Fantasy Football Projection Analysis

Nathan Dunnington

University of Oregon

Eugene, OR

3/13/2015

A research thesis presented to the Department of Economics, University of Oregon

In partial fulfillment for honors in Economics

Under the supervision of Professor Nicholas Sly

Abstract

The scope of this paper is to provide analysis of weekly fantasy football player projections made by industry leaders, and evaluate projection accuracy. Furthermore, to apply concepts of information aggregation and test for increases in projection accuracy. A system for recommended player selection will be provided using linear regression techniques, as well as a comprehensive ex-post analysis of projections from the 2014 season. The findings of this paper suggest that aggregating expert fantasy football projections may yield slight increases in forecast accuracy.

Approved: _____

Professor Nicholas Sly Date

Table of Contents

1. Introduction

To optimize game strategy, Daily Fantasy Sports (DFS) players use a variety of methods to predict how professional athletes will perform. In making their prediction, DFS players rely on past results, intuition, and the dispersed opinions of information sources. It has been demonstrated in research that the wisdom of the crowd, known as information aggregation, is often more accurate than any one member of the group. This paper tests this theory of information aggregation by comparing the accuracy of aggregated projections with the accuracy of individual sources.

There are two main goals of this paper: First, evaluate the accuracy of fantasy football scoring projections made by industry experts. Specifically, identifying trends in accuracy by NFL position (QB, RB, WR, and TE) and comparing the accuracy of various projection sources. Included in this process is analysis of residuals and identifying systematic failure of projection models. Second, determine if methods of information aggregation can lead to increases in forecast accuracy. Both of these goals will be achieved using linear regression techniques.

Statistical differences of model fit between positions (QB, RB, WR, and TE) were found. The model for RB and WR were both a better fit than the model for TE at $P<.05$ using F-tests, suggesting that fantasy performance of RBs and WRs may be more predictable than TEs. At RB, WR, and TE, the model failed systematically resulting in positive skew in residuals. The reason for this occurrence is related to the dynamics of predicting touchdown performance. The results of this paper fail to show statistically significant increases in forecast accuracy using information aggregation; however, small increases in accuracy were found in certain metrics. Most notably, the arithmetic mean projection delivered the highest R^2 value in comparison with each individual source R^2, and this was observed at every position. Within the context of Fantasy Football, narrow differences in forecast accuracy can have a substantive impact. Therefore, the findings of this paper may be of use to Fantasy Football players.

1.1 Market Description

It is estimated that 41 million Americans participate in Fantasy Sports with nearly 50% of players wagering money in some capacity (1). A few years ago, fantasy sports were only available in season long formats where players drafted teams before the season and maintained the same

team throughout the year. Today, players can draft a new team prior to each game and legally wager money on their selected team. The leaders in this booming market known as Daily Fantasy Sports (DFS) are FanDuel.com and DraftKings.com. These companies recently received $70M and $41M in venture capital funding respectively, have partnerships with professional sports franchises, and advertise extensively through multiple channels (2). The scope of this paper focuses on Daily Fantasy Football player selection on FanDuel.com.

In fantasy sports, players "draft" professional athletes to their fantasy team. When real world games are played, the fantasy player receives points based on the statistics of the professional athletes the player drafted to his or her respective fantasy team. Generally speaking, higher real-life performance equates to higher fantasy scores. Fantasy sports are available in some capacity for all major professional athletics.

There are three players that interact in the DFS market place: Sellers, Buyers, and Information Sources.

1. *Sellers* – The sellers in this market are websites that offer daily fantasy sports games to supply the market with the platform to participate in DFS. The market structure in DFS is categorized as an oligopoly, with FanDuel.com and DraftKings.com dominating market share among sellers of Daily Fantasy services (2). Sellers generate profit from "rake", similar to a casino. The rake percentage per contest in DFS is calculated as (Entry Fees – Payouts) / (Entry Fees). For reference, the industry standard for rake is roughly 10%.
2. *Buyers* – Buyers are the DFS players that demand the service, a platform on which to participate in DFS contests.
3. *Information Sources* – Information Sources in this context are all sports related media including player statistics, and sports news and analysis. In fact, certain sports entertainment programs are geared specifically for fantasy sports players. These programs provide fantasy specific analysis used by buyers to make playing decisions in this market. In addition, online companies provide information on projected fantasy point totals which buyers can use to assist in game strategy.

DFS players can consult the aforementioned information sources to assist in their player selection process. This paper uses information sources that provide projected point totals to analyze the expected performance of each player.

1.3 Research Objectives

It is theorized that aggregating information from multiple sources improves accuracy, as studied A. H. Ashton & R. H. Ashton (3), Bernnouri, Gimpel, & Robert (4), and Plott, Wit, & Yang (5).

This thesis examines this effect in the context of fantasy football. The methods of information aggregation used in this paper are arithmetic mean, geometric mean, and "average efficiency rating" (detailed in *section 3.4*).

In addition, this thesis will provide a system for identifying "efficient players" expected to exceed the value of their DFS salary on FanDuel.com. This will be achieved by proposing a quadratic regression model that accounts for the aggregated efficiency rating of four professional fantasy football sources. The explanatory power of this system will be evaluated on statistical significance $P<.05$.

1.4 Research Questions

The scope of this paper is to address the following questions.

Q1: How accurate are the leading online fantasy football projection sources?
Q2: Do fantasy football projection models fail in systematic fashion?
Q3: Does NFL fantasy projection accuracy vary by position? If so, why does this occur?
Q4: Are there statistically significant differences in model fit between positions and sources?
Q5: Does information aggregation provide an increase in projection accuracy?
Q6: Can an ex-ante metric (efficiency rating) explain production relative to salary at a statistically significant level?
Q7: How can this information be applied to real-word player selection strategy?

1.5 Research Process

Step 1: Create an automated spreadsheet to compile weekly projections for each NFL player from four online projection sources recognized as the industry leaders. For convenience and future use, this spreadsheet was built with "refresh-all" capabilities to download new projections from web sources each week of the NFL season.
Step 2: Download player statistics from Yahoo Sports to provide the fantasy score actual for each player, each game.
Step 3: Perform empirical analysis of projection accuracy by position and projection source, and evaluate the distribution of residuals. Apply methods of information aggregation, and test for increases in forecasting accuracy.

1.6 Rules of the Game in Daily Fantasy Sports

The process for participating in DFS is as follows. Each athlete is given a "salary" based on their perceived market value with higher performing players garnering higher salaries. DFS players then select a team that fits the salary constraint, and enter contests. Once games begin, teams are locked, and athletes receive points for their in-game performance. DFS contestants place in contests based on the number of points their selected team accumulated, and earn winnings based on the given contest's payout structure.

DFS professional "msize44" said "My approach is 80-percent numbers based and 20-percent feel based. I have spreadsheets for everything with projected point totals, and those point totals are (used) to come up with the most efficient players and most efficient lineups." By efficient players, msize44 is referring to players with low dollar per projected point ($/point) values: meaning players who are projected to score the most points relative to their salary for that game. Research process step 1 (*section 1.5*) created a similar system as described by "msize44".

In DFS, there is a trade-off between player salary and expected scoring. In the absence of a salary cap, DFS players could simply select superstar players and expect a high fantasy score. But selecting too many superstars is not possible because superstar players come with high DFS salaries, and therefore, this method would exceed the salary cap constraint. The challenge for a DFS player is drafting a team that will outscore the competition, while still within the salary limits. When drafting teams, DFS players must decide if they project an athlete to produce enough fantasy points to justify their salary cap expense. Essentially, DFS players are attempting

to indentify and draft athletes that are “undervalued” at their DFS salary price point. The big question facing all DFS players is predicting how each athlete will perform. This paper will apply methods of information aggregation to predict fantasy scoring, and indentify player value.

