STOCKHOLM SCHOOL OF ECONOMICS
Master Thesis in Finance

Avoiding longshots and parlays

- An empirical study on the behavior of bettors acting on a fixed-odds betting market

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Abstract

This paper examines an online fixed-odds betting market from market and individual perspectives by using a unique dataset giving details about up to 500 of the latest placed bets made by 536 individual bettors. At the market level, the total number of single-game bets made by those bettors is used to analyze the efficiency of the market in terms of the returns obtained from betting on various odds. At the individual level we examine the characteristics of the bettors using theories from behavioral finance in order to discuss the rationality of their behavior. We find that the odds set by the betting company are good approximations of the objective winning probabilities for the outcome of the games, which means that the market is efficient in pricing probabilities. When studying bettor characteristics we find that only a small number of bettors are affected by prior successes when placing their next bet. We also find that most bettors show a tendency of placing relatively more money on bets with higher odds when betting on different odds over time. Such a tendency is captured in an adjustment factor which is, in combination with the variable "Weighted Average Number of Games", shown to have a negative effect on a bettor's monetary performance over time.

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1. Introduction

The aim of this thesis is to investigate an online betting market and to study the behavior of its participants i.e. the bettors. The theoretical framework employed in this study will mainly revolve around the contrasting views of the efficient market hypothesis and the field of behavioral finance, with much focus given to the individual behavioral tendencies discussed in the psychological side of behavioral finance.

The betting markets have been used in several previous studies examining both the behavior of individual actors and the structure of the market itself in search of explanation for psychological biases and market anomalies found on other markets. The most common analogies made are those between betting markets and financial markets, as a betting market can in many aspects be seen as a simplified and more direct version of a financial market.

We believe that these analogies have gotten even stronger as the betting markets have been able to reach out to more people through the use of online betting sites, much in the same way that equity trading has been taken to a wider market with the use of internet brokers. With the larger market and the ability to update odds faster, the betting market has become even more similar to the financial markets.

Besides, the relation to financial markets, the online betting markets are interesting to study based simply on the outstanding growth this industry has seen over the last couple of years and the growth it is expected to have for the time to come. In 2009 the yearly revenue for online betting reached 26 billion USD and it is estimated to reach levels of above 35 billion USD in 2012.[1] As an example of the magnitude of the market one can mention the Centaur Galileo Managed Sports Fund which is an absolute return fund operating solely on betting markets.

In our thesis we analyze a unique dataset consisting of individual bettor's accounts registered at a major international betting company in order to describe individual behavior. By combining all the bets made by these bettors we are also able to draw conclusions about the market as a whole. On an individual level we aim to investigate if bettors show any distinguishable pattern as they place their bets on this fixed-odds market. In order to be able to judge the rationality of these choices we also investigate the efficiency of the market. The behavior observed is then discussed in relation to commonly used theories in the behavioral finance literature.

[1] http://www.economist.com/node/16507670

1.1 Contribution

The contribution made by this thesis consists of both a current evaluation of the efficiency of an online fixed-odds betting market and a deeper investigation of the individual behavior of bettors acting on this market. By analyzing betting behavior on a fixed-odds betting market we hope to contribute to the ongoing academic discussion of how people make decisions under risk. What differentiate our study from previous studies using data from betting markets is that we are able to study individuals directly by using data from individual betting accounts. Many earlier studies (see Sauer 1998 for a summary of this literature) analyze aggregate data to come up with explanations to individual behavior. The unique data set we use offer the possibility to separate between different behavior and hence the opportunity to compare bettors within the sample. The descriptive models are designed to capture behavior that if found would challenge the assumption of rationality implied by the Efficient Market Hypothesis.

1.2 Outline

This thesis will begin with a section that introduce the concept of odds to the reader. Thereafter we show how betting markets share many characteristics with the financial markets, which will enable us to further discuss the implications of our findings later in the thesis. In section 3 we will review findings from earlier studies using the betting market. In section 4 we present the theoretical framework that is later used to formulate four different research questions in section 5. We thereafter, in section 6 provide an explanation of the data set and the information it entails together with descriptive statistics. In section 7 we develop a number of descriptive models which are constructed to capture significant behavior by the bettors. The empirical findings are presented in section 8 and analyzed in section 9 where we also advocate possible weaknesses with our descriptive models. Finally a concise conclusion and suggestions for further research is found in section 10 and 11 respectively.

2. Odds-setting and betting markets

The section will begin with an introduction to odds, i.e. how they are calculated and quoted. We will also describe the takeout ratio imposed by the betting company and its implication on the odds. As we aim to describe how behavior in financial markets are linked to behavior in betting markets we thereafter go on to describe the common characteristics of the two markets.

2.1 Introduction to odds

Odds setters can choose to form odds either by a fixed-odds system or by using a pari-mutuel system. When betting on a fixed-odds market you are assured that the odds on which you place your bet will be fixed even though the quoted odds may change as time passes.[2] However using a pari-mutuel system the odds will change in relation to how much money that is placed on each outcome. Odds setters who use a pari-mutuel betting system will unlike odds setters who offer a fixed-odds system never risk to be exposed to any specific outcome and will know before the game/race starts how much profit they will make. This thesis will mainly focus on fixed-odds betting and the reader can expect the discussion to relate to fixed-odds betting if not clearly stated otherwise.

Odds are used in the betting industry as a simple way of quoting the payoff that would occur should a bettor pick the correct outcome from a random draw. There are however several different ways in which to quote odds and the preferred way is mostly dependent on region and sport. The three most common quotations are fractional odds, decimal odds and moneyline odds.

Fractional odds are mostly used in the United Kingdom and Ireland and represent a multiple for the gain one would make on a bet. This means that the fair odds of a random day being a Monday would be quoted as 6/1 (six-to-one) and a bet of 100 would yield a gain of 600 if it was successful.

Decimal odds, or European odds, are most common in Europe, Canada and Australia. Decimal odds differ from fractional odds in that they state the total amount that will be paid to the bettor, instead of the gain, from a successful bet. A bet of 100 on a random day being a Monday would have a fair odds of 7, making the total amount paid out on a successful bet 700 (which is equivalent to a gain of 600).

Moneyline odds are quoted as the actual amount one would gain on a bet with a given stake, calculated by the fractional odds. For a wager of 100 on a fractional odds of 4/1, the odds would be quoted as +400. For a bet on the fractional odds 1/4 this will instead read the amount that must be wagered in order to win 100, which in this case would be 400.

The preferred way of quoting odds in online betting is by decimal odds, largely due to the ease with which decimal odds can be used to calculate the odds of combined probabilities. Decimal odds are calculated as one over the probability of an event, meaning that a probability of 20% would imply that the odds of that event taking place is 1/0.2 = 5.

A combined bet, or parlay bet, is a bet on several specific events taking place. For the bet to succeed all of the chosen events in the combined bet need to occur. Consider four teams, team A, B, C and D, where A plays B and C plays D. A combined bet could in this setting be a bet that A beats B and that C beats D. Given that the odds of A beating B is 2 and that the odds of C beating D is 4 then the combined odds constructed of these two sub odds would be 2*4=8.

[2] On a fixed-odds market odds are generally set through a combination of statistical methods and the discretion of expert odds setters. The odds may later be adjusted to account for new information or to better match the demand for certain

In online betting, like in most betting, there is a takeout ratio imposed by the betting company. This takeout ratio, or transaction cost, must be considered when translating an odds into a probability. Given no transaction costs we would expect the implied probabilities of all possible outcomes from a match to sum up to one. Transaction costs would instead mean that the implied probabilities that can be derived from the odds on home win (1), draw (X) and away win (2) on a match will not add up to 1 even tough they are in fact mutually exclusive and collectively exhaustive. Table 1 below shows actual decimal odds obtained from an internet betting company. Note that the implied probabilities from the given odds sum up to more than one which implies that there are transaction costs. If the transaction costs are accounted for we get somewhat higher odds for each outcome.

Table 1: Example of odds and their relation to probabilities.

Outcomes	1	X	2
Odds	1.36	4.5	8.5
implied Probability	0.74	0.22	0.12
Odds without transaction cost	1.46	4.84	9.14
Probability without transaction cost	0.68	0.21	0.11

[3]

Forrest et al. (2005) use odds data from 10 000 UK football matches played between 1998-2003 offered by five major bookmakers and find that the returns obtained if a bettor would bet on each of the three possible outcomes were in the range (-12%) - (-10%). The transaction costs vary between different games and betting-categories as well as between companies. The intensifying competition in the market for internet betting, where the bettors now, without much effort, can compare odds from different firms, works to reduce the takeout ratio. For internet betting companies today that offer odds on home, draw and away win on football matches the usual costs are in the range 6-8%.[4] A bettor who has information of odds on all outcomes of a match can easily calculate this transaction cost[5], but will have no way of knowing how the cost is distributed over the different outcomes. In the numerical example given in Table 1 the transaction cost is evenly distributed over the outcomes, but this does not have to be the case. It is important to understand that the implied probabilities reflect the subjective view of the odds setter. The “true” probabilities might be different from the subjective probabilities why it is hard to calculate the transaction cost for a single odds. Odds setters can choose to set the transaction cost lower on certain odds in order to make them more attractive and thereby attract more bettors or alternatively set a higher transaction cost on outcomes they believe will attract many bettors anyway.

