Finding Inefficiency in Sports Betting Markets;

a Look through NFL Confidence Pick'Em Biases

by

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Abstract

This thesis deals with the relationship between bettor behavior and the overall efficiency of the NFL betting markets. Using data from an NFL Confidence Pick'em Pool, I attempted to answer three important questions: 1) Are bettors behaving optimally? 2) What drives bettor behavior?, and 3) How does bettor behavior create opportunities in the betting markets? After scouring and analyzing the data, I came to various conclusions. Firstly, bettors, on average, are not economically rational and deviate significantly from the optimal strategy. Secondly, bettor behavior can be traced to several key tenets of behavioral economics, namely Overconfidence, Availability Heuristic, and Anchoring. Finally, upon revealing the bettor behavioral biases, the prudent bettor can leverage this information by comparing the implied win odds from the spread against the objective, adjusted win odds offered by Teamrankings.com. Pinpointing the games which are most affected by bettor behavioral can give the opportunistic bettor a consistent, tangible advantage in the betting markets over the long run, thereby proving, at least on some scale, the inefficiency of the sports betting markets.

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I. Introduction

Every day, millions of confident sports fans eagerly place their bets. They wait with anticipation as the game goes back and forth, as their prospect of winning rises and falls with every play. They have thoroughly done their research, watched hours of ESPN coverage, read every preseason projection, analyzed every highlight; their effort is indisputable. Yet, much to their dismay, the game starts to go awry. A pebble causes a sharp groundball to fly pass a steady shortstop. An NFL back judge misses an obvious holding call, resulting in extra throwing time for the quarterback and an easy touchdown. Pretty soon, the betting fans' confidence wanes, as the inconceivable becomes the reality and their meticulous planned bets become losers.

This is the life of a chronic sports bettor.

The random whims of sports games seem to constantly snatch victory out of hand, resulting in overall dismay for the bettor. While even the worst bettor experiences short runs of success, over the long-term, he is met with crippling disappointment as the 50-50 nature of the sports betting market rudely snaps him back to reality. It is a never-ending cycle, with exuberant, unlikely wins being met the next week with heart-wrenching, spirit-crushing losses.

However, can this cycle be broken? Is there a way to consistently, over the long-term, gain an advantage in the sports betting markets? Or are most sports bettors doomed to a life of bitter disappointment and unredeemed betting receipts?

Fortunately, there is hope. There are unique, inherent opportunities in sports betting which affords a potential long-term profit to the advantageous and informative bettor. By looking at previously unanalyzed data from NFL Confidence Pick'Em pools, I have found that sports betting markets are profoundly affected by several behavioral biases suffered by the average fan and bettor. As a result, an astute bettor can isolate these biases and bet accordingly, thereby breaking the aforementioned cycle of mediocre bets and dismaying losses.

To fully understand the inefficiencies and opportunities in the sports betting markets, four main areas must be explored:

I. What is "efficiency" in the sports betting markets?

II. Are bettors behaving optimally?

III. What drives bettor behavior?

IV. How does bettor behavior create opportunities in the betting market?

Part I of this paper discusses the application of the Efficient Market Hypothesis ("EMH") to the sports betting markets. Part II deals with the merits of analyzing the NFL Confidence Pick'em data, the "optimal strategy" in such a league, and the deviation of said strategy by bettors in several key instances. Part III seeks to derive meaning from these deviations, categorizing the deviations, and explaining the deviations in line with prevailing behavioral economic tenets. Finally, Part IV aims to apply the findings of Parts II and III to the betting markets, thereby exposing and highlighting the glaring opportunities for profit in the sports betting sphere.

1.1 Literature Review

Over the last few decades, the comparison between the financial markets and the sports betting markets has been widely mentioned and discussed. More specifically, there have been numerous papers attempting to affirm or disprove the theory that sports betting markets are efficient, particularly in the NFL. However, where this paper differs than the prevalent literature is the method and approach taken to prove inefficiency in the sports betting markets. Previously, the most common method was to focus on the relationship between the betting markets and the results of the games. The goal was to simply over-fit a profitable betting strategy on past results, and prove efficiency or inefficiency based on the profitability level of such an exercise. For example, this was the approach taken by Golec and Tamarkin in their article "The degree of inefficiency in the football betting market: Statistical tests," and PK Gray and SF Gray in their paper "Testing market efficiency: Evidence from the NFL sports betting markets." While ambitious in their attempts to prove or disprove betting market efficiency, these papers fall short due to their ignorance of fickle bettor behavior and its impact on the betting lines.

Recently, further attempts have been made to incorporate behavioral biases into the NFL discussion, as seen by Massey and Thaler's "Overconfidence vs. Market Efficiency in the National Football League," a discussion of the incentives and decision making process that goes into the NFL player draft. However, that discussion has not yet transitioned to directly addressing bettor behavior.

This paper seeks to bridge that gap, to uncover the link between bettor biases and inefficiency in the sports betting market. While previous literature has primary used the spread as a means of testing market efficiency, I used data from an NFL Confidence Pool, a unique and informative divergence. The novel analysis gleaned from this data set allowed me to concentrate on bettor behavior, and subsequently apply the reasons for that behavior to construct a profitable betting strategy.

II. What is "efficiency" in the sports betting markets?

2.1 Efficient-Market Hypothesis

Before delving into the data, it is imperative to establish a basic understanding of Efficient-Market Hypothesis ("EMH"), and the application of that theory to sports betting markets. On a fundamental level, the EMH states that it is impossible for an investor to "beat the market," as efficiency in the markets cause current share prices to reflect all relevant information. Because stocks always trade at their fair value, it is impossible for investors to reap any benefit from technical or fundamental analysis, thus making it virtually impossible to beat the market through timing or "expert price selection." The only way to gain an edge over the market is by purchasing riskier investments to reap higher returns[1]. While dissenters reference Warren Buffet's fabulous career and the "Black Monday" stock market crash of 1987 as proof of market inefficiencies, those instances seem to be the exception rather than the rule, as multitudes of statistical and anecdotal evidence document the market consistently outperforming various investment strategies.

However, it is important to note that a key tenet of the EMH is that investors cannot beat the market *over the long run*. While it is possible to garner significant returns in the short term, that success is chalked up more to luck than a conscious beating of the market. For example, in a famous experiment, EMH proponent Burton Malkiel had his students flip a coin, and then graphed the results based on the outcome of the flip. The ensuing graph remarkably resembled a stock chart graph, so much so that when Malkiel showed the graph to a friend, the friend

[1] "Efficient Market Hypothesis - EMH." *Investopedia.com*. N.p., n.d. Web. 08 May 2013. <http://www.investopedia.com/terms/e/efficientmarkethypothesis.asp>

immediately recommended a strong buy on the stock[2]. Since the market is perfectly efficient, it is impossible to accurately predict the future direction of stocks; its direction is as random as a coin flip. As the investor spends increased time betting on the markets (or as the coin is flipped more times), his luck is bound to run out, until he eventually yields a return less than the market yield itself.

2.2 Efficient Sports Betting Markets

Similarly, proponents of applying the EMH to sports betting would advocate that it is impossible to consciously "beat the market;" success in the sports betting markets is simply a function of good fortune. Fundamentally, this theory should be correct given the nature of the sports betting markets. Traditionally, the most common form of sports betting is "Straight Bets with a Point-Spread[3]." In this method, bookmakers set the amount of points by which the "favorite" is expected to beat the "underdog." The bettor then has the option of choosing the favorite or underdog. If he chooses the favorite, the favorite must win by more than the "line" set by the bookmakers in order to win the bet; if he chooses the underdog, the bettor wins the bet if the underdog wins, or loses by less than the "line" on the games[4]. The bookmakers act as a market maker, seeking 50-50 action on both sides of the bet (equal number of people betting on the favorite and underdog) and subsequently taking a "rake" of the betting pool.

Therefore, bookmakers are incentivized to set lines that accurately reflect the most probabilistic outcomes of games. In order to achieve equal action on both sides of a bet, bettors must perceive the bet as fair; any other perception will result in betting on the undervalued team,

[2] Malkiel, Burton G. "Technical Analysis and the Random-Walk Theory." *A Random Walk down Wall Street: The Time-tested Strategy for Successful Investing*. New York: W. W. Norton, 2011. 130-31. Print.
[3] "Spread" and "Line" are used interchangeably
[4] "Sports Betting. About Betting on Sports in Las Vegas by VegasInsider.com."*VegasInsider.com*. N.p., n.d. Web. 08 May 2013. <http://www.vegasinsider.com/sports-betting/>.

thereby resulting in potential catastrophic losses for the bookmaker. For example, if the current Super Bowl champion Baltimore Ravens was slated to play the dreadful Jacksonville Jaguars, bettors would expect a significant spread on the game. However, if bookmakers only gave the Ravens a line of -1, indicating the Ravens would have to win by 1 point for bettors to win their bet, almost every bettor would confidently place their money on the Ravens. On the other hand, a spread of -14 for the Ravens is a more plausible number, given the tenacity of the Ravens' defense and the atrociousness of the Jaguars' offense. This spread is likely to be deemed "fair" by the betting public, resulting in equal action on both sides and a guaranteed profit for the bookmakers. This 50-50 action can be viewed in a unique fashion: bookmakers are trying to create a situation where every bettor has a 50% chance of winning. Naturally, if bettors identify their chances to win are less than 50%, with no additional compensation for the added risk, they will not take the bet. Therefore, bookmakers must set the line to exactly reflect equal odds of winning by betting on either the favorite or the underdog; anything else will result in a glaring discrepancy and potential pitfall for bookmakers.

The natural result of this system is that, theoretically, bettors have an equal chance of winning as they do losing. Similar to Malkiel's coin-toss example, any win by a bettor is just a function of luck, a direct result of the fact that the outcomes of sports games are binary and thus *must* result in a winner or loser[5]. Therefore, while bettors can achieve short-term gains, over the long term, one can expect a regression to the mean, as losses eliminate prior profits. Fundamentally, one cannot skillfully navigate the sports betting market to achieve predictable positive returns because the result of one's bets is essentially a toss-up; by definition, each bet has a 50% chance of winning.

[5] Interestingly, some sports, such as soccer, can end in a tie. To avoid the complications of this result, in sports where ties are possible, many bookmakers declare a game must be completed in regulation time to be considered a "good bet."

As with the stock market, the "efficient sports betting marketing hypothesis" is contingent on the full availability of information regarding the individual games (stocks) in the market. Obviously, if the bookmakers cannot accurately assess the prospects of certain teams, the bookmakers will be unable to precisely pinpoint a spread for those teams, resulting in potential inefficiencies. Therefore, games must have widespread visibility with teams popular enough to garner significant bettor interest and detailed analysis pertaining to each team's prospects. Without these conditions, it is impossible for bookmakers to set a line on a game and useless to the efficiency of the sports betting markets debate, as they fall outside the scope of the preconditions (fully incorporated information) necessary for efficient markets.

2.3 The NFL as a Test Case for Market Efficiency

With this in mind, the National Football League ("NFL") betting markets serve as a perfect test case for market efficiency. There are several key advantages to looking at the NFL betting markets: 1) NFL teams play once a week, 2) NFL games are watched by a tremendous amount of fans, 3) NFL games get overhyped and overblown coverage in the press.