2. Literature Review

2.1 Introduction to Information Aggregation

Information Aggregation has been widely studied in a variety of contexts. The premise of this theory is that the combined wisdom, or average value, from numerous sources is more accurate than the information given by an individual source. For example, the average of 100,000 people’s opinion on a given value (x) is likely to be closer the true value of (x) rather than if one person’s opinion were used.

2.2 Efficient Markets Hypothesis (EMH)

The EMH states that market prices fully reflect all available information. In essence, the efficient market price is the result of information aggregation. The buying and selling an assets cause the market price to reflect the combined opinions of the asset’s true value. The EMH was cited by Wolfers & Zitzewitz 2005a as an explanatory model for efficient information aggregation in markets (6).

2.3 Condorcet’s Jury Theorem

The Condorcet’s Jury Theorem aligns with the theory of information aggregation. The Condorcet’s Jury Theorem states that adding more voters to a majority vote will be more likely to yield the correct majority decision, assuming the probability that the additional voters will vote correctly is greater than ½.

2.4 *Wisdom of the Crowds* – by James Surowiecki

Published in 2004, this book focuses on information aggregation in several fields, primarily economics and psychology. Surowiecki argued that the aggregation of information in groups results in decisions that are better, or more accurate, than could have been made by any single member of the group.

2.5 Existing Research on Aggregating Fantasy Football Projections

Fantasyfootballanalystics.net found that FantasyPros.com, which combines many sources of projections to yield their own, was more accurate than projections sourced from ESPN.com, CBS.com, NFL.com in both 2012 and 2013 in terms of r-squared and MASE (mean absolute scaled error). As sated on Fantasyfootballanalystics.net, "projections that combined multiple sources of projections were more accurate than single projections … no single projection source outperformed the others year to year, suggesting that differences between them are due in large part to chance. … In sum, crowd projections are more accurate than individuals' judgments." (8)

3. Research Methodology

3.1 Projection Algorithm Variables

The projections used in this paper are sourced from online companies that use algorithms to forecast the performance of every NFL player, each week. The four projection sources are Numberfire.com, ProFootballFocus.com, 4for4.com, and BloombergSports.com. The specifics of projection algorithms are proprietary trade secrets of each company. However, some assumptions can be made about the methodology used in these projections. I observed specific trends and patterns in week to week forecasts for each player that helped uncover the variables likely used in the projection algorithms. I determined that player projections were most dependent on 3 factors:

1. Recent Performance – This is the most telling variable in how a player will be projected. If Player A greatly exceeded expectations in week t, his projection will likely increase in week t+1. This indicates that projection algorithms share characteristics with an auto regressive moving average model with exogenous inputs.
2. Playing Time – Projections will fluctuate if a change in playing time is expected. This typically occurs as a result of injuries. For example, an injury to a starter will cause that player's backup to see an increase in playing time, and thus, an increase in projected points.
3. Matchup – In short, a player's projection is partially dependant on the defense he is facing. Players will often receive an increased scoring projection when facing a defense that allows above average fantasy points per game. The betting line spread and over/under, set by Las Vegas, is one indicator of scoring expectations. Thus, players

involved in games that Las Vegas projects as high scoring often received a bump in projected fantasy points.

Projected points are a function of two expectations: expected yards, and expected touchdowns. Assuming a standard scoring system awarding .1 points per yard, and 6 points per touchdown, projected fantasy points can be written as:

$$\textbf{Projected Points} = .1*\textbf{yards} + 6*\textbf{touchdowns}$$

3.2 Data Analysis Methodology

This analysis will provide answers to the questions outlined in section 1.4 using the following process:

1. Evaluate the overall accuracy of the leading online fantasy football projections by source and by position, and analyzing the statistical significance of coefficients of conceptual model part I. Model fit will be compared using F-tests at significance $P<.05$.
2. Examine patterns in the mean projection residuals. The distribution of error terms will be displayed using a histogram plot and a Kernel Density Estimation to identify any systematic model failure. An explanation for the residual distributions will be given.
3. Compare accuracy metrics of the arithmetic mean and geometric mean projection with individual projections to examine the impact of information aggregation.
4. Evaluate the statistical significance of the aggregated efficiency rating formula to determine if efficiency rating can be used to predict value.
5. Evaluate accuracy based on the practical application of information using qualitative analysis.

3.3 Efficiency Rating Formula

Daily Fantasy Football players face a discrete choice problem when constructing lineups. The Efficiency Rating Formula categorizes players into five bucket, reflecting the discrete nature of this process. Success in DFS requires identifying undervalued players in order to formulate a high performing lineup relative to salary. The purpose of the efficiency rating is to quantify each player's projected value relative to their salary. Efficiency rating is calculated as follows: All player's $/point projection scores are divided into five percentiles, top 15%, 15%-30%, 30%-45%,

45%-60%, and bottom 40%. A player scoring in the top 15% in $/point gets a efficiency rating of 4, 15%-30% gets a rating of 3 and so on. We are only interested in indentifying the degree to which a player is efficient, so all "in-efficient" players in the bottom 40% simply receive a score of 0.

3.4 Aggregated Efficiency Rating

The aggregated efficiency rating is the mean efficiency rating given by the four projection sources. In comparison to the efficiency rating of the mean projection, this method has three distinct advantages in determining player efficiency. First, it allows for decimal ratings. Second, it controls for the total projected points allocated by each source. For clarification, each projection source has systematic differences in total projected points allocated among all players. This method controls for these differences. Third, this method is similar to a median opinion since total efficiency is given on a definite scale the impact of outliers is mitigated.

4. Conceptual Framework & Model Specification

4.1 Introduction

The conceptual framework of this thesis is comprised of three separate models.

Conceptual model Part I is used to test for differences in forecasting accuracy between positions, and differences in forecasting accuracy between projection sources using linear regression techniques.

Conceptual model part II is used to test the explanatory power of the aggregated efficiency rating on efficiency (where efficiency = points per $1,000 in FanDuel.com salary). The resulting coefficients of this model will be evaluated using t-tests at significance $P<.05$ to determine the explanatory power of this model.

Conceptual model part III addresses the practical application of this information. This is an analysis of the real-world results on FanDuel.com resulting from using efficiency rating to construct DFS lineups.

4.2 Conceptual Model (Part I)

Conceptual model part I regresses actual fantasy points on projected fantasy points and is defined as:

$$\mathbf{FP_{actual} = Constant + S_1FP_{predicted}}$$

Where:

FP = Fantasy Points

S_1 = Scalar of projected point value

Null Hypotheses:

H_0: Constant = 0

H_0: $S_1 = 1$

Predictions with 100% accuracy would yield an R^2 value of 1, an intercept of 0, and a scalar of projected points of 1. These values will be used as benchmarks to evaluate accuracy. T-tests will be performed on the constant and coefficient. An F-test will be used to compare model fit between positions and sources where $F = [(SS_1 – SS_2) / (df_1 – df_2)] / (SS_2 /df_2)$.

