A STUDY OF BEHAVIORAL BIASES PRESENT IN SPORTS BETTING MARKETS

Warari Jordan Kipkorir - 077762

Submitted in partial fulfillment of the requirements for the Degree of Bachelor of Business Science – Financial Economics at Strathmore University

[*Strathmore Institute of Mathematical Sciences*]

Strathmore University

Nairobi, Kenya

[January, 2017]

DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Proposal contains no material previously published or written by another person except where due reference is made in the Research Proposal itself.

..… … … … … .... [*Name of Candidate*]

… … … … … .... [*Signature*]

… … … … … .... [*Date*]

This Research Proposal has been submitted for examination with my approval as the Supervisor.

..… … … … … .... [*Name of Supervisor*]

… … … … … .... [*Signature*]

… … … … … .... [*Date*]

School of Finance and Applied Economics

Strathmore University

ABSTRACT

This study seeks to establish the behavioral biases exhibited by individuals who participate in sports betting. The biases are manifested by how the individuals (bettors) analyze data pertaining the gamble in order to place their bet on the team that they think will win. The study was carried out using a questionnaire which was distributed to bettors which contained a variety of scenarios that were created to capture the behavioral biases. The data is then analyzed using a logit model. The study finds that the three most common biases exhibited by bettors are Representative bias, Anchoring bias and Favorite/Longshot Bias. In terms of gender, it was also established that the Favorite/Longshot Bias was exhibited more frequently amongst males than females, due to the different perception of risk between males and females.

ACKNOWLEDGEMENTS

I would like to acknowledge my supervisor whose guidance and insight was immense and greatly aided in the writing and completion of this proposal; my family which gave me endless encouragement and most importantly, The Almighty Father who granted me good health and wisdom to accomplish writing this proposal.

Table of Contents

~~Table of Figures~~List of Tables

1 Introduction

1.1 Background to the study

Sports betting, or gambling[1] as it is commonly referred to, has been an activity that whose origin can be traced as far back as the Roman Empire in the 1st Century. Contests that have winners and losers often attract wagers from the spectators who would place bets on the outcome of these competitions, in favour of their preferred competitor. According to (Palmer, 2013) sports betting can be defined as "placing a financial wager on the outcome of a sporting match, as well as on events that occur within the larger match or fixture."

Betting today has grown exponentially due to the proliferation of internet and mobile communication devices. Book makers have embraced these new technologies to increase the span and coverage around the globe, as well as incorporate different types of sports played all around the world

Formation of betting expectations too has changed over time. The biggest driver of sports betting was the complexity of human behavior. (Ates, 2004). Today's betting market takes the form of simple financial markets whereby decisions are made under risk after assessing all available information. The true value of the gamble in this case manifests itself at the end of the game, unlike financial markets whereby securities are continuously traded (Hansen, 2006).

1.2 The Betting Process

In very simple definition, betting involves prediction of the outcome of a game (i.e. win for the home team, a draw or a loss).

The possible outcomes are expressed in terms of odds. An *odd* is the return in monetary terms offered for each unit bet. The person who offers the odds is called the bookmaker. Odds are expressed in two ways:

American Odds: These are expressed in terms of fractions. E.g. an American odd of 9/10 will means that $9 out of every $10 placed in the bet will be earned, in the event that the prediction is correct. American odds state the profit alone.

---

[1] Sports betting is a subset of gambling that implies knowledge of the sport by the gambler, according to (Ates, 2004). We shall thus refer to the action as 'Sports Betting'

European Odds: These take the form of decimals and include the capital. Using the same example above, the European Odd equivalent would be stated as 1.9, which is simply 1+ (9/10). European odds state the total income, which is obtained by multiplying the amount placed in the bet by the odd. European odds will always be > 1 hence creating an illusion to the bettor (Ates, 2004). Only European odds are used in Kenya and will therefore be used from hereafter.

Odds set by bookmakers hold the single-price[2] principle, meaning that bookmakers set the same odds for the same games. This principle's usage has been greater especially with the spread of internet usage by both companies and players. Several betting companies nowadays have similar odds for the same games, thus eliminating arbitrage possibilities by bettors who hold several accounts within those companies. Furthermore, all Kenyan betting companies are registered under & regulated by the Betting Control and Licensing Board, which is tasked with reviewing all odds before they are commissioned to the public, in order to ensure fair play.

The rationale of the assumption of no arbitrage is further strengthened by the self-correcting mechanism of betting markets. Once an opportunity arises, bettors would opt for that opportunity which leads to bookmakers correcting the pricing, causing the opportunity to disappear in a short period of time (Jansa, 2012).

Odds are set in two main ways by bookmakers; *point-spreads*[3] which focus on the difference in points of the two teams playing, and *single odds* which are set based on the probability of a team winning the game at hand. Under single odds, bookmakers gain profit by setting a fixed amount of the payout share as their profit and the rest is shared out, in the event of a correct prediction by the bettor. For instance, two teams, A & B are playing, and the probability of team A winning the game is 50%, probability of a draw is 15% and the

[2] Similar to the Law of One Price in Arbitrage Pricing Theory, whereby assets with the same payoff have the same price.
[3] Common in American sports and not used in Kenya and most parts around the world. Thus we will not focus on it.

probability of team B winning is 35%. The bookmaker's profit margin is set at 9% of payouts. Thus the odds[4] are set as follows:

Odd for team A = Payout Share / Probability of team A winning

$$= 91\% / 60\%$$

$$= 1.52$$

Odd for draw = Payout Share / Probability of draw

$$= 91\% / 15\%$$

$$= 6.07$$

Odd for team B = Payout Share / Probability of team B winning

$$= 91\% / 35\%$$

$$= 2.6$$

From here, bettors are now able to predict the outcome of the game and stand to win or lose the money they bet, depending on the accuracy of their bet.

1.2.1 Types of bets

The types of bets that bettors use in their betting strategies include:

Single bets where the bettor places a bet in a single game's outcome. The payoff is the sum of money placed by a single bet multiplied by the odd of the predicted outcome.

Multibet strategy where the bettor places several bets on different game with a single input of money. The payoff is the product of all the odds of the outcomes and the money placed on the bets. This strategy has the highest payoff but one single wrong prediction could cause an entire loss for the gambler.

[4] The odds are by default European odds.

1.3 Motivation of the Study

There is generally very little research conducted on sports betting markets around the world, and even far less from a behavioral finance point of view. This is despite the size and growth rate of such markets, as well as the participation by millions of people around the world and the large sums of money spent by people. For instance, the local betting market is valued at over Ksh5 Billion and is still forecasted to grow further[5]. This begs the need for financial research within markets with such high monetary value.