[3] http://www.unibet.com. For calculations on takeout ratio, see Appendix 13.1
[4] See appendix 13.2
[5] For calculations on takeout ratio, see Appendix 13.1

In order to be able to compare different amounts placed on different odds over time we will define exposure as the amount placed per implied winning probability. When studying the equation below we can see that the amount placed per implied probability is the same as potential winning a bettor would stand to win, should their bet be successful.

$$Exposure = \frac{placed}{1/odds} = placed \times odds = potential\ winning \tag{1}$$

For an odds setter not to be exposed to a certain outcome of a bet (1, X and 2) the potential winnings (built on aggregate placed amounts to each odds) needs to be the same. For an individual who chooses to bet on one of the outcomes he/she will be exposed through both the amount placed as well as the odds of the outcome.

2.2 How betting markets compare to the financial markets

The betting markets are in many ways similar to the financial markets. Perhaps the most obvious characteristic that the two markets have in common is the fact that actors on both markets use real money that is associated with some level of utility. This feature is critical as theories on investor behavior in financial markets are based on maximization of utility, and a common ground of utility is therefore necessary for most comparisons. The common characteristic that is of greatest importance for our thesis is in fact that choices in both markets have risky outcomes.

Some instruments on the financial markets do have payoff structures that closely resembles odds bets, such as the digital call option which pays the holder a fixed amount if the price of the underlying asset is above the strike price at expiration, but it should be noted that most financial instruments differ from odds in a number of aspects. Many financial instrument do not for instance have a definite time horizon upon which a profit or loss has to be realized. They can also be traded at any point in time and the price does not have to have a upper boundary. Odds bets on the other hand have very clear time horizons, with binary outcome, which gives both the bettors and the odds setters more direct feedback on their choices.

In financial markets a single private investor will seldom have an effect on the prevailing prices on the market. In the same way there will mostly not be an effect on the set odds following a bet by a single bettor, which means that individuals in both markets can be seen as price takers.[6] Also, as previously discussed there is a fee or transaction cost imposed by the betting company on the bets placed, much in the same way as there are transaction costs involved in the trading of financial instruments.

Two main areas in which capital markets and betting markets differ are in the expected return and in the range of available instruments. While most financial instruments are associated with positive expected returns the average odds offered by betting companies are associated with negative expected

[6] A single bettor/investor who bet/trade very large volumes will most likely affect prices.

returns. Given that an odds is fair it will have an expected return of 0. The odds set by a betting company will however not be fair as there is a transaction cost imposed and the expected return will therefore be negative by a percentage equal to the transaction cost. On financial markets there are many different types of instruments available making it possible for investors to tailor both expected return and variance to a large degree. While there are vast opportunities to create exotic financial instruments the betting market has a much more limited supply of instruments. However, many betting companies in Europe offer the possibility for bettors to create parlay bets in which the bettor can combine several different games. Given that there are a large number of available games a bettor can construct bets with odds ranging from the lowest single odds available to combinations with odds of millions.

A difference put forth by Levitt (2004) is that the relatively infrequent changing of odds by the betting companies compared to the frequency in which prices of asset change in a financial market suggest that betting markets do not behave as an ordinary market driven simply by supply and demand. However, many financial products are traded on OTC-markets where dealers act as market makers much in the same way as odds setters quote odds on a fixed-odds betting market.

3. Using the betting market to study economic behavior

Using betting markets to study individual behavior under risk is desirable from a number of aspects. The different odds can easily be translated into implied probabilities and the subjective probability of an outcome can hence be measured. Compared to many experimental settings the individuals on a betting market are faced with judgments where their own money is at stake and are studied without knowing that they are studied. By using betting markets, economists are given the opportunity to study how asset pricing models work in a context where outcomes are repeatedly revealed.

Griffith (1949) and McGlothlin (1956) were the first to use data from racetrack betting markets in order to perform studies on how bettors behaved under uncertainty. The authors compared the implied probabilities given by the odds with the actual winning probabilities revealed after the race was settled and found that the subjective winning probabilities are good estimates of the objective winning probabilities. Thaler and Ziemba (1988) provide a discussion of anomalies found in economic theory by using empirical data from pari-mutuel betting markets such as racetrack betting. The authors bring up the so called favorite-longshot bias which is hard to rationalize using economic models. Studies have shown that when favorites and longshots are compared relative their respective odds, favorites tend to win more often while longshots tend to win less often. The favorite-longshot bias hence indicates that betting on a favorite should generally be more profitable than betting on a longshot. Snyder (1978) uses data from six studies on pari-mutuel horse racing to compare returns for different odds categories. The author finds a clear favorite-longshot bias in the data. Cain (2000) uses data from

2 855 UK football matches from the season 1991-1992 and finds that bets on favorites generate a substantially better return than bets on longshots also supporting this bias. However Woodland (1994) examines the efficiency of the US baseball betting market which is a fixed-odds market and find a reverse relationship, namely that favorites tend to be overbetted instead of underdogs.

Even though market anomalies such as the favorite-longshot bias have been discovered Thaler and Ziemba's (1988) view of the racetrack betting markets is that they are surprisingly efficient in the sense that the subjective probabilities indicated by the odds are good estimates of the winning probabilities.

Sauer (1998) analyzes the economics of betting by raising a number of questions relating to market efficiency on these markets. He argues that an asset pricing model which assumes investors to have identical information and preferences is not sufficient to explain prices in the betting market.

4. Theoretical framework

In this section we aim to present the reader with a description of the theories underlying the thesis. We will begin with an introduction to the Efficient Market Hypothesis and the area of behavioral finance. We thereafter turn the focus to the psychology part of behavioral finance and present a number of cognitive and behavioral biases that are related to market anomalies observed in the financial markets. Finally we present a brief overview of two major theories in the field of individual risk preferences.

4.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) states that the asset prices prevailing in a capital market will be unaffected by historical performance and information and will therefore be impossible to predict. This implies that under the assumption of a perfectly efficient capital market neither technical analysis nor fundamental analysis will generate above market returns. Rather than being affected by past performance and information, which will already be incorporated into the price, changes in the price will be due to new information concerning the current and future performance of the firm. It is also assumed under the EMH that the flow of new information will have an almost immediate impact on the asset prices (Malkiel (2003)).

The EMH is closely related to the notion of asset prices following a "random walk", meaning that subsequent price changes will be randomly distributed. This follows the fact that news by definition are unpredictable, and the resulting effect on the asset prices will therefore also be unpredictable (Malkiel (2003)).

In his article, Fama (1970) introduces three different forms of the EMH, namely: weak form, semi-strong form and strong form. Under the weak form, investors cannot use the information about historical prices in order to predict future prices. The semi-strong form suggests further that all publically available information is fully reflected in market prices. For the strong form of market efficiency to hold investors with insider information are not able to achieve above normal returns using their superior information.

From an individual perspective the EMH is built on rational expectations among the investors. Wärneryd (2001) argues that rationality implies that an individual will try to maximize gains by using the best available information. Trading will occur when the marginal income from an alternative portfolio is greater than from the current portfolio. Wärneryd (2001) also discusses how deviations from the predictions of this theory is explained by random deviations from rationality. These deviations are mainly described by limited cognitive psychology and emotion driven behavior. The author points out that the defenders of the efficient market theory withstand that these deviations are not large enough to reject the theory.

Snyder (1978) argues that betting markets can be used to study market efficiency as they have the characteristics of perfect competition, namely a large number of participants with good knowledge of the market and ease of entry. He also points out the fact that bettors on a betting market are faced with decisions involving risk and uncertainty much like actors on a financial market. Snyder (1978) tests the theory of efficient markets by studying if subjective odds can be used to earn above average returns. If people acted in the way that the theory suggests he expects all returns to be equal to the negative takeout ratio. Thaler and Ziemba (1988) formulate two different definitions of market efficiency on a pari-mutuel betting market contingent on the fact that actors are value maximizing individuals with rational expectations:

Market efficiency condition 1 (weak): No bets should have positive expected values.

Market efficiency condition 2 (strong): All bets should have expected values equal to (1-t) times the amount bet, where t represents the takeout ratio.

While efficiency tests on the financial markets suffer from the fact that the true value of an asset cannot be revealed Gray and Gray (1997) argue that sports betting markets offer a good opportunity to construct direct tests of market efficiency. The instruments on betting markets, odds bets, have in relation to most financial assets a distinct horizon where the true outcome is observed.

4.2 Behavioral finance

During the 1970s an academic discussion began to take form where researchers reacted to EMH by pointing at market anomalies that were not in line with this theory. However it was first during the 1980s that researchers started to show significant empirical results and came up with evidence against the theory of efficient markets. Shiller (1981) found that the volatility in stock market prices was in excess of the volatility implied by EMH. West (1988) came to the same conclusion using a test for expected volatility which modeled dividends and stock prices in a more general way. West found that the variance in stock prices due to innovations (surprises) was four to 20 times its theoretical upper bound.

In the 1990s the discussion took a more psychological direction which meant more focus on how the human psychology was related to the prevailing asset prices on financial markets (Shiller 2003). Researchers started to study the behavior of investors in order to find answers to why market anomalies could exist.

In today's literature the field of behavioral finance can roughly be divided into two categories, namely: *Limits to Arbitrage* and *Psychology*. While the Limits to Arbitrage theory focus on market limitations the psychology part instead address individual behavior as explanations to why the financial markets are not always efficient.

4.2.1 Psychology

Investors are humans with limited cognitive ability and this will affect their judgment and decision-making. We will present some major theories used to describe how people behave under uncertainty which all have implications for the efficiency of financial markets.