4.3 Conceptual Model (Part II)

Conceptual model Part II is used to test the explanatory power of efficiency rating. A quadratic model was used to determine if the marginal impact of efficiency rating varied across the domain. This model is defined as:

$$\mathbf{Efficiency = Constant + B_1EF + B_2EF^2}$$

Where:

Efficiency = Points per $1,000 of Fan Duel Salary

EF = Efficiency Rating

B_1 = Efficiency Rating Coefficient

B_2= Efficiency Rating squared Coefficient

Null Hypotheses:

H_0: Constant = 0

H_0: $B_1 = 0$

H_0: $B_2 = 0$

4.4 Conceptual Model (Part III)

The real-world use of fantasy football projections is to use the information to construct winning lineups. Conceptual Model Part III details the practical application of this information.

Players with an Efficiency Rating of 4 can be used as a proxy to represent the suggested player selection strategy by each projection source. Constructing lineups with all efficiency rated 4 players isn't always possible given the salary constraint and discrete nature of the problem. But a lineup of all efficiency 3 and 4 players (top 30% in projected $/point) is virtually always possible. As such, the actual performance (in $/point) of efficiency rated 3 and 4 players is indicative of the results one could expect from using this information. Projection accuracy in this context is measured by low $/point totals of efficiency rated 3 and 4 players. Production of $500/point is typically sufficient to win contests on FanDuel.com, thus, this will be used as a benchmark to determine if this information can result in real-world benefit to player strategy.

The goal of this analysis is to determine if information aggregation can improve results in practical application. The methodology is as follows: Players were grouped into buckets based on efficiency rating. Total cost, projected points, and actual points were summed for all players based on efficiency rating to calculate projected $/point and actual $/point totals. An R^2 value is given resulting from actual $/point regressed on efficiency rating. The aggregate efficiency rating (Agg. Eff. Rate) is rounded to the nearest integer. *Note*: Aggregated efficiency rating 3.25 was rounded to 4 to increase the sample size of recommended selections.

Conceptual Model Part III will display the results in the following format:

Position												
	NumberFire		PFF		4for4		Bsports		Mean		Agg. Eff. Rate	
Eff. Rating	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt
4												
3												
2												
1												
0												
Total												
Eff. Rating R^2												

5. Data Analysis – Conceptual Model Part I

$$FP_{actual} = Intercept + S_1FP_{predicted}$$

5.1 Regression Results

Conceptual model Part I was used to test for differences in forecasting accuracy between positions, and differences in forecasting accuracy between projection sources. The following regression analysis is done on actual fantasy points regressed on mean predicted fantasy points. Regression results for each projection source and position can be found in *Appendix 1-4.*

5.1.1 QB

Regression Statistics	
R Square	13.6%
Adjusted R Square	13.2%
Standard Error	6.84
LLF	-697.30
AIC	1396.62
SBIC	1399.94
Observations	209

ANOVA

	df	*SS*	*MS*
Regression	1	1528	1528.4
Residuals	207	9673	46.7
Total	208	11202	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.07	2.85	-0.02
X1	0.90	0.16	5.72

5.1.2 RB

Regression Statistics	
R Square	35.9%
Adjusted R Square	35.7%
Standard Error	6.53
LLF	-1208.22
AIC	2418.45
SBIC	2422.34
Observations	367

ANOVA

	df	*SS*	*MS*
Regression	1.0	8694	8693.6
Residuals	365.0	15549	42.6
Total	366.0	24243	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.28	0.79	-0.36
X1	1.01	0.07	14.29

5.1.3 WR

Regression Statistics	
R Square	26.3%
Adjusted R Square	26.1%
Standard Error	6.59
LLF	-2053.43
AIC	4108.87
SBIC	4113.30
Observations	620

ANOVA

	df	*SS*	*MS*
Regression	1	9080	9080.5
Residuals	618	27332	44.2
Total	619	36413	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.74	0.73	-1.01
X1	1.05	0.07	14.33

5.1.4 TE

Regression Statistics	
R Square	9.4%
Adjusted R Square	8.8%
Standard Error	6.01
LLF	-484.00
AIC	970.03
SBIC	973.02
Observations	151

ANOVA

	df	*SS*	*MS*
Regression	1	557	556.7
Residuals	149	5377	36.1
Total	150	5934	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	2.04	1.65	1.24
X1	0.73	0.18	3.93

5.2 Results Interpretation: Accuracy by Position

The RB position delivered the highest R^2 (.359), a coefficient closest to 1 (1.01), an intercept closest to 0 (-.28). This suggests that RB may be the most predictable position based on the criteria for forecast accuracy outlined in Section 5. TE had the lowest resulting R^2 (.094), a coefficient farthest from 1 (.73), and an intercept farthest from 0 (2.04), suggesting TE may be the least predictable position.

The null hypothesis intercept or coefficient was not rejected for any source at QB, RB and WR using T-tests at P<.05 (*Appendix 1-4*). At TE, the Numberfire null hypothesis intercept = 0 was rejected (P<.05). At TE, the Bloomberg sports null hypothesis coefficient = 1 was rejected (P<.05). All sources had intercept > 0 and coefficient < 1, indicating that low scoring TE's may be under projected and (or) high scoring TE's may be over projected.

Differences between projection accuracy by position are likely the result of the in-game dynamics of the NFL. RBs have consistent game to game workload relative to WRs and TEs. WR production is dependent on the accuracy of the QB. The dynamics of the NFL make it easier for a defense to game plan coverage to specifically shut down a star receiver than a star running back. This defensive game plan variable can be unpredictable, even for expert algorithms. Running teams will often continue to run the ball regardless of the defensive game plan, whereas a QB will likely to throw the ball elsewhere if a WR faces double coverage. WR and TE production results from fewer plays than RB production, potentially causing higher variance. QBs have a relatively consistent number of attempts per game, yet the R^2 at QB is lower than WR and TE. QBs may be more susceptible to hot and cold streaks due to the mental aspect of the position. This phenomenon is represented in the data by a higher standard deviation among QB scores than any other position.

5.3 Statistical Difference in Model Fit by Position

An F-Test using $F = [(SS_1 - SS_2) / (df_1 - df_2)] / (SS_2 / df_2)$ at P<.05 was used to determine statistical differences in model fit between each position using the mean projection. RB showed improved fit compared to TE (F_{stat} = 1.64 and F_{crit} = 1.24). In addition, WR showed improved fit compared

to TE (F_{stat} = 1.29 and F_{crit} = 1.22). No other statistical differences in model fit between positions using were found.

5.4 Statistical Difference in Model Fit by Projection Source

Using regression results from *Appendix 1-4*, an F-Test where $F = [(SS_1 – SS_2) / (df_1 – df_2)] / (SS_2 /df_2)$ was used to determine statistical differences in model fit between sources at each position at $P<.05$. No statistically significant difference in model fit between any two sources was found. Furthermore, aggregating projections using mean and geometric mean did not provide a statistically significant increase in fit over any single projection source. It should be noted that projections between sources are highly correlated, so the lack of statistical difference in model fit is unsurprising.

5.5 Observed Differences in Accuracy by Projection Source

Although no statistically significant differences were found, differences in accuracy metrics were observed nonetheless. As shown in Appendix 1-4, no source outperformed others (in terms of R^2) at every position. Bloomberg Sports had the highest R^2 among projection sources at QB, RB, and WR, but had the lowest at TE. ProfootballFocus had the lowest R^2 at QB and RB, but tied for second highest at WR.

Mean and geometric mean projections provided the highest R^2 value at *every* position compared with each individual source. Within the context of fantasy football, this finding is congruent with data published by Fantasyfootballanalystics.net, which found that the mean projection of multiple fantasy football projection sources delivered a higher R^2 value than any single projection source used to calculate the mean.