1.4 Problem Statement

The development of well organized sports betting markets has led to the rise of sports betting around the world (Palmer, 2013). This has been attributed to the rise of technology platforms such as the internet and communication devices, as well as a shift in sports betting from horse-track betting to sports. The widespread use of the internet, according to Jansa (2012), has led to further decline in state intervention and more liberty by bettors. Gambling is a high risk venture that has the potential to earn the gambler very high returns. Ideally, the gambler predicts the outcome of a game and stand to win or lose the money they placed on a bet depending on their prediction. Incentives for betting include placing multiple bets of which the wins are calculated by multiplying all the odds of the games by the amount bet. Additionally, correct prediction of a certain number of games (usually >10) will earn the bettor a much larger sum (in this case, referred to as a Jackpot[6]).

However, prediction of outcomes is not based solely on chance. Gamblers themselves are irrational beings who differ in their reaction to information as well as having heterogeneous beliefs on the outcomes of games, which may be driven by biases. There is no known research conducted in Africa, more so in Kenya of such nature. Thus the need arises to address this gap, and open it up for further research to be conducted.

[5] A report presented by PwC on December 2015 forecasted that growth in gambling revenue in Kenya will rise to $21.5 million (Sh2.2 Billion), up from $20.1 million in 2014. Source: https://www.pwc.co.za/en/assets/pdf/gambling-outlook-2015-2019.pdf

[6] Jackpots take the form of a pari-mutuel defined by Thaler & Ziemba (1988) as a lottery where all bets are pooled together and the winners share out the pool, less transaction costs.

Thus, this paper aims at unravelling the different behavioral motives of gamblers to make their choices, as well as strategies undertaken in order to maximize their gains/ minimize their losses.

1.5 Research Objectives

1.) To investigate the behavioral sentiments and biases that influence decision making amongst bettors.

1.5.1 Research Questions

1.) What behavioral characteristics does a bettor exhibit when placing a bet?

2.) What behavioral patterns are exhibited by each gender of the betting population?

1.6 Justification

This study serves as an in-depth analysis of the participants in the sports betting market in Kenya. The betting market in Kenya is very large, with several bookmakers already present within the market. This research will pave the way for other tests of financial theories not only within the Kenyan context, but also within several other countries within Africa. This research is also beneficial to bookmakers who aim to study the market, psychologists who are interested in studying behavior of bettors as well as bettors themselves who seek to find behavioral biases that may influence strategies.

2 Literature Review

In this section we shall look at traditional finance theories as a build up to more recent behavioral finance theories. Finally, I shall highlight any relevant past literature that deals with my field of interest and outline the gap which I seek to address.

2.1 Traditional Finance Theories

Traditional finance theories were built on the assumption that investors were rational and aimed at building an efficient portfolio that earned the highest amount of returns with the lowest possible level of risk. (Birău, 2012)

Below we shall look at the theories that are considered the pillars of finance theory.

2.1.1 The Utility Function and Expected Utility Hypothesis

The Utility Function dates back to the 1700s when Daniel Bernoulli formulated it to explain relationship between the expected payout from a coin toss (gamble) and the wealth of the individual (Daza, 2004). The theory also refers to the diminishing marginal utility of money. It is however important to note that the diminishing marginal utility of money exhibits the decision maker's risk aversion. An individual is risk averse if they prefer a payout with certainty to one with likelihood to earn a higher return with uncertainty. We shall address this later on.

The Expected Utility Hypothesis as presented by of John Von Neumann and Oskar Morgenstern in their 1944 book, "The Theory of Games and Economic Behavior" built on the Utility Function in explaining rational decision making in times of uncertainty. The theory works around certain axioms that help the investors choose the option that maximizes their expected utility. The axioms are listed below.

i.) Completeness: The completeness axiom implies that there is enough information about the lotteries at hand i.e. L_1 and L_2 such that the individual is able to make an informed choice between the two, or be indifferent to choosing either.

ii.) Continuity. If there is a monetary value x which is greater than y, and y is greater than z, there exists a level where the individual is indifferent between receiving y

with certainty and a gamble with payoffs of $x + z$ with a probability of *(p)* & *(1-p)* respectively i.e.

$$P.u(x) + (1-p).u(z) = u(y)$$

iii.) Independence: If the individual is indifferent to gambles x and y, then they should be indifferent to two gambles that offer x and z in the first game and y and z in the second game, for any value of z and probability value p i.e.

$$G(x, y; P) \approx G(y, z; P)$$

iv.) Unequal Ranking: If x is preferred to y, and there exists two lotteries L_1 and L_2 that contain both payouts, then lottery L_1 will be preferred to L_2 if the probability p of gaining x in L_1 is greater than the probability q of gaining x in L_2.

An important assumption in Expected Utility Hypothesis, as stated above, is risk aversion.

2.1.2 Efficient Market Hypothesis

The Efficient Market Hypothesis has been the backbone of Finance for over thirty years. According to Fama (1970)'s work, an efficient market is that which prices always "fully reflect" all available information within the market. The implication of this theory is that profiting from any new information is very unlikely because of the speed at which it is absorbed into the prices in the market, due to competition within it. Consequently, a lot of time is wasted trying to detect mispricing of securities.

Despite securities prices being rationally based on information available, not all new information will have the same effect on prices. This causes the random walk behavior observed to be prevalent in security prices. The different kinds of information available and its impact gives rise to three different types of market efficiency:

i.) Weak Form Efficiency: This form of efficiency is whereby prices only reflect all historical information regarding the securities up to the given date. Thus, an investor cannot "beat the market" through analysis of past information alone

ii.) Semi-Strong Form Efficiency: This form of efficiency suggests that prices reflect all historic as well as publicly available information. Publicly available information includes financial statements, earnings and announced dividend payouts, expansion plans and expectations with regards to macroeconomic factors. The information may not necessarily be that of a financial nature. (Clarke, Jandik, & Mandelker, 2001). This implies that an investor cannot beat the market by using publicly available information.

iii.) Strong Form Efficiency: The last of the three form of efficiency dictates that prices of securities reflect historical information, all publicly available information as well as insider information regarding the market. This form of efficiency is the strictest of the three and prohibits any profits from any new or insider information not yet released to the public, as it will be already reflected in the prices.

2.1.3 The Efficiency Frontier

Markowitz (1952) used the Efficient Market Hypothesis to develop the mean-variance model which used means as a measure of expected returns and standard deviations as a measure of risk in order to create an optimal portfolio for investors. The combination of all risky assets was plotted on a risk- return diagram to create the Efficient Frontier, from which investors could choose the portfolio which suited their needs most. It was evident that investors preferred a higher average return with the lowest possible risk. The idea of the efficient frontier was to minimize risk and increase returns along it through diversification.

2.2 Emergence of Behavioral finance

"Behavioral Finance is the study of how psychology affects finance" (Shefrin, 2002)

Much of traditional finance was built on simplistic assumptions about the investor and the market. This severely undermined the explanatory power with regards to investor behavior and market trends.

In as much as traditional finance theories played a key role in formulation of pricing mechanisms within the market, they fell short in explaining persistent anomalies. The implication that these theories had that any market imperfections would be corrected over time did not hold. Shiller (2003) Points out that these anomalies, which were represented by the excess volatility witnessed in the 1980s was a deeper situation with regards to Efficient Market theories, rather than other anomalies such as the January effect.

