market perceptions about disparate team quality, as well as other circumstances that could influence the outcome of a game (such as home field advantage). Betting lines are listed as negative numbers for the favorite, and positive numbers for the underdog. For example, if a sportsbook lists Team A "-7" vs Team B, that means that in order to win the bet, Team A must defeat Team B by more than 7 points in order for Team A's bettors to "cover" (win the bet). Conversely, the sportsbook would list Team B as "+7," meaning 7 points would be added to Team B's score in order to determine who won the bet. If Team B achieves any outcome better than a 7 point loss, Team B's bettors have "covered." If Team A defeats Team B by exactly 7 points, then the result for bettors is a tie, called a "push." Another popular form of college football wagering is betting on "totals" or "over/under," which refers to the total points scored in a game. If the combined score exceeds the total then the "over" wins, but if the combined score is less than the total then the "under" wins. If the combined score is exactly equal to the total then the result for bettors is a tie, and as above is referred to as a "push."

For college football wagering, lines for spread betting are typically initially posted on Sunday evening for games for the coming week (most of which occur on Saturday, though a limited number take place on other days. All games in the 2003-2015 season, regardless of day, are included in our sample.). Bettors, in Las Vegas, other states that allow sports wagering, and online via offshore sportsbooks, then may place wagers. Opening totals lines are usually posted later in the week. These opening lines are set by the casinos based on their interaction with the sharp, or expert, bettors. Bets on both take place usually until the game kicks off, and lines move accordingly throughout the week in an effort to keep betting relatively balanced.

College football betting markets continue to be of interest to researchers, particularly the potential for inefficiencies in that market. For example, Coleman (2017) investigates whether the spread and totals markets correctly integrate the effects of visiting teams' travel, concluding that market is an "…inaccurate and inefficient processor of travel effects." Salaga and Tainsky (2015) find that interest in live sports programming, i.e. television ratings, are sensitive to scores closer to spreads and to outcomes in relation to totals. Sinkey and Logan's (2014) results indicate that home teams are statistically underpriced and favorites are statistically overpriced. Additionally, Kuester and Sanders (2011) find that climate aridity has a "dramatic" effect on the spread market.

Additionally, inefficiencies in sports wagering more generally have attracted the attention of economists. Dare and Dennis (2011) used the closing lines and spreads on NFL games from the 1980s to the mid 2000s to evaluate potential biases of what they called "inherent characteristics," such as home/away, offense/defense, and favorites/underdogs. They found that bettors demonstrated a bias toward the offense of home underdogs and defense of away-favorites, but did not show a bias against the offense of away-favorites. Sung and Tainsky (2014) tested a series of naïve strategies in NFL wagering markets over the 2002-2009 seasons. They found that while the NFL markets were mostly efficient, bye weeks could lead to inefficiencies in certain circumstances. They found that favorites, and especially road favorites, coming off of bye weeks won a non-random portion of games.

Another code of football – association football, or "soccer" – has also attracted the attention of researchers. Flepp, Nuesch, and Franck (2014) analyzed the totals markets in soccer, in an effort to determine whether bettor sentiment led to biased betting action. They found that, despite evidence that bettors prefer to bet on overs, their actual betting decisions are unbiased. Angelini and DeAngelis (2019) used data from 41 book makers covering 11 major soccer leagues over a span of 11 years to measure efficiency. They found that, assuming selection of best odds across bookmakers, 8 of the league markets are efficient, while 3 show inefficiencies capable of profitable exploitation (those 3 being the top leagues in Italy, Portugal, and Greece).

This paper attempts to synthesize the existing literatures on the role of wisdom of crowds in prediction and that of gambling markets, by applying the tests from the latter to the ideas of the former. This will permit us to assess whether the "crowds" of college football bettors show the "wisdom" we've seen in other areas. The remainder of the paper is organized as follows. Section 2 presents relevant wisdom of crowds and prediction market literature. Section 3 describes the data and efficiency testing results. Section 4 reports on the wisdom of crowds and concerns with the analysis. Section 5 provides the conclusion.