NFL teams play once a week: Unlike other sports, such as the MLB and the NBA, NFL teams are only scheduled to play once a week. Although the recent addition of Thursday night games, along with the traditional Monday Night Football, expands the number of days with football games, the important factor is that individual teams only play once a week[6]. Consequently, this allows bookmakers ample time to accurately calculate the winning odds of each team. Furthermore, bookmakers can adjust appropriately injury reports, team strategies, and coaching decisions become apparent over the course of the week. There is minimal risk of crucial information "falling through the cracks," due to the sufficient time in between games.

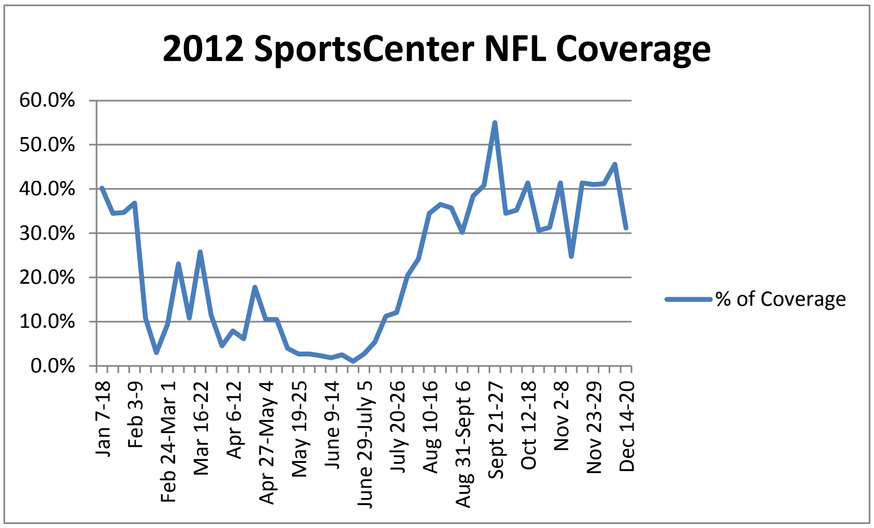
[6] Although teams can theoretically play Monday night and then the following Sunday, the spacing between games is significantly greater than that of the MLB (play daily) and the NBA (play every 2-3 days)

Widespread Fan Appeal: More than any other sport in the U.S., the NFL boasts incredible fan interest and attention. The decline of baseball as "America's Pastime" has shifted both the causal and avid fans' focus to football, "America's Game." As such, the number of fans and game viewers has reached astronomical numbers. For example, since 2010, the NFL games have accounted for 55% of all TV shows averaging 20 million viewers, 70% of all TV shows averaging 30 million viewers, and 92% of all TV shows averaging 40 million viewers[7]. Perhaps even more unbelievable is the fact that the Super Bowl, the NFL's ultimate game and spectacle, drew over 108 million viewers in 2013[8]; America cannot get enough of football. Naturally, as a result of the NFL's popularity, there is an extreme amount of betting surrounding the league. According to the Nevada Gaming Commission, in 2011 over $1.34 billion was wagered in the state's casinos on football, comprising 41% of total sports bets. Furthermore, the National Gambling Impact Study Commission approximates $380 billion is wagered annually on football through offshore accounts and illegal betting.[9] Therefore, clearly, the stakes are immense for bookmakers to accurately set lines. As opposed to obscure college basketball games, the amount of action on every NFL game totals millions of dollars[10]; bookmakers cannot afford to approximate lines, but must determine the spreads with ultimate precision. Therefore, one would expect no inherent flaws in NFL spreads (and thus no betting advantage), as bookmakers are highly incentivized to put in the effort to accurately match up spreads with expected win odds.

[7] Lee, Tony. "Football Television Ratings." *Breitbart News Network*. N.p., 30 Jan. 2013. Web. 08 May 2013. <http://www.breitbart.com/Breitbart-Sports/2013/01/30/Football-television-ratings>.
[8] Mirkinson, Jack. "Super Bowl Ratings: 108.41 Million Tune In, Down From Last Year." *The Huffington Post*. TheHuffingtonPost.com, 04 Feb. 2013. Web. 08 May 2013. <http://www.huffingtonpost.com/2013/02/04/super-bowl-ratings-2013_n_2615432.html>
[9] Green, Miranda. "NFL's Shadow Economy of Gambling and Fantasy Football Is a Multibillion Dollar Business." *The Daily Beast*. Newsweek/Daily Beast, 06 Oct. 2012. Web. 08 May 2013. <http://www.thedailybeast.com/articles/2012/10/06/nfl-s-shadow-economy-of-gambling-and-fantasy-football-is-a-multibillion-dollar-business.html>.
[10] There are 256 regular season games in an NFL season, plus 11 playoff games. On average, there is over $5 million wagered in Vegas casinos on each NFL game, and over $1.42 billion per NFL game wagered through offshore account and illegal betting

Ubiquitous NFL Coverage: Not surprisingly, content providers go overboard with their NFL coverage, enough to satisfy even the most voracious NFL fan. Through around the clock NFL coverage by the likes of ESPN, the NFL Network, or Yahoo! Sports, fans are constantly bombarded with statistics, analysis, and projections. Furthermore, the timing of this barrage is not restricted to the NFL season. As seen in Figure 1 (label the figure), NFL coverage dominates ESPN's SportsCenter[11], the preeminent sports program on the preeminent sports network. Except for the early summer period, a time dominated by NBA Finals coverage, the NFL commands the largest share of coverage. Immediately after the NBA Finals are completed, NFL coverage ramps up throughout the summer, despite the NFL season not beginning until September.

Figure 1: 2012 SportsCenter NFL Coverage



This abundant NFL coverage is imperative to the efficient sports betting markets hypothesis because it ensures that fans and bettors are well-informed and, therefore, placing economically rational bets. Just as an eager day trader may carefully watch the Bloomberg

[11] The 11 p.m. ET edition of SportsCenter was used because most games are finished by then; sportscasters have the full array of games across all sports to discuss and analyze.

channel or scour financial statements to make educated stock picks, the sports bettor carefully watches ESPN and pours over team scouting reports to enable logical bets. Consequently, on a superficial level, bettors should be acting objectively rationally, as the obscene amount of NFL coverage aptly prepares and informs bettors.

III. Are bettors behaving optimally?

3.1 NFL Confidence Pick'em Pool

While other attempts at explaining sports betting market efficiency have focused on sports as a whole or exclusively used betting lines data, this data set is solely based on NFL Confidence Pick'em pool data, an innovative and informative betting system. Every week, players are presented with the list of games being played. Players then select a winner for each of the sixteen games and weight each from 16 to 1 based on their confidence about the outcome, with each number being used only once (see appendix for more details).

For example, if San Francisco 49ers were playing the Buffalo Bills, one can all but guarantee a dominant 49ers win. Consequently, a bettor would rank that game as a "16" as he is fully confident of a 49ers win, and thus wishes to place the most value on that game (if the 49ers do indeed win, the player gains the 16 points). However, in a match between the Carolina Panthers and the Tampa Bay Buccaneers, a closely contested match and essentially a "toss up," the prudent play would be to assign the favorite a ranking of "1," thereby minimizing the potential losses. Each week, the player gains the sum total of the games he picked correctly (the winners of the game) and the corresponding "value" he placed on each team. The highest total score at the end of the season wins the league.

3.2 Advantages of a Confidence Pool

Confidence Pools are a better proxy for bettors' intentions than normal spread betting for one key reason: observational value. Normal betting is a binary action as the bettor simply chooses one team or the other to win. As mentioned above, because spread betting is designed to have equal action on both sides of the bet, the individual bets themselves tell us nothing about bettor behavior. While bettors may be incorporating biases and opinions into their bets, there is no way to distinguish that possibility by looking at spread betting. In confidence picks, however, the better still chooses one team over another but then *tells us how he feels about the pick* by weighting each game. Confidence picks provide insight into the value placed on each game and help to highlight bettor biases. A cursory analysis of bettor picks reveals both the percentage of people that picked a certain team and the value placed on that team. Consequently, by comparing that data to the optimal strategy, it is possible to root out where and why the bettor, and by extension the general betting market, deviated from the objective and rational strategy. Confidence Pools allow us to see the difference between bets and how bettors react to certain teams, whereas with normal betting, all bets are essentially a bet on chance, and expose nothing about bettor intentions.

3.3 Optimal Strategy for Confidence Pool

Fortunately for bettors, determining the optimal strategy for Confidence Pools is a fairly straightforward task. As with any probabilistic endeavor, the goal for the bettor is to maximize his expected value. For Confidence Pools, this translates into betting in a fashion that incorporates each team's expected win odds with the value placed on that team. Using an objective metric such as Teamrankings.com's win odds, one can easily rank each team by win probability[12]. Once this list is completed, the bettor simply assigns the "16" value to the top spot, and proceeds down the list accordingly. This strategy yields the highest expected value for the bettor, as he is placing the most value on teams that *objectively* have the best chance of winning.

Table 1: Optimal Strategy for NFL Confidence Pool

Favorite	Underdog	Win Odds	Confidence Ranking	Expected Value
Houston Texans	Miami Dolphins	86.0%	16	13.76
Philadelphia Eagles	Cleveland Browns	78.8%	15	11.82
Chicago Bears	Indianapolis Colts	78.3%	14	10.962
Detroit Lions	St. Louis Rams	75.5%	13	9.815
New Orleans Saints	Washington Redskins	75.4%	12	9.048
Baltimore Ravens	Cincinnati Bengals	71.0%	11	7.81
Green Bay Packers	San Francisco 49ers	69.6%	10	6.96
New England Patriots	Tennessee Titans	65.6%	9	5.904
New York Giants	Dallas Cowboys	61.5%	8	4.92
Minnesota Vikings	Jacksonville Jaguars	60.4%	7	4.228
New York Jets	Buffalo Bills	57.3%	6	3.438
Carolina Panthers	Tampa Bay Buccaneers	56.3%	5	2.815
Denver Broncos	Pittsburgh Steelers	56.1%	4	2.244
Seattle Seahawks	Arizona Cardinals	53.1%	3	1.593
Atlanta Falcons	Kansas City Chiefs	51.9%	2	1.038
Oakland Raiders	San Diego Chargers	51.0%	1	0.51
Total Expected Value				**96.865**

While dissenters may argue this strategy fails to account for upsets (where the favorite loses to an underdog), the important factor is that this strategy maximizes *expected* value. Understandably, upsets will occur, yet over the course of the full 256-game season, one expects results consistent with the probabilistic predetermination.

3.4 Methodology

Therefore, for bettors to be considered rational, their picks must be consistent with the "optimal strategy," as any other deviation would devalue their bets and reduce the chance of success.

[12] It is also possible to root out implied win odds from the betting lines, but this is more complicated and problematic, as addressed later in this paper.

In order to analyze bettors' picks, I examined games from the 2012-2013 seasons. Unfortunately, due to the "new" nature of Confidence Pools, data was limited. However, because each week is represented by thousands of bettor picks, I felt confident in the reliability of the data. The first step of the analysis entailed applying an optimal pick number for each game. As mentioned above, this process called for simply ranking each game by win odds (as determined by Teamrankings.com), and assigning a score of 16 to the top team, 15 to the next highest, and so on.