Behavioral finance tries to explain this phenomenon by integrating human psychological behavior and sociology into decision making, in order to explain anomalies within financial markets[7]. (Birău, 2012). For instance, the Expected Utility Theory assumed that investors are intrinsically risk-averse and would thus opt for less risky investments that would have the greatest outcome on their final wealth. This assumption was also carried by Markowitz (1952) when building the efficiency frontier whereby investors were averse to the risk contained within their portfolio.

2.2.1 Prospect Theory

In their Prospect Theory paper, Kahneman & Tversky (1979) reject prior assumptions about investor rationality presented by the Expected Utility Hypothesis after studying decision making for gambles under different conditions, rather than as strictly functions of their probabilities of outcomes. Some of the revelations that they made were that

i.) Investors were risk-seeking in a domain of losses as they would rather pick a gamble with a probabilistic outcome for loss rather than certain outcome (*The Reflection Effect*)

ii.) In evaluation of alternatives, investors often disregard the attributes that the alternatives share, instead focusing on their differences (*Isolation effect).* This leads to inconsistent preferences amongst investors. This is further proven by different representation of probabilities.

They then brought about an alternative to EUH, which they called 'Prospect Theory'. Prospect Theory distinguishes two steps in the choice process. The first step, *editing*, involves a preliminary analysis of the offered prospects. The second phase, *evaluation*, is where the choice with the highest prospect is picked. The major steps of the editing phase include:

---

[7] Ritter (2003) does however clarify that not all cases of mispricing are as a result of psychological biases. Instead, they come as a result of temporary demand and supply imbalance.

- *Coding*- Perception of outcomes as gains and losses, rather than the final state of wealth. These gains and losses are expressed relative to a reference point. Location of the reference point and consequent coding of outcomes as gains or losses can be affected by the formulation of the offered prospects and expectations of the decision maker.
- *Combination*- Prospects can be simplified by combining those probabilities with similar outcomes.
- *Segregation*– Prospects with a riskless outcome are segregated from the risky component in the editing phase
- *Cancellation* – Components shared by offered prospects are discarded (isolation effect).

Two other components include *simplification* (rounding probabilities/outcomes & eliminating extremely unlikely outcomes) and *detection of dominance* (scanning offered prospects to detect dominated alternatives & rejecting them).

Another important feature presented in the theory is that decision weights do not coincide with the probabilities of outcomes. This leads to anomalies in preference.

In conclusion, Prospect theory brought forward the proposition that investors were instead loss avers, rather than risk averse, as earlier assumed. The implication therefore was that investment losses must be compensated for by the expected returns.[8]

Prospect Theory laid the foundation for research into behavioral patterns & biases that could result in anomalies within the market, paving way for Behavioral Finance as an academic field.

According to Barberis & Thaler (2003) there are two building blocks of behavioral finance:

- Limits to arbitrage: This argues that it is difficult to undo the disparities caused by less rational traders. In other words, it refers to predicting in what circumstances arbitrage forces will be effective, and when they will not be. (Ritter, 2003)

[8] Obtained from (Credit Suisse AG, 2015).

- Psychology (Behavioral biases): This catalogues the deviations from full rationality observed.

Behavioral biases, also known as cognitive biases, is one of the two building blocks of behavioral finance, and the focus of the study. The behavioral patterns are listed below:

- *Heuristics* which is driven by trial-and-error, leads people to develop some rule of thumb by which they base their decision making on. The decisions may be subject to bias as they are solely based on experiences.
- *Overconfidence*[9] in one's own abilities causes people to be biased in decision making. For example, a person investing a lot of money in the stock of a company they works for.
- *Representativeness* is whereby one uses past information to base their decision-making (stereo-typing). The best example of this bias the law of small numbers[10]. This may seem like a safe bet, but it is also subject to biases such as base-rate neglect[11] and sample-size neglect[12].
- *Anchoring Bias* is whereby the most recent event is given the biggest weighting when making a decision. It may take the form of an initial value from which adjustments are made, despite the value being a random number.
- *Mental Accounting* is whereby a person may separate decisions when in real sense they should be combined e.g. investors separating paper losses from actual losses leads to investors being too slow in disposing of loss-bearing stocks.
- *Confirmation Bias* is whereby one seeks selective information that supports their own beliefs.
- *Availability Bias* is whereby information that is readily available will be considered whereas scarce information will not.

---

[9] May arise as a result of two things: self-attribution bias (the tendency to ascribe any success to one's own talents and failure to bad luck, rather than ineptitude) and hindsight bias (the tendency to believe that after an occurrence of an event, the person predicted it and thus uses this belief to predict future outcomes) (Barberis & Thaler, 2003)

[10] A sequence of events generated by a random process will represent the essential characteristics of that process, even when the sequence is short. Also known as the Gambler's fallacy (Ates, 2004)

[11] Neglect of the initial value

[12] Neglect of the size of the sample from which an inference is derived.

- *Conservatism* is the reluctance to change with regards to new information, placing a lot of emphasis on the base value[13].
- *Framing* is all about how a concept is presented to a person. The way a problem is presented can alter a person's choice. For example, focusing on the potential gains instead of the losses. (Four out of 10 wins is the same as 6 out of 10 losses)
- *Disposition Effect* is the bias whereby investors seek to cash in on paper gains but avoid cashing in on paper losses. The investor would rather hold on to the loss making stock until it realizes a gain, which is highly improbable.
- *Favorite/ long-shot bias* is whereby one places a bet on the most unlikely win because it will result in the highest returns, forgetting that it is both unlikely to win and also the team's loss will lead to loss of the money placed on the bet. (Thaler & Ziemba, 1988)
- *Home Bias* is the tendency to bet on home teams or invest in home-based companies.

Behavioral Finance is aptly summarized by Mitroi & Oproiu (2014) as follows

> "Behavioral finance does not eliminate but complements the standard evaluation approaches - fundamental, technical and markets analysis… Behavioral analysis considers the elements of human perception and evaluation of outside situation and events, and most importantly, the emotions associated, both ex ante and ex post with any financial decision. "

2.3 Empirical Research

Hetherington (2006) acknowledges that the explosion of internet based betting exchanges and information markets has given a valuable platform for market research to be conducted. He further states that in this environment, gambling behaviour can be studied due to the nature of such markets whereby the fundamental value is always revealed at the end of each contract (game), unlike financial markets whereby the prices are estimates of the fundamental value. Past research undertaken in this field can be divided into two parts: First,

[13] Conservatism differs from representativeness through the representation power of the data. "At first sight, the evidence of conservatism appears at odds with representativeness. However, there may be a natural way in which they fit together. It appears that if a data sample is representative of an underlying model, then people overweigh the data. However, if the data is not representative of any salient model, people react too little to the data and rely too much on their priors." (Barberis & Thaler, 2003)

there is research that deals with studying the characteristics of betting/prediction markets and secondly, there is research to do with the individual behavioral biases in such markets.

