

MARKET EFFECIENCY: IS THE NFL BETTING MARKET EFFICIENT?

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Abstract

This paper aims to examine the efficiency of the domestic NFL betting market. Specifically, the paper tests if the prices and implied odds of the closing money line given by the market makers (bookies) in the 2010-2011 season are efficient. The results of this analysis are that the market is not efficient, and that there are effective betting strategies that can take advantage of said inefficiency. The analysis does not contain data from either succeeding or preceding seasons, limiting the generalizability of the results to future seasons.

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I. Introduction: Testing the Market Efficiency of NFL Betting

Sports betting is a large and thriving industry in the United States, with NFL betting residing comfortably as king. Besides being the most popular sporting event domestically as measured by television ratings, it also generates significant economic activity. According to the American Gaming Association football rakes in a massive \$2.58 billion dollars of legal gambling and according to the National Gambling Impact Study, an additional \$380 billion of illegal gambling annually¹. If U.S. NFL betting were a country it would have a higher GDP than 20% of the world's nations listed in the IMF and World Bank 2010 GDP per country list². While NFL betting is surely a large market, is it an efficient one?

Throughout this paper, I will use the same definition of an efficient market that the architect of Efficient-Market Hypothesis (EMH), Professor Eugene Fama used in his hallmark paper, "Efficient Capital Markets: A Review of Theory and Empirical Work." Said paper posited that financial markets are efficient if one cannot consistently achieve returns in excess of the market on a risk-adjusted basis, given the publicly available information extant at the time the investment is made.

Abstracting away from a solely finance application, EMH implies that a market is efficient if endogenous agents cannot use publicly available information to make an abnormal, consistent profit, over their peers by way of free information because all publicly available data has already been incorporated into the market price. Due to the number of agents, funds involved, and history of the practice, many have made the assumption that the NFL betting market is efficient. This paper will test that assumption by comparing the 2011 market price to model that explicitly incorporates selected publicly available information into its price. If the 2011 market price is efficient, then the selected data that I use to model the price should be statistically insignificant because the information has already been included in the market price. If however, the variables that I introduce are statistically significant, then the market is inefficient.

I.I Betting Terminology

The data that I use from the bookies are the closing money lines. A money line is a positive-negative integer pair that represents the payoffs from betting (laying) money on a football match, where the favorite is assigned the negative integer and the underdog is given the positive. For example, during week 1 the Green Bay/New Orleans game had a closing money line of -245/+205. This means that a bettor who believes the favorite will win must lay \$245 to win \$100 (net), and a bettor who believes the underdog will win must lay \$100 to win \$205 (net). The money line changes over time depending on the relative amounts layed for each team, closes before kick-off, and the closing money line is the last line offered by bookies to bettors.

I.II Bookmakers as Market Makers

I have adopted the closing money lines as a proxy for the market price. While not officially labeled as the market price, the underpinnings of basic microeconomic

theory illustrate why the closing bookie money lines are a valid proxy of market price.

Assumptions

Appreciating the amount of money involved, let us assume that bettors and bookies are sufficiently incentivized to incorporate all freely available information into their forecasts of the winning team, and that bookmakers function in a manner consistent with Bertrand competition. Combining these assumptions, one concludes that bookies will offer their impression of fairest odds once their variable costs have been accounted for, and fans will purchase the bets that offer the best price.

Argument From Example

Let us assume that the initial price of betting, set by the bookies, is lower than what bettors believe it should be. Demand at this lower price is high and bettors will flock to the perceived deal.



Fig. 1: At a price below bettor expectation, demand is so high that there is almost no residual demand for the substitute good: the money line for the opposing team.

This will cause an imbalance in the in the bookies' balance sheet. An imbalance can cause major losses for the bookie, if the team that is heavily favored by the bettors performs as anticipated by the bettors. To avoid this possibly devastating loss, the bookies will lower the price on the relatively overpriced team. At a low enough price point this will draw bettors to the opposite side of the money line, therein putting the books back in balance. In this way, the bookies act as a market maker, adjusting the odds until equilibrium is reached.