For the next step, I found the actual average pick associated with each game by subtracting the amount of points placed on the home team from the amount of points placed on the away team, and then dividing by the total number of bettors. Fortunately, as seen in Table 2, this was a simple procedure, as the data were readily available and easily manipulated.

Table 2: Average Pick Calculations

Road Team	Home Team	Spread	Road Team Picks	Road Team Points	Home Team Picks	Home Team Points	Average Pick
DAL	**NYG**	-3.5	14	72	95	738	-6.11
BUF	**NYJ**	-2.5	42	220	67	358	-1.27
IND	**CHI**	-9.5	7	48	102	1304	-11.52
PHI	CLE	7.5	105	1306	4	10	11.89
WAS	**NOR**	-9.5	4	32	105	1362	-12.20
JAC	**MIN**	-3.5	32	115	77	433	-2.92
STL	**DET**	-8.5	1	14	108	1401	-12.72
ATL	KC	2.5	78	523	31	148	3.44
MIA	**HOU**	-10.5	1	12	108	1537	-13.99
NE	TEN	6.5	107	1238	2	17	11.20
SF	**GB**	-5.5	13	64	96	805	-6.80
CAR	TB	2.5	73	421	36	131	2.66
SEA	AZ	2.5	70	381	39	157	2.06
PIT	**DEN**	-0.5	42	194	67	294	-0.92
CIN	**BAL**	-6.5	8	40	101	964	-8.48
SD	**OAK**	1.5	38	207	71	278	-0.65

For the sake of consistency, a "negative" average pick indicates an average bet on the home team, while a "positive" average pick indicates an average bet for the road team. This is congruent with spread betting, which assigns a negative spread when the home team is favored, and a positive spread when the home team is the underdog.

After finding the average pick, the next step called for comparing the optimal pick (as determined by the optimal strategy) to the actual pick. Once again, the existence of deviations from the optimal pick indicates a level of irrationality on behalf of the bettor, and opens the door for possible market exploitation.

Table 3: Deviation from Optimal Strategy

Road Team	Home Team	Spread	Average Pick	Optimal Pick	Deviation
DAL	**NYG**	-3.5	-6.11	-8	-1.89
BUF	**NYJ**	-2.5	-1.27	-6	-4.73
IND	**CHI**	-9.5	-11.52	-14	-2.48
PHI	CLE	7.5	11.89	15	-3.11
WAS	**NOR**	-9.5	-12.20	-12	0.20
JAC	**MIN**	-3.5	-2.92	-7	-4.08
STL	**DET**	-8.5	-12.72	-13	-0.28
ATL	KC	2.5	3.44	2	1.44
MIA	**HOU**	-10.5	-13.99	-16	-2.01
NE	TEN	6.5	11.20	9	2.20
SF	**GB**	-5.5	-6.80	-10	-3.20
CAR	TB	2.5	2.66	5	-2.34
SEA	AZ	2.5	2.06	3	-0.94
PIT	**DEN**	-0.5	-0.92	-4	-3.08
CIN	**BAL**	-6.5	-8.48	-11	-2.52
SD	**OAK**	1.5	-0.65	-1	-0.35

Finding these deviations necessitated subtracting the optimal pick from the actual pick for each game analyzed. Consequently, a negative deviation indicates a team is undervalued by the "betting market," while a positive deviation indicates a team is overvalued by the "betting market."

Finally, after deriving these deviations, the concluding step entailed determining whether the resulting deviations were significant and point to any real market inefficiencies. Fundamentally, deviations alone do not definitely prove market inefficiencies. Because there is an element of randomness and variation, for example, when two teams have almost identical win odds, it is possible bettors are still economically rational, while simultaneously causing variations from the optimal strategy. Furthermore, because the data set comes from a league where participants are pitted against one another, there is an element of game theory and "outsmarting" the league. As a result, bettors may try to pick upsets to gain an advantage over other league participants. Naturally, this causes slight deviations from the optimal strategy. However, while every player in the league might choose a game or two to gamble and pick against the prevailing optimal strategy, it is highly unlikely that the *majority* of participants will take the underdog on the same game. Consequently, while deviations exist, *most* of the bettors are well-intentioned, betting in the seemingly rational matter.

Therefore, in order to test whether the resulting deviations were significant, I statistically tested the absolute values[13] of all found deviations. In order for a deviation to be considered "significant," it would have to lay several standard deviations away from the mean. A large presence of such deviations indicates a fundamental divergence by the betting market from optimal efficiency.

[13] The absolute value of the deviations was used because of the presence of both positive and negative deviations; for the purpose of significance, we are concerned with the size of the deviation and not the direction of the deviation relative to the optimal strategy.

3.5 Data Results

Statistically testing the data yielded a multitude of intriguing and useful results. Firstly, the deviations have a mean of 2.79 and a standard deviation of 2.00. The existence of a mean higher than 0 is expected, albeit higher than originally predicted, and consistent with the idea that bettors may purposefully stray from the optimal strategy to gain an advantage over other pool participants. Furthermore, the relatively small standard deviation of 2 suggests most of the data are tightly bunched around the mean. Because of the "whole number" nature of the league, where bettors can only designate whole numbers (1,2,3…) in their bets, a standard deviation of 2 represents a very small variance from the optimal strategy on the part of the bettor.

Table 4: Descriptive Statistics

Abs Deviation	
Mean	2.79
Standard Error	0.13
Median	2.49
Mode	2.12
Standard Deviation	2.00

On a season-wide scale, there are a significant amount of results that fall outside the standard deviation of the dataset. As indicated by the table below, this deviation is not restricted to one standard deviation from the mean, but, in some instances, varies greatly, thus attesting to some interesting characteristics.

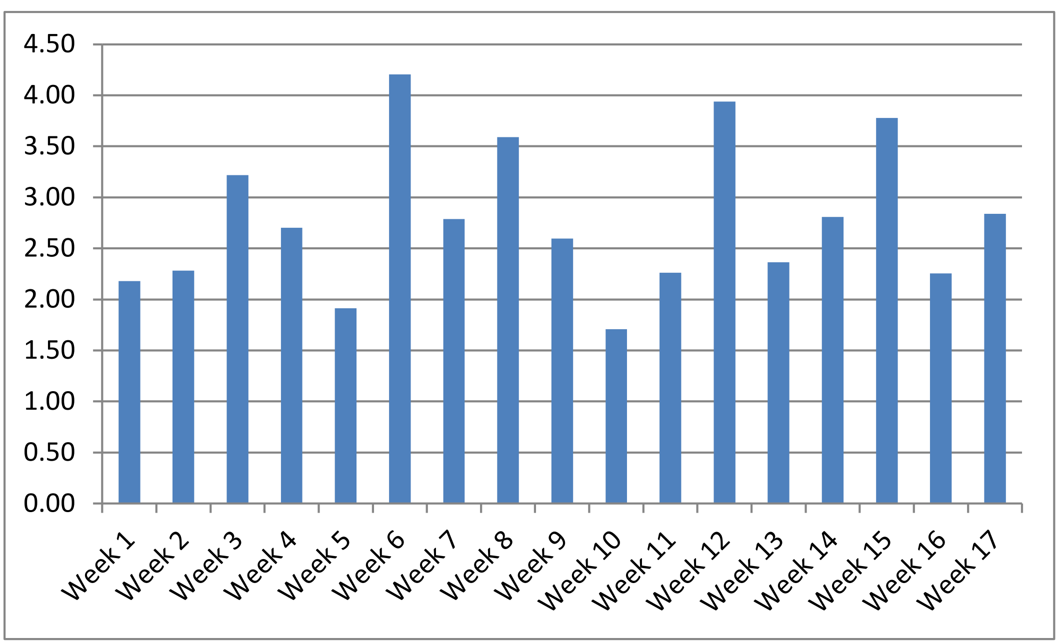
Table 5: Scale of Standard Deviations

Standard Deviation Levels	Number of Occurences	% of Total Dataset
>1 SD (4.79)	31	12.11%
>2 SD (6.80)	14	5.47%
>3 SD (8.80)	3	1.17%

Therefore, any result outside the standard deviation must be analyzed, as it indicates a possible, systematic deviation from the optimal, efficient strategy. The existence of many enigmatic deviations on a broad scale provides the first hint at bettor inefficiency.

Looking deeper, these deviations are not constant across season weeks, but seem to occur in bunches. For example, the majority of large deviations occur in the middle weeks of the season; if these deviations were truly random, one would expect a consistent pattern of deviations throughout the course of the season. Another curious anomaly can be seen from the graph below, which plots the deviations by week over the course of the season (title and label chart).

Figure 2: Average Weekly Deviations



It appears as if bettor deviations from the optimal strategy occur in bunches, as each peak in the deviations is surrounded by a build-up and subsequent contraction in bettor deviations. Once again, this is a significant result as it points to predictable bettor behavior. Rather than randomly, inappropriately valuing bets and teams, bettors act in a consistent matter; a spike in betting deviations can be predicted. Consequently, this presents major market inefficiency, as discussed above, randomness is an integral part of the efficient sports betting markets hypothesis. If, however, overall market behavior can be forecasted by an opportunistic bettor, as is the case based on this data, the bettor can adjust accordingly and gain the all-important edge. Especially when considering the fact that betting lines are set based on bettor action on both sides of a bet, comprehending when bettors are most volatile relative to the rational, optimal strategy allows for a clearer picture of the "true odds" associated with a spread.

Finally, looking at the deviations on a team-by-team basis reveals noteworthy disparity between the value, or, more precisely, the assessment of that value, that bettors place on individual teams. Table 6 below lists all the NFL teams, the total season deviations associated with each team, and the deviation per game for each team.

Table 6: Team by Team Deviations

Team	Total Deviation	Deviation Per Game	Team	Total Deviation	Deviation Per Game
PHI	58.75	3.67	TEN	44.92	2.81
NYJ	56.72	3.55	SF	44.83	2.80
STL	55.72	3.48	ATL	44.56	2.78
IND	55.31	3.46	KC	39.87	2.49
MIA	53.62	3.35	DEN	39.35	2.46
TB	51.62	3.23	DET	38.68	2.42
NYG	50.64	3.16	OAK	38.53	2.41
BUF	50.42	3.15	SEA	38.35	2.40
MIN	49.50	3.09	NOR	38.29	2.39
PIT	47.56	2.97	CHI	37.57	2.35
WAS	47.42	2.96	DAL	37.57	2.35
HOU	46.97	2.94	BAL	37.40	2.34
CIN	46.93	2.93	AZ	37.21	2.33
CLE	46.86	2.93	CAR	35.20	2.20
JAC	46.69	2.92	NE	34.85	2.18
SD	45.79	2.86	GB	30.31	1.89

As mentioned above, a level of deviation is expected due to imprecise bettor calculations and the inherent incentives of a "risky pick." However, as with the season distribution of deviations, one would expect the deviations to be consistent across teams. If sports were an efficient market, the exact risk and win odds of teams would be known, as all available information is captured in the spread. Therefore, the risk bettors are willing to take should be spread out across all teams, as deviating from the optimal strategy, and succeeding, is a result of a random process. However, as clearly evident by the above table, this is not the case. Why are bettors inaccurately assessing value for some teams, such as the Philadelphia Eagles and the New York Jets, on a greater scale than that of other teams? Once again, these results highlight glaring market inefficiencies. The large deviations associated with specific teams suggest market troubles with valuing those teams. Accordingly, the prudent bettor should easily pick out the ill-valued teams and take advantage at the expense of other bettors.