2.3.1 Research on Sports Betting Markets

The main focus of this research was to do with the organization of sports betting markets and tests of EMH theory on the markets. Thaler & Ziemba (1988) first proposed that it is more effective to test betting markets for efficiency, rather than financial markets due to its defining characteristic of quick, repeated feedback. This paved the way for subsequent research to be conducted.

Levitt (2004) investigates why gambling markets are organized differently from financial markets despite the similarities. He begins by outlining the similarities of both. First, investors with heterogeneous beliefs and information seek to profit through trading as uncertainty is resolved over time; sports betting is a zero sum game just like financial derivatives with each party on either side of the transaction; and large amounts of money are at stake in both markets. However, the major difference is that bookmakers in gambling markets do not play the traditional role of matching buyers and sellers, but instead take large positions with respect to the outcome of the game. They therefore dictate the prices of gambles in such markets. In light of this, the author concludes that bookmakers are much better at predicting outcomes than the bettors themselves, hence yielding greater profits than if the played the role of traditional market-maker. This incentive for profits leads to bookmakers hiring talented individuals to set the odds, who continuously do better in the prediction of outcomes than the larger betting markets.

In Wolfers & Zitzewitz (2004) study of prediction markets[14], they outlined that such markets are continuously double-auction, where buyers (bettors) submit bid prices and sellers (bookmakers) submit asking prices with the mechanism executing a trade whenever the two sides of the market reach a mutually agreeable. They also propose that the main feature that a prediction market should exhibit to work well is that “contracts must be clear, easily understood and easily adjudicated.” The presence of arbitrage opportunities in such markets is also investigated, with two possible strategies outlined. First, prices of similar contracts

[14] Prediction markets in this case are not only limited to sports betting markets, but also prediction of significant events.

can be arbitraged across different exchanges and secondly, arbitrageurs can identify and exploit deviations from rationality. The authors suggest it is impossible for the first arbitrage strategy to occur, hence give more emphasis on the second one. However, Marshall (2005) finds that significant profits can be made using this strategy, known as “sports betting arbitrage”. It involves betting on different outcomes on different sites, and the riskless profit will be the difference in the gains of the two outcomes.

Goddard & Asimakopoulos (2004) test the efficiency of sports betting markets by forecasting English league football results over a period of 10 years using an ordered probit regression. Specifically, they were testing weak-form efficiency. The variables found to contribute to the forecasting model’s performance in their regression were: significance of the match for championship, promotion or relegation issues; the involvement of the teams in cup competition; and the geographical distance between the teams’ home towns. Their results indicated that the model produced information not contained within bookmakers’ odds. Thus, the bookmaker’s odds were weak-form inefficient. They particularly found stronger evidence of market inefficiency in matches played towards the end of the football season.

On the other hand, Vlastakis, Dotsis, & Markellos (2009) sought to test market efficiency in the same markets using arbitrage and trading strategies. They achieve this by examining the predictability of match outcomes using information contained in different online fixed odds quotes from six different bookmakers. Market effeciency, in this case, implies that no bettor or bookmaker can sustain returns that exceed the transaction costs. Arbitrage in this case would be taking advantage of the difference in odds set by different bookmakers. Their results indicate a limited number of highly profitable arbitrage opportnities (about 1 in 200), thus violating weak-form effeciency. These arbitrage opportunities were exploited by combining betting across 2-3 bookmakers. However, the opportunities appear to decrease in more recent study periods, and even further when strictly using online betting markets (less than 1 in 1000). The causes of these arbitrage opportunities were outlined as behavioral biases, such as homefield advatage bias and the favorite/longshot bias.

Jansa (2012) tests market effeciency of betting markets through comparison of the convergance of odds of different betting offices in the Czech Republic. He suggests that such tests of efficiency of betting markets should be based on live data (odds, information about actual form of each player) during the game and not data before the game because it is assumed that odds set prior contain any available information as was done in prior studies. His study finds there is nearly no convergence of odds. He thus rejects the model of market efficiency - model of perfect market with fully rational, risk neutral, bettors. In spite of this conclusion, the author adds that it does not necessarily mean that markets have to be fully inefficient.

2.3.2 Research on Behavioral biases within sports betting markets

Just as behavioral biases were tested in financial markets, the presence of behavioral biases is tested in sports betting markets and its effect on pricing, on market efficiency and the presence of arbitrage opportunities.

Avery & Chevalier, (1999) test whether betting sentiments are the cause of mispricing. Investor sentiment is defined as "any non-maximizing trading pattern among noise traders that can be attributed to a particular exogenous motivation." They hypothesize that sentimental traders follow false advice, believe excessively in momentum strategies and bet excessively on popular teams with wide media coverage. They find that trading caused by the set of sentimental variables alters the path of prices, indicating inefficiency in the market. Additionally, movements in the point spread line that cannot be predicted from sentimental variables are strongly predictive of game outcomes, hence giving rise to an arbitrage opportunity that exploits the sentiment-induced mispricing of the betting line.

Chesir (2013) sought to find the relationship between bettor behavior and overall market efficiency. He first sought to find if bettors behave optimally by analyzing data from an NFL confidence pool, and the assumption that a rational bettor would pick teams consistent with the optimal strategy of maximizing expected value. Secondly, the author sought to find what drives bettor behavior and lastly, how bettor behavior create opportunities in betting markets. The findings of the author are that 1.) Bettors are not rational since a large number deviate from the optimal strategy 2.) Bettor behavior can be traced to behavioral biases namely overconfidence, availability heuristic and anchoring and 3.) Pinpointing games most affected by bettor biases can give the opportunistic bettor an advantage in the betting markets, at least in the long run, thereby proving inefficiency in the market.

Andrikogiannopoulou & Papakonstantinou (2011) also combines both tests for market efficiency and behavioral biases, by examining whether prices set on soccer betting markets on a large number of soccer events are efficient, and the extent to which individuals are either affected by inefficiencies, or contribute to them. They use both individual-level and aggregate-level data. Their results reveal that markets violate weak-form efficiency in a manner that is consistent with the favorite long shot bias, which is, the tendency of bettors to consistently underbet outcomes with small odds and overbet outcomes with large odds in comparison to their observed frequency of winning. The inefficiency is mainly driven by the underbetting of favorite odds on the home win and the away win, and an overbetting of longshot odds on the draw outcome. The analysis of individual-level data shows that contrary to the common perception that the majority (or totality) of bettors contributes to the generation of the favorite/longshot bias, only 6% of the bettors under study have systematically bet on biased odds associated with longshot outcomes, while 2% of the bettors earns significant positive returns from betting on favorite outcomes. Finally, they find that around 4% of the bettors have a home bias which is manifested as overbetting of the home-area team for each individual.