2. WISDOM OF CROWDS AND BETTING FORECASTS

The wisdom of crowds is the name given to the phenomenon whereby large groups of people generate a collective forecast that is generally accurate, even compared with those of “experts.” Prediction markets provide a mechanism for evaluating the “wisdom of crowds” effect in the real world. Surowiecki (2005) cited amongst his inspirations for this theory Sir Francis Galton’s (1907) observation about the accuracy of the mean guess of a crowd of non-expert observers of the weight of oxen. These markets include predictions involving industry decisions, elections, weather predictions, public administration, and the Department of Defense among others. The value of prediction markets is well known in the field of economics. This value was shared with a wider audience by Arrow et al (2008). They state that prices in these markets reflect expectations about the likelihood of an outcome and that “...prediction markets have been used with success in a variety of contexts.” In their theoretical model with various simulations regarding betting strategies and the wisdom of the crowd, Kets et al (2014) find that the market price reflects “... the objective probability of the event on which bets are placed.”

We are focused on a specific prediction market involving betting on college football games. Our prior is that the actual game outcomes will be closer to the closing spread (total) than the opening spread (total) as the individuals placing wagers have time to gather information and potentially be presented with new information between the open and close. For example, gamblers may use this time to access more resources such as the internet. While their work focuses on online reputation systems, Kremer et al (2014) state that the “...internet has proven to be a powerful channel for sharing information among agents. As such, it has become a critical element in implementing what is known as the ’wisdom of the crowd.’”

The use of betting as a forecast for sporting events is common. Strumbelj (2014) writes, “The widespread use of betting odds is not surprising, as there is substantial empirical evidence that betting odds are the most accurate publicly available source of probability forecasts for sports.” Additionally, these forecasts may have improved. Strumbelj et al, (2010) using data from European soccer leagues, finds that “...the effectiveness of using bookmaker odds as forecasts has increased over time.”

Hueffer et al (2013) provide a method for assessing the accuracy of “crowd” forecasts: taking the Mean Squared Deviation (MSD) and Mean Absolute Deviation (MAD) of both the forecast and the actual result. *t*-testing for differences between the means then allows one to conclude whether or not the crowd forecast was “wiser” (i.e. whether or not it the crowd forecast had a lower mean deviation from the actual outcome).

While our approach builds on that of Hueffer et al (2013), it differs in crucial ways. First, our "expert" forecast is the opening line as actually set by the casinos based on their interaction with the sharp bettors. Our "crowd" is a sample of actual college football bettors, based on aggregate college football wagering data obtained from the firm Sports Insights, LLC. Thus, we are able to build upon their method as we do not need to construct artificial experts for comparison with the crowd. Additionally, our data set includes more observations.

Simmons et al (2011) evaluating the accuracy of betting markets in the NFL to test the "wisdom of crowds" hypothesis. Using data from a season long experiment, they found mixed results. The crowds tended to overrate favorites when making choices involving point spreads, including those that were purposely designed to disadvantage favorites. However, when the "crowd" was tasked with predicting point differentials, its predictions were "unbiased and wiser." Our study differs from Simmons et al (2011) not only in that we will be examining college football rather than the NFL, but also because we will be utilizing actual wagering data over a series of many seasons, not experimental data over a much shorter period.

We expect that closing lines will reflect the "wisdom of the crowd." This means that actual game outcomes will be closer to those in the closing spread (total) than in the opening spread (total). If the "crowd" possesses information advantages, and uses the information effectively, then any movements from opening to closing should generally reflect these advantages.

3. DATA AND EFFICIENCY

We analyze opening and closing lines on spreads and totals in Division I college football games from the 2003-4 through 2015-16 seasons. The data were acquired from the analytics firm Sports Insights. During the seasons included in our sample, there were 9,761 games in which there was an opening line on the spread. Excluding games in which there was no line movement, and those in which the outcome was exactly halfway between the opening and closing line, left us with 8,313 games in which we could ascertain whether the opening or closing line was closer.