IV. What drives bettor behavior?

Of course, the presence of deviations alone does not attest to market inefficiency. Rather, they can merely point to illogical betting strategy. Therefore, in order to prove market inefficiency, these deviations need to fall in line with a consistent pattern or system. Most importantly, the inefficiencies must be predictable using current market information. In other words, if the aforementioned deviations conform to prevalent behavior biases, the deviations can be deemed more than just a fluke in the data, and thus relevant to the discussion of sports betting markets inefficiency. Suboptimal bettor strategy must be continual, rather than episodic.

No discussion of behavior biases and their impact on market inefficiencies would be complete without incorporating the seminal works of leading behavioral economists such as Daniel Kahneman and Amos Tversky. Consequently, the goal of this section is to frame the results from the Confidence Pool within the parameters and frameworks established by the behavioral economists. Doing so provides a level of support to the above findings, as well as adding a new component to sports betting markets. If the stock market is a suitable comparison for sports betting markets, it is only natural to explore the "behavioral finance" aspect of the sports market, to glean market inefficiencies from innate bettor biases.

4.1 Overconfidence: The ESPN Effect

Perhaps the most prevalent bias in sports betting is overconfidence. The idea of overconfidence is very simple: people overstate their abilities and skill. As Kahneman states, "Overconfidence arises because people are often blind to their own blindness[14]." Essentially, confidence is not necessarily tied to a reasoned evaluation of one "being right," but rather,

[14]Kahneman, Daniel. "Don't Blink! The Hazards of Confidence." *The New York Times*. The New York Times, 23 Oct. 2011. Web. 08 May 2013. <http://nytimes.com/2011/10/23/magazine/dont-blink-the-hazards-of-confidence.html?pagewanted=all>.

confidence stems from "the coherence of the story and by the ease with which it comes to mind, even when the evidence for the story is sparse and unreliable.[15]" An important point is that people *think* they are behaving rationally; they are oblivious to the fact that their positions and predictions do not always accurately reflect reality. In today's world, where a breadth of information is available for just about any topic, it is not hard to imagine the prevalence of overconfidence.

Kahneman further argues that investors tend to display particularly strong signs of overconfidence. Possibly because of the "swagger" involved in betting on the financial markets, investors overemphasize their own skill, while simultaneously rejecting the role of chance[16]. In a perfect example of this investor overconfidence, Barber and Odean (2000), in their paper "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," show that the more an investor traded, the worse he performed. For example, they found that the households that trade the most earned an annual return of 11.4%, compared to market returns of 17.9%. Barber and Odean postulated this disparity is caused by overconfidence; the more confident the investor, the more trades he made. Naturally, this overconfidence not only led to increased trades, but increased *questionable* bets, which obviously contributed to reduced returns[17].

Following a similar train of thought, sports fans, practically by definition, suffer from overconfidence. One only has to listen in to callers on the Mike Francesa Show or suffer through Skip Bayless's clownery on ESPN's First Take to comprehend the baseless confidence prevalent

[15] Ibid
[16] Malkiel, Burton G. "Behavioral Finance." *A Random Walk down Wall Street: The Time-tested Strategy for Successful Investing*. New York: W. W. Norton, 2011. 220-21. Print.
[17] Barber, Brad M., and Terrance Odean. "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors." *The Journal of Finance* 55.2 (2000): 773-806. Print.

throughout sports. It seems every sports fan is supremely confident that he "would be a better coach," or "can draft better than any current general manager."

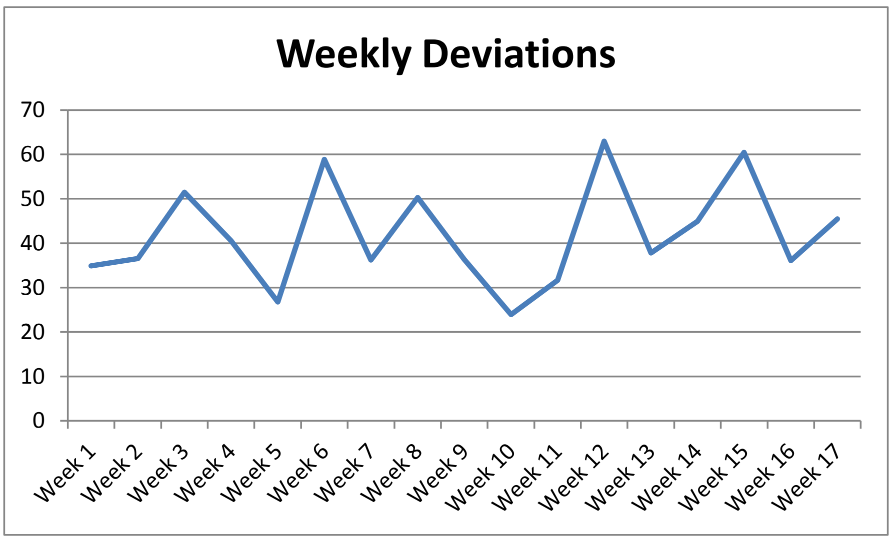
The root of this overconfidence is what I like to call, "The ESPN Effect." As highlighted in Part I, over the course of a typical week during the football season, the average fan is bombarded with constant football coverage. Given the popularity of pre-game coverage (i.e. NFL Countdown), post-game coverage, and constant daily coverage (SportsCenter, NFL Live), it is clear that fans are constantly exposed to highlights, analyst opinions, and player interviews over the course of the week. The effect of this all-encompassing coverage is that fans, after several hours of research and highlight-watching, feel confident they are amply prepared to discuss, analyze, and predict games. However, given the nature of today's 24-hour news cycle, the majority of "information" on ESPN is repetitive, hyperbolic coverage presented for the sake of attracting viewers. As such, instead of focusing on advanced statistics or relevant analysis, ESPN chooses to present a superficial analysis of games, ripe with the usual buffoonery talking heads and former players often bring. Consequently, despite their belief to the contrary, the marginal benefit of watching ESPN or reading online analysis is very small; the only impact it has is luring bettors into a false sense of confidence.

Simply put, unfortunately, fans experience baseless convictions regarding their sports knowledge; every sports fan thinks he is an expert. Similar to the study that found most students considered themselves above average drivers, an impossible result given the fact that not everyone in a population can be above average[18], sports fans overestimate their skill at "understanding sports" (after all, everyone watches ESPN also!) and deem themselves above average predictors of games and appraisers of talent.

[18] Malkiel, Burton G. "Behavioral Finance." *A Random Walk down Wall Street: The Time-tested Strategy for Successful Investing*. New York: W. W. Norton, 2011. 219. Print.

It is precisely this reason that accounts for the significant bettor deviations in the data. As stated above, each game carries an average deviation of 2.79 points. While, on an individual game basis, this deviation seems relatively small, it is imperative to underscore that this number represents the deviation *per game by the average bettor***.** When considering the fact that there are typically 16 games in a week, and 256 games in a season, the small per game deviation becomes a serious aberration optimal strategy. As seen in the tables below, each week contains substantial deviations, with an average deviation of 39.73 per week.

Figure 3: Total Weekly Deviations



Considering the maximum deviations possible per week in a Confidence Pool are 272 points, the prospect that a bettor would consciously deviate 39.73 points, or 14.61%, from the optimal strategy is laughable.

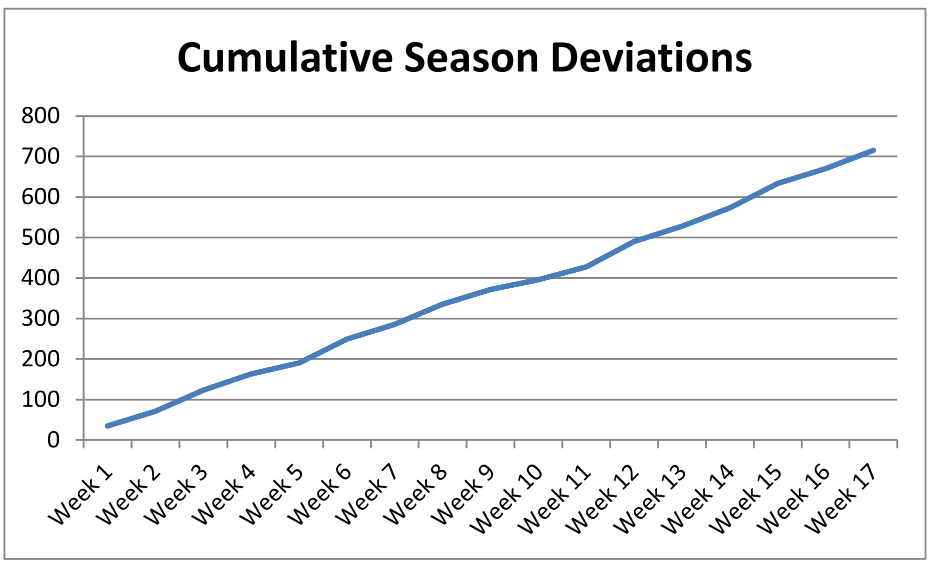
Figure 4: Maximum Weekly Deviations

Maximum Deviations

Optimal Pick	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
Actual Pick	-16	-15	-14	-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Deviation	-32	-30	-28	-26	-24	-22	-20	-18	-16	-14	-12	-10	-8	-6	-4	-2
Abs Deviation	32	30	28	26	24	22	20	18	16	14	12	10	8	6	4	2
Max Deviation	**272**															

Furthermore, for the overall season, the average bettor deviates from the optimal strategy by a whopping 715.11 points! Keep in mind, theoretically, to optimize potential gains, bettors should have zero total deviations. The fact that the average bettor deviates by 715.11 points is a mind blowing number, and indicates objectively foolish behavior by the overall betting market.

Figure 5: Cumulative Season Deviations



Cumulative deviations of this magnitude cannot simply be a reflection of bettor randomness, but is a classic case of bettor overconfidence. Rather than simply betting purely based on win odds, bettors try to outsmart the market, relying on their own expertise as opposed to the objectivity of a win odds percentage (which, if done correctly, already incorporates any knowledge a fan can hope to acquire). Buoyed by the extensiveness of sports analysis and information, fans place their faith in their abilities to process and apply this information. Similar to the conclusions drawn by Barber and Odean, the more risk bettors take on by choosing upsets, the worse they perform. Based on the data, bettors seem to be taking on too much risk, by unnecessarily overvaluing or undervaluing the prospects of various teams. The large scale of such risk-taking suggests frequent dubious picks, a reflection of bettors' overconfidence in their fandom and football expertise. As with the doomed, over active trader, bettors are confidently laying down risky bets; not only does this increase the amount of potential variations, but it also increases the magnitude of those variations, as bettor confidence pulls them increasingly further from the optimal strategy.