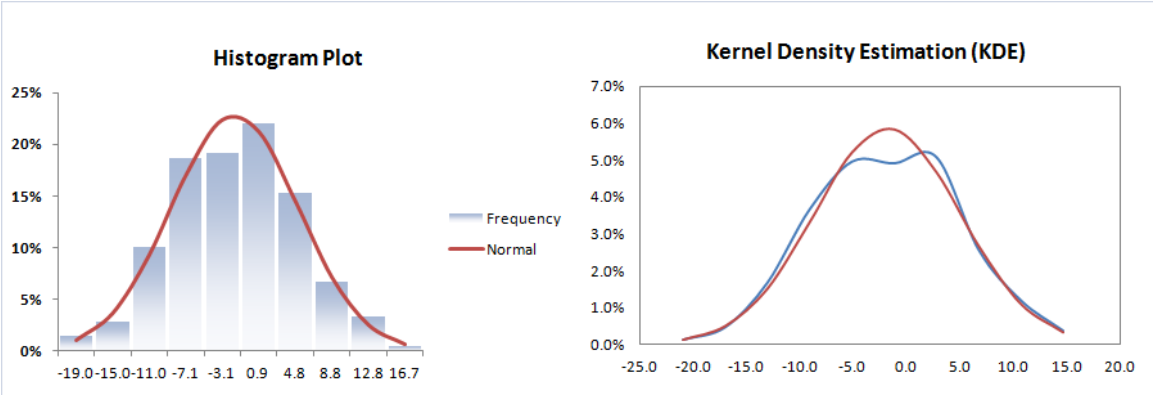
5.6 Mean Projection Residuals - Histogram Plots & KDEs

The following analysis was done on the error term of the arithmetic mean projection using conceptual model part I.

5.6.1 QB

Mean: -1.8

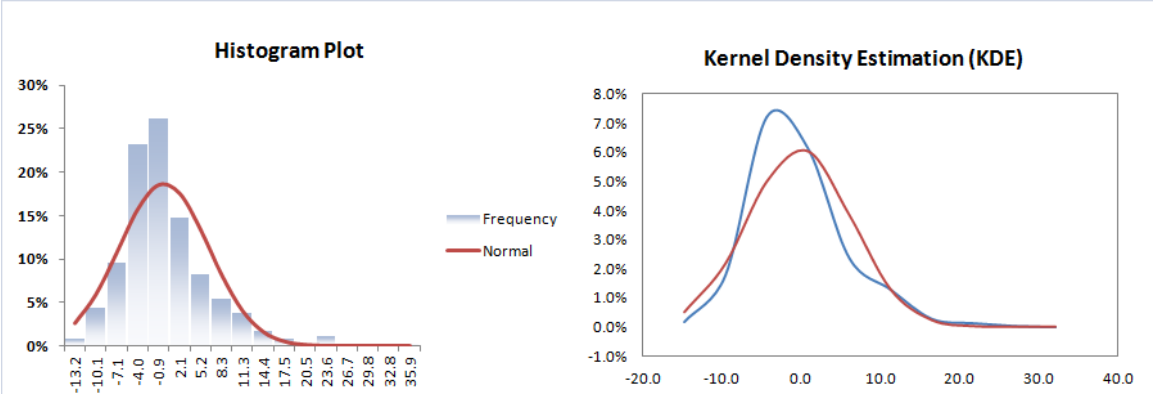
Standard Deviation: 6.8



5.6.2 RB

Mean: -.2

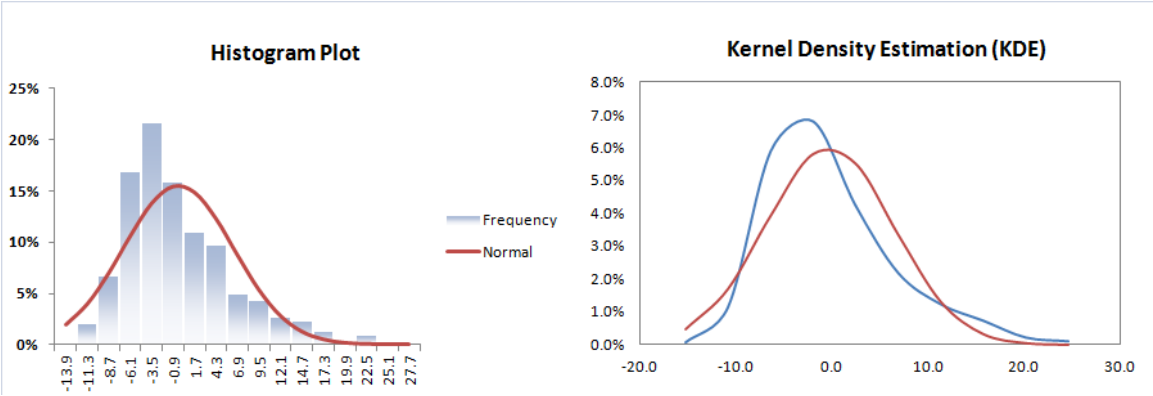
Standard Deviation: 6.5



5.6.3 WR

Mean: -.2

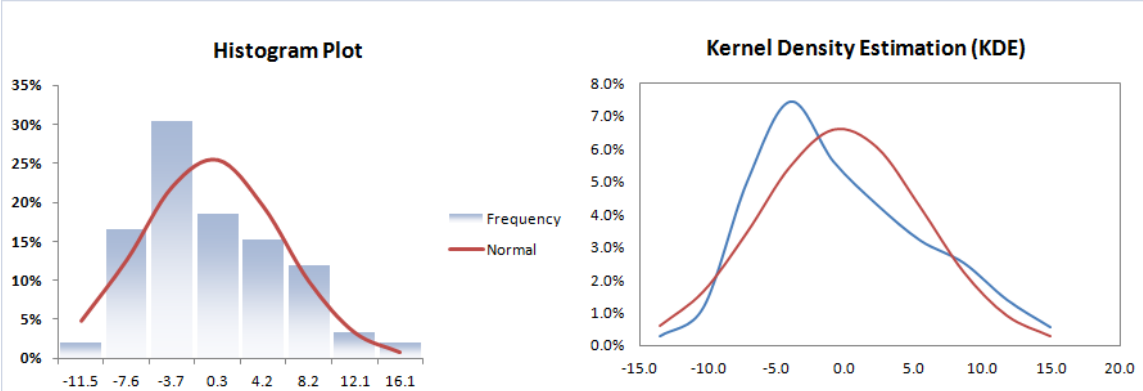
Standard Deviation: 6.6



5.6.4 TE

Mean: -.3

Standard Deviation: 6.0



5.7 Mean Projection Residuals Analysis

At QB, there appears to be a slight negative skew in the residuals. Most notably, at residual +5 the density appears to drop more significantly than the more gradual drop observed at the -5 counterpart. However, we observe a residual distribution that most closely resembles a normal distribution in comparison with other positions.

The residuals at RB, WR and TE all show a positive skew. Why does this occur? To understand, we need to uncover the mechanics of a fantasy score projection. Each projection is a function of a yards projection, plus a touchdown projection, as shown below. With the exception of superstars, the majority of NFL RBs, WRs, and TEs score fewer than 8 touchdowns in a 16 game season. By extrapolating this fact, we can assume that the value of B_2 (expected TDs) for most players is usually < .5 per game. But projections still receive points for the expected "fraction" of a touchdown, so when a player misses on the touchdown points they fall short of their forecast (unless B_1 was grossly underestimated). To further illustrate this point, if the number of players with $B_2 < .5$ is greater than 50% of total players, and the error term on B_1 followed a normal distribution, we would observe a positive skew. Compounding this effect is the fact that touchdowns are worth a considerably

$$Y = B_1X_1 + B_2X_2$$

Where:

Y = projected points

B_1 = expected number of yards

X_1 = fantasy points per yard = .1

B_2 = expected number of touchdowns

X_2 = fantasy points per touchdown = 6

large portion of total expected production. And since they are the result of a single play, they are inherently subject to high variance.