4.2.1.1 Overconfidence

Studies that aim to describe how people make judgment under uncertainty have shown that people tend to be overconfident in their judgments. When experimental subjects are asked to assess probabilities to uncertain events they often overestimate their own ability. Alpert and Raiffa (1969) for example show that people tend to set confidence intervals that are too narrow. In a review by McClelland & Bolger (1994) they study a popular research method which involves a series of general knowledge questions given to subjects who are supposed to for each question choose one of two answering alternatives and assess a probability that he/she has chosen the correct alternative. When comparing the assessed probabilities with the actual correct answers the authors find that people are poorly calibrated in that they consistently assess too high subjective probabilities. However Juslin (1994) argues that the overconfidence phenomenon shown in these experiments (using general knowledge questions) is a result of the method used rather than a result of cognitive bias. In a paper by Svensson (1981) he asks subjects to assess their competence as drivers compared to a group of drivers. The author finds that for US (Swedish) respondents 50% regards themselves to be among the 20% (30%) most skilled drivers and 88% (77%) to be safer than the median driver.

Langer (1975) shows that people have a tendency to feel that they can control situations that are driven purely by chance. This form of overconfidence is called illusion of control and a good discussion of the phenomena can be found in Thompson (1999). In one of Langer's studies subjects were either given the opportunity to choose a lottery ticket by their own or got a ticket picked for them. In the next stage the subjects were given the opportunity to exchange their ticket against a ticket with more favorable odds. It was shown that subjects who had picked their own number did not exchange their ticket even if it would have increased their chances of winning. Thompson (1999) argues that people overestimate control and proposes that personal involvement as well as familiarity can explain this behavior.

Researchers in finance have observed the phenomena of overconfidence. Barber and Odean (2000, 2001) use primary data from a large discount brokerage firm to study investments of 78 000 households between 1991 and 1996. Barber and Odean (2000) find that poor performance can be traced to households that trade "too much". The authors argue that overconfident investors overestimate their private information which leads to excessive trading and that the total transaction costs associated with excessive trading will affect returns negatively. In another paper by Barber and Odean (2001) they use the same data to study if there are differences in overconfidence between men and women. The authors find evidence for that men trade 45 percent more than women and that men experience lower net returns compared to women.

Golec and Tamarkin (1995) use betting data from 3,473 NFL games to study if the documented favorite-longshot bias is explained by bettor's risk preferences or instead a result of bettors being overconfident. The method used to separate these two explanations is to study data consisting of information on simple bets, teaser bets as and parlay bets. The teaser bet is a combination of n adjusted simple bets. Borrowing the notation used by Golec and Tamarkin (1995) we define the adjusted spread as (S-T) where S is the spread (positive number for favorites and negative for underdogs) and T is the number of teaser points. It follows that a teaser bet composed of a number of games will be less risky than its corresponding parlay bet. By comparing expected return from a given teaser to the return from other bets that have similar or higher objective winning probabilities they find that teaser returns are smaller. If bettors were risk lovers the authors would expect the teaser bets with lower winning probabilities to yield higher returns. Instead they argue that their findings indicate that bettors are overconfident in the sense that they overestimate the value of teaser points.

4.2.1.2 Mental accounting

Thaler (1999a) defines mental accounting as "the set of cognitive operations used by individuals and households to organize, evaluate and keep track of financial activities". The author argues that mental accounting is important as it violates the economic principal of fungibility of money. The fact that people treat money differently depending on how it is categorized indicates that money is not perfectly substitutable.

An example of how mental accounting can be present in betting markets is studied by Thaler and Johnson (1990). The authors find support for the ”house money effect”, a tendency to be less loss averse when betting ”ahead” (playing with earlier winnings). The winnings from a previous period is in this setting separated from the overall wealth of the individual and is therefore in a sense expendable. Barbaris, Huang and Santos (1999) use the fact that prior outcomes tend to have an effect on people’s risk aversion to construct a model where an agent’s risk-aversion changes over time in relation to investment performance. Their model, which incorporates the impact of prior outcomes on risky choice, can explain the excess volatility, the equity premium as well as the predictability of stock returns seen on the market.

4.2.1.3 Representativeness

Kahneman and Tversky (1974) argue that people use a form of representativeness heuristic when making judgment under uncertainty. This representativeness heuristic can be observed when people are supposed to determine if an event A originates from a process B. The way people approach this kind of problem is to examine to what extent A is representative of B, that is how similar it is to B. The problem arises when people tend to neglect information of base rates and instead focus too much on the representativeness of an outcome or alternative.

To illustrate the fact that people tend to neglect base rates we use Kahneman and Tversky’s (1974) description of Linda:

“Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.”

When people are supposed to determine whether it is more likely that Linda is a bank teller (A) or that Linda is a bank teller and active in the feminist movement (B) most people tend to answer that alternative (B) is more likely. Alternative (B) can never be more probable than (A) because (B) is conditioned on (A) and the fact that people violate this fundamental principal of rationality is explained by the representativeness heuristic, namely that (B) is more representative than (A).

Another example linked to the representativeness heuristic is that people tend to believe that randomly drawn small samples are good representations of their parent population, regardless of the size of the sample. Rabin (2002) develops the model “law of small numbers” and show that people from a rational Bayesian perspective tend to believe too much in short sequences and nonexistent variation.

Thaler and Barbaris (2003) suggests that the representativeness heuristics holds a possible explanation to the volatility premium puzzle. They argue that when people observe a big increase in dividends they tend to be too quick to believe that the mean dividend growth rate has increased. Their resulting behavior raise prices relative the dividends and hence add to the volatility of returns. This illustrates how behavior in line with the “law of small number” can explain the excess volatility in P/D ratios seen on the market. The authors also propose that the representativeness heuristic can explain the observed volatility puzzle if people tend to extrapolate past returns too far into the future when they form expectations of future returns.

Nilsson and Andersson (2009) show that bettors tend to believe that the likelihood of a predicted outcome increases when it is integrated with outcomes which they consider highly likely to come true. Their findings indicate that bettors violate a fundamental principle of probability, namely the conjunction rule. The conjunction rule states that the probability of the conjunction P(A&B) cannot exceed the probability of its parts, P(A) or P(B). The authors explain the attractiveness of parlay bets with an existence of a conjunction fallacy among bettors. If bettors do not fully understand the implication of the reduced likelihood that a combination will occur the potential winning on a combined bet will look more attractive than by studying the combined matches separately. The conjunction fallacy observed by Nilsson and Andersson (2009) is often explained by the representativeness heuristic where the conjunction is viewed as more representative (see ex. of Linda above). However Nilsson (2008) argues that the representativeness heuristic plays a minor role when conjunction fallacies are committed. Instead this fallacy rest solely upon an inability of people to correctly combine probabilities.

4.2.1.4 Hot Hand

In an article by Gilovich, Vallone and Tversky (1985) they investigate a belief called "hot hand" which relates to sequential hits and misses in basketball. A belief in hot hand means that a bettor can have periods of significantly better performance compared to what is expected by the bettor's overall historical record. The authors carry out a survey which shows that both fans and professional basket players believe that the chances of hitting the next shot is dependent on the outcomes of the previous shot. The authors show, by studying a number of matches, that the belief in hot hand is just an illusion because the success of a shot attempt could not be explained by previous attempts. They also show that the frequency of streaks could be explained by a binominal model that includes a constant hit rate. The hot hand phenomena is related to the neglecting of sample size proposed by the representativeness heuristic.

Croson and Sundali (2005) also find evidence of the hot hand phenomenon when using videotapes from a casino to review the behavior of bettors playing roulette. By studying 18 hours of film the authors get a sample consisting of 139 unique bettors who together place a total of 24 131 bets. The authors first show that 80% of the 139 subjects quit playing after losing on a spin while 20% quit after winning on a spin and argue that this behavior is consistent with "hot hand" as people continue playing after a win because they are hot. The authors develop a model in which they suggest that the number of bets placed on a given spin is a function of the outcome of the previous spin. They show that the individuals studied place relatively more bets after they have won in the previous round and this tendency was significant on the 5% significance level.

4.3 Risk preferences of individuals

As an alternative to the traditional Expected Utility Theory, Kahneman and Tversky (1979) introduced the Prospect Theory which offers a contrasting view of how people make choices under risk. Although a full review of The Prospect Theory is outside the scope of this thesis we will give a short presentation of two important features that are relevant for our discussion.

According to the Expected Utility Theory an individual is assumed to value new prospects by integrating them together with the existing wealth and then comparing the utility of the different final-states while the Prospect Theory instead suggests that an individual values gains and losses from a fixed reference point. This means that a person can be risk-loving/-averse irrespective of the actual marginal utility of the money at stake in a risky prospect. In other words it is possible for a wealthy person to be risk-loving even when there are small amounts of money at stake, as the prospect is valued separately from the rest of the wealth.

The Expected Utility Theory suggests that people are capable of objectively comparing the probabilities of different outcomes, after which they choose the prospect with the highest expected utility. The Prospect Theory on the other hand proposes that people utilize a weighting function in which they over-weight small probabilities and under-weight moderate and high probabilities. People may therefore show a tendency of being risk-averse for certain probabilities, but risk-loving for others.

5. Research questions

The aim of this thesis is to investigate if individual bettors show any significant betting patterns during the studied period. In order to discuss the rationality behind any significant betting pattern found we must first know if returns are similar between different odds categories. While the first research question addresses market efficiency from a market perspective the other three research questions are instead more focused on individual behavior.

5.1 Research question 1

Do odds (adjusted for take-out ratio) reflect the objective winning probabilities?

Based on the Efficient Market Hypothesis we would expect different odds levels to yield similar returns, as one of the basic assumptions of an efficient market is that past returns do not have explanatory value for future returns. By comparing returns between different odds categories after the takeout ratio has been accounted for we can study if there are more and less profitable betting strategies.