Despite bettor realization that using the spread may be the most efficient way of betting, bettors often think they can outsmart the market due to "superior" knowledge. Most sports fans overestimate their sports knowledge, and thus think they can outsmart and outthink the competition. As a result, bettors often pick inefficiently, in a risky attempt to gain a huge advantage by picking against the league's sentiment. This is akin to investors trying to outdo the S&P 500. Influenced by the tremendous success of a few investors (i.e. Warren Buffet), less skilled investors prefer to "trust their instincts," resulting in disastrous losses. This optimistic arrogance is what spurs inefficient betting and deviations from the optimal strategy.

4.2 Availability Heuristic: Winning Streaks, Losing Streaks, Upsets, and Blowouts

Another of Kahneman and Tversky's discoveries that has deep connections to bettor behavior is the existence of the availability heuristic. The availability heuristic is essentially "the process of judging frequency by the ease with which instances come to mind[19]." In other words, people will overestimate the probability of an event, based on how easily he can recall examples of that event occurring. For example, divorces among Hollywood celebrities and sex scandals among politicians are disproportionately covered in the media when compared to how frequently these events occur (a search for "Anthony Weiner scandal" brought over 8.5 million results). Consequently, the average person is likely to exaggerate how often celebrity divorces and sex scandals actually occur[20].

Similarly, sports offer the perfect test case for the availability heuristic. A major component of the aforementioned ESPN Effect is that all sports games do not receive equal coverage in sports media. Rather, games with the most potential for accompanying analysis and fan viewership are overplayed and overemphasized. No one needs a half hour segment on how the mighty New England Patriots dismantled the Kansas City Chiefs; however, if the opposite occurred, the game would transform from minimal and inconsequential to a monumental upset, a game of the year candidate. Because most sports games are mundane affairs, especially over the course of a long season, fans and bettors crave the unbelievable, the events that break the potential banal cycle of sports. Consequently, these games stick out in fans' minds, and affect the way bettors behave in subsequent weeks.

Streaks: One of the most discussed topics over the course of a season is the concept of "streaks," the amount of consecutive wins or losses a team can string together. One has to look no further than the coverage the Miami Heat received this past season while they endeavored to break the Los Angeles Lakers' record of 33 wins in a row to understand the impact streaks have

[19] Kahneman, Daniel. "The Science of Availability." *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux, 2011. 129. Print.
[20] Ibid

on the sports fans' psyche. Sports professionals, media, and fans are obsessed with the ideas of streaks, as they mistakenly believe winning games in a row is indicative of team greatness. What they fail to realize is that games are largely independent from each other. Yes, good teams have a higher chance of winning several games in a row, but that is simply a function of the team commanding high win odds, not because of some mythical power bestowed upon a team during a "hot streak." For example, if one were to flip, a hundred times, a weighted coin with a 65% chance of being heads, he would not be surprised by a long streak of heads. However, would that increase the chance of the 101st flip landing on heads? No, the chances would remain at 65%.

However, because of the availability biases, streaks stick out more in bettors' minds, and thus bettors overestimate (or underestimate) the chances of a team on a winning (or losing) streak. Furthermore, this can result in two, distinct results. Either bettors can view teams as "due" for a win after a long losing streak, or bettors can devalue a team's prospects due to their unfortunate losing streak. This is evident by measuring the total deviations associated with "streaking" teams. For the purpose of this exercise, I defined a streak as winning or losing at least four games, as that constitutes a streak that occurs often enough to <u>output relevant data</u>, (not clear to me) while concurrently being a "newsworthy" event. Furthermore, I eliminated games that demanded a value-rating of 14-16, as the one-sided nature of those games leaves little room for deviation, and thus not relevant for measuring fan behavior. Doing so yielded an average deviation of 3.03, higher than that average deviation of 2.65 for all non-streak games. While minimal, the larger deviation with respect to streaking teams speaks to the impact streaks have on bettor behavior. As opposed to objectively and independently assessing teams, bettors hone in on recent results, thereby affecting their behavior and opening the door for predictable be (????)

Upsets and Surprises: As with streaks, upsets and exciting games receive a disproportionate amount of press coverage. Because of the unexpected nature of such events, sports networks and analysts devote substantial time to breaking down the games, showing highlights, and interviewing players and coaches. Consequently, fans and bettors are over-exposed to coverage of the unanticipated stellar play of a downtrodden team and the demise of a powerhouse. As a result, bettors place too much emphasis on these games, significantly altering their perception and evaluation of teams away from the objective assessment. Naturally, these result in bettors often overvaluing a team after an upset win, and undervaluing a team after a surprising loss.

To measure this phenomenon, I looked at the two different metrics:1) the 10 biggest upsets in the 2012 season according to the line[21] and by APR[22] (an advanced algorithm designed to rank teams) and 2) the "Top 10 NFL Games of the 2012 Season,[23]" a list composed by factoring pacing, rivalry of teams, comebacks, momentum shifts, etc..

As seen from the table below, big upsets have some impact on bettor behavior. Overall, the losing team tends to be slightly undervalued, with a deviation of -0.70, while the winning team is slightly overvalued, with a deviation of 1.24. Although the sample size is small, a possible reason why losing teams are not tremendously undervalued stems from fan realization of the "fluky" nature of an upset loss. It is entirely possible, within the realm of a bettor's thought process that a good team can occasionally lose to a bad team. However, a poor team overcoming the talents of a stronger team causes bettors to reevaluate their original assessment of the poor team, resulting in perceptible overvaluation in following weeks.

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[21] "NFL Wrapup APR's Biggest Upsets of 2012." *FSPI*. N.p., 11 Jan. 2013. Web. <http://fspi.blogspot.com/2013/01/nfl-wrapup-aprs-biggest-upsets-of-2012.html>
[22] Ibid
[23] "Top 10 NFL Games of 2012 Season." *THUUZ Sports*. N.p., 16 Jan. 2013. Web. 08 May 2013. <http://blog.thuuz.com/2013/01/16/top-10-nfl-games-of-2012-season/>.

Table 7: Deviations for 2012 Top Upsets

Week	Game	Line	Next Week	Losing Team	Winning Team	Losing Team Abs Deviation	Winning Team Abs Deviation
	Top Spread Upsets						
5	Packers 27, **Colts 30**	Packers -7	6	5.24	6.39	5.24	6.39
17	Texans 16, **Colts 28**	Texans -7	N/A	N/A	N/A	N/A	N/A
14	**Chargers 34**, Steelers 24	Steelers -7	15	-2.13	-3.84	2.13	3.84
13	49ers 13, **Rams 16**	49ers -7	14	-2.62	5.72	2.62	5.72
3	49ers 13, **Vikings 24**	49ers -7.5	4	-0.87	3.10	0.87	3.10
14	**Eagles 23**, Buccaneers 21	Buccaneers -7.5	15	2.15	6.98	2.15	6.98
3	**Chiefs 27**, Saints 24	Saints -8.5	4	4.47	1.53	4.47	1.53
16	**Vikings 23**, Texans 6	Texans -9	17	-7.46	-0.64	7.46	0.64
13	**Steelers 13**, Ravens 10	Ravens -9	14	1.19	-3.11	1.19	3.11
1	**Redskins 40**, Saints 32	Saints -9.5	2	-0.70	-3.10	0.70	3.10
2	**Cardinals 20**, Patriots 18	Patriots -14	3	2.24	3.29	2.24	3.29
Average				**0.15**	**1.63**	**2.91**	**3.77**
	Top APR Upsets						
13	Panthers 21, **Chiefs 27**	Panthers -5.5	14	-1.42	4.52	1.42	4.52
1	Seahawks 16, **Cardinals 20**	Seahawks -3	2	1.01	0.35	1.01	0.35
4	Giants 17, **Eagles 19**	Eagles -2	5	-0.46	3.23	0.46	3.23
8	Seahawks 24, **Lions 28**	Lions -3	9	-4.11	-3.98	4.11	3.98
2	Ravens 23, **Eagles 24**	Eagles -2	3	-2.24	-3.29	2.24	3.29
12	Seahawks 21, **Dolphins 24**	Seahawks -3	13	-2.83	1.16	2.83	1.16
3	Steelers 31, **Raiders 34**	Steelers -3.5	4	Bye	2.78	Bye	2.78
Average				**-1.67**	**0.68**	**2.01**	**2.76**
Cumaltive Average				**-0.53**	**1.24**	**2.57**	**3.35**

Additionally, looking at the "best NFL games" and the subsequent week evaluation of those teams yields fascinating results. On average, bettors deviate from the optimal strategy by 3.27 points when evaluating teams that previously participated in a great game. Naturally, exciting games command the most media attention, and are thus highly situated in bettor consciousness. As we have seen before, the impact of the ESPN Effect is pitiable valuations of teams. Furthermore, it is interesting to note how the *quality of the game* affects bettor valuations. For example, in the Rams vs. 49ers game in Week 10 that resulted in a rare NFL tie, each team had multiple chances to win the game, yet could not capitalize. Because of the rarity of an NFL tie, this game was highly discussed, thereby exposing the flaws of each team. As a result, we see severe undervaluing of both teams (-5.29 and -4.31) the following week. On the flip side, the Buccaneers vs. Giants game in Week 2 was lauded for exceptional play by both teams. Star quarterback Eli Manning threw for a mind-boggling 510 yards, and 4 touchdowns were scored in the final 6:48 of play. Consequently, media coverage focused on the great play of both teams and commended the "toughness" of both sides. The result? A bump in bettor valuation the following week for the Bucs and Giants, with a respective 4.42 and 3.87 deviation. Finally, we see the impact of a "good try," a severe underdog that put up a formidable fight only to fall short. For the Jets in Week 7 (11 point underdogs to the Patriots) and the Jaguars in Week 11 (15.5 point underdogs to the Texans), staying in the game and almost pulling off a huge upset were huge accomplishments. As with the upset games, this closeness and excitement factor of these games attracted widespread highlights and analysis. Unsurprisingly, bettors processed this information and incorrectly applied the results to their team valuations, resulting in a monumental 5.59 and 7.85 point deviations for the Jets and Jaguars, respectively.

Table 8: Deviations for 2012's Most Exciting Games

Week	Game	Line	Next Week	Losing Team	Winning Team	Losing Team Abs Deviation	Winning Team Abs Deviation
6	Cowboys 29, **Ravens 31**	Ravens -3	7	-2.01	4.60	2.01	4.60
16	**Saints 34,** Cowboys 31	Cowboys -2.5	17	-1.95	-2.19	1.95	2.19
2	Buccaneers 34, **Giants 41**	Giants -7.5	3	4.42	3.87	4.42	3.87
13	**Seattle 23,** Bears 17	Bears -3	14	-2.36	-2.22	2.36	2.22
7	Jets 26, **Patriots 29**	Patriots -11	8	5.59	-3.93	5.59	3.93
3	Lions 41, **Titans 44**	Lions -4	4	-3.10	1.74	3.10	1.74
10	**Rams 24, 49ers 24**	49ers -13.5	11	-4.31	-5.29	4.31	5.29
12	**Texans 34,** Lions 31	Texans -3.5	13	-6.81	1.06	6.81	1.06
4	Panthers 28**, Falcons 30**	Falcons -7	5	0.07	-1.07	0.07	1.07
11	Jaguars 37**, Texans 43**	Texans -15.5	12	7.85	-0.89	7.85	0.89
Average				**-0.26**	**-0.43**	**3.85**	**2.69**

Hometown Bias: The last major effect of the availability heuristic that I analyzed is the impact of hometown bias. Hometown bias is the tendency for fans of a certain team to overvalue that team, due to factors such as unbridled optimism, misplaced hope, or simply being unable to "pick against a team." Fortunately, a significant portion of my data comes from a pool centered on the New York metropolitan area. As a result, the deviations surrounding the New York Jets and New York Giants provide a perfect test case for the influence of hometown fans.