This trend in the residuals is not observed at the QB position. This is likely because value of B_2 (expected TDs) for QBs is almost always >1. Thus, the aforementioned explanation for RBs, WRs, and TEs does not apply.

6. Data Analysis – Conceptual Model Part II

The following regression results use the aggregated efficiency rating in conceptual model part II.

Efficiency (points per $1,000) = Constant + B_1EF + B_2EF^2

6.1 Regression Results

6.1.1 QB

Regression Statistics	
R Square	4.4%
Adjusted R Square	3.5%
Standard Error	0.87
LLF	-265.63
AIC	535.32
SBIC	541.95
Observations	209

ANOVA

	df	*SS*	*MS*	*F*
Regression	2	7	3.6	4.79
Residuals	206	155	0.8	
Total	208	163		

Regression Coefficients

	Value	*std. Error*	*t-stat*	*P-Value*
Intercept	1.64	0.16	10.03	0.0%
X1	0.31	0.20	1.59	5.6%
X2	-0.04	0.05	-0.81	20.9%

6.1.2 RB

Regression Statistics	
R Square	21.8%
Adjusted R Square	21.3%
Standard Error	1.00
LLF	-518.38
AIC	1040.78
SBIC	1048.56
Observations	367

ANOVA

	df	*SS*	*MS*	*F*
Regression	2	101	50.4	50.59
Residuals	364	362	1.0	
Total	366	463		

Regression Coefficients

	Value	*std. Error*	*t-stat*	*P-Value*
Intercept	0.88	0.09	10.02	0.0%
X1	0.41	0.13	3.10	0.1%
X2	-0.01	0.04	-0.21	41.9%

6.1.3 WR

Regression Statistics	
R Square	10.0%
Adjusted R Square	9.7%
Standard Error	1.04
LLF	-901.28
AIC	1806.59
SBIC	1815.43
Observations	620

ANOVA

	df	*SS*	*MS*	*F*
Regression	2	74	36.9	34.26
Residuals	617	665	1.1	
Total	619	738		

Regression Coefficients

	Value	*std. Error*	*t-stat*	*P-Value*
Intercept	0.98	0.07	13.27	0.0%
X1	0.25	0.11	2.30	1.1%
X2	0.00	0.03	0.12	45.1%

6.1.4 TE

Regression Statistics	
R Square	1.1%
Adjusted R Square	-0.3%
Standard Error	1.06
LLF	-221.58
AIC	447.24
SBIC	453.20
Observations	151

ANOVA

	df	*SS*	*MS*	*F*
Regression	2	2	0.9	0.81
Residuals	148	166	1.1	
Total	150	168		

Regression Coefficients

	Value	*std. Error*	*t-stat*	*P-Value*
Intercept	1.33	0.15	8.66	0.0%
X1	0.02	0.22	0.11	45.6%
X2	0.02	0.06	0.27	39.3%

6.2 Results Interpretation: Explanatory Power

Statistically significant coefficients were found at RB and WR, rejecting H_0: $B_1 = 0$ ($P<.05$) and indicating that this model has explanatory power in predicting efficiency. However, H_0: $B_1 = 0$ was not rejected at QB or TE ($P<.05$). It should be noted that at QB the coefficient is nearly significant at $P = 5.6$, while at TE this model has virtually no explanatory power.

H_0: $B_2 = 0$ was not rejected at any position indicating that the marginal impact of efficiency rating does not vary across the domain.

H_0: Constant = 0 was rejected at every position indicating that all players, regardless of efficiency rating, display a level of efficiency > 0.

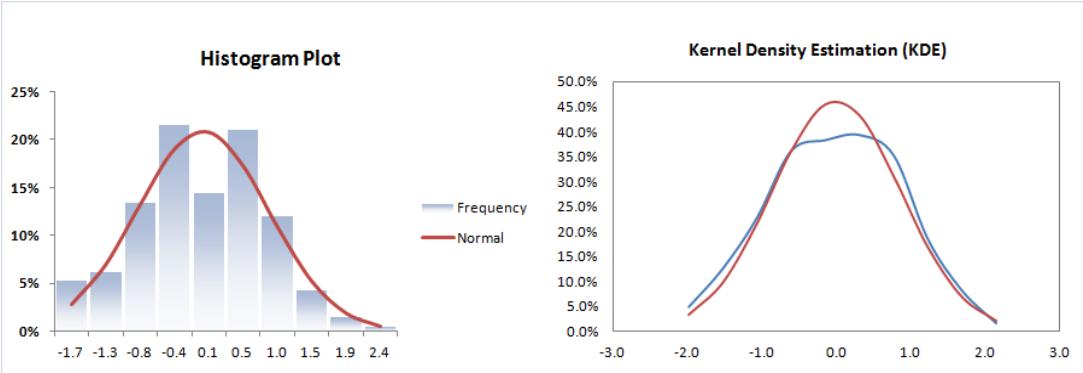
6.3 Mean Efficiency Rating Residuals - Histogram Plots & KDEs