Ates (2004) uses behavioral finance theory in the analysis of sports betting as a tool to understand betting markets, and in return betting markets can help find some understanding for behavioral finance theory. Despite this research being very theoretical, the author clarifies that its intention is to lay the ground for financial research on betting markets, more so when studying behavioral biases common to both investors and bettors. Analysis of these traits, according to the author, may help understand decision making under uncertainty as well as risk management. Furthermore, betting markets provide the platform to conduct financial research that is difficult to undertake in financial markets. The author highlights that one of the problems faced while following this route is in spite of yielding positive and significant results, researchers would still not be convinced that betting markets is a suitable alternative platform to conduct financial research.

Hansen (2006) similarly uses behavioral finance theory and empirical findings to formulate betting strategies which he uses to test whether behavioral finance can be justified in a different setting other than the finance world. The market of choice in this case is the NFL point spread market. The author uses financial theory to define anomalies as violations of EMH whereby abnormal risk-adjusted returns can be obtained. In the context of betting, anomalies are represented by a betting strategy that gives the bettor abnormal returns. Each strategy is formed using an aspect of biases in behavioral finance. Tests were performed using a binomial distribution and a null hypothesis that the profitable strategy is one with >52.38% frequency of wins. The study finds that the most profitable strategies were influenced by representativeness (specifically sample size neglect) and overreaction (home bias & favorite/longshot bias).

Hetherington (2006) tests the existence of the two main behavioral theories, overreaction (representativeness) and underreaction (anchoring/conservatism), in the National Football League markets. The biases are distinguished by their time frames or different circumstances. Overreaction is caused by long-term patterns of information, whereas underreaction occurs in response to isolate informational shocks. He further focuses on two anomalies specific to the NFL which are mispricing of contracts which depend on multiple distinct events; and prices of different point-spread contracts. The author does not find existence of either of the behavioral theories, but finds strong evidence of mispricing of contracts (which he refers to as "implication ignorance").

2.3.3 Behavioral Biases and Genders

This section highlights past literature on how gender affects behavioral biases.

Tekçe (2011) sought to find out the factors that affect behavioral biases in individual stock investors in Turkey. The author takes the transactions within the year 2011 to analyze the occurrence of common biases such as overconfidence, familiarity bias, representativeness and status quo bias within the investors, and the factors causing the biases. The author uses a regression whereby the dependent variable is the bias to be studied (represented by proxies such as turnover, previous ownership ratio, 90 day positive return trend and portfolio percentage change which are used as main measures of overconfidence, familiarity bias, representativeness heuristic and status quo bias respectively), and the independent variables are age of the investor, experience of trading, Investor wealth and development of the regions. The findings of the study were that overconfidence and familiarity bias were common among individual investors, with younger male investors with lower portfolio values and in less developed regions exhibiting the biases more.

Onsomu (2014) studies the behavioral biases affecting individual investors in the Nairobi Securities Exchange, as well as studying the relationship between gender and the behavioral biases in the same context. The author conducted their research by means of a questionnaire distributed amongst investors. The findings were that investors were affected by Availability bias, Representativeness bias, Confirmation bias and Disposition effect. However, there was no significant correlation between the biases and gender.

Lee et al. (2013) determine the behaviors that male and female investors exhibit when making investment decisions. They survey 84 finance and accounting majors using a portfolio simulation tool to investigate their investment decisions over a 3 month period. They find that there was no significant difference betwee portfolio performance and gender. There was, however, a significant difference between gender and risk. The conclusion is that the difference arises from the perception of actual risk undetaken, rather than the desire to engage in risky behavior.

3 Methodology

For this section, I seek to define the area and limits of the research, as well as the methods and model I shall use to conduct the research. The research will be based on the building blocks of behavioral finance.

3.1 Research Design

The research design for this proposal shall take the form of a survey intended to collect the data necessary to conduct the research. This is because the research itself seeks to study human behavior, and thus requires data from the population itself. The survey will be distributed to the population sample.

3.2 Population and Sampling

The population used in this research is sports bettors in Kenya. This is in line with the research objective presented in the paper. The defining characteristic of this population is that they actively participate in sports betting.

From this population, the sampling frame will be bettors who bet at least once a week. A sample size of 150 bettors will be picked from the sample frame. The sample size should also be adequate enough to represent the entire population and capture the behavioral traits required in the model. The sample size will be obtained through stratified random sampling from the sample frame, in order to eliminate any sampling bias and ensure that it is representative of the whole population. In this case, the strata will be divided into two parts: those who bet only once a week and those who bet more than once a week.

3.3 Data Collection

3.3.1 Type of data

The type of data to be used in this research is quantitative in nature. Data will be binary, involving simple yes/no responses (which take the form of (1, 0) respectively). The questions to be answered will be set in a way that will capture the independent variables contained within the model.

3.3.2 Data Collection Method

Data will be collected by means of a questionnaire[15] with questions tailored to meet the research objectives. I have chosen these as they are the most efficient methods to reach out to bettors, due to time and financial constraints. Furthermore, many bettors use the internet as well as social media platforms as their primary access to betting markets. The questionnaire will be distributed on social media platforms (Facebook, Twitter), emails as well as physical collection of data.

3.4 Data Analysis

Due to the qualitative nature of the data, I shall use a Logit model in order to capture the qualitative variables that cause a bettor to bet. The data will be non-linear in nature and have a binary output of (0, 1) which further reinforces the appropriateness of the choice of model.

The model takes the form

$$\Pr(Y = 1|X_1, X_2 \ldots X_k) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_k X_k)$$

$$\Pr(Y = 1|X_1, X_2 \ldots X_k) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_k X_k}}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_k X_k)}}$$

The output of the model will be in form of odds ratios, which are the exponent of the coefficients of the independent variables. They will be interpreted as the odds ratio of the independent variable having an effect on the dependent variable.

Estimates of β_i will be obtained through the Maximum Likelihood technique.

The independent variables (X_i) for this model will be as follows:

- X_1: Past history of performance of the team *(Representativeness bias)*
- X_2: Recent form/performance of the team *(Anchoring Bias)*
- X_3: Odds set *(Favorite/Long Shot Bias)*
- X_4: Team Bias *(Familiarity Bias)*
- X_5: Outcome of prior bets (Overconfidence Bias)

[15] A copy of the questionnaire will be attached to the report in the appendix section.

Each of these independent variables contains an aspect of behavioral bias that causes irrational decision making amongst bettors.

3.4.1 Assumption

The main assumption I make for my study is that betting markets are semi-strong form efficient i.e. information in it combines all past relevant information, as well as all publicly available information. Insider information- in this case match-fixing[16]- is still possible but very unlikely. Thus, prediction markets provide very few arbitrage opportunities (Wolfers & Zitzewitz, 2004).