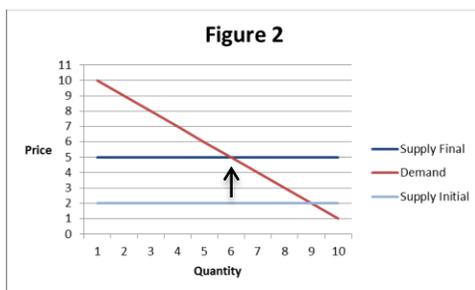


Fig. 2: As the bookies lower the price on New Orleans the opportunity cost of betting on Green Bay increases, effectively increasing the price of betting on them. This will cause bettors to move up the demand curve towards equilibrium.

Being that the closing money lines are the final odds offered, and that the bookies have an extremely strong incentive to have balanced books, the closing

money line should be the odds that are best adjusted to represent the market equilibrium.

II Summary of Results

The null hypothesis is that my explicitly added factor does not, in a statistically significant way, add information or value to the exigent market model. The alternative hypothesis is that the added variable, at a statistically significant level, does add predictive and consequently pricing value. Stated more formally:

Null H_0 : $Y = \beta_0 + \beta_1 FP + \beta_2 MP$; where $\beta_1 = 0$

Alternative H_1 : $Y = \beta_0 + \beta_1 FP + \beta_2 MP$; where $\beta_1 \neq 0$

Where *MP* is the exigent market prediction variable and *FP*, or a fan prediction proxy, is the variable explicitly added to check for market efficiency. In fact, for both the modified probit and linear probability models, the variable for aggregate fan prediction is statistically significant at conventional levels. Further, the pricing discrepancy is large enough that in back testing a simple betting strategy renders significant profits. Appreciating both the statistical significance, and viable betting strategy, I conclude that the domestic NFL betting market is inefficient. Alternatively stated, we can soundly reject the null such that:

$$\beta_1 \neq 0$$

III Data

III.I Closing Money Line

I used the closing money lines given on footballlines.com because of their superior formatting. This totaled to 256 observations for the 2011 NFL football season. Due to arbitrage opportunities, the odds offered by one bookie should be essentially the same as the odds offered by any other bookie. If the odds for one bookie were drastically different than the odds of another, bettors could effectively hedge their bets and make risk free profit. Therefore, if a bettor were to observe a mispricing of this nature, he would buy the money line in large quantities and the bookie would change his odds to balance his books, thereby returning his price to that of his peers and market equilibrium. While it is generally accepted that the price of betting across bookies is equivalent, there is a chance that a large player, or set of players, could collude to push the money line one way or another. To ensure that this was not the case, and that money lines did in fact converge, I ran a correlation between the lines obtained from www.footballlines.com and those of www.docsports.com. Docsports is an aggregate odds webpage that lists the closing lines from 6 other major NFL betting sources: bodog, BM Bookmaker, BetOnline, Dimes, Intertops, and Legends. The correlation between footballlines and docsports was 0.97.

III.II Aggregate Fan Forecast

To test whether or not the NFL betting market satisfies weak form EMH, I explored the possibility that a piece of publicly available data could improve the extant market prediction model. I decided to use ESPN's "Week X: Pick 'Em" poll results as the piece of publicly available data.

At week t , the ESPN poll asks fans to pick who they believe will win in week $t+1$. For a participant's vote to count, he/she must vote for every game occurring during the upcoming week. After the participant votes, ESPN displays the aggregated results of all participants in the poll. The only barrier to entry is access to a computer with internet. There is no fee or application process required to vote. However, if a participant does have an ESPN SportsNation account and is signed in, he/she may only vote once per account (said account is free and the application is a basic questionnaire that takes ~3min to complete). Otherwise, only one vote is allowed per IP address. The webpage does not contain odds, predictions, or links to betting pages. The only information available before a participant votes is how well the ESPN analysts did in the preceding week/season to date, and how well the aggregated participants did over the past week/season to date. There is a short paragraph blurb at the top of the page, but it contains no information, simply serving to restate common knowledge/questions about the upcoming matchups such as, "Will the Chiefs have what it takes to topple the Packers in week 3?" There were, on average, 10,938 respondents per week, with a standard deviation of 3,278. Full summary statistics are available in the appendix.

The only confounding factor with the data is that the poll never closes. If you wanted to vote on week 1 and you haven't already done so, you could go to ESPN.com right now and your vote would count towards the total. However, given the complete lack of incentive for this action and the already large sample size, I believe it is reasonable to dismiss the possibility that enough fans voted *ex post facto* to skew the results.