For the totals market, our sample included 7,557 games that featured opening and closing totals, excluding those in which there was no line movement, and those in which the actual total fell exactly halfway between the opening and closing total.

Table 1 presents summary statistics for the opening and closing lines, along with actual outcomes, from the games. Note that the spread data is presented from the point of view of the favorite.

Table 1. Summary Statistics

SPREAD	Obs	Mean	Std. Dev.	Min	Max
Actual	8,313	-12.928	18.619	-77	59
Open	8,313	-12.449	9.855	-61	0
Close	8,313	-12.57	10.071	-59.5	0
Difference open to close	8,313	0.121	2.087	-21	20
TOTAL	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Actual	7,556	54.444	18.443	3	136
Open	7,556	54.047	8.192	34.5	88.5
Close	7,556	54.064	8.147	34	88
Difference open to close	7,556	-0.017	2.62	-25	15.5

We expect the closing lines for both the spread and total to be efficient. Francisco and Moore (2018) found the total lines to be efficient for college football betting over a similar period as our data. We believe we are the first to test for market efficiency in the opening lines. We expect for these lines to be efficient as well as there would otherwise be simple profitable betting strategies in the market.

Gandar, et al (1988) examined the efficiency of sports wagering by testing whether the betting line generates a "fair bet." The authors defined a "fair bet" in the context of football wagering as one in which generates a .5 probability of covering for both the favorite and the underdog. Equating fairness with efficiency, the authors tested efficiency by jointly testing the intercept and slope coefficients in the following equation:

$$(1)\ PS_1 = \beta_0 + \beta_1 VL_i + u_i\ ,$$

where PS = the actual point spread, and VL = the Vegas line. The authors tested the joint hypothesis of "fairness" that $\beta_0 = 0$, and $\beta_1 = 1$ (Gandar et al 1988), asserting that such a condition would indicated no profit as a result of the wagering. This is known as a weak efficiency test.

Even and Noble (1992) expanded on the measures of fairness and market efficiency in NFL wagering. Using both the OLS methods employed by Gandar et al (1988), as well as a likelihood ratio test, the authors were generally unable to reject the null hypothesis of fairness/efficiency across NFL betting on both spreads and totals (the combined score of both teams; bettors can wager on whether the combined total is "over" or "under" the total). However, the authors also concluded that "fairness," as such, is neither necessary nor sufficient to sports wagering matchups.

We utilize the log likelihood efficiency test employed by Even and Noble (1992), as shown below:

(2) $L^u = n[ln(\hat{q})] + (N - n)ln(1 - \hat{q})$, where n is number of covers, N is number of matchups, and q^ is ratio of covers to matchups.

Because this method assumes that an efficient market means that q=.5, we substitute .5 for q^, which yields the following likelihood ratio for the null hypothesis:

(3) $2(L^u - L^r) = 2\{n[ln(\hat{q}) - ln(0.5)] + (N - n)[ln(1 - \hat{q}) - ln(0.5)]\}$

Badarinathi and Kochman (1996) provide a test for fairness/efficiency, which is commonly referred to as non-randomness. We also utilized their test for non-randomness, as shown below:

(4) $Z_1 = [W - 0.5(B)]\ x\ [B(p)(1 - p)] - 1/2$,

where W is number of covers, B is the number of matchups, and p is probability of winning, i.e. 0.5.

Table 2 present the results of the weak efficiency testing using regressions as described in equation (1). The F-tests suggest there may be inefficiencies in the opening lines, yet no individual coefficients are statistically significant at even the five percent level.