Not surprisingly, Jets and Giants games beget serious deviations, with the Jets averaging 3.55 deviations per game and the Giants averaging 3.16 deviations per game. However, contrary to my expectations, these deviations were not consistently positive; bettors were not exclusively overvaluing the Jets and Giants. For example, in Week 6, the Jets were undervalued by an exorbitant 6.385 points; where was the hometown bias in this game?

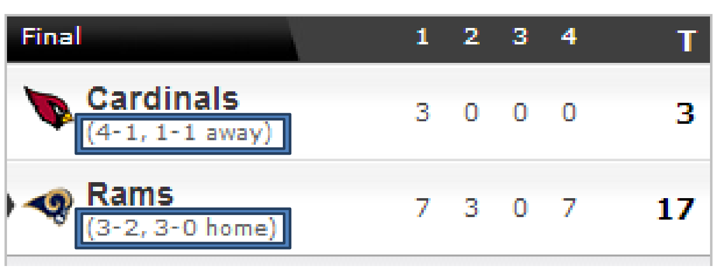
Rather, the effect of a home team is not attributable to the illogical fusion of fan and bettor, but a factor of the availability heuristic. On a universal scale, the ESPN Effect draws national attention to high-profile games, bombarding bettors with highlights and coverage, thereby leading to poor valuations. On the local scale, however, *every Jets and Giants game* is treated with the same attention as an unpredictable upset. In addition to national media outlets, local fans tune in to the Yes Network, SNY, the Fan, and various other local stations to get their sports fix. Over the course of a week, there is only a limited amount of valid concerns and productive topics to discuss; coverage eventually goes "over the line," nitpicking and over-analyzing mundane game details. Therefore, the bettor is treated to a full display of bluster and meaningless discussion, an experience that results in the bettor losing sight of the true value and prospects of the home team. Losses are treated as the "end of the world," while mundane, mid-season wins all but guarantee a Super Bowl appearance. In short, bettors become fans, losing sight of the real winning percentages of their team, and falling victim to short-term memory, clear evidence of the availability heuristic.

4.3 Anchoring: Team Records

Finally, to understand bettor behavior I analyzed my results in line with the cognitive bias known as anchoring. Anchoring occurs when people put too much emphasis on a first piece of information or impression when making decisions. Although why and how people anchor is disputed,[24] there is sufficient evidence that people are significantly impacted by the initial "anchor." Failure to shake the anchor results in poor estimates of values and probabilities, as people fail to adjust accordingly[25]. While Kahneman elucidates the fascinating result that "anchors that are obviously random can be just as effective as potentially informative anchors[26]," it stands to reason that when initially given a useful piece of information, as opposed to random and unrelated information, it is *harder* for people to resist the effects of anchoring. This is consistent with the "anchoring as adjustment" theory advocated by Tversky. People, when given relevant information, start with that information and adjust by "mentally moving from the anchor[24]." This adjustment often falls short, as people become uncertain about the level of appropriate adjustments.

Expanding on this definition, I define anchoring in the sports betting markets as relating specifically to team record. On any bet, the first information bettors see is team record, a piece of information that gravely affects bettors' perception of a team.

Figure 6: Sample NFL Matchup



[24] Kahneman, Daniel. "Anchors." *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux, 2011. 120. Print.
[25] "Judgment Under Uncertainty: Heuristics and Biases," Tversky and Kahneman
[26] Kahneman, Daniel. "Anchors." *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux, 2011. 125. Print.

Understandably, a 10-0 team looks like a more attractive bet than a 5-5 team. However, many bettors fail to realize the chance factor of a record. Is a team that wins every game by one point better than a team whose wins come by a sizable margin but whose losses come by a single point? Team records provide a reference point for fans to compare teams; however, often that record is an inaccurate assessment of team talent. Bettor inability to properly adjust from this record anchor results in overvaluing and undervaluing teams purely based on team record.

In order to measure the anchoring effect of records, I looked for a way to objectively measure disparity between a team's record and how "good" they actually are. To do this, I applied footballoutsiders.com's DVOA rating, a metric that measures the Defense-adjusted Valued Over Average for each team by calculating a team's success based on the down and distance of each play, and converting that into a percentage detailing how much greater or worse a team is compared to the league average[27]. Because there is no scientific method for comparison, I employed a simple "eye test," noting where a team's objective ranking disagreed with its record, and then measuring the deviations for that game. For the purpose of my measurements, I started with Week 6, because I felt that was ample time for teams to build meaningful records (most fans realize a 2-1 start does not destine a team for greatness; a 5-0 start might). While there are a multitude of individual games that satisfy the anchoring effects of team records, two teams, in particular, provide ample evidence to its effect: the Indianapolis Colts and the Denver Broncos.

After letting go of their franchise player, Peyton Manning, the Colts looked to rebound by drafting the top quarterback in the draft, Andrew Luck. Much to the surprise of many, the young star brought the Colts to a respectable 2-2 start, equaling their win total from the entire previous

[27] Schatz, Aaron. "Methods." *Football Outsiders Everything*. N.p., n.d. Web. 08 May 2013. <http://www.footballoutsiders.com/info/methods>.

season. Yet, that was only the start, as the Colts went on a tear, finishing the season at 11-5 and earning an unlikely playoff berth; Luck established himself as a formidable and "clutch player." However, the Colts' impressive record belied their actual skill; they benefited from playing weak opponents and squeaking out close victories.

Table 9: Indianapolis Colts Season Deviations

	Record	Deviations	Total DVOA	League Rank
Week 6	2-2	6.39	-11.50%	18
Week 7	2-3	0.40	-22.20%	29
Week 8	3-3	5.11	-20.70%	28
Week 9	4-3	3.86	-25.70%	29
Week 10	5-3	2.08	-22.50%	27
Week 11	6-3	4.16	-20.70%	27
Week 12	6-4	-1.92	-26.00%	28
Week 13	7-4	6.81	-22.00%	28
Week 14	8-4	2.74	-19.60%	28
Week 15	9-4	5.21	-20.10%	28
Week 16	9-5	0.39	-21.00%	28
Week 17	10-5	7.46	-20.80%	28
Average		**3.56**	**-21.07%**	**27.17**

As can be seen from the table above, the Colts consistently ranked at the bottom of the league in Total DVOA. However, despite this fact, the Colts were vastly overvalued, with an average overvaluation of 3.56 points a week. Once again, in normal circumstances, the average *direction* of bettors' valuation should be zero. Although deviations will occur on an individual basis, the expectation is teams should be appropriately undervalued and overvalued. The fact the Colts have such a strong positive directional deviation indicates some forces at play, namely bettor overreliance on team record in their team valuation. While some of this deviation can be explained by the availability heuristic outlined above (every Colts loss is met with marginal overvaluation or undervaluation), it seems the record itself contributes to bettor calculations, especially in the latter part of the season as the Colts made a run for the playoffs.

Table 10: Denver Broncos Season Deviations

	Record	Deviations	Total DVOA	League Rank
Week 6	2-3	-3.34	22.30%	9
Week 7	BYE	BYE	BYE	BYE
Week 8	3-3	-5.29	30.70%	5
Week 9	4-3	-3.88	36.70%	1
Week 10	5-3	-1.32	33.00%	3
Week 11	6-3	-1.82	39.80%	1
Week 12	7-3	-1.86	38.40%	3
Week 13	8-3	-6.94	35.00%	3
Week 14	9-3	-0.69	37.00%	2
Week 15	10-3	-1.39	35.50%	3
Week 16	11-3	-2.27	37.20%	3
Week 17	12-3	-1.84	35.30%	2
Average		**-2.79**	**34.63%**	**3.18**

On the flip side, the Denver Broncos entered the 2012 season with a lot of question marks. While they poached Peyton Manning from the Colts, Manning had undergone several neck surgeries and missed the previous season; the Broncos were unsure what to expect. Initially, the Broncos seemed to underperform, posting a poor 2-3 start. While they later went off on a tremendous 13-game win streak, their early struggles clearly leaked into bettor evaluation, as the Broncos posted an overall negative 2.79 deviation, indicating severe undervaluation. Specifically in the early weeks of the study, when the Broncos had a pedestrian record yet top-notch objective stats, the Broncos were severely undervalued. Interestingly, despite their long streak and strong record, the Broncos were still undervalued at the end of the season. Although this may conflict slightly with the team-record anchoring, I feel it reflects an overall "season" anchor, whereby fans have trouble adjusting from their initial perception of teams. Because of the Broncos' slow start, many fans and bettors were down on their prospects; this initial thought served as the basis for future team valuation. Consequently, as the Broncos were streaking, both in record and

DVOA, bettors were unable to adjust completely from their original observations, resulting in an overall season undervaluation.

V. How does bettor behavior create opportunities in the betting markets?

Up until now, the primary focus of this paper has been to show that bettors and betting markets are not always rational and efficient. While these results are clearly useful for participants in a Confidence Pool, how can one armed with this information achieve long-term success in the betting markets?

The solution to this conundrum lies in the inherent nature of the betting markets. To recap, the betting spreads are designed to have equal action on both sides, fundamentally setting lines that give each bettor a 50% chance of winning the bet. However, that is predicated on the assumption that fans would necessarily recognize value discrepancy and over bet the undervalued team. Yet, what if, on average, bettors were unable to ascertain the true value of a team? In this case, the lines would still be set to obtain equal action on both sides, but there would no longer be a 50% chance for all bettors to win the bet.

To make this clear, let us look at the example of the Ravens and Jaguars I brought up earlier. Let's assume the bookmakers established the Ravens as a 14 point favorite, based on the fact that they have an 80% chance of winning the game outright. With such a high win odds, it is likely the Ravens will crush the Jaguars, thus justifying the high point spread. However, if for some reason, bettors mistakenly valued the Ravens at 55% win odds, bettors would view the 14 spread with incredulity, and bet on the Jaguars. Consequently, bookmakers would lower the spread on the game, in order to incentivize fans to bet on the Ravens, thereby achieving equal action on both sides. Therefore, while the true spread for the Ravens may be 14 points (meaning there is a 50% chance they will win by 14 points), the actual spread will be less than that, resulting in a tremendous opportunity for the aware bettor to pick the undervalued Ravens.

It is this exact scenario that causes bettor behavior to play such a crucial role in the betting markets. Unlike the stock market, where individual irrational behavior can be clouded out by mostly rational institutional investors, there are situations where the betting market *as a whole* is irrational. Capitalizing on bettor biases towards streaks, upset wins, and records creates a consistent, substantial advantage for the prudent bettor.