III.III Conversion of Odds

Unfortunately, the fan prediction variable is stated in percentage terms, and the closing money line is given as a positive-negative integer pair. In order to assess my hypothesis, I needed both the fan prediction and market price to be in the same units. To do this, I converted the closing money line to a percentage forecast of the game winner, utilizing the same method as E. Strumbelj and M. Robnik-Sikonja (2009). This entailed converting the money line from fractional form to decimal, then converting the decimal into a percentage, then eliminating the bookie overround from the percentage via normalization.

Example: = In week one, the odds for the Green Bay/St. Louis game were -245 Greenbay/ +205 St. Louis.

$$\text{Moneyline: } \frac{-245}{+205}$$

$$\text{Decimal Conversion: } \frac{100}{245} = .41\bar{6} \quad \frac{205}{100} = 1.9$$

$$\text{Percentage Conversion: } \frac{1}{1 + .41\bar{6}} = 70.59\% \quad \frac{1}{1 + 1.9} = 34.48\%$$

$$\text{Overrund Calculation: } (.7059 + .3448) - 1 = .0507$$

$$\text{Normalize Percentage: } \frac{.7059}{1.0507} = 67.23\% \quad \frac{.3448}{1.0507} = 32.84\%$$

Because of the number of steps and observations, I used Microsoft Excel to calculate the conversion, therein eliminating the possibility of operator error. See appendix for a full summary of the automation process.

IV Model

IV.I Two tailed difference of means *t*-test.

Previous academic works have attempted to ascertain whether or not sports betting markets are efficient; and my model selection process began with the perusal of such works. In Wise, Miric and Valliere (2010), the authors compared fan voting data and bookie odds, using a 2 tailed difference of means *t*-test in their final statistical analysis. As a grounds for comparison, I used this as my first statistical test. When turned on my data, the *t* test reveals that there is no statistical difference in the fans' vs. bookies' selection of game winners.

In my data set, the fans correctly predicted the winner 66.80% of the time, and the closing money line correctly predicted the winner 66.01% of the time¹. The results from a two tailed difference of means *t*-test are as follows:

$$\frac{\bar{x}_f - \bar{x}_m}{se}$$

$$\left(\frac{0.66796875 - 0.66015625}{0.00887577029} \right) = .88020529$$

Given my degrees of freedom, the *z* value of .88 is not statistically significant at conventional levels. From this, we can conclude that fans are not superior binary predictors of NFL matchups. However, this does not fully address the question of

¹ If >50% of the fans selected a team as the favorite to win, I counted said team as the fans' prediction of the winner. Similarly, I chose the market favorite based on which team had a higher percentage prediction of victory as given by the money line. The fans selected a favorite by <55%, 24 times, and the market selected a favorite by <55% 30 times.

whether or not the NFL betting market is efficient. In order to improve on this statistical test, I turned to the linear probability model and the probit binary response model.

IV.II Linear Probability and Probit Binary Response Models

The advantage of the linear probability model (LPM) over a t test is that it has the ability to incorporate the strength of the confidence of fan picks. This property of LPM allows me to test if the inclusion of fan data in a predictive model of NFL game outcomes is statistically significant, and if so how does the importance of fan certainty vary over the spectrum of possible confidences. While an appealing model in some respects, LPM does have two distinct drawbacks: it can return impossible fitted values and it is not efficient. For this reason, I also tested my hypothesis using a probit binary response model. Due to the nature of the probit distribution, it is more efficient than the LPM, and cannot exceed the bounded range of logically possible fitted values. Given the advantages of a probit model, the inclusion of a LPM analysis might appear to be a superfluous exercise. However, the partial effect of an LPM more accurately describes certain aspects of the relationship between fan certainty and game outcomes. The distribution of the probit function increases at an increasing rate, and then begins increasing at a decreasing rate. This is probably not the most realistic interpretation of betting forecasts. It seems more reasonable to assume that as market and fan forecasts become more certain of the game winner, the partial effect should increase at an increasing, or flat rate. Because of this difference in the interpretation of the partial effect of an explanatory variable, I utilize both models to test my model, with particular diligence being paid to the possibility of fitted values that exceed the realm of logical possibility while using the LPM.

IV.III Probit Transformation

While the distribution of the probit function has positive resultants, it does require that I transform my data so as to maintain integrity under my hypothesis. It is essential for the model to be correct under the null, otherwise there is no basis for testing. However, if I were to simply input my data in its original form into a probit model that would not be the case. I will illustrate this via juxtaposition with the LPM, which is valid with my raw data under the null.