Table 2. Weak efficiency results

Line (or point spread)				
	Open	*F*-stat of β_0= 0 and β_1= 1	Close	*F*-stat of β_0= 0 and β_1= 1
β_0	-0.202*	4.69	-0.143	2.71
	(0.277)	0.009	(0.273)	0.067
β_1	1.022		1.017	
	(0.017)		(0.017)	
Totals (or over/under)				
	Open	*F*-stat of β_0= 0 and β_1= 1	Close	*F*-stat of β_0= 0 and β_1= 1
β_0	2.422	3.42	-1.038	2.66
	(1.28)	0.033	(1.269)	0.07
β_1	0.963		1.026	
	(0.023)		(0.023)	

Notes: * indicates significance at the 10% level and ** indicates significance at the 5% level.

Tables 3 and 4 present the results from the log-likelihood and non-randomness tests as shown in equations (3) and (4). These test results do not reject the null of efficient markets for both the spread and the totals markets, for both opening and closing lines.

Table 3. Spread Market Results

	Open spread	**Close spread**
Games	8313	8313
Favorite covers	4110	4100
Favorite does not cover	4065	4091
Pushes	138	122
% favorite covers	49.44	49.32
log like test – fair bet	1.040	1.536
Z test - nonrandom	-1.020	-1.239

Notes: The log-likelihood test statistics have a *chi-squared* distribution with one degree of freedom. The *Z* test statistics have a normal distribution. * Indicates significance at the 10% level and ** indicates significance at the 5% level.

Table 4. Totals Market Results

	Open Total	**Close Total**
Games	7557	7557
Under covers	3785	3789
Under does not cover	3672	3680
Pushes	100	88
% Under covers	50.09	50.14
Log like test - fair bet	0.022	0.058
Z test - nonrandom	0.150	0.242

Notes: The log-likelihood test statistics have a *chi-squared* distribution with one degree of freedom. The *Z* test statistics have a normal distribution. * Indicates significance at the 10% level and ** indicates significance at the 5% level.

The results for the closing totals, in tables 3 and 4, is similar to that of Francisco and Moore (2018). Those authors reported that the totals market, over the 2003-2015 period, is an efficient market. This is in contrast to the earlier findings of Paul and Weinbach (2005), who found evidence of inefficiency using data over a shorter period from 1998-2003.

4. WISDOM OF CROWD RESULTS

A simple test for evidence of wisdom of crowds would indicate that the "crowd," reflected by the closing line, provides a more accurate prediction of the actual game outcome than that of the "experts," as reflected by the opening line set by casinos with the aid of betting sharps. At a minimum, for wisdom of crowds to be evident the closing line must be more accurate than the opening line more than 50 percent of the time.

We found that the closing line for the spread was closer 4,289 times, or about 51.59% of the time. Further, as indicated in Table 3, both the opening and closing spread lines are efficient, as we are unable to reject the null hypothesis that the favorite covers both exactly 50% of the time (our sample means are 49.44% and 49.32% for the opening and closing spreads, respectively). The closing total was closer than the opening total 4,032 times, or 53.35% of the time. As with spreads, we cannot reject the null hypothesis that both the opening and closing totals are efficient as shown in Table 4 (50% cover rate for each).

Table 5 shows the results of one-sided t-tests for the above closing line results being closer to the actual outcomes in excess of 50% of the time. The opening and closing lines are both significantly greater than 50% at better than the 1 percent level of statistical significance. These show at least some evidence of the "wisdom of crowds" at work.

Table 5. Tests of closing lines

	***t*-stat**	***p*-value**
Closing Spread closer to Actual Outcome	2.9078	0.0018
Closing Total closer to Actual Outcome	5.857	0.0000

Stronger evidence still of the wisdom of crowds effect is shown in by the Mean Squared Deviation (MSD) and Mean Absolute Deviation (MAD), as applied by Hueffer et al (2013). The prediction of the closing spread is significantly better than the opening spread (MSD: 241.88 < 245.42, t-test 5.04, 1-sided t-test, $p<0.0000$; MAD: 12.33 < 12.42, t-test 4.24, 1-sided t-test, $p < 0.0000$). Additionally, the prediction of the closing total is significantly better than the opening spread (MSD: 270.40 < 278.20, t-test 6.71, 1-sided t-test, $p<0.0000$; MAD: 13.08 < 13.28, t-test 7.75, 1-sided t-test, $p < 0.0000$).