5.1 Methodology

In order to take advantage of bettor bias, I had to devise a strategy to extrapolate the impact these biases had on the betting markets. To do so, I analyzed a form of betting known as "straight bets with a money-line," or simply the "money-line." Similar to spread-betting, money-line entails picking the game winner between two teams. However, bettors must choose the *outright* winner of the game, without the benefit of a point-spread; to compensate for talent disparity between teams, each team is assigned a money-line. The favorite is assigned a minus number, indicating the bettor has to lay that amount to win $100, while the underdog is assigned a positive number, indicating the bettor would win that amount for every $100 wagered[28]. For example, in Week 1 of the 2012 NFL season, the Houston Texans had a money-line of -900, while their opponent, the lowly Miami Dolphins, had a money-line of 650. This means that a bettor must lay $900 on the Texans to win $100, while, on the flip side, a bettor must lay $100 on the Dolphins to win $650.

[28] "Sports Betting. About Betting on Sports in Las Vegas by VegasInsider.com."*VegasInsider.com*. N.p., n.d. Web. 08 May 2013. <http://www.vegasinsider.com/sports-betting/>.

The major benefit of looking at this betting system is that it is possible to derive implied winning odds from the money-line, to get a concrete win percentage assigned to a particular money-line number. To do so, I used the same conversion method suggested by E. Strumbelj and M. Robnik Sikonja[29], namely conversion of the money-line from fractional form into decimal form, and then from decimal form to a percentage, all the while eradicating the bookmaker "rake" on the game. Using the above example of the Texans and Dolphins:

Moneyline: ——

Decimal Conversion: —— = .111, —— = 6.5

Percentage Conversion: —— = 90%, —— = 13.3%

Normalized Percentage: —— = 87.1%, —— = 12.9%

As you can see, added together the percentages total over 100%. This extra amount accounts for the rake, the amount taken by bookmakers as a spread. To adjust for this, I simply normalized the percentage. Therefore, the implied win odds for the Texans and Dolphins are 87.1% and 12.9%, respectively. Once I calculated the implied win odds for each team in every game of the 2012 NFL season, I compared those findings to the objective win odds calculated by Teamrankings.com, in order to determine the effect of bettor biases, and develop a strategy accordingly.

[29] Kuper, Alexander. "Market Efficiency: Is the NFL Betting Market Efficient?" Thesis. University of California Berkeley, 2012. Web.

5.2 Data Results

Overconfidence: The first trend I looked for in the data was the overall average difference between the implied win odds garnered from the money-line and the adjusted win odds presented by Teamrankings.com. Based on the prevalent, pervasive overconfidence in sports betting I felt it was highly likely the absolute value of the difference would be greater than zero. The constant risk-taking by bettors was all but guaranteed to affect the betting lines, thereby moving the lines from their inherent true value. Sure enough, the data revealed a positive difference of 1.26%, indicating the money-line overvalued the favorites by 1.26%.

Table 11: Average Difference Between Implied Win Odds and Objective Win Odds

Week	Average Difference
Week 1	1.88%
Week 2	1.10%
Week 3	1.41%
Week 4	1.34%
Week 5	1.48%
Week 6	1.07%
Week 7	1.83%
Week 8	0.36%
Week 9	0.48%
Week 10	0.79%
Week 11	1.60%
Week 12	0.84%
Week 13	1.33%
Week 14	1.11%
Week 15	1.58%
Week 16	1.59%
Week 17	1.71%
Average	**1.26%**

Given this information, when in doubt, the suggested bet is to bet on the underdog, as the underdogs are undervalued by an average of 1.26%. Consequently, this translates into a higher payoff for correctly picking the underdog than mandated by true odds. Granted the underdog has a smaller chance of winning, but over the long term, the difference in true odds and implied odds, combined with the high payouts for an underdog win, will outweigh the losses. Although not an earth shatteringly high number, it is important to note that the 1.26% gives the bettor an edge *over the long term*; losses may pile up in the short run, but given enough time (if the trend holds), the bettor will eventually recoup his losses and turn a profit. Although the sample size is small, pegging the difference in odds to bettor overconfidence lends some support to the continuation of the trend, and allows for a measure of predictability. Remember, beating the sports market requires beating 0% return. The existence and knowledge of a constant edge of 1.26% is an obvious market inefficiency, one in which the opportunistic bettor should take advantage.

Availability Heuristic: Using the same parameters for streaks mentioned above (4+ streak), I tested the inefficiencies associated with the availability heuristic. Looking at the 37 instances of a winning streak longer than 4 games, I found a positive difference of .75% between the money-line odds and Teamranking.com's adjusted winning odds. While this number was lower than expected, its positive directions imply, at the very least, a marginal impact of winning streaks on bettor psyche. Naturally, the obvious strategy is to bet against streaking teams, to capture the small winning odds incongruity. On the other hand, a study of the 37 instances of a losing streak longer than 4 games yielded a negative difference of -1.49%, demonstrating universal bettor undervaluation of "down on their luck" teams. Bettor focus on recent games, and the fallacious application of recent results to overall team win chances, drastically shifted the betting market.

As a result, teams on losing streaks present more value than the appropriate level, given the innate risk of picking the team.

Table 12: Win Odds Difference for Longest Streaks in 2012 Season

New England Patriots

Week	Streak	Difference
Week 12	W4	-0.92%
Week 13	W5	1.39%
Week 14	W6	-2.08%
Week 15	W7	0.97%
Average		**-0.16%**

Atlanta Falcons

Week	Streak	Difference
Week 5	W4	2.70%
Week 6	W5	3.65%
Week 8	W6	4.29%
Week 9	W7	2.79%
Week 10	W8	0.35%
Average		**2.76%**

Denver Broncos

Week	Streak	Difference
Week 11	W4	2.19%
Week 12	W5	3.20%
Week 13	W6	-2.64%
Week 14	W7	2.90%
Week 15	W8	-2.62%
Week 16	W9	1.20%
Week 17	W10	1.34%
Average		**0.80%**

Philadelphia Eagles

Week	Streak	Difference
Week 10	L4	-2.40%
Week 11	L5	-5.89%
Week 12	L6	0.10%
Week 13	L7	-3.60%
Week 14	L8	-0.51%
Average		**-2.46%**

Kansas City Chiefs

Week	Streak	Difference
Week 9	L4	-1.84%
Week 10	L5	-1.70%
Week 11	L6	-1.50%
Week 12	L7	-3.20%
Week 13	L8	-4.20%
Average		**-2.49%**

Jacksonville Jaguars

Week	Streak	Difference
Week 9	L4	-1.59%
Week 10	L5	-4.67%
Week 11	L6	-4.18%
Week 12	L7	1.60%
Average		**-2.21%**

Arizona Cardinals

Week	Streak	Difference
Week 9	L4	0.55%
Week 11	L5	-1.04%
Week 12	L6	-3.15%
Week 13	L7	-1.40%
Week 14	L8	-1.63%
Week 15	L9	-2.23%
Average		**-1.48%**

Detroit Lions

Week	Streak	Difference
Week 14	L4	-1.27%
Week 15	L5	-2.23%
Week 16	L6	-2.19%
Week 17	L7	0.97%
Average		**-1.18%**

Furthermore, the tables above break down the longest streaks of the NFL season, all totaling at least 7 games. Apart from the Patriots, every team represented was either overvalued or undervalued in a perfectly consistent manner, as bettors flocked to winning teams while shunning the losing teams. Naturally, this predictable bettor behavior represents a remarkable inefficiency, as bettors overestimate the risk associated with losing teams. Once again, the optimal, and ultimately profitable, strategy is to bet the opposite direction of a streaking team. The longer a streak, the more chance of off-target valuation; streaks are prime betting opportunities and, if exploited correctly, can help bettors tackle market inefficiencies.

Anchoring: According to my previously outlined connection between team record and improper valuation, teams with better records than actual performance should be vastly overvalued, thereby presenting an opportunity to exploit. To test this theory, I looked at the Houston Texans and Atlanta Falcons, teams which boasted the top 2 records in the NFL, yet languished outside the top 10 in DVOA for most of the season[30]. Not surprisingly, I found that the Texans and Falcons were overvalued respectively at 1.53% and 2.15%, opening the door for bettors willing to bet against these overrated teams. Looking further, over Weeks 9-17, a period when the Texans were winning games yet slipping in the DVOA rankings, the Texans were overvalued by 2.27%. Furthermore, over Weeks 1-9, a time when the Falcons rocketed to a 9-0 start, the Falcons were overvalued by a whopping 3.05%, despite ranking 9th in DVOA rankings. These results show, at least on some level, that the effects of record anchoring are real. Armed with this information, the optimal strategy for bettors is to value games independent of team records. Doing so eliminates the record anchor, thus removing the impact of a false signal. Furthermore, the bettor, understanding the inherent inefficiencies of the betting market, should look for discrepancies between team record and actual performance. Doing so provides the bettor with an attractive betting opportunity, one that, over the long term, should pay dividends and help systematically beat the market.

[30]I also looked at the Colts and Broncos, the two examples of anchoring brought up above. While the Colts were slightly overvalued and the Broncos undervalued, I felt the Texans and Falcons were better examples of betting opportunity.

Table 13: Anchoring Effects for Houston Texans and Atlanta Falcons

Houston

Week	Difference
Week 1	1.10%
Week 2	-1.39%
Week 3	0.07%
Week 4	1.20%
Week 5	2.44%
Week 6	0.89%
Week 7	-0.33%
Week 8	BYE
Week 9	2.33%
Week 10	1.63%
Week 11	4.18%
Week 12	5.27%
Week 13	1.21%
Week 14	2.08%
Week 15	1.90%
Week 16	0.29%
Week 17	1.53%
Average Season	**1.53%**
Average Weeks 9-17	**2.27%**

Atlanta

Week	Difference
Week 1	3.36%
Week 2	3.13%
Week 3	1.50%
Week 4	2.98%
Week 5	2.70%
Week 6	3.65%
Week 7	BYE
Week 8	4.29%
Week 9	2.79%
Week 10	0.35%
Week 11	1.04%
Week 12	0.65%
Week 13	2.79%
Week 14	2.67%
Week 15	0.08%
Week 16	2.19%
Week 17	0.28%
Average Season	**2.15%**
Average Weeks 1-9	**3.05%**

VI. Further Research

Looking towards future research, I think it is tenable that the same behavioral biases that exist in NFL betting can be found in order sports, thereby indicating widespread inefficiency in the sports betting markets. In order to prove this belief, I will first test the sporting events that most closely resemble that of the NFL, in terms of its popularity and widespread coverage. The goal is to recreate a situation as similar to the NFL, to test the impact of behavioral effects on bettor strategy. As such, NCAA March Madness and the FIFA World Cup are perfect candidates for future testing of my theory. If the same biases exist in NFL betting as in March Madness and World Cup betting, namely overconfidence, availability heuristic, and anchoring, these events would open the door for significant betting opportunities, and further proof of inefficient sports betting markets.

VII. Conclusion

Based on my above analysis and findings, it is clear that bettor behavior has a direct impact on the sports betting markets. Bettors, due to their flawed decision making and unfortunate subconscious biases, are not economically rational; their betting strategy widely deviates from the optimal strategy, one that maximizes expected value. Consequently, the prudent bettor, one who calmly awaits the proper opportunities, can take advantage of these bettor biases and consistently gain an edge over the sports betting market.