Where Y is the probability of the favorite winning the game, under the null:

$$E(Y|X) = \beta_0 + \beta_1 \textit{favorite}; \textit{where } \beta_0 = 0, \beta_1 = 1$$

$$E(Y|X) = \textit{favorite}$$

Substituting a value in for *favorite*, we can see more concretely how this works:

$$E(Y|X) = \beta_0 + \beta_1 \textit{favorite}; \textit{where } \beta_0 = 0, \beta_1 = 1, \textit{favorite} = 0.5$$

$$E(Y|X) = 0.5$$

That is to say under the null, the expected chance of a team winning is the same as the percentage predicted by the market. However, because the evaluation of the probit is nonlinear, the results for the probit model do not match this:

$$Prob(Y = 1) = \int_{-\infty}^{favorite} \phi(t)dt$$

Substituting the same value for *favorite* that we did for the LPM:

$$Prob(Y = 1) = \int_{-\infty}^{0.5} \phi(t)dt$$

$$\int_{-\infty}^{0.5} \phi(t)dt = 0.69$$

$$E(Y|X) \neq favorite$$

As you can see, if I were to insert raw data into the probit model, the fitted values would be bounded within (0,1) and the model would be efficient, but it would not be valid under the null hypothesis. To correct for this, I transformed my data by the inverse of the cumulative normal distribution using Stata 12. Once transformed, the data is valid under the null.

IV.IV Model Form

While the mechanism used to test each model was different, the form of each was identical. To calculate the statistical significance of my variables, I ran a probit/linear regression of the game winner (Y_i) on the market prediction (MP_i) and the aggregate fan prediction (FP_i) where:

$$Y_i = \begin{cases} 1 & \text{if market favorite wins} \\ 0 & \text{if market favorite loses} \end{cases}$$

The general form of the model is:

$$\Pr(Y=1 | X_j) = \beta_0 + \beta_1 FP_i + \beta_2 MP_i$$

Where β_0 is the intercept and β_1 and β_2 are the coefficients for market and fan prediction respectively. As stated earlier, both the probit and LPM models use the same data inputs, and variable names.

V Estimates and Results

I used the statistical package Stata 12 to calculate the estimates of my model. The resultant equations for both the probit and LPM models are enumerated below.

Probit Estimates:

$$\hat{Z} = -0.247 + 0.419FP + 0.783MP$$

FP has a P value of 0.025 which is statistically significant at conventional levels and allows me to reject the null.

LPM Estimates:

$$\hat{X} = -0.242 + 0.470FP + 0.814MP$$

FP has a P value of 0.019 which is statistically significant at conventional levels and allows me to reject the null. Further, none of the fitted values were outside of the bounded range (0,1).

See appendix for full output tables and summary statistics of fitted values.