5.2 Research question 2

Are choices in the current period affected by the success in previous periods?

Previous studies (see for example Thaler (1990) and Croson and Sundali (2005)) have shown that prior gains have a positive effect on people's risk-taking. We will study if bettors will take on more risk following good results, expressed as an increase in the exposure through the potential winnings in their bets and the number of games entered into. To answer this question we will run two different regressions for each bettor where we use prior success as an explanatory variable for number of bets entered into and potential winnings played to respectively. If a market is efficient then there will be no increased benefit from increasing your exposure in the next betting sequence, hence we consider being influenced by prior outcomes to be a sign of irrational behavior.

5.3 Research question 3

Do bettors show different preferences for different intervals of odds?

Given that the market is efficient, in the sense that all odds yield the same expected returns, we expect a bettor to bet equal amounts per implied probability independent of the size of the odds. A bettor with a given preferred level of exposure (expressed as a potential winnings on the bets entered into) will adjust his/her placed amount in relation to the odds chosen so that the potential winnings remain fairly constant over time. For a bettor who does not "fully" adjust the placed amount as the odds change we will observe higher potential winnings on games with higher odds. If however the opposite holds for some bettors then they will be observed having their highest potential winnings on bets with low odds. Choosing to have a greater exposure i.e. stronger preferences for certain intervals of odds can only be explained rationally if those intervals prove to have a better return than others.

5.4 Research question 4

Are bettor characteristics related to performance?

If odds adjusted for takeout reflect true probabilities of the outcomes we would expect bettors who combine more matches when constructing the odds to perform relatively worse, because the higher transaction costs associated with combining more matches would work to reduce the expected value of the bet. If however bettors were able to pick games to combine which had positive expected values we would instead expect the weighted average number of games to be positively correlated with performance, as combining bets would give the bettors better leverage on their placed amount.

Another characteristic that could explain performance is the extent to which a bettor alter the betted amount in relation to the odds (as expressed by the resulting coefficient from research question 3). The value of this coefficient would give an indication of a bettor's risk awareness. A bettor who is sensitive to changes in odds when considering the placed amount might be better at judging if a given odds is favorable or not.

6. The Data

The data employed in this thesis consist of randomly chosen bettor accounts from a major online European betting company. In this section we start by providing an explanation of the data and the information it entails. The descriptive statistics of the data set are summarized in Table 2 and Table 3.

6.1 Explaining the data

The dataset used in this thesis comes from Ladbrokes which is a British based major international online betting company. The original data set includes information from 1 000 randomly chosen bettors and their betting accounts. The data is structured around the last bets made by the bettors and range up to a maximum of the 500 latest bets. With the median number of bets being 498 this means that the dataset is quite extensive. The final number of bettors used in this study has been reduced from 1 000 to 536 bettors. This reduction is due to observed defects when comparing actual winnings with theoretical winnings.[7] Each bettor has a unique customer id and because all information is linked to this specific id we can easily track a specific bettor.

All bets relates to football games and on each game the bettor can choose to bet on three different outcomes; home win (1), draw (X) and away win (2). The bettor has the opportunity to combine matches and hence bet on a combination of results. For each bet placed by a bettor the following information is obtained:

Placed – The amount of money (£ **-** Pound sterling) placed on the bet. The minimum stake per bet placed is £ 0.1. We have no information of any maximum stake.

Bet time – The date and the time during the day (GMT) that the bet was placed.

The total odds – The odds to which the bet was placed.

Number of games – The total number of games included in the bet.

Winnings – The amount won on the bet.

Additional to the information relating to the bets we also have background information from each bettor:

Gender – The gender of the bettor.

[7] Theoretical winnings were constructed using the odds and the placed amount and thereafter compared to the actual winnings stated in the data.

Age – The age of the bettor.

Membership time – How many days the bettor has been registered at the betting company.

Average stake – The average bet placed since registration.

Number of bets placed – The total number of bets placed since registration.

We would also like to stress the uniqueness of our dataset. Even though there are many different papers that examine the betting market, there are only a few that can match the magnitude of our dataset. Most other datasets used are also limited as they are either composed of aggregate market data, which does not permit analysis of individual behavior, or composed of shorter series of individual choices, which limits tests of overall market efficiency.[8]

[8] Levitt (2004), however, used a similar dataset consisting of bets placed by individual bettors that entered into a contest in which they were supposed to pick five games per week against a point spread during the NFL season (17 weeks and 85 games). The author does however point out a number of shortcomings with this dataset, many which can be linked to the structure of the tournament. For example bettors did not receive direct monetary feedback because the payoff was determined by the cumulative number of successful bets. Also the fact that bettors had to choose a predetermined number of games per week made it hard to study preferences.

Table 2: Descriptive statistics of the entire sample across the 258 692 bets placed.

Sample information (N = 258 692 bets)	MAX	MIN	AVERAGE	MEDIAN
Placed (£)	7 000	0.1	9.25	2
Odds[9]	21	1	2.78	2.2
Number of games included in the bet	25	1	4.22	3

Table 3: Descriptive statistic of information relating to the 536 investigated bettors.

Player information (N = 536 players)	MAX	MIN	AVERAGE	MEDIAN
Number of bets	500	15	483	498
Number of days studied	300	4	167	172
Unique days	230	4	98	95
Performance[10]	466%	-100%	-21%	-18%

Background data (N = 536 players)	MAX	MIN	AVERAGE	MEDIAN
Membership time (days)	4 795	51	1 077	785
Number of bets	46 133	504	2 951	1 776
Stake (£)	485.66	0.10	9.00	2.98

Age	No. of Players
< 20	1
20-29	107
30-39	166
40-49	139
50-59	72
60-69	25
70-79	6
80-89	2
Unknown	18

Gender	No. of Players
Male	472
Female	37
Unknown	27

7. Method

In this section we will present the methods that are used in order to be able to answer the four research questions stated in section 5.

[9] We present information from the 77 000 single odds used in research question 1

[10] Performance is calculated using the ratio of sum of winnings over sum of placed minus one and describes return on the placed amount

7.1 Research question 1

Do odds (adjusted for take-out ratio) reflect the objective winning probabilities?

In order to investigate this question we will compare the actual number of winning outcomes from a range of odds to the number of winning outcomes that is implied by the odds after the takeout ratio has been added back. The method used by Snyder (1978) to calculate rate of return (RR) for different odds-categorizes will also be applied on our data. Snyder (1978) calculates RR using data from six different studies of horse racing. We will use the same notation as Snyder except for that we adjust for decimal odds instead of fractional odds:

$$RR = \frac{(W \times O) - N}{N} \tag{2}$$

W is the number of ex post correct outcomes, O is the decimal odds with the takeout added back and N is the number of odds in the odds-group. If the objective winning probabilities are equal to the odds after the takeout is added back we expect RR to be zero.

As we have no information of the different odds that a parlay bet is constructed of we will take single bet odds and use these for investigating this question. When all single odds are obtained we divide the sample into eleven odds-groups with equally many observations. In the study performed by Snyder (1978) he uses eight sub-groups, but also states that this number of groups is arbitrary. The average odds in each odds group, after takeout has been accounted for, is used to calculate RR for this group. As we do not have access to the betting outcomes (1, X and 2) for a given game we are therefore unable to calculate the takeout ratio. We will instead use a ratio of 7% for all the bets placed as this is a fair estimate of the prevailing ratio used by the betting companies.[11]

We do not include odds that are higher than 21 due to the small number of observations.[12] It should be noted that odds higher than 21 on home win, draw or away win are rare.

7.2 Research question 2

Are choices in the current period affected by the success in previous periods?

The method we develop in order to be able to study if prior outcomes affect risky choice has to take into account some of the limitations of our dataset. Our dataset contains information about all the bets placed by the bettors and whether or not these bets were successful, but we do not know when the actual games betted on are settled and potential winnings are paid out. The odds for a game are usually available at least a couple of days before the game is played which means that there will be many instances in our dataset where the bet is placed on a different date from when the result is

[11] For calculations on the used takeout ratio, see appendix 13.2.
[12] 372 observations are not enough to test if the returns are significantly different from zero at the 5% level.

realized. This problem is aggravated as there are also many bettors in our dataset who place several bets in a single day and often with less time between them then what is necessary for a game to be played, which makes it impossible for the outcome of one game to have an effect on the following bet. In order to mitigate this problem we decided to group all the bets made during a day together. To capture the effect prior outcomes have on the exposure during a day, we create the variable Potential Winnings (PW) by multiplying the placed amount with the odds for each bet. By summing the Number of Games entered into and the Potential Winnings on each day we get the following dependent variables:

$NB_{i,d} = number\ of\ bets\ during\ day\ d\ for\ player\ i$

$PW_{i,d} = placed\ amount\ multiplied\ by\ the\ odds\ for\ each\ bet\ during\ day\ d\ for\ player\ i$

The variables that are supposed to capture the effect of previous wins are called win-day streak (WDS) and are constructed in three steps. First we define a win-day as a day when the sum of winnings is greater than the sum of placed. Thereafter we sum win-days in a row to create the integer variable WDS. The variable is then lagged one, two and three days respectively in order to increase the chances of capturing the settlement of the bet. We believe that using a larger window than three days will not yield any large improvements in our estimation as the amount of factors that can cloud the effects of prior outcomes will increase with time.