6.3.1 QB

Residual Plots

Mean: 0

Standard Deviation: .9

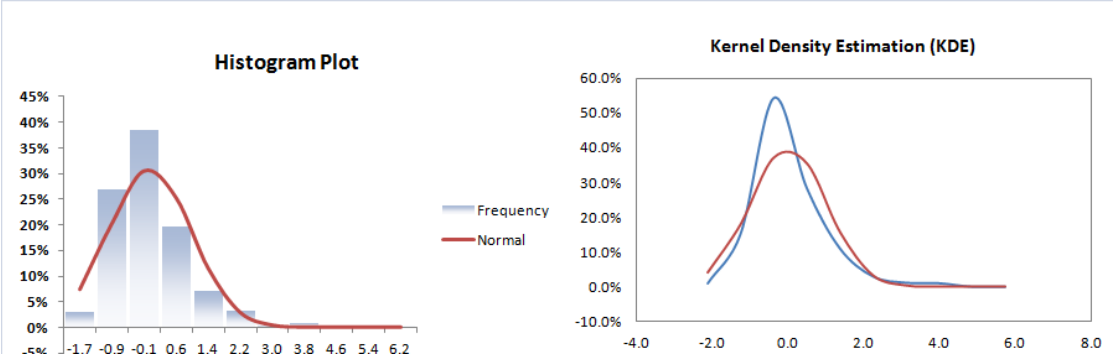


6.3.2 RB

Residual Plots

Mean: 0

Standard Deviation: 1.0

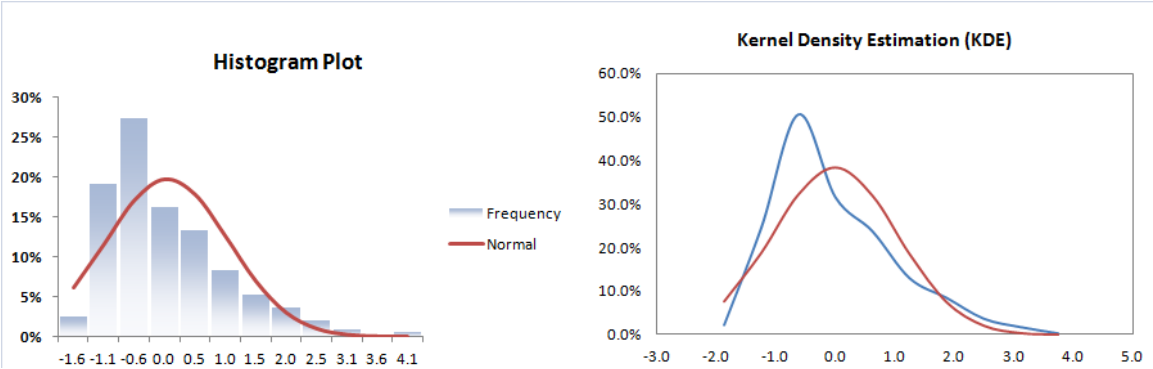


6.3.3 WR

Residual Plots

Mean: 0

Standard Deviation: 1.0

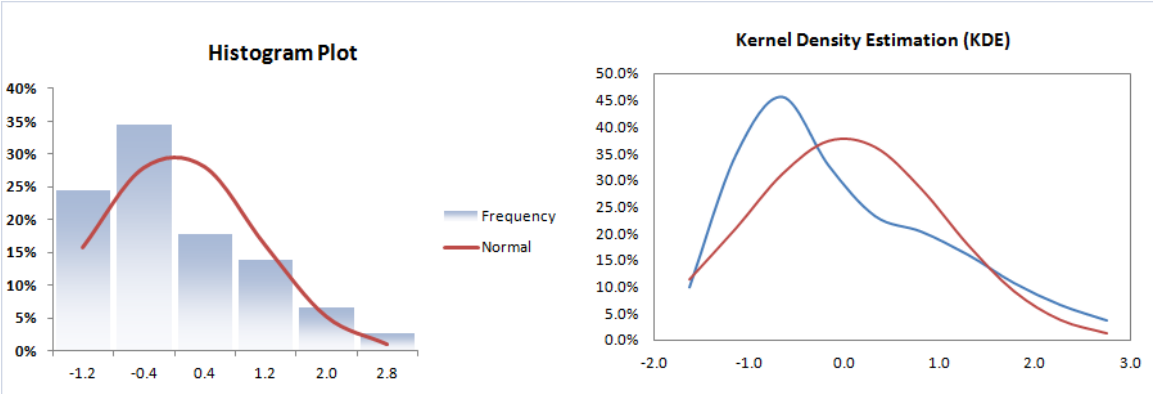


6.3.4 TE

Residual Plots

Mean: 0

Standard Deviation: 1.1



6.4 Efficiency Rating $/point Residual Analysis

The residual distribution at QB most closely resembles a normal distribution in comparison to RB, WR and TE. The residuals at RB, WR and TE all follow a similar distribution. This could be viewed as either positively skewed or lognormal. There are two main reasons for this distribution: First, the distribution may be due in part to the lower bound on the residuals. Given the parameters of the model, the lowest possible residuals are -2.4 at RB, -2.0 at WR, and -1.7 at TE, while no theoretical upper bound exists. Second, the distribution may be the result of the effect that touchdowns have on scoring. The explanation given in *section 5.4* on the impact of predicting touchdown fantasy points applies here. This would also explain why the distribution at QB differs from RB, WR, and TE.

7. Data Analysis – Conceptual Model Part III

7.1 Results Categorized by Efficiency Rating

QB												
	NumberFire		PFF		4for4		Bsports		Mean		Agg. Eff. Rate	
Eff. Rating	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt
4	$ 374	$ 445	$ 383	$ 475	$ 380	$ 494	$ 376	$ 460	$ 388	$ 477	$ 385	$ 466
3	$ 403	$ 458	$ 417	$ 482	$ 413	$ 439	$ 402	$ 440	$ 405	$ 426	$ 407	$ 440
2	$ 426	$ 509	$ 437	$ 477	$ 428	$ 459	$ 417	$ 443	$ 426	$ 446	$ 430	$ 448
1	$ 451	$ 464	$ 456	$ 484	$ 445	$ 443	$ 437	$ 605	$ 447	$ 502	$ 457	$ 533
0	$ 514	$ 538	$ 519	$ 514	$ 482	$ 555	$ 476	$ 548	$ 483	$ 551	$ 506	$ 558
Total	$ 447	$ 493	$ 457	$ 493	$ 441	$ 493	$ 432	$ 504	$ 444	$ 493	$ 444	$ 493
Eff. Rating R^2	0.040		0.001		0.027		0.035		0.029		0.047	

RB												
	NumberFire		PFF		4for4		Bsports		Mean		Agg. Eff. Rate	
Eff. Rating	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt
4	$ 474	$ 479	$ 433	$ 461	$ 440	$ 411	$ 471	$ 430	$ 465	$ 439	$ 463	$ 430
3	$ 561	$ 517	$ 507	$ 535	$ 503	$ 583	$ 529	$ 536	$ 530	$ 515	$ 517	$ 498
2	$ 625	$ 624	$ 561	$ 554	$ 549	$ 589	$ 577	$ 632	$ 577	$ 618	$ 574	$ 618
1	$ 708	$ 666	$ 636	$ 794	$ 615	$ 831	$ 662	$ 703	$ 647	$ 734	$ 679	$ 760
0	$ 1,122	$ 998	$ 1,044	$ 927	$ 967	$ 983	$ 1,065	$ 1,122	$ 1,015	$ 1,056	$ 1,091	$ 1,112
Total	$ 688	$ 655	$ 629	$ 648	$ 613	$ 655	$ 655	$ 665	$ 645	$ 655	$ 645	$ 655
Eff. Rating R^2	0.112		0.102		0.132		0.141		0.150		0.157	

WR												
	NumberFire		PFF		4for4		Bsports		Mean		Agg. Eff. Rate	
Eff. Rating	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt
4	$ 529	$ 568	$ 516	$ 579	$ 527	$ 526	$ 544	$ 479	$ 544	$ 519	$ 534	$ 487
3	$ 595	$ 566	$ 580	$ 610	$ 572	$ 585	$ 593	$ 646	$ 599	$ 587	$ 589	$ 589
2	$ 650	$ 650	$ 625	$ 613	$ 607	$ 663	$ 641	$ 725	$ 630	$ 682	$ 636	$ 694
1	$ 741	$ 757	$ 686	$ 687	$ 652	$ 746	$ 685	$ 754	$ 683	$ 769	$ 722	$ 818
0	$ 1,115	$ 963	$ 925	$ 967	$ 897	$ 981	$ 901	$ 968	$ 901	$ 943	$ 983	$ 1,003
Total	$ 725	$ 707	$ 679	$ 710	$ 664	$ 707	$ 685	$ 712	$ 688	$ 707	$ 688	$ 707
Eff. Rating R^2	0.109		0.087		0.116		0.108		0.097		0.132	

TE																
	NumberFire		PFF		4for4		Bsports		Mean		Agg. Eff. Rate	
Eff. Rating	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt	Proj $/pt	Act $/pt
4	$ 552	$ 575	$ 496	$ 551	$ 500	$ 648	$ 479	$ 617	$ 537	$ 603	$ 533	$ 554
3	$ 601	$ 765	$ 579	$ 679	$ 566	$ 559	$ 704	$ 716	$ 584	$ 561	$ 597	$ 789
2	$ 647	$ 700	$ 629	$ 651	$ 605	$ 709	$ 677	$ 791	$ 618	$ 740	$ 637	$ 716
1	$ 711	$ 644	$ 688	$ 811	$ 659	$ 915	$ 490	$ 562	$ 645	$ 879	$ 706	$ 732
0	$ 1,001	$ 758	$ 821	$ 722	$ 805	$ 722	$ 755	$ 643	$ 779	$ 731	$ 868	$ 750
Total	$ 721	$ 696	$ 656	$ 678	$ 641	$ 696	$ 631	$ 661	$ 672	$ 696	$ 672	$ 696
Eff. Rating R^2	0.008		0.007		0.010		0.016		0.019		0.019	

7.2 Observations & Interpretation

The aggregate efficiency rating provides the largest R^2 at every position. Aside from R^2, these results are difficult to quantify with one metric. However, it appears that the aggregate efficiency rating provides the lowest $/point values of efficiency rated 3 and 4 players.