Although the percentage return per game of such a strategy is small, it is imperative to consider that many of these fan biases are not mutually exclusive. For example, the presence of a streak does not preclude the prime opportunity of a poor team with a good record. Rather, the bettor must actively search for these biases in each game of every week, to aggregate to inherent betting opportunities built into the market. Doing so will enable the bettor to break the currently inevitable cycle of elation and dismay that is so rampant in the sports betting sphere. As such, these inefficiencies in the sports betting market affords the bettor a weighted coin, one that over the long run will produce positive returns for the bettor and help him beat the market.

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Appendix

Appendix 1: NFL Confidence Pool Format

				Thursday, October 04
Arizona (5-11) -1.5	**ST. LOUIS (7-8-1) +1.5**	3-17	W	8 Pts
				Sunday, October 07
Cleveland (5-11) +9.5	**NY GIANTS (9-7) -9.5**	27-41	W	14 Pts
Atlanta (14-4) -2.5	**WASHINGTON (10-7) +2.5**	24-17	L	9 Pts
Philadelphia (4-12) +3.5	**PITTSBURGH (8-8) -3.5**	14-16	W	11 Pts
Green Bay (12-6) -6.5	INDIANAPOLIS (11-6) +6.5	27-30	L	10 Pts
Baltimore (13-6) -4.5	KANSAS CITY (2-14) +4.5	9-6	W	4 Pts
Miami (7-9) +4.5	CINCINNATI (10-7) -4.5	17-13	W	6 Pts
Seattle (12-6) +2.5	CAROLINA (7-9) -2.5	16-12	W	7 Pts
Chicago (10-6) -5.5	JACKSONVILLE (2-14) +5.5	41-3	W	5 Pts
Tennessee (6-10) +5.5	**MINNESOTA (10-7) -5.5**	7-30	W	3 Pts
Buffalo (6-10) +9.5	**SAN FRANCISCO (13-4-1) -9.5**	3-45	W	16 Pts
Denver (13-4) +6.5	**NEW ENGLAND (13-5) -6.5**	21-31	W	13 Pts
San Diego (7-9) +3.5	**NEW ORLEANS (7-9) -3.5**	24-31	W	12 Pts
				Monday, October 08
Houston (13-5) -7.5	NY JETS (6-10) +7.5	23-17	W	15 Pts
Tiebreaker Game: Houston at NY Jets (40.5) Your Prediction: 35				
				Win-Loss: 12-2, Points: 114

Appendix 2: Sample Data Set

GB,2	BAL,4	MIN,8	NE,15	KC,1	NYG,6	CIN,10	HOU,16	NOR,9	OAK,12	DAL,7	WAS,13	PIT,5	SD,14	SF,11	DEN,3	45
GB,3	BAL,6	MIN,2	NE,16	KC,1	NYG,14	CIN,12	HOU,15	NOR,11	OAK,5	DAL,13	WAS,10	PIT,4	SD,9	SF,8	ATL,7	55
GB,15	PHI,14	IND,6	NE,16	BUF,13	NYG,8	CLE,5	HOU,4	NOR,3	OAK,7	DAL,12	WAS,11	NYJ,10	SD,2	SF,9	DEN,1	53
GB,11	BAL,12	MIN,2	NE,16	KC,4	NYG,14	CIN,5	HOU,15	NOR,3	OAK,1	DAL,6	WAS,7	PIT,13	SD,9	SF,10	DEN,8	51
CHI,5	BAL,8	IND,1	NE,16	BUF,6	NYG,13	CIN,14	HOU,15	NOR,11	OAK,12	DAL,9	STL,2	PIT,4	SD,10	SF,3	DEN,7	51
GB,5	PHI,2	MIN,4	NE,13	KC,6	NYG,7	CIN,9	HOU,16	NOR,10	OAK,12	DAL,15	WAS,14	PIT,3	SD,8	SF,1	ATL,11	59
GB,5	BAL,1	MIN,4	NE,16	BUF,2	NYG,13	CIN,10	HOU,15	NOR,6	OAK,9	DAL,12	WAS,7	PIT,3	SD,11	SF,14	ATL,8	55
GB,6	BAL,4	MIN,5	NE,16	BUF,7	NYG,15	CLE,3	HOU,14	NOR,9	OAK,13	SEA,2	WAS,8	NYJ,1	SD,10	SF,12	ATL,11	53
CHI,5	BAL,3	IND,4	NE,16	KC,14	NYG,6	CIN,13	HOU,15	NOR,9	OAK,12	SEA,2	WAS,7	PIT,8	SD,11	SF,10	ATL,1	55
GB,8	BAL,6	MIN,3	NE,16	KC,2	NYG,15	CIN,9	HOU,12	NOR,14	OAK,4	DAL,13	WAS,10	PIT,11	SD,5	SF,7	ATL,1	49
GB,4	BAL,3	MIN,5	NE,16	BUF,2	NYG,9	CIN,15	HOU,14	NOR,7	OAK,6	DAL,10	WAS,8	PIT,11	SD,13	SF,12	ATL,1	50
GB,5	BAL,8	MIN,11	NE,16	KC,3	NYG,9	CIN,13	HOU,15	NOR,7	OAK,2	DAL,4	WAS,14	PIT,12	SD,6	SF,10	DEN,1	50
GB,8	BAL,5	IND,1	NE,16	KC,3	NYG,11	CIN,7	HOU,14	NOR,9	OAK,4	DAL,10	WAS,13	NYJ,2	SD,12	SF,15	DEN,6	52
CHI,2	BAL,12	MIN,3	NE,16	KC,6	NYG,10	CIN,15	HOU,14	NOR,9	OAK,13	DAL,7	WAS,1	PIT,5	SD,8	SF,11	ATL,4	53
CHI,13	BAL,4	MIN,7	NE,16	BUF,2	NYG,15	CIN,14	HOU,12	NOR,3	OAK,1	DAL,8	WAS,9	PIT,11	SD,5	SF,10	DEN,6	45
GB,6	BAL,14	MIN,5	NE,16	BUF,1	NYG,7	CIN,13	HOU,15	NOR,8	MIA,2	DAL,11	WAS,10	PIT,4	SD,9	SF,12	ATL,3	55
GB,8	BAL,7	IND,11	NE,16	BUF,4	NYG,14	CIN,6	HOU,15	CAR,5	MIA,9	DAL,12	STL,10	NYJ,13	TEN,1	SF,2	ATL,3	45
CHI,1	BAL,5	MIN,10	NE,16	KC,4	NYG,11	CIN,14	HOU,15	NOR,8	OAK,6	DAL,12	WAS,7	NYJ,3	SD,13	SF,9	ATL,2	45
GB,7	BAL,12	MIN,5	NE,16	KC,3	NYG,6	CIN,11	HOU,15	NOR,10	OAK,4	DAL,9	WAS,14	PIT,8	SD,1	SF,13	DEN,2	48
CHI,8	BAL,5	IND,2	NE,16	BUF,4	NYG,11	CIN,10	HOU,15	NOR,13	OAK,12	DAL,9	WAS,7	NYJ,3	SD,6	SF,14	DEN,1	60
GB,9	BAL,12	MIN,13	NE,16	BUF,6	NYG,5	CIN,14	HOU,15	NOR,7	OAK,11	DAL,10	STL,3	NYJ,4	SD,2	SF,8	DEN,1	42
GB,7	PHI,8	IND,3	NE,15	BUF,6	NYG,11	CIN,10	JAC,9	NOR,13	OAK,4	DAL,5	WAS,12	NYJ,1	SD,14	SF,16	ATL,2	45
GB,3	BAL,4	MIN,9	NE,16	KC,7	NYG,12	CLE,2	HOU,15	NOR,8	OAK,14	DAL,10	WAS,11	PIT,6	SD,13	SF,1	DEN,5	55
CHI,6	BAL,10	IND,3	NE,16	BUF,2	NYG,11	CIN,12	HOU,13	NOR,9	OAK,5	DAL,7	WAS,4	PIT,15	SD,8	SF,1	DEN,14	50
GB,4	BAL,15	MIN,11	NE,16	BUF,3	NYG,13	CLE,5	JAC,8	NOR,14	OAK,6	DAL,10	STL,7	NYJ,2	TEN,1	SF,12	DEN,9	44
18	73	64	0	41	1	7	107	86	87	95	77	22	4	5	38	
67	470	316	0	170	3	29	1424	661	580	805	559	92	6	34	204	
91	36	45	109	68	108	102	2	23	22	14	32	87	105	104	71	
705	167	168	1706	369	1304	1223	17	83	84	43	134	805	1101	1093	402	

Appendix 3: Sample Implied Win Odds vs. Objective Win Odds Comparison

Team	Opponent	Adj Win Odds	Favorite	Underdog	Dec. Conversion Fav	Dec. Conversion Dog	% Fav	% Dog	Implied Win %		Difference
Houston	vs. Miami	86.00%	-900.00	650.00	0.11	6.5	0.9	0.133333	87.10%		1.10%
Philadelphia	at Cleveland	78.80%	-450.00	350.00	0.22	3.5	0.818182	0.222222	78.64%		-0.16%
Chicago	vs. Indianapolis	78.30%	-500.00	400.00	0.20	4	0.833333	0.2	80.65%		2.35%
Detroit	vs. St Louis	75.50%	-375.00	315.00	0.27	3.15	0.789474	0.240964	76.62%		1.12%
New Orleans	vs. Washington	75.40%	-400.00	320.00	0.25	3.2	0.8	0.238095	77.06%		1.66%
Baltimore	vs. Cincinnati	71.00%	-350.00	290.00	0.29	2.9	0.777778	0.25641	75.21%		4.21%
Green Bay	vs. San Francisco	69.60%	-270.00	230.00	0.37	2.3	0.72973	0.30303	70.66%		1.06%
New England	at Tennessee	65.60%	-240.00	200.00	0.42	2	0.705882	0.333333	67.92%		2.32%
NY Giants	vs. Dallas	61.50%	-200.00	170.00	0.50	1.7	0.666667	0.37037	64.29%		2.79%
Minnesota	vs. Jacksonville	60.40%	-200.00	170.00	0.50	1.7	0.666667	0.37037	64.29%		3.89%
NY Jets	vs. Buffalo	57.30%	-150.00	130.00	0.67	1.3	0.6	0.434783	57.98%		0.68%
Carolina	at Tampa Bay	56.30%	-160.00	140.00	0.63	1.4	0.615385	0.416667	59.63%		3.33%
Denver	vs. Pittsburgh	56.10%	-125.00	105.00	0.80	1.05	0.555556	0.487805	53.25%		-2.85%
Seattle	at Arizona	53.10%	-145.00	125.00	0.69	1.25	0.591837	0.444444	57.11%		4.01%
Atlanta	at Kansas City	51.90%	-135.00	115.00	0.74	1.15	0.574468	0.465116	55.26%		3.36%
Oakland	vs. San Diego	51.00%	-115.00	-105.00	0.87	1.05	0.534884	0.487805	52.30%		1.30%