Independent variables:

$WDS_{i,d-1} = the\ win\ day\ streak\ variable\ lagged\ one\ day$

$WDS_{i,d-2} = the\ win\ day\ streak\ variable\ lagged\ two\ days$

$WDS_{i,d-3} = the\ win\ day\ streak\ variable\ lagged\ three\ days$

Each regression will have a control variable in the form of the dependent variable lagged one day because yesterday’s behavior might explain today’s behavior. We also construct the variable Results which is lagged one day representing the absolute result from the previous day.

Control variables:

$DV_{i,d-1} = the\ dependent\ variable\ lagged\ one\ day$

$Results_{i,d-1} = the\ net\ result\ from\ the\ previous\ betting\ day$

Regressions using daily data for bettor i:

$$NB_{i,d} = \beta_0 + \beta_1 WDS_{i,d-1} + \beta_2 WDS_{i,d-2} + \beta_3 WDS_{i,d-3} + \beta_4 Results_{i,d-1} + \beta_5 DV_{i,d-1} + \mu_{i,d}$$

$$PW_{i,d} = \beta_0 + \beta_1 WDS_{i,d-1} + \beta_2 WDS_{i,d-2} + \beta_3 WDS_{i,d-3} + \beta_4 Results_{i,d-1} + \beta_5 DV_{i,d-1} + \mu_{i,d}$$

7.3 Research question 3

Do bettors show different preferences for different intervals of odds?

Every data point in our sample represents a certain choice made by a specific bettor at a point in time. The choice made by this bettor involves a placed amount, an odds and the number of games used to construct the bet. Even though we can observe the choice made by this bettor, we are unaware of the set of opportunities which the bettor did not choose, i.e. the odds available at the time.

We will therefore use a method which compares the amount that is placed by a bettor on different odds chosen over time in order to describe the bettor's preferences. If there is no range of odds that offers a higher than average return, as tested for in our first question, we would expect bettors to be indifferent between bets on different magnitudes of odds as long as the bets have the same potential winnings. Below we will present a model which is constructed to capture individual preferences for odds.

In order to study the degree of adjustment of the placed amount when betting to different odds over time we define k as the amount a bettor is willing to place when the odds goes to one. In the formula below, m is the level of adjustment of the placed amount depending on the odds.

$$placed = \frac{1}{odds^m} \times k \tag{3}$$

By taking the natural logarithm of this expression we obtain the following linear relationship:

$$ln(placed) = m \times \ln\left(\frac{1}{odds}\right) + \ln(k) \tag{4}$$

Given the fact that k is a constant the regression model becomes:

$$ln\left(placed_{i,t}\right) = \beta_0 + \beta_1 \ln\left(\frac{1}{odds_{i,t}}\right) \tag{5}$$

where

β_0 is the intercept of the regression and describes bettor stake i.e. the size of the amount that the bettor is willing to wager.

β_1 describes a bettor's willingness to adjust his/her betted amount. If (β_1 > 1) a bettor can be characterized as over-adjusting the betted amount when placing money on bets with greater odds (greater exposure on low odds). If (β_1 < 1) he/she can instead be characterized as under-adjusting the betted amount (greater exposure on bets with high odds).

We will use $ln(odds)_{i,t}$ as the independent variable and therefore have that:

$$ln(placed_{i,t}) = \beta_0 - \beta_1 \ln(odds_{i,t}) \tag{6}$$

We will control for the possibility that a bettor might be affected by the number of games that are included in the bet. We suspect that a bettor may suffer from the conjunction fallacy discussed earlier and we therefore choose to use number of games as a control variable in order to separate this effect.

$NG_{i,t} = number\ of\ games\ that\ the\ odds\ is\ composed\ of$

Regression using bet specific data for bettor i:

$ln(placed)_{i,t} = \beta_0 - \beta_1 ln(odds)_{i,t} + \beta_2 NG_{i,t} + \mu_{i,t}$

7.4 Research question 4

Can bettor characteristics explain performance?

To measure performance for a bettor (i) we sum the total amount won during the studied period and divide this by the total amount placed. We thereafter subtract by one to express this measure as return (in the form of winnings) on amount placed.

$$Performance_i = \frac{\sum Winnings_i}{\sum Placed_i} - 1 \tag{7}$$

Independent variables:

$\beta_{1,i}\ \ from\ regression\ used\ in\ research\ question\ 3$

$WANG_i = weighted\ average\ number\ of\ games\ that\ the\ bet\ is\ composed\ of$

Control variables:

$ND_i = number\ of\ days\ studied$

$UD_i = unique\ number\ of\ days\ studied$

$AGE_i = years$

$MT_i = membership\ time\ (days)$

$NBT_i = total\ number\ of\ bets\ placed\ since\ registration$

$SEX_i = dummy\ variable\ which\ takes\ 1\ for\ female\ and\ 0\ for\ male$

Cross sectional regression:

$$Performance_i = \propto_0 + \propto_1 \beta_{1,i} + \propto_2 WANG_i + \propto_3 ND_i + \propto_4 UD_i + \propto_5 AGE_i + \propto_6 MT_i + \propto_7 NBT_i + \propto_8 SEX_i + \mu_i$$

8. Empirical findings

8.1 Research question 1

Research question 1: Do odds (adjusted for take-out ratio) reflect the objective winning probabilities?

After having sorted our single odds bets into intervals of 7 000 observations we compared the number of successful bets in each interval to the number of successes implied by the mean odds of the interval. The results are presented below:

Table 4: Summary of Rate of Return for 11 different odds-intervals (N = 7 000 for each interval).

Odds (adjusted) interval	Implied probability	Average Implied probability	Objective probability	RR	Significance level	RR (not adjusted)
1.08 - 1.43	0.93 - 0.70	75.89%	79.80%	5.15%	***	-2.21%
1.43 - 1.61	0.70 - 0.62	65.41%	65.56%	0.22%		-6.80%
1.61 - 1.80	0.62 - 0.56	58.38%	58.76%	0.65%		-6.40%
1.80 - 1.97	0.56 - 0.51	52.72%	53.17%	0.85%		-6.21%
1.97 - 2.26	0.51 - 0.44	47.74%	47.23%	-1.06%		-7.99%
2.26 - 2.47	0.44 - 0.40	42.66%	43.41%	1.77%		-5.35%
2.47 - 2.83	0.40 - 0.35	37.58%	37.93%	0.93%		-6.13%
2.83 - 3.44	0.35 - 0.29	31.57%	29.86%	-5.42%	***	-12.04%
3.44 - 3.76	0.29 - 0.27	28.01%	27.34%	-2.38%		-9.21%
3.76 - 5.38	0.27 - 0.19	23.42%	20.39%	-12.97%	***	-19.07%
5.38 - 22.58	0.19 - 0.04	11.99%	11.76%	-1.94%		-8.80%

***Significantly different from zero at 1% level.

As can be seen in Table 4, most of the returns (8 out of 11) are not significantly different from zero. The only significant positive return is found on the lowest odds, while the two significant negative returns are found among the higher odds. These results suggests that odds adjusted for takeout are good estimates of actual winning probabilities. However we can interpret the small tendency of higher returns among relatively lower odds and lower returns among relatively higher odds as a sign of favorite-longshot bias.

8.2 Research question 2

Research question 2: Are choices in the current period affected by the success in previous periods?

To study the effect of prior outcomes on risky choice we have run, for each bettor, two different regressions where the dependent variable refers to either number of bets during a day (NB) or played amount multiplied by odds (PW). Table 5 and Table 6 report the result of those regressions for all bettors. In particular the tables show the frequencies of bettors with significant and non-significant coefficients. The coefficients were divided into groups depending on their sign and if they were significant at the 5% level.[13]

Table 5: The table shows the number, as well as the percentage, of bettors with coefficients that are positive/negative and significant/insignificant at the 5% level when using Number of Bets as the dependent variable.

$$NB_{i,d} = \beta_0 + \beta_1 WDS_{i,d-1} + \beta_2 WDS_{i,d-2} + \beta_3 WDS_{i,d-3} + \beta_4 Results_{i,d-1} + \beta_5 DV_{i,d-1} + \mu_{i,d}$$

Coefficient (β_i)	β_0		β_1		β_2		β_3		β_4		β_5	
Negative Significant	0	*0.0%*	15	*2.8%*	4	*0.7%*	3	*0.6%*	11	*2.1%*	14	*2.6%*
Negative Insignificant	0	*0.0%*	231	*43.1%*	248	*46.3%*	250	*46.6%*	215	*40.1%*	162	*30.2%*
Positive Insignificant	21	*3.9%*	252	*47.0%*	236	*44.0%*	236	*44.0%*	266	*49.6%*	237	*44.2%*
Positive Significant	514	*95.9%*	28	*5.2%*	38	*7.1%*	40	*7.5%*	42	*7.8%*	122	*22.8%*

Table 6: The table shows the number, as well as the percentage, of bettors with coefficients that are positive/negative and significant/insignificant at the 5% level when using Potential Winnings as the dependent variable.

$$PW_{i,d} = \beta_0 + \beta_1 WDS_{i,d-1} + \beta_2 WDS_{i,d-2} + \beta_3 WDS_{i,d-3} + \beta_4 Results_{i,d-1} + \beta_5 DV_{i,d-1} + \mu_{i,d}$$

Coefficient (βi)	β_0		β_1		β_2		β_3		β_4		β_5	
Negative Significant	0	*0.0%*	12	*2.2%*	3	*0.6%*	3	*0.6%*	10	*1.9%*	5	*0.9%*
Negative Insignificant	8	*1.5%*	294	*54.9%*	272	*50.7%*	300	*56.0%*	214	*39.9%*	233	*43.5%*
Positive Insignificant	121	*22.6%*	197	*36.8%*	221	*41.2%*	196	*36.6%*	274	*51.1%*	219	*40.9%*
Positive Significant	406	*75.7%*	23	*4.3%*	31	*5.8%*	29	*5.4%*	36	*6.7%*	78	*14.6%*

When studying the results presented in Table 5 and Table 6 we noticed that there were only a small number of bettors with significant coefficients. For Number of Bets we found that out of the coefficients for the lagged winnings variables only around 5.2-7.5% were significant and positive. An even smaller number of coefficients (0.6-2.9%) were negative and significant. The regressions for Potential Winnings (see Table 6) showed a weaker but similar pattern to the one seen in Number of Bets with the amount of positive significant coefficients in the range of 4.3-5.9% and the negative significant coefficients in the range of 0.6-2.3%.