3.4.2 Fitting the data to the model

To estimate the $\beta_i$coefficients, the Maximum Likelihood method shall be used. The effect of each independent variable, represented by the coefficient, will thus give us the marginal effect the on the output; in this case, the bettor placing a bet. The t-test of significance will be performed on the independent variables in order to assess the explanatory power of each on the overall model. The test will be as follows:

$$H_0: \beta_i = 0$$

I.e. the variable has no effect on the output. The output of the model is the probability that a bet will be placed (i.e. Y=1) taking into consideration the outlined behavioral biases (the independent variables). These probabilities of each independent variable as well as a combination of variables will be compared. A combination of these variables provides information on how bettors plan to maximize gains.

[16] Match-fixing is defined as "A dishonest activity by participants, team officials, match officials or other interested parties to ensure a specific outcome in a particular sporting match or event for competitive advantage and/or financial gain which negatively impacts on the integrity of the sport." (Carpenter, 2013)

4 Results~~, Findings and Discussion~~

This section presents the findings after running the data collected through the model, and seeks to discuss the findings of the study, in accordance with the research objectives mentioned in the first chapter, taking into consideration past studies highlighted in the literature review.

The chapter's sections will be organized according to the research questions.

4.1 Behavioral Characteristics (biases)

The first objective of the study was to determine the behavioral characteristics (biases) exhibited by bettors. The data collected was analyzed using the model below:

The model is a logit regression which takes the form

$$\Pr(Y = 1|X_1, X_2 \dots X_k) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_k X_k}}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_k X_k)}}$$

For this section, the output (Y) is Bet (i.e. if the respondent is a frequent bettor or not) and the independent variable (X) are the behavioral biases discussed above.

Upon collection of data that was a sufficient representation of the population size, the model was run using STATA software and it produced the following results:

The constant term was suppressed since the model is non-linear in nature, and it has no significance on the output i.e. the model is to test the likelihood that a bet placed is as a result of the given biases.

The first test produced results that are tabulated as follows:

```
. logistic Bet RepBias AnchBias FavLSBias FamBias OverCBias, noconstant

Logistic regression                             Number of obs   =        106
                                                Wald chi2(5)    =      30.01
Log likelihood = -52.835177                     Prob > chi2     =     0.0000
```

Bet	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
RepBias	2.590084	1.379356	1.79	0.074	.9120201	7.35569
AnchBias	5.565916	2.77201	3.45	0.001	2.097057	14.77281
FavLSBias	2.401786	1.343304	1.57	0.117	.8025326	7.187965
FamBias	1.118801	.9555834	0.13	0.895	.2097633	5.967274
OverCBias	1.1864	.6002547	0.34	0.735	.440118	3.19811

Table 1: The Initial data analysis

The null hypothesis for the first objective is:

H_0: The bias has no effect on the bettor's decision to place a bet

$$H_0: \beta_i = 0$$

i.e. The coefficient of the independent variable is zero, meaning that the variable has no effect on the output. This hypothesis is tested using the P Values, at a 95% level of confidence. For the null hypothesis to be rejected (and the coefficient to be statistically significant), the P value should be less than 0.05.

The Odds Ratios are the logs of the coefficients of the independent variables. An odds ratio, x, takes the form

$$x = \frac{p}{1 - p}$$

Where p is the probability

The odds ratios (or coefficients) of the variable show the effect of the variable on the output, holding all other variables constant. The only significant variable in the model was Anchoring Bias. The variables with the highest P values were dropped, since they mean that there is a high likelihood that they are zero (according to the null hypothesis), meaning that they have no effect on the output, holding all other independent variables constant. As a result, two more variables (Representative and Favorite/Longshot Bias) were then significant to the model.

```
. logistic Bet RepBias AnchBias FavLSBias, noconstant
```

Logistic regression		Number of obs	=	106
		Wald chi2(3)	=	29.92
Log likelihood = -52.906362		Prob > chi2	=	0.0000

Bet	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
RepBias	2.981402	1.145551	2.84	0.004	1.403981	6.331106
AnchBias	6.080106	2.675227	4.10	0.000	2.56676	14.40247
FavLSBias	2.666667	1.276569	2.05	0.040	1.043487	6.814758

Table 2: After dropping the Familiarity and Overconfidence Bias variable

Logistic regression		Number of obs	=	106
		Wald chi2(3)	=	29.92
Log likelihood = -52.906362		Prob > chi2	=	0.0000

Bet	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
RepBias	1.092394	.3842323	2.84	0.004	.339312	1.845475
AnchBias	1.805022	.4399967	4.10	0.000	.9426443	2.6674
FavLSBias	.9808293	.4787136	2.05	0.040	.0425679	1.919091

Table 3: Table of Coefficients of Independent Variables

The trimmed down model gives the odds ratios (Table 2) and coefficients (Table 3) of the independent variables. 'RepBias', 'AnchBias' & 'FavLSBias' represent the Representative Bias, Anchoring Bias and Favorite/Longshot Bias respectively.

4.1.1 Representative Bias

As indicated in table 2 the coefficient of the Representative Bias is 1.092394, giving an odds ratio of 2.981402. This means that for every bet placed by an individual, the odds that their decision to bet on a team has been influenced by the history of the team(s) performances is

2.981402. Alternatively, this can be interpreted as a 74.8832% probability that the decision to place a bet on a given team is influenced by the history of the team's performance.

4.1.2 <u>Anchoring Bias</u>

The coefficient of the Anchoring Bias is 1.863682, which results in an odds ratio of 6.44743. This can be interpreted as for every bet placed, the odds that the decision was based on the most recent performance of the team(s) is 6.44743. It is interesting to note that this bias has the highest odds of the three significant biases highlighted. Alternatively, this can be interpreted as an 86.5725% probability that the decision to place a bet on a given team is influenced by the team's most recent performance.

4.1.3 <u>Favorite/Longshot Bias</u>

The coefficient of the Favorite/Longshot Bias is .9808293, which gives an odds ratio of 2.66667. This means that for every bet placed, the odds that the individual was influenced by the odds of the outcome of the match (i.e. the returns they get from placing the bet) is 2.66667, or a 72.7273% probability.

4.2 Biases exhibited by Gender

This section uses the same logit model as above.

The second objective of the study was to determine the likelihood of the behavioral patterns to be exhibited by each gender of the betting population.

The data collected was analyzed using the model below:

$$\Pr(\mathrm{Y} = 1|\mathrm{X}_1, \mathrm{X}_2 \ldots \mathrm{X}_\mathrm{k}) = \frac{e^{\beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 \ldots + \beta_\mathrm{k} \mathrm{X}_\mathrm{k}}}{1 + e^{(\beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 \ldots + \beta_\mathrm{k} \mathrm{X}_\mathrm{k})}}$$

Where the dependent variable (Y) is behavioral biases ('RepBias', 'AnchBias' & 'FavLSBias') and the independent variables (X) is the gender (Male or Female). The dependent variables will be the biases that had failed to be rejected under the initial hypothesis test carried out above.