One potential confounding issue is the impact of "reverse line movement" (RLM). As noted earlier, typically, bookmakers adjust the lines according to market movement in an effort to keep the betting relatively balanced (thus ensuring a safe profit based on the vig). However, on some occasions, the books will move the lines in reverse. For example, if 70% of the wagered money were on the favorite, under normal circumstances, the line would increase, effectively making the favorite more expensive.

However, in some circumstances, the books may reduce the line, making the favorite "cheaper," and thus encouraging even more wagering on the favorite. In essence, this is an example of the books themselves "betting" on the outcome of the game, typically in response to a perceived information or perception gap between the professional bettors and the public.

While there is not research examining RLM specifically in college football spread markets, Francisco and Moore (2019) have shown that it occurs approximately 20-25% of the time in college football betting markets for totals. This is in keeping with similar findings from Crawford (2015) in professional football betting. It is certainly possible, and even likely, that if we were able to remove the instances in which the books move the lines against the market, that the "wisdom of crowds" effect would be substantially larger.

5. Conclusion

Based on our results, we can conclude that the opening and closing lines for both spreads and totals in college football betting markets appear to be efficient. Further, the evidence suggests that closing lines on both spreads and totals were better predictors of actual game outcomes than the opening lines providing confirmation of the wisdom of crowds hypothesis. This finding distinguishes college football from certain of the findings cited above in professional football and soccer. Such a finding should, at the very least, indicate that casinos and bookmakers/linesmakers ought proceed with caution in applying lessons from those other sports to college football markets. This potentially has implications for bookmakers and linesmakers also in terms of how they view the relationship between the "sharps" (the expert class in this setup) and the "crowd."

We find this "wisdom" to be more pronounced in the totals market than in the spread market, suggesting bettors are better able to predict overall scoring more so than scoring differences when compared to opening lines makers. However, the magnitude of the "wisdom" for both markets was relatively small compared to our expectations. But given the discussion above concerning RLM, it is possible to view our results as lower bounds on the betting market's "wisdom of crowds."

Potential future extensions to this paper might include both an examination of the similar effects in other sports, and accounting for RLM to ascertain how often the betting of crowds improve the line's accuracy when the linesmakers are not intentionally moving the line against the market. While Francisco and Moore (2019) have found that

RLM is not generally a profitable strategy in college football totals wagering, it nevertheless happens relatively frequently. Moreover, there is not currently any research showing whether RLM is profitable in college football spread wagering.

References

Angelini, G., & De Angelis, L. (2019). Efficiency of online football betting markets. *International Journal of Forecasting, 35*(2), 712-721.

Arrow, K.J. et al. (2008). The promise of prediction markets. Science 16, 877-878.

Badarinathi, R. & Kochman, L. (1996). Football betting and the efficient market hypothesis. *American Economist, 40*(2), 52-65.

Badarinathi, R. & Weinbach, A. P. (2005). Bettor Preferences and market efficiency in football totals markets. *Journal of Economics and Finance, 29*(3), 409-415.

Bottazzi, G. & Giachini, D. (2016). Far from the madding crowd: Collective wisdom in prediction markets, laboratory of economics and management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy, LEM Papers Serie.

Coleman, B. J. (2017). Team travel effects and the college football betting market. *Journal of Sports Economics, 18*(4), 388-425.

Crawford, P. S. (2015). *Reverse line movements in NFL Gambling: Parallels to financial market biases and the imitation of informed bettor strategies*. CMC Senior Theses. Paper 1007

Dare, W. H., & Dennis, S. A. (2011). A test for bias of inherent characteristics in betting markets. *Journal of Sports Economics, 12*(6), 660-665.