Table 7: The table shows the number of players with one, two and three significant coefficients for the independent variables. The regression results on Number of Bets and Potential Winnings are presented separately and the number of bettors are divided into different columns depending on if they have positive or negative coefficients.

[13] We do not present the absolute value of the coefficients as these are dependent on bettor's stake and it would therefore be meaningless to present this data in an aggregate format.

Number of bets			Potential winnings		
Number of Significant WDS-coefficients	Positive	Negative	Number of Significant WDS-coefficients	Positive	Negative
1	95	22	1	79	17
2	4		2	2	1
3	1		3		
SUM	100	22	SUM	81	18

Even though none of the studied independent variables seemed to capture individual behavior by itself we could by investigating bettors which were associated with at least one significant coefficient show more distinct results. Table 7 shows that the percentage of bettors with at least one positive coefficient in the regression for Number of Games was 18.7 % and that almost none of the bettors display an effect from more than one lagged variable. The same results apply to the regression on Potential Winnings, in which 15.1% of the bettors had at least one significant coefficient and only 0.4% had more than one positive significant coefficient. Even though Table 7 shows that quite a few people seem to alter their behavior following a successful day we still feel that the results are a bit too ambiguous for us to conclude that previous wins have an effect on betting behavior.

8.3 Research question 3

Research question 3: Do bettors show different preferences for different intervals of odds?

To study preferences we have run a regression for each bettor where the amount placed is described by the odds of the bet. The resulting coefficient β_1 (which we refer to as the adjustment factor) will capture the extent to which a bettor adjust the betted amount in relation to the odds. The resulting coefficients are presented below in Table 8.

Table 8: The table shows the number, as well as the percentage, of bettors with coefficients that are positive/negative and significant/insignificant at the 5% level.

$$ln(placed)_{i,t} = \beta_0 + \beta_1 ln(odds)_{i,t} + \beta_2 NG_{i,t} + \mu_{i,t}$$

Coefficient (βi)	β_0		β_1		β_2	
Negative Significant	79	*14.7%*	12	*2.2%*	56	*10.4%*
Negative Nonsignificant	12	*2.2%*	11	*2.1%*	70	*13.1%*
Positive Nonsignificant	21	*3.9%*	24	*4.5%*	107	*20.0%*
Positive Significant	424	*79.1%*	487	*90.9%*	283	*52.8%*

Table 8 indicates that the adjustment factor (β_1) is positively significant from zero for almost our entire sample of bettors. Notable also is that the coefficient for the control variable number of games is also significant for a majority of bettors. We have used the information in the table above in order to construct a cross-tabulation (Table 9) which shows that most bettors have positive significant coefficients for both variables.

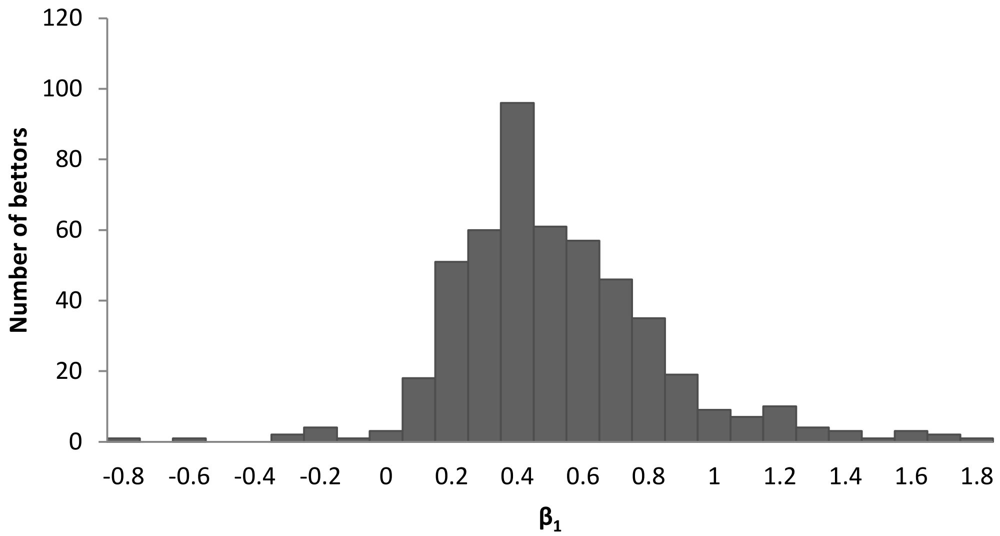
Table 9: The table shows the different combinations of positive significant, negative significant and insignificant coefficients for the independent variables ln(odds) and NG at the 5% level presented in cross-tabulation format.

$ln(placed)_{i,t} = \beta_0 + \beta_1 ln(odds)_{i,t} + \beta_2 NG_{i,t} + \mu_{i,t}$

		ln(Odds)		
		(β_1) Positive Significant	(β_1) Insignificant	(β_1) Negative Significant
Number	(β_2) Positive Significant	273	11	3
of	(β_2) Insignificant	159	15	3
Games	(β_2) Negative Significant	41	7	4

The distribution of bettors over different values of the adjustment factor (β_1) is shown in Figure 1 below. The graph shows that most bettors have adjustment factors in the range 0.2-0.8. Hence the majority of bettors under-adjust the betted amount when placing money on bets with different odds over time. A conclusion that can be drawn from these results is that bettors in general show preferences for bets with higher odds as they have higher exposure on higher odds.

Figure 1: The distribution of bettors over different values of the adjustment factor (β_1). $ln(placed)_{i,t} = \beta_0 + \beta_1 ln(odds)_{i,t} + \beta_2 NG_{i,t} + \mu_{i,t}$



8.4 Research question 4

Research question 4: Are bettor characteristics related to performance?

We studied bettors with an adjustment factor that was significantly different from zero at the 5% level, i.e. dropped observations where $p > 0.05$. For the control variables AGE and SEX we did not have information for all bettors and therefore excluded bettors without registered AGE and/or SEX. The sample was thereby reduced from 536 to 467 observations. Note that this is a cross sectional regression that was run using information from all individuals. The results are presented in Table 10 below.

Table 10: Regression output for below cross sectional regression.

$$Performance_i = \propto_0 + \propto_1 \beta_{1,i} + \propto_2 WANG_i + \propto_3 ND_i + \propto_4 UD_i + \propto_5 AGE_i + \propto_6 MT_i + \propto_7 NBT_i + \propto_8 SEX_i + \mu_i$$

Variable	Coefficient	t-statistics	Signifcance level	Adjusted R-squared	N
$\beta_{1,i}$	0.0821	4.19	***	0.34	467
$WANG_i$	-0.0528	-10.79	***		
ND_i	-0.0005	-2.75	***		
UD_i	0.0013	4.31	***		
AGE_i	0.0000	0.02			
MT_i	0.0000	0.04			
NBT_i	0.0000	-0.03			
SEX_i	0.0571	1.45			
_cons	-0.1170	-2.37	**		

***Significantly different from zero at 1% level.

** Significantly different from zero at 5% level.

Table 10 shows that both explanatory variables are significantly different from zero at the 1% level. We therefore conclude that the level of adjustment (adjustment factor) as well as the weighted average number of games used to construct the bets are related to performance. We also note that the two control variables that capture number of days played as well as unique days played are significant.

9. Discussion

In this section we will discuss the results from the previous section while keeping focus on the research questions stated in section 5. We will also discuss some implications and limitations of the models employed.

Research question 1: Do odds (adjusted for take-out ratio) reflect the objective winning probabilities?

By analyzing the results presented in Table 4 we saw that 8 out of 11 odds-intervals had returns not significantly different from zero at the 5% level. However we also noted that the only interval with positive returns significantly different from zero could be found in the interval with the lowest odds while the negative returns significantly different from zero were located among relatively high odds. This finding would give some support to the favorite-longshot bias which earlier studies have found using fixed-odds data from football games (see Cain 2000). Even though we find some signs of favorite-longshot bias in our data we feel comfortable saying that odds adjusted for the takeout ratio are good measures of objective winning probabilities.

By analyzing our results in relation to the two conditions for market efficiency put forward by Thaler and Ziemba (1988) we can see that none of the chosen odds-intervals (studying actual odds with takeout) have positive returns. This would imply that condition 1 (weak form) of market efficiency is satisfied. However by studying average odds we can never be sure that there are no specific bets with positive expected values. For condition 2 to hold (strong form) we would expect all bets to have an expected value of (1-t). The fact that three of our odds-intervals (adjusted for takeout) have returns that are significantly different from zero at the 5% level indicates that condition 2 cannot be fulfilled.

What should be considered when analyzing our results from an efficient market perspective is that we only include bets that bettors in our sample have actively chosen to bet on. We therefore do not include all available odds in each period which might have some implications on our results. If our bettors are significantly better (worse) than the average bettor at choosing odds we would expect our data to be biased and include relatively more (less) valuable odds than the parent population of odds offered.