At QB, no source is able to provide superior information. Actual $/point is relatively unpredictable with efficiency rating at QB, perhaps unsurprising, given the analysis of QB with conceptual model I & II. At RB efficiency lower $/point are observed with higher efficiency ratings. All sources are able to provide efficiency rated 4 players that produced <$500/point – which is the production needed to place in contests on FanDuel.com. 4for4 was the best at efficiency rating 4, with a total of $411/point, however, 4for4 efficiency rating 3 totaled only $583. Aggregated efficiency rating was the only source with both efficiency rated 3 and 4 <$500/point. At RB, the aggregated efficiency rating appears to provide the lowest $/point for 3 and 4 rated players. At WR, $/point for efficiency rated 4 players is greater than RB for all projection sources. The practical application of this finding suggests players aim to spend high salary at RB, as RBs tend to provide superior $/point compared to WRs. Bloomberg Sports and aggregated efficiency rating are the only sources that provide <$500/point. Like RB, at WR, the aggregated efficiency rating provides the lowest $/point for efficiency rating 3 and 4. At TE, no source is able to provide superior information, and the aggregated efficiency rating is unable to distinguish player efficiency. This is congruent with the findings of conceptual model I & II that indicate the fantasy scoring from the TE position is relatively unpredictable.

8. Conclusion

The projections given by the four sources for each individual player in a given week, are highly correlated. Thus, no statistical difference in projection accuracy between sources was found, and information aggregation did not provide a statistically significant increase in accuracy.

However, the arithmetic mean projection resulted in a higher R^2 value than any single projection source, supporting the theory of information aggregation.

The model fit for RB and WR was found to be statistically better than TE at $P<.05$. Trends in residuals indicated that the projection for RB, WR, and TE is more likely too high than too low. When projections miss too low, the miss is more significant, which resulted in a mean residual with no statistical difference from 0. The aggregated efficiency rating formula used in Conceptual Model II was found to be a statistically significant predictor of efficiency at RB and WR, but not at QB and TE.

To apply the findings of this paper to game strategy on FanDuel.com, the aggregated efficiency rating formula can be used when selecting RBs and WRs to optimize $/point, but outside information should be used to select QBs and TEs. This recommendation stems from the fact that this model has explanatory power at RB and WR but not QB or TE. Numberfire.com, 4for4.com, Profootballfocus.com and Bloombergsports.com all provided a similar level of forecast accuracy, and no statistical difference in model fit between sources was found. However, mean projections result in a higher R^2, at every position, compared with individual source projections. Since narrow increases in accuracy are useful to Daily Fantasy Sports players, this paper suggests using mean projections from several sources to attain the most accurate fantasy score projections.

References

1) http://www.fsta.org/?page=Demographics
2) http://www.forbes.com/sites/darrenheitner/2014/10/03/early-fanduel-investor-excitingly-forecasts-future-of-daily-fantasy-sports/
3) A. H. Ashton and R. H. Ashton. Aggregating subjective forecasts: Some empirical results. Management Science, 31:1499–1508, 1985.
4) Moez Bernnouri, Henner Gimpel, and Jacques Robert. Measuring the impact of information aggregation mechanisms: An experimental investigation. Journal of Economic Behavior and Organization, 78:302–318, 2011.
5) Charles R. Plott, Jorgen Wit, and Winston C. Yang. Parimutuel betting markets as information aggregation devices: experimental results. Economic Theory, 22(2):311–351, 09 2003.
6) Wolfers, Justin and Eric Zitzewitz, 2005a. "Interpreting Prediction Market Prices as Probabilities," NBER Working Paper No. 10359.
7) James Surowiecki. *Wisdom of the Crowds*. N.p.: n.p., 2004. Print.
8) Fantasyfootballanalystics.net

Appendix

Appendix 1: Model Part I Results - QB

A) NumberFire

Regression Statistics	
R Square	12.8%
Adjusted R Square	12.4%
Standard Error	6.87
LLF	-698.27
AIC	1398.56
SBIC	1401.88
Observations	209

ANOVA	*df*	*SS*	*MS*
Regression	1	1438	1438.1
Residuals	207	9764	47.2
Total	208	11202	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	3.48	2.32	1.50
X1	0.71	0.13	5.52

B) ProFootballFocus

Regression Statistics	
R Square	9.2%
Adjusted R Square	8.8%
Standard Error	7.01
LLF	-702.54
AIC	1407.10
SBIC	1410.42
Observations	209

ANOVA	*df*	*SS*	*MS*
Regression	1	1031	1030.7
Residuals	207	10171	49.1
Total	208	11202	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	4.05	2.66	1.52
X1	0.69	0.15	4.58

C) 4for4

Regression Statistics	
R Square	12.8%
Adjusted R Square	12.4%
Standard Error	6.87
LLF	-698.34
AIC	1398.69
SBIC	1402.02
Observations	209

ANOVA	*df*	*SS*	*MS*
Regression	1	1432	1431.7
Residuals	207	9770	47.2
Total	208	11202	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	-1.10	3.15	-0.35
X1	0.96	0.17	5.51

D) BloombergSports

Regression Statistics	
R Square	13.4%
Adjusted R Square	13.0%
Standard Error	6.75
LLF	-611.33
AIC	1224.67
SBIC	1227.87
Observations	184

ANOVA	*df*	*SS*	*MS*
Regression	1	1366	1365.5
Residuals	182	8282	45.5
Total	183	9648	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	0.43	2.84	0.15
X1	0.83	0.15	5.48

E) Mean

Regression Statistics	
R Square	13.6%
Adjusted R Square	13.2%
Standard Error	6.84
LLF	-697.30
AIC	1396.62
SBIC	1399.94
Observations	209

ANOVA	*df*	*SS*	*MS*
Regression	1	1528	1528.4
Residuals	207	9673	46.7
Total	208	11202	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	-0.07	2.85	-0.02
X1	0.90	0.16	5.72

F) Geometric Mean

Regression Statistics	
R Square	13.7%
Adjusted R Square	13.3%
Standard Error	6.83
LLF	-697.18
AIC	1396.38
SBIC	1399.71
Observations	209

ANOVA	*df*	*SS*	*MS*
Regression	1	1539	1539.1
Residuals	207	9663	46.7
Total	208	11202	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	0.15	2.80	0.05
X1	0.90	0.16	5.74

Appendix 2: Model Part I Results - RB

A) NumberFire

Regression Statistics	
R Square	32.3%
Adjusted R Square	32.1%
Standard Error	6.71
LLF	-1218.19
AIC	2438.39
SBIC	2442.28
Observations	367