Even, W. E. & Noble, N. R. (1992). Testing efficiency in gambling markets. *Applied Economics, 24*. 85-88.

Francisco, J. & Moore, E. (2018). A comment on Paul and Weinbach's (2005), Bettor preferences and efficient markets in totals markets. *Journal of Economics and Finance, 42*(4), 836-840.

Francisco, J. & Moore, E. (2019). Betting with house money: Reverse line movement based strategies in college football totals markets. *Journal of Economics and Finance,* doi.org/10.1007/s12197-019-09479-3.

Flepp, R., Nüesch, S., & Franck, E. (2014). Does bettor sentiment affect bookmaker pricing? *Journal of Sports Economics, 17*(1), 3-11.

Fuhrman, T. (2015). Most bet on college football. Retrieved from http://www.outkickthecoverage.com/most-bet-on-college-football-games-021815

Football Bets to Top $90 Billion for Second Straight Year. (2016). Retrieved from https://www.americangaming.org/newsroom/press-releasess/football-bets-top-90-billion-second-straight-season

Galton, F. (1907). Vox Populi. *Nature, 75*(1949), p. 450.

Gandar, J., Zuber, R., O'Brien, T., & Russo, B. (1988). Testing rationality in the point spread betting market. *Journal of Finance, 43*. 995-1007.

Hueffer, K., Fonseca, M. A., Leiserowitz, A., & Taylor, K. M. (2013). The wisdom of crowds: predicting a weather and climate related event. *Judgment and Decision Making, 8*(2), 91-105.

Kremer, I., Mansour, Y., & Perry, M. (2014). The wisdom of the crowd. *Journal of Political Economy, 122*(5), 988-1012.

Kuester, D. D. & Sanders, S. (2011). Regional information and market efficiency: The case of spread betting in United States College Football. *Journal of Economics and Finance, 25*(1), 116-22.

Manski, C. F. (2006). Interpreting the predictions of prediction markets. *Economics Letters, 91*(3), 425-29.

Moore, E. C. & Francisco, J. D. (2018). Comment on Paul and Weinbach's (2005) Bettor preferences and efficient markets in totals markets. *Journal of Economics and Finance, 42*(4), 836-840.

Paul, R. J., & Weinbach, A. P. (2005). Bettor preferences and market efficiency in football totals markets. *Journal of Economics and Finance, (29)*3, 409-415.

Poister, T. H. & Thomas, J. C. (2007). The wisdom of crowds: Learning from administrators' predictions of citizen perceptions. *Public Administration Review, 67*(2), 279-289.

Salaga, S. & Tainsky, S. (2015). Betting lines and college football television ratings. *Economics Letters, 132*(C), 112-116.

Simmons, J. P., & Nelson, L. D., Galak, J., & Frederick, S. (2011). Intuitive biases in choice versus estimation: Implications for the wisdom of crowds. *Journal of Consumer Research, 38* (1), 1-15.

Sinkey, M., & Logan, T. D. (2014). Does the hot hand drive the market? Evidence from college football betting markets. *Eastern Economic Journal, 40*(4), 583-603.

Strumbelj, E. (2014). On determining probability forecasts from betting odds. *International Journal of Forecasting, 30*(4), 934-943.

Strumbelj, E., & Sikonja, M. R. (2010). Online Bookmakers' Odds as Forecasts: The Case of European Soccer Leagues. *International Journal of Forecasting, 26*(3), 482-488.

Sung, Y. T., & Tainsky, S. (2014). The National Football League Wagering Market: Simple strategies and bye week-related inefficiencies. *Journal of Sports Economics, 15* (4), 365-384.

Surowiecki, J. (2005). *The wisdom of crowds*. New York, NY. Anchor Books.

Willemien K. Sethi, R., Pennock, D., & Shah, N. (2014). Betting strategies, market selection, and the wisdom of crowds. Proceedings of the 28th AAAI Conference on Artificial Intelligence. 735-741.