The responses consisted of 93 male respondents and 13 female respondents. Thus, to determine the likelihood of a given gender exhibiting the biases, the model was used, but

“Gender” was taken as the independent variable, with the significant biases taking the place of the dependent variable. (In this case, the “Gender” variable was binomial, with “1” representing male and “0” representing female).

```
. logistic RepBias Gender, coef

Logistic regression                             Number of obs   =        106
                                                LR chi2(1)      =       0.54
                                                Prob > chi2     =     0.4604
Log likelihood = -69.458743                     Pseudo R2       =     0.0039

------------------------------------------------------------------------------
     RepBias |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Gender |  -.4436863   .5970708    -0.74   0.457    -1.613924    .7265509
       _cons |  -.1541507   .5563486    -0.28   0.782    -1.244574    .9362726
------------------------------------------------------------------------------

. logistic RepBias Gender

Logistic regression                             Number of obs   =        106
                                                LR chi2(1)      =       0.54
                                                Prob > chi2     =     0.4604
Log likelihood = -69.458743                     Pseudo R2       =     0.0039

------------------------------------------------------------------------------
     RepBias | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Gender |   .6416667   .3831204    -0.74   0.457     .1991049    2.067936
       _cons |   .8571429   .4768703    -0.28   0.782     .2880636    2.550457
------------------------------------------------------------------------------
```

Table 4: Results of Regression between Representative Bias and Gender

4.2.1 Representative Bias

The coefficient of the Gender is -0.4436863, resulting in an odds ratio of 0.64. This can be interpreted as the odds of a male exhibiting the Representative Bias when placing a bet as compared to a woman is 0.6416667, or 39.0863% probability. The odds/probability of a female exhibiting the Representative bias are much higher (1.558441 or 60.9137%), indicating that females are more likely to exhibit the bias when placing a bet than their male counterparts.

```
. logistic AnchBias Gender, coef

Logistic regression                               Number of obs   =        106
                                                  LR chi2(1)      =       0.08
                                                  Prob > chi2     =     0.7738
Log likelihood = -72.220124                       Pseudo R2       =     0.0006
```

AnchBias	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Gender	-.1712718	.5947128	-0.29	0.773	-1.336888	.9943439
_cons	-.1541506	.5563486	-0.28	0.782	-1.244574	.9362727

```
. logistic AnchBias Gender

Logistic regression                               Number of obs   =        106
                                                  LR chi2(1)      =       0.08
                                                  Prob > chi2     =     0.7738
Log likelihood = -72.220124                       Pseudo R2       =     0.0006
```

AnchBias	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Gender	.8425925	.5011006	-0.29	0.773	.2626619	2.70295
_cons	.8571429	.4768703	-0.28	0.782	.2880636	2.550457

Table 5: Results of Regression between Anchoring Bias and Gender

4.2.2 Anchoring Bias

The coefficient of Gender is -0.1712718, resulting in an odds ratio of 0.8425925. This means that the odds of a male exhibiting the Anchoring Bias when betting is 0.8425925 (or 45.7286%), as compared to a female which is 1.186813 (or 54.2714%), which is higher.

```
. logistic FavLSBias Gender, coef

Logistic regression                               Number of obs   =        106
                                                  LR chi2(1)      =       1.86
                                                  Prob > chi2     =     0.1725
Log likelihood = -53.202283                       Pseudo R2       =     0.0172
```

FavLSBias	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Gender	1.252762	1.069972	1.17	0.242	-.8443447	3.34987
_cons	-2.484906	1.040833	-2.39	0.017	-4.524901	-.4449114

```
. logistic FavLSBias Gender

Logistic regression                               Number of obs   =        106
                                                  LR chi2(1)      =       1.86
                                                  Prob > chi2     =     0.1725
Log likelihood = -53.202283                       Pseudo R2       =     0.0172
```

FavLSBias	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Gender	3.499998	3.744901	1.17	0.242	.4298389	28.49902
_cons	.0833334	.0867361	-2.39	0.017	.0108358	.6408811

Table 6: Results of Regression between Favorite/Longshot Bias and Gender

4.2.3 Favorite/Longshot Bias

The coefficient of Gender is 1.252762, resulting in an odds ratio of 3.499998. This implies that the odds of a male exhibiting the Favorite/Longshot Bias when placing a bet is 3.499998, or 77.78%, as compared to female whose odds are 0.285714, or 22.22%.

5 Discussions, Conclusions and Recommendations

This section provides a discussion of the findings obtained in the preceding chapter, as well as gives some closing remarks about the study and gives recommendations for future research within the field of study.

5.1 Discussions

5.1.1 Behavioral Biases displayed by bettors

The key behavioral biases bettors display that were brought out by the model are Representative Bias, Anchoring Bias and Favorite/Longshot bias.

They are in line with the ones that were found present in the papers of Hansen (2006), Hetherington (2006) and Andrikogiannopoulou & Papakonstantinou (2011).

In the works of Hansen (2006), the trading strategies that the author formulated that were deemed the most successful by the respondents included elements of Representative Bias and Favorite/Longshot Bias. Similarly, Andrikogiannopoulou & Papakonstantinou (2011) in their study encountered Favorite/Longshot bias which led to market ineffeciencies.

The study that was conducted by Hetherington (2006) sought to test the existence of overreaction (representativeness) and underreaction (anchoring) in the National Foootballl League. These theories were found to exist among the beting population in the study conducted above.

These similarities are as a result of how bettors analyse gambles, payoffs and potential losses differently. This is evidence of the theory brought forward by Kahneman & Tversky (1979) on behavioral finance and the irrationality of human beings in decision making.

5.1.2 Biases exhibited by Gender

The study by Onsomu (2014) on behavioral biases and investor decisions in Kenya based on genders found that there was no direct correlation between the biases she studied and genders. The biases in the author's study similar to this one are Representativeness Bias and Anchoring Bias.The result that males are more likely to exhibit the Favorite/Longshot bias wen placing a bet than females is in line with the study done by Lee et al. (2013) whose study found out that males are more likely to perceive risk differently from females, as they focus more on the potential rewards that they stand to gain, and not the losses they are vulnerable to.

5.2 Conclusions

The aim of the study was to bring to light which behaviors are exhibited by bettors when analyzing and placing bets. The methodology included use of a survey that used scenarios that enabled the researcher obtain the biases they desired to study.

Of the biases that were in the initial study, only the explanatory power of Representative Bias, Anchoring Bias and Favorite/Longshot bias were significant to the model and were used in explaining the biases present when placing the bet. Furthermore, the biases were grouped into genders in order to analyze how each gender displayed biases when placing a bet.

5.3 Shortcoming of the study

The study encountered a number of shortcomings. First, the sample size was relatively small, given the time constraint. Second, the mode of distribution of the questionnaire was limited to online distribution due to time and resource constraints.

5.4 Recommendations

For future research purposes, researchers may look into integrating other biases, as well as looking for a larger sample size that will reduce the noise in the model. Lastly, the biases may be grouped into demographics of the betting population.