VI Betting Strategy

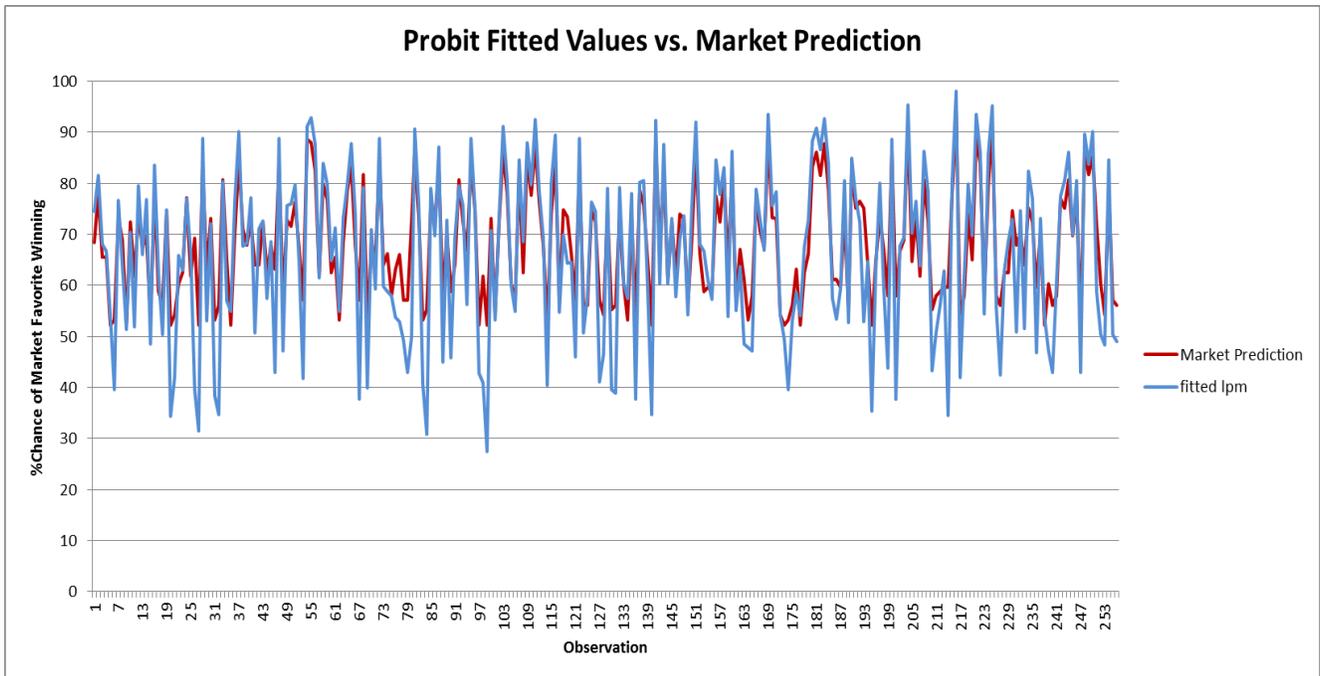
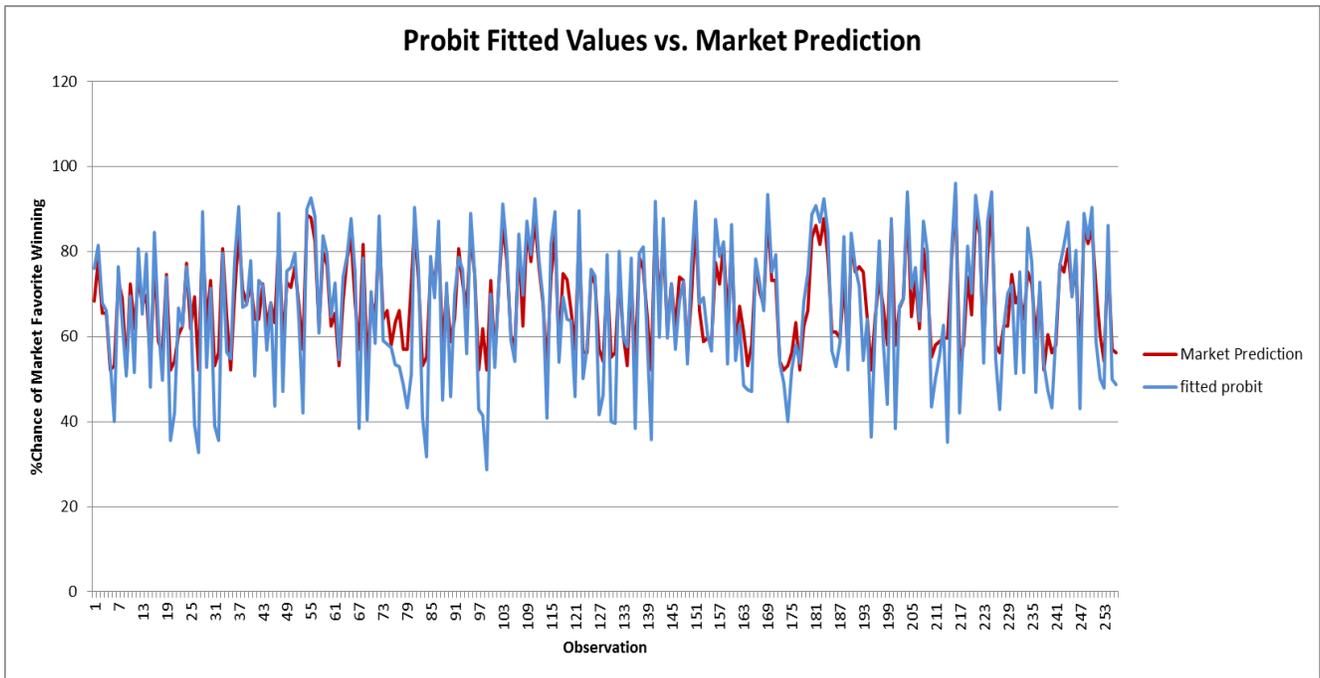
Having established that the market is not efficient is necessary for there to be a viable betting strategy, but not wholly sufficient. In addition to there being a market mispricing, there must also be a serviceable strategy. To find said strategy it is useful to first examine how the fitted values of the model juxtapose to the market values. The following table displays just that:

Variable	Obs	Mean	Std. Dev.	Min	Max
Y_i	256	.6602	.4746	0	1
FP	256	.7771	.6656	-1.0027	1.9600
MP	256	.6805	.1064	.5217	.9425
Fitted-probit	256	.6602	.1647	.2876	.9615
Fitted-LPM	256	.6602	.1648	.2754	.9805

As you can see, the probit and LPM models are not only statistically significant, but also return strikingly similar fitted values. Further examination of the table also reveals Ariadne's thread: both probit and LPM models have fitted values of <50. *The fact that there are fitted values <50 means that the models are predicting different winners than the market.* A brief summary of the values is provided below:

Model	Fitted <50	Fitted <45
Probit	50	33
LPM	49	33

See the following page for graphs comparing the fitted values of the models compared to the market predictions.



While never matching exactly, the values tend to mirror each other on the upper register. The serious discrepancies occur when the market prediction is around 50.

Appreciating this information, a simple and effective betting strategy is to bet on every game in which the model predicts a different winner than the market. This strategy is appealing because both the odds and payouts are more in the bettors favor. Traditionally if you were to bet on a favorite you would have to lay more

money than you would net, therefore even if you were to predict the winner the majority of the time you could end up losing money. Conversely, if you were to consistently bet on the underdog you might make more money per correct prediction, but you should on average lose most bets. By betting on the model's favorites, the odds are in your favor, and you should correctly predict the game winner at a higher rate. That is, as long as the model predicts the winner relatively consistently, then there will be a profit. The table below summarizes various simple betting strategies.

PROBIT

Fitted Value	Obs	Return	Games Predicted Correctly
≤50	53	7.96%%	38.00%
≤45	34	34.39%	48.48%

LPM

Fitted Value	Obs	Return	Games Predicted Correctly
≤50	49	5.63%	36.73%
≤45	33	34.39%	48.48%

As you can see, a simple betting strategy is extremely effective. As one would imagine, both models become more accurate when their selectivity is increased. That is to say the higher the disparity between the model's prediction and the market prediction, the higher the chance that the model will correctly predict an underdog victory. While an alluring model, the strategy suffers from being tested endogenously. The next section will summarize a new model created that does not use all the data points.

VII Model Test

To more stringently test my model, I re-parameterized it using the same programs and methodology, but only incorporating the observations from the first three quarters of the season. In both the linear probability model and probit binary response model the variable for fan pick remains significant at conventional levels, whereas the variable for market prediction drops to 0.20 in the probit model and 0.107 with LPM. Re-parameterizing the model gives:

$$PROBIT: Y = -0.173 + 0.701MP + 0.497FP$$

$$LPM: Y = -0.161 + 0.608MP + 0.457FP$$

I then took this new model and tested it on the remaining games in the season. When I bet on every game with a fitted value below 50, the return and percent of games predicted correctly was astonishingly high.

Model	Obs	Return	Predicted Correctly
Probit	20	34.25%	50.00%
LPM	11	47.27%	54.55%

Because the variable MP is statistically insignificant, I eliminated it, re-parameterized and tested the betting strategies once more.

$$PROBIT: Y = -0.028 + 0.661FP$$

$$LPM: Y = 0.083 + 0.779FP$$

The betting results using the previous model are as follows:

Model	Obs	Return	Predicted Correctly
Probit	30	27.00%	46.67%
LPM	15	72.67%	60.00%

It is interesting to note that the LPM model appears to be a more accurate predictor of game outcomes. This is mostly a function of the fact that the LPM is less sensitive to the variable FP and therefore a bet will only be triggered on games where fans are more certain that the market price is off. One could increase the accuracy and payoff of the probit model, by only making bets where the threshold is a lower fitted, at the expense of having fewer games to bet on. While not conclusive, this last test is indicative of a successful model.

See appendix for full Stata output tables.