The method we use to separate the total number of single game bets from the data cannot guarantee that there are no duplicates, i.e. that we have not included the same game more than once. The great number of games to choose from in each period together with the extensive time window that our data is obtained from should work to reduce this problem.

Research question 2: Are choices in the current period affected by the success in previous periods?

Looking at the output from the regressions on Number of Games and Potential Winning we found that very few bettors experienced a significant effect from the lagged Win Day Streak variables. By instead looking at the number of bettors who had a significant coefficient for at least one of the three lagged variables we could, however, see that a larger proportion of the bettors were affected by previous wins when placing bets in the following days. 100 (18.7%) bettors showed a tendency of placing a greater number of bets after experiencing wins and 81 (15.1%) showed tendencies of betting to a greater potential winning.

One explanation for why the bettors have significant coefficients on different lags might be that they have a tendency to bet on games a different number of days in advance. This would however require that the bettors consequently choose to bet a specific number of days prior to the games which we deem as fairly unlikely. It could also be the case that the mental effect from a win does not last very long and that this is the reason why a significant one day lag is not followed by a significant coefficient for a two day lag.

The fact that we cannot see a clearer relationship between prior outcomes and choices in the current period raise some questions concerning the behavioral theories linked to hot hand and "house money”-effect, namely if representativeness and mental accounting can be used to explain the behavior of bettors acting on a fixed-odds betting market.

Croson and Sundali (2005) found a clear relationship between the number of bets placed and the outcome in a previous betting round supporting the view of “hot hand”. Even though we can see a small tendency by bettors to enter into more games after a prior success we do not consider the number of bettors affected to be large enough to support Croson and Sundali’s results. However as feedback from choices made on a betting market is not as direct as feedback from playing roulette at a casino we must be somewhat careful when drawing conclusions relating to the hot hand phenomena.

Neither did we find any clear results from studying changes on our measure of exposure, Potential Winnings. In his study, Thaler (1990) found support for increased risk taking among the studied subjects after they had experienced prior gains. If our bettors would act in accordance with the findings by Thaler (1990) we would expect Potential Winnings on a betting day to increase following success in a previous betting day, something for which we find only weak support.

In a more general conclusion we consider these results to be more in line with an efficient market than they imply the existence of psychological biases, as described in the behavioral finance literature. As only few bettors show signs of being affected by prior outcomes when placing their next bet we speculate that the noise from these bettors would not be sufficient to induce a significant effect on prices.

What must be considered when analyzing our results is the fact that we do not have information relating to when winnings are paid out. The method used to handle this problem, where we use daily data instead of bet-specific data and lag the variable one, two and three days to capture the effect, is associated with much uncertainty. Because we use daily data we cannot capture behavior which is linked to a specific bet. If for example the studied bettor will change his behavior intra-daily and this change has a small effect on the overall behavior during the day we will not capture this behavior with our model.

Research question 3: Do bettors show different preferences for different intervals of odds?

Table 8 indicates that a majority of bettors have an adjustment factor (β_1) that is positive. The logic behind this tendency is clear, namely that bettors will bet less when the odds is greater. What is interesting is instead to look at the distribution of bettors with significant adjustment factors (Figure 1). Most bettors have an adjustment factor in the range between 0.2 and 0.8 suggesting that they are relatively more exposed to bets with greater odds. Another way of explaining this is that these bettors, when betting to different odds over time, will constantly choose to bet more per implied probability (be more exposed) when betting on higher odds.

We have shown earlier that the implied probabilities given by the odds are good approximations of objective winning probabilities why we expect a rational individual to be indifferent between different odds. The finding that most bettors consequently tend to be relatively more exposed when the odds of the bet is high compared to when it is low might suggest that a bettor's perceived value of an odds can differ from the objective value depending on the size of the odds. Higher odds would in this case be more attractive not because they have higher expected values, but instead it is the odds itself that attract a bettor to be more exposed. The observed preferences for higher odds could explain why we find a tendency towards a favorite-longshot bias in the data as this bias might enable bookmakers to apply a higher takeout ratio on higher odds than they do on lower odds.

The weight function used in Prospect Theory (Kahneman and Tversky (1979)) suggests that people when faced with a risky prospect generally tend to over-weight small probabilities and under-weight moderate and high probabilities. If individuals have a tendency to over-weight small probabilities this could work as an explanation to why bettors choose to be more exposed when the odds is higher i.e. when the implied probabilities are lower.

Even though our results can be explained by the weighting function used in the Prospect Theory we must also consider other less academically satisfactory explanations. Thaler and Ziemba (1988) propose that bettors might experience higher levels of utility by just holding a bet on a longshot. Also picking the right longshot is associated with more bragging rights than simply picking a favorite. However the explanations provided are more linked to which type of odds (high or low) a bettor choose to pick over time instead of explaining why bettors do not adjust the amount placed when betting to different odds over time. We suggest an alternative explanation which is linked to mental accounting (see Thaler 1990), namely that playing budgets limits the amount placed but not the odds betted to. With budget constraints but no constraints on the odds a bettor has the opportunity to reach high potential winnings only by betting at high odds. Playing budgets will therefore limit the possibility to reach high potential winnings on low odds.

The results in Table 8 show that the control variable for number of games is positive and significantly different from zero for a majority of bettors. The results indicate that the number of games that are used to construct a bet explain its attractiveness. This tendency would mean that when bettors are faced with the choice of two identical bets, where one bet involves, for example, three matches and the other involves five matches, we expect most bettors to place more money on the latter option.

The findings may also in part be explained by the possibility that bettors suffer from a conjunction fallacy when combining matches (see Nilsson and Andersson (2010)). If bettors do not fully take into account the decreased winning probabilities when combining matches we would expect a bet consisting of more matches to look more attractive. Another possible explanation using the behavioral literature could be that bettors are overconfident as a result of an increase in their personal involvement. Personal involvement has been proposed by Thompson (1999) as a possible explanation to the illusion of control phenomena first discussed in Langer (1975). Combining more matches may be associated with higher levels of personal involvement resulting in higher amounts placed.

Research question 4: Are bettor characteristics related to performance?

The regression output presented in Table 10 shows a clear negative relationship between the weighted average number of games used to construct the bets and performance which indicates that bettors achieve worse returns by combining more matches. Bettors who combine bets with fewer matches perform relatively better. The findings give some support to the first condition of market efficiency (Thaler and Ziemba (1988)) namely that no odds should have positive returns. If bettors were able to combine bets of odds with positive expected values they could create combined bets with even greater expected values resulting in better performance.

The coefficient for the adjustment factor is positive and significantly different from zero on a 5% significance level indicating that the level of sensitivity for the placed amount in relation to the odds can explain performance. This could imply that a bettor who is more willing to alter the betted amount when betting to different odds over time is more capable of objectively judging if an odds is attractive or not. A necessary condition for this bettor characteristic to relate to performance is that there exists more and less favorable odds on the market, something which would challenge the second condition of market efficiency suggested by Thaler and Ziemba (1988), namely that all odds should have the same expected value. As we show that the adjustment factor for placed amount in relation to odds can explain performance we thereby also challenge this condition of market efficiency.

Two of the control variables were significant at the 5% level, namely the number of days from the first bet to the last bet (ND) as well as the number of unique days (UD) both calculated using data from the studied period. A possible explanation for these results could be that more successful bettors will search the market for more valuable odds and therefore may be more selective when choosing which games to enter into. With the number of preferable games (i.e. games with better than average return) per day being limited the bettor will only pick a small number of games to play. It might also be the case that a more successful bettor will be more disciplined and have enough time to play more days of the week. A less successful bettor might enter the market less frequently and therefore be less updated on the market.

10. Concluding remarks

In this thesis we formulated four research questions in order to study individual behavior of bettors acting on a fixed-odds betting market. While the first research question addressed market efficiency directly by studying returns from different odds-categories the other three research questions focused on individual behavior. By studying the behavior of participants on the market we were thereby able to address market efficiency indirectly.

When studying returns in our first research question we found that odds relatively well reflect objective probabilities after takeout has been accounted for. This suggests that the online betting market is efficient in the sense that past outcomes from different odds intervals cannot be used to construct future profitable strategies. This finding also proved to be very useful when determining whether or not bettors were motivated by a rational reasoning when placing their bets. Although we did show that no interval of odds produced a positive return when accounting for the takeout ratio, we could observe a slight favorite-longshot bias which is in violation of a strong form of market efficiency.

When examining individual betting behavior we found that only a small number of bettors showed tendencies of altering their behavior after experiencing success in previous periods. This result may however have been the result of certain harsh but necessary assumptions in our model.

A large number of bettors did show a significant tendency to place a relatively greater amount on bets with greater odds compared to bets with lower odds and also a preference for placing greater amount of money even though the odds of the bets were identical. The level of adjustment when betting at different odds over time for a bettor (captured by the adjustment factor) was later used as an input variable together with a variable for the weighted average number of games and could explain differences in performance between bettors.

Under the efficient market hypothesis it is believed that the marginal investor is rational and in a position to exploit any mispricing that occurs on the market, but if the number of irrational investors is large enough then this does not have to hold (see Thaler 1999b). For our part it is hard to determine if the number of bettors who act irrational, in that factors which should not matter for the perceived value of the betting opportunity do have an effect (prior outcomes and odds), is large enough to explain the small mispricing that we observe.

11. Suggestions for further research

We have throughout this thesis argued that individual information from bettors who act on a betting market offers a good opportunity to study economic behavior under risk. Our data set offers valuable information relating to what choices a bettor makes over time but with additional information some analysis could have been more precise..