ANOVA	*df*	*SS*	*MS*
Regression	1	7825	7825.3
Residuals	365	16417	45.0
Total	366	24243	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	0.85	0.77	1.11
X1	0.96	0.07	13.19

B) ProFootballFocus

Regression Statistics	
R Square	31.6%
Adjusted R Square	31.4%
Standard Error	6.69
LLF	-1061.11
AIC	2124.24
SBIC	2128.00
Observations	320

ANOVA	*df*	*SS*	*MS*
Regression	1	6570	6570.1
Residuals	365	14220	44.7
Total	319	20790	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	0.80	0.84	0.96
X1	0.89	0.07	12.12

C) 4for4

Regression Statistics	
R Square	34.9%
Adjusted R Square	34.7%
Standard Error	6.58
LLF	-1210.96
AIC	2423.93
SBIC	2427.83
Observations	367

ANOVA	*df*	*SS*	*MS*
Regression	1	8459	8459.4
Residuals	365	15783	43.2
Total	366	24243	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	-0.15	0.79	-0.19
X1	0.95	0.07	13.99

D) BloombergSports

Regression Statistics	
R Square	35.1%
Adjusted R Square	34.9%
Standard Error	6.54
LLF	-1072.90
AIC	2147.82
SBIC	2151.59
Observations	326

ANOVA	*df*	*SS*	*MS*
Regression	1	7955	7955.0
Residuals	365	13783	42.5
Total	325	21738	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	-0.44	0.82	-0.53
X1	1.03	0.08	13.67

E) Mean

Regression Statistics	
R Square	35.9%
Adjusted R Square	35.7%
Standard Error	6.53
LLF	-1208.22
AIC	2418.45
SBIC	2422.34
Observations	367

ANOVA	*df*	*SS*	*MS*
Regression	1	8694	8693.6
Residuals	365	15549	42.6
Total	366	24243	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	-0.28	0.79	-0.36
X1	1.01	0.07	14.29

F) Geometric Mean

Regression Statistics	
R Square	35.7%
Adjusted R Square	35.5%
Standard Error	6.53
LLF	-1208.67
AIC	2419.34
SBIC	2423.24
Observations	367

ANOVA	*df*	*SS*	*MS*
Regression	1	8656	8655.5
Residuals	365	15587	42.7
Total	366	24243	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	-0.13	0.78	-0.16
X1	1.00	0.07	14.24

Appendix 3: Model Part I Results - WR

A) NumberFire

Regression Statistics	
R Square	21.9%
Adjusted R Square	21.8%
Standard Error	6.78
LLF	-2065.74
AIC	4133.49
SBIC	4137.92
Observations	620

ANOVA

	df	*SS*	*MS*
Regression	1	7973	7973.3
Residuals	618	28439	46.0
Total	619	36413	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	1.26	0.65	1.94
X1	0.88	0.07	13.16

B) ProFootballFocus

Regression Statistics	
R Square	24.3%
Adjusted R Square	24.1%
Standard Error	6.55
LLF	-1757.08
AIC	3516.17
SBIC	3520.44
Observations	533

ANOVA

	df	*SS*	*MS*
Regression	1	7310	7310.4
Residuals	618	22784	42.9
Total	532	30095	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.41	0.77	-0.53
X1	1.00	0.08	13.05

C) 4for4

Regression Statistics	
R Square	24.3%
Adjusted R Square	24.2%
Standard Error	6.68
LLF	-2055.97
AIC	4113.95
SBIC	4118.37
Observations	620

ANOVA

	df	*SS*	*MS*
Regression	1	8856	8855.9
Residuals	618	27557	44.6
Total	619	36413	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.73	0.74	-0.99
X1	1.02	0.07	14.09

D) BloombergSports

Regression Statistics	
R Square	25.9%
Adjusted R Square	25.7%
Standard Error	6.62
LLF	-1848.37
AIC	3698.75
SBIC	3703.07
Observations	559

ANOVA

	df	*SS*	*MS*
Regression	1	8504	8503.8
Residuals	618	24377	43.8
Total	558	32881	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-1.20	0.78	-1.54
X1	1.09	0.08	13.94

E) Mean

Regression Statistics	
R Square	26.3%
Adjusted R Square	26.1%
Standard Error	6.59
LLF	-2053.43
AIC	4108.87
SBIC	4113.30
Observations	620

ANOVA

	df	*SS*	*MS*
Regression	1	9080	9080.5
Residuals	618	27332	44.2
Total	619	36413	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.74	0.73	-1.01
X1	1.05	0.07	14.33

F) Geometric Mean

Regression Statistics	
R Square	26.4%
Adjusted R Square	26.2%
Standard Error	6.58
LLF	-2053.78
AIC	4109.56
SBIC	4113.99
Observations	620

ANOVA

	df	*SS*	*MS*
Regression	1	9050	9050.0
Residuals	618	27363	44.3
Total	619	36413	

Regression Coefficients

	Value	*std. Error*	*t-stat*
Intercept	-0.53	0.72	-0.73
X1	1.04	0.07	14.30

Appendix 4: Model Part I Results - TE

A) NumberFire

Regression Statistics	
R Square	7.7%
Adjusted R Square	7.0%
Standard Error	6.06
LLF	-485.42
AIC	972.87
SBIC	975.86
Observations	151

ANOVA	*df*	*SS*	*MS*
Regression	1	454	454.5
Residuals	149	5479	36.8
Total	150	5934	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	3.41	1.45	2.35
X1	0.61	0.17	3.52

B) ProFootballFocus

Regression Statistics	
R Square	8.8%
Adjusted R Square	8.2%
Standard Error	5.89
LLF	-430.00
AIC	862.02
SBIC	864.90
Observations	135

ANOVA	*df*	*SS*	*MS*
Regression	1	448	448.1
Residuals	149	4617	34.7
Total	134	5066	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	2.63	1.70	1.55
X1	0.67	0.19	3.59

C) 4for4

Regression Statistics	
R Square	9.2%
Adjusted R Square	8.6%
Standard Error	6.01
LLF	-484.12
AIC	970.27
SBIC	973.26
Observations	151

ANOVA	*df*	*SS*	*MS*
Regression	1	548	548.2
Residuals	149	5386	36.1
Total	150	5934	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	2.22	1.62	1.38
X1	0.67	0.17	3.89

D) BloombergSports

Regression Statistics	
R Square	5.7%
Adjusted R Square	5.0%
Standard Error	5.94
LLF	-431.19
AIC	864.41
SBIC	867.29
Observations	135

ANOVA	*df*	*SS*	*MS*
Regression	1	283	282.8
Residuals	149	4700	35.3
Total	134	4983	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	3.36	1.73	1.94
X1	0.56	0.20	2.83

E) Mean

Regression Statistics	
R Square	9.4%
Adjusted R Square	8.8%
Standard Error	6.01
LLF	-484.00
AIC	970.03
SBIC	973.02
Observations	151

ANOVA	*df*	*SS*	*MS*
Regression	1	557	556.7
Residuals	149	5377	36.1
Total	150	5934	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	2.04	1.65	1.24
X1	0.73	0.18	3.93

F) Geometric Mean

Regression Statistics	
R Square	9.3%
Adjusted R Square	8.7%
Standard Error	6.01
LLF	-484.04
AIC	970.11
SBIC	973.10
Observations	151

ANOVA	*df*	*SS*	*MS*
Regression	1	554	553.9
Residuals	149	5380	36.1
Total	150	5934	

Regression Coefficients	*Value*	*std. Error*	*t-stat*
Intercept	2.14	1.63	1.31
X1	0.72	0.18	3.92