VIII Further Research

The next steps for this model are to acquire more data and see if the market inefficiency is a long term trend, or if 2011 was simply an extraordinary year. Another interesting area of exploration would be to see how the strength of the variable for fan prediction varies over the course of a season. Do fans get more, or perhaps less intelligent as the season goes on? This model opens the door for the testing and possible inclusion of other variables as well as some interesting behavioral applications.

IX Conclusion

I conclude that the domestic NFL betting market for the closing money lines of the 2011 season are statistically inefficient. Further, once transaction costs have been accounted for, the inefficiency is such that a true profit rendering strategy can

be utilized. I intend to test this strategy on the upcoming 2012 season, and continue researching these findings to establish whether this strategy can be generalized for future season or if the results were merely serendipitous.

Appendix

ESPN Pick 'Em Data & Summary Statistics

ESPN Week X: Pick 'Em Data

Week	Participants
1	18,950
2	11,537
3	11,662
4	10,785
5	12,386
6	15,565
7	11,159
8	9,268
9	10,146
10	13,582
11	9,902
12	7,329
13	7,848
14	6,883
15	13,906
16	8,042
17	6,988

Summary Statistics

Mean	10,937.53
SD	3,278.22
Mode*	12,000.00
Median	10,785.00
Min	6,883.00
Max	18,950.00

rounding data to the nearest

E. ˇ Strumbelj and M. Robnik ˇ Sikonja (2009) Excel Automation Formula:

1.) Convert money line to decimal

Column G = Bookie money line payout for favorite

Column H = Bookie money line payout for underdog

[Column K] Decimal Favorite = $(G2/100)$

[Column L] Decimal Underdog = $(100/H2)$

2.) Convert to percentage

Column K = Decimal form of money line odds for favorite

Column L = Decimal form of money line odds for underdog

[Column M] Non-normalized bookie chance of win as percent for favorite
= $1/(1+K2)$

[Column N] Non-normalized bookie chance of win as percent for underdog:
= $1/(1+L2)$

3.) Normalize Percentages

Column M = non normalized favorite percentage

Column N = non normalized underdog percentage

[Column O] Normalized bookie chance of win as percent for favorite
= $M2/(M2+N2)$

NOTE: This last step, and the data it delivers are not used in the thesis.

[Column P] Normalized bookie chance of win as percent for underdog
= $ABS(O2-1)$

Linear Probability Model Stata Output & Summary Statistics

LPM Stata Output					
Source	SS	df	MS	Number of obs =	256
Model	6.92492281	2	3.4624614	F(2, 253) =	17.34
Residual	50.5086709	253	.199639016	Prob > F =	0.0000
Total	57.4335938	255	.225229779	R-squared =	0.1206
				Adj R-squared =	0.1136
				Root MSE =	.44681

GameOutcome	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
MP	.8140583	.3672831	2.22	0.028	.0907366	1.53738
FP	.4701419	.199453	2.36	0.019	.0773421	.8629417
_cons	-.2423609	.1830115	-1.32	0.187	-.602781	.1180592

LPM Stata Summary Statistics for Fitted Values

Variable	Obs	Mean	Std. Dev.	Min	Max
fitted	256	.6601562	.1647925	.2754533	.9804607

Stata Output Tables for 3/4 Observations

Probit Binary Response Model

Probit regression Number of obs = 192
LR chi2(2) = 21.38
Prob > chi2 = 0.0000
 Log likelihood = -110.81589 Pseudo R2 = 0.0880

GameOutcome	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
tfp192	.4565702	.2206079	2.07	0.038	.0241866	.8889538
tmp192	.6083177	.4747943	1.28	0.200	-.322262	1.538897
_cons	-.1605013	.1768751	-0.91	0.364	-.5071701	.1861674

Linear Probability Model

Source	SS	df	MS	Number of obs = 192	
Model	4.69094383	2	2.34547192	F(2, 189) = 11.78	Prob > F = 0.0000
Residual	37.6371812	189	.199138525	R-squared = 0.1108	Adj R-squared = 0.1014
Total	42.328125	191	.22161322	Root MSE = .44625	

GameOutcome	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
mp192	.7009246	.4332421	1.62	0.107	-.1536867	1.555536
fp192	.4969747	.2350004	2.11	0.036	.033414	.9605354
_cons	-.1731726	.2141343	-0.81	0.420	-.5955729	.2492277

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