6 Works Cited

Andrikogiannopoulou, A., & Papakonstantinou, F. (2011). *Market Efficiency and Behavioral Biases in the Sports Betting Market*. London.

Ates, C. O. (2004). Behavioral Finance & Sports Betting Markets. *Aarthus School of Business Journal*.

Avery, C., & Chevalier, J. (1999). Identifying Investor Sentiment from Price Paths: The Case of Football Betting. *The Journal Of Business Vol.72*, 493-521.

Barberis, N., & Thaler, R. (2003). A Survey of Behavioral Finance. In E. S. B.V, *Handbook of the Economics of Finance.*

Birău, F. R. (2012). The Impact of Behavioral Finace on Stock Markets. *Annals of the „Constantin Brâncuşi" University of Târgu Jiu, Economy Series*.

Carpenter, K. (2013). Global Match-Fixing and the United States' Role in Upholding Sports Integrity. *Berkely Jurnal of Entertainment and Sports Law*, 214-229.

Chesir, J. (2013). *Finding Inefficiency in Sports Betting Markets; a Look through NFL Confidence Pick'Em Biases.* New York.

Clarke, J., Jandik, T., & Mandelker, G. (2001). The Effecient Market Hypothesis. *Expert Financial Planning: Advice From Industry Leaders*, 126-141.

Credit Suisse AG. (2015). *Behavioral Finance: The Psychology of Investing*. New York: Credit Suisse Securities.

Daza, J. R. (2004). The Utility Function and The Emotional Well-Being Function. *Electronic Journal of Business Ethics and Organization Studies*, 22-29.

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and Evidence. *The Jourlan of Economic Perspectives*, 25-46.

Fama, E. K. (1970). Effecient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 383-417.

Goddard, J., & Asimakopoulos, I. (2004). Forecasting Football Results and the Efficiency of Fixed-odds Betting. *Journal of Forecasting*, 51-66.

Hansen, K. B. (2006). *Sports Betting from a Behavioral Finance Point of View: Betting on the NFL*. Aarhus School of Business.

Hetherington, A. (2006). *Betting Against Efficiency: Behavioral Finance in an NFL Gambling Exchange*. New Haven: SSRN.

Jansa, B. J. (2012). *Fair Bets in Sports Betting*. Prague: Charles University, Prague; Faculty of Social Sciences; Institute of Economic Studies.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica*, 263-293.

Kevin Lee, S. M. (2013). The Effect of Invetor Bias and Gender on Portfolio Performance and Risk. *International Journal of Business and Financial Research*.

Levitt, S. D. (2004). Why Are Gambling Markets Organized So Differently From Financial Markets? *The Economic Journal*, 223-246.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 77-91.

Marshall, B. (2005). *Arbitrage Opportunities in Sports Betting Markets.* SSRN.

Mitroi, A., & Oproiu, A. (2014). Behavioral Finance: New Trends, Socionomics and Investor Emotions. *Theoretical And Applied Economics Vol. XXI*, 153-166.

Onsomu, Z. N. (2014). The Impact of Behavioral Biases on Investor Decisions In Kenya: Male Vs Female. *IMPACT: International Journal of Research in Humanities, Arts and Literature (IMPACT: IJRHAL)*, 87-92.

Palmer, P. C. (2013). *Sports Betting Research: Literature Review*. Tasmania: School of Social Sciences, University of Tasmania.

PwC. (2015, December). *PwC South Africa*. Retrieved from PwC South Africa Website: https://www.pwc.co.za/en/assets/pdf/gambling-outlook-2015-2019.pdf

Ritter, J. R. (2003). Behavioral Finance. *Pacific-Basin Finance Journal*, 429-437.

Shefrin, H. (2002). *Beyond Greed and Fear: Understanding Behavioral Finance and The sychology of Investing*. New York: Oxford University Press.

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives Vol. 17*, 83-104.

Tekçe, B. (2011). What Factors Affect Behavioral Biases? Evidence From Turkish Individual Stok Investors.

Thaler, R. H., & Ziemba, W. T. (1988). Anomalies: Parimutuel Betimg Markets: Racetracks and Lotteries. *Journal of Economic Perspectives*, 161-174.

Thomas E. Copeland, J. F. (2005). *Financial Theory & Corporate Policy*. Pittsburgh: Addison-Wesley.

Vlastakis, N., Dotsis, G., & Markellos, R. N. (2009). How Efficient is the European Football Betting Market? Evidence from Arbitrage and Trading Strategies. *Journal of Forecasting*, 426-444.

Wolfers, J., & Zitzewitz, E. (2004). Prediction Markets. *Journal of Economic Perspectives*, 107-126.

7 Appendix A: Questionnaire

1.) What gender are you?

A.) Male

B.) Female

2.) What age are you?

A.) 18-21 yrs

B.) 22-25 yrs

C.) 26-29 yrs

D.) 30 and above

3.) What is your occupation?

A.) Student

B.) Part-Time Employed

C.) Full-Time Employed

D.) Unemployed

E.) Other (Specify)

4.) During a football season or event how often do you bet?

A.) Every day

B.) More than once a week

C.) Once a week

D.) Other (specify)

<u>Case 1</u>

Team X is playing Team Z, where X is the home team and Z is the away team. You are to predict the outcome of the game. The odds of the outcome are (1.52) (2.13) (4.31) representing a win for Team X (W), a draw (D) or a win for Team Z (L). Team X won the league championship two seasons ago and finished third in the last season. Their performance of late however has been dwindling. The results of their last three games are as follows: 1D, 2L. Team Z is a mid-table team that survived relegation in the last season. Its performance has been fair, with the results of the last three matches as follows: D, W, D. They are considered the underdogs of the match.

5.) Which team would you bet on winning the match?

A.) X

B.) Z

6.) For 5.) above, what would be the reason behind your choice? (You can pick more than one answer)

A.) Past performance of team X

B.) Past performance of team Z

C.) Recent Performance of team X

D.) Recent performance of team Z

E.) Odds set

<u>Case 2</u>

Suppose now that you are a die-hard supporter of Team X. Team X's recent form has been poor and the results of the last four games are as follows: DLDL. Team X currently stands at 5^{th} on the league table. Their next game is against team Y, their competitive rival in the league, in a derby-style match. Team Y's performance has been good, with their past four performances as follows: DWWW. Team Y currently stands at 3^{rd} in the league table. The odds of the outcome of the derby are W (1.54), D (2.01), and L (1.43).

7.) How would your loyalty to Team X influence your bet in this case?

A.) Remain loyal: I would bet on Team X

B.) No influence: I would bet on Team Y

C.) I will not bet at all

8.) Given the above 2 scenarios, assume you bet on Team X, and you won the first bet and lost the second bet, does the outcome of that bet (win or loss) influence your decision to bet again on team X?

A.) Yes, I believe that Team X is likely to correct its mistakes and win the next match.

B.) No, I don't think that they will win the next game given the outcome of the last game.