We suggest that further research projects look for data that reveals information about the development of individual bettor's balance of account over time, including information of deposits and withdrawals. Also information relating to when the games betted on are settled and winnings are paid out would be valuable. Our analysis of market efficiency could have been more rigorous if we had information of the entire population of odds when each choice was made.

What would be interesting to study is if the willingness to "gamble"/risk a larger portion of the bankroll could be explained by how the bankroll has changed over time. By having balance of account information together with when winnings are paid out research projects would also be in a better position to separate any "house money"-effects from "hot hand"- effects. It would be interesting to see if big winnings change the behavior more/less than streaks of good results.

The time between when a bet is placed and winnings are paid out could be used to see if "early" odds are more/less calibrated than odds quoted just before the game starts. It would also be interesting to test for market efficiency by analyzing how key news affect the odds. One method that could be considered when analyzing market efficiency is to study how fast and to what extent odds change when important information i.e. injuries/illness of key players reach the market.

In this study we have mainly focused on the behavior of bettors and the implications this may have on their performance but one can also choose to further this analysis in order to discuss implications for odds setters and online betting companies.

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12.2 Non Academic, electronic and other resources

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Unibet, 2010, 10 Oct. and 5 Nov. 2010 <http://www.unibet.com>

Bet365, 2010, 5 Nov. 2010 <http://www.bet365.com>

Betway, 2010, 5 Nov. 2010 <http://www.betway.com>

13. Appendicies

13.1 Calculating the takeout ratio

To calculate the takeout ratio of the odds we use the same method as was used in Andersson (2008) when calculating implied probabilities (similar to Forrester et al. (2005)).

First the decimal odds for home team win (h), draw (d) and away team win (a) are transformed to p(h) = 1/h, p(d) = 1/d and p(a) = 1/a. Given the assumption that the takeout ratio (t) is uniformly distributed over all odds we have that t = [(1/h) + (1/d) + (1/a) - 1] / [(1/h) + (1/d) + (1/a)].

13.2 Takeout ratio for different internet bookmakers

	Bolton	-	Tottenham	Bolton	-	Tottenham	Takeout Ratio
Unibet	3.00	3.25	2.30	33.33%	30.77%	43.48%	7.05%
Bet365	3.00	3.30	2.40	33.33%	30.30%	41.67%	5.04%
Betway	2.90	3.20	2.40	34.48%	31.25%	41.67%	6.89%
	Birmingham	**-**	**West Ham**	**Birmingham**	**-**	**West Ham**	
Unibet	1.95	3.25	3.90	51.28%	30.77%	25.64%	7.14%
Bet365	1.90	3.40	4.20	52.63%	29.41%	23.81%	5.53%
Betway	1.95	3.30	3.90	51.28%	30.30%	25.64%	6.74%
	Blackburn	**-**	**Wigan Athletic**	**Blackburn**	**-**	**Wigan Athletic**	
Unibet	1.80	3.40	4.40	55.56%	29.41%	22.73%	7.14%
Bet365	1.80	3.60	4.50	55.56%	27.78%	22.22%	5.26%
Betway	1.75	3.45	4.75	57.14%	28.99%	21.05%	6.70%
	Blackpool	**-**	**Everton**	**Blackpool**	**-**	**Everton**	
Unibet	4.40	3.40	1.80	22.73%	29.41%	55.56%	7.14%
Bet365	4.50	3.60	1.80	22.22%	27.78%	55.56%	5.26%
Betway	4.75	3.45	1.75	21.05%	28.99%	57.14%	6.70%
	Fulham	**-**	**Aston Villa**	**Fulham**	**-**	**Aston Villa**	
Unibet	2.30	3.25	3.00	43.48%	30.77%	33.33%	7.05%
Bet365	2.30	3.25	3.25	43.48%	30.77%	30.77%	4.78%
Betway	2.25	3.25	3.10	44.44%	30.77%	32.26%	6.95%
	Manchester United	**-**	**Wolverhampton**	**Manchester United**	**-**	**Wolverhampton**	
Unibet	1.22	5.65	13.00	81.97%	17.70%	7.69%	6.85%
Bet365	1.22	6.00	15.00	81.97%	16.67%	6.67%	5.03%
Betway	1.22	5.75	15.00	81.97%	17.39%	6.67%	5.68%
	Sunderland	**-**	**Stoke City**	**Sunderland**	**-**	**Stoke City**	
Unibet	2.15	3.25	3.30	46.51%	30.77%	30.30%	7.05%
Bet365	2.10	3.30	3.60	47.62%	30.30%	27.78%	5.39%
Betway	2.05	3.25	3.60	48.78%	30.77%	27.78%	6.83%
	Arsenal	**-**	**Newcastle**	**Arsenal**	**-**	**Newcastle**	
Unibet	1.25	5.50	11.00	80.00%	18.18%	9.09%	6.78%
Bet365	1.25	5.75	13.00	80.00%	17.39%	7.69%	4.84%
Betway	1.25	5.25	12.00	80.00%	19.05%	8.33%	6.87%
	West Bromwich	**-**	**Manchester City**	**West Bromwich**	**-**	**Manchester City**	
Unibet	3.60	3.25	2.05	27.78%	30.77%	48.78%	6.83%
Bet365	3.75	3.20	2.10	26.67%	31.25%	47.62%	5.25%
Betway	3.60	3.25	2.05	27.78%	30.77%	48.78%	6.83%
	Liverpool	**-**	**Chelsea**	**Liverpool**	**-**	**Chelsea**	
Unibet	3.75	3.25	2.00	26.67%	30.77%	50.00%	6.92%
Bet365	4.00	3.30	2.00	25.00%	30.30%	50.00%	5.04%
Betway	3.60	3.25	2.05	27.78%	30.77%	48.78%	6.83%
					Average Takeout Ratio		6.280%

13.3 Data description

Below we present selections of the information that could be obtained from each player.

Placed amount

Cust. ID	1	2	3	4	5	6	7	8	9	10
Player 1	5.00	5.00	20.00	5.00	20.00	10.00	15.00	10.00	20.00	15.00
Player 2	5.00	5.00	5.00	12.00	40.00	2.50	40.00	4.00	10.00	1.00
Player 3	1.75	2.00	1.50	1.50	2.00	0.70	2.00	2.40	0.50	2.05
Player 4	6.00	4.00	3.00	4.00	2.00	6.00	2.00	6.00	2.00	7.00
Player 5	100.00	10.00	100.00	20.00	100.00	500.00	100.00	200.00	25.00	100.00
Player 6	5.00	5.00	5.00	5.00	4.00	5.00	2.07	4.00	4.00	14.00
Player 7	5.00	10.00	8.60	10.00	5.00	3.00	10.00	5.00	10.00	10.00
Player 8	37.14	12.50	10.00	15.00	50.00	45.00	22.00	50.00	20.00	20.07
Player 9	1.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Player 10	10.00	24.30	20.00	30.00	44.00	20.00	10.00	100.00	5.00	5.00
Player 11	5.00	4.00	10.00	3.00	10.00	5.00	5.00	50.00	10.00	10.00
Player 12	5.00	30.00	10.00	10.00	10.00	10.00	5.00	5.00	5.00	5.00
Player 13	5.00	5.00	20.00	5.00	20.00	5.00	20.00	5.00	5.00	5.00
Player 14	5.00	5.00	5.00	5.00	5.00	5.00	2.00	5.00	5.00	3.57
Player 15	1.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	20.00	5.00
Player 16	1.50	2.00	5.00	5.00	5.00	5.00	5.08	5.20	5.00	5.00
Player 17	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
Player 18	10.00	22.57	7.43	10.00	20.00	25.00	10.00	10.00	10.00	20.00
Player 19	10.00	0.54	10.00	1.00	2.00	1.00	1.00	1.00	10.00	12.00
Player 20	0.60	0.60	0.60	0.60	0.50	0.67	0.40	0.14	0.14	0.40
Player 21	0.40	2.07	2.00	2.00	2.00	2.00	2.00	2.00	5.00	5.00
Player 22	1.20	1.20	2.25	1.40	0.60	1.41	0.59	2.50	12.00	25.00
Player 23	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	2.00
Player 24	5.00	10.00	10.00	5.00	10.00	5.00	12.50	20.00	20.00	14.52
Player 25	25.00	75.19	100.00	800.00	25.00	25.00	25.00	100.00	25.00	100.00

Total odds

Cust. ID	1	2	3	4	5	6	7	8	9	10
Player 1	110.80	23.03	7.92	67.59	3.20	18.56	6.42	14.47	7.31	9.79
Player 2	3.10	2.63	3.30	2.25	1.91	4.01	1.62	2.75	1.57	5.18
Player 3	6.70	36.31	17.07	19.04	38.70	77.40	24.64	10.67	441.31	14.85
Player 4	2.10	2.20	3.50	2.75	2.80	1.73	6.00	2.10	4.00	2.00
Player 5	6.80	238.76	7.60	44.35	4.32	2.02	2.73	1.79	13.50	5.65
Player 6	4.20	3.24	4.18	2.40	2.56	2.75	2.30	4.21	4.86	1.57
Player 7	167.85	14.95	8.82	10.00	63.15	116.31	4.31	98.83	8.71	5.46
Player 8	2.90	2.56	5.28	3.27	1.40	1.44	1.73	1.40	1.33	1.57
Player 9	1.20	2.10	1.57	3.30	3.20	1.25	2.25	2.25	1.62	1.80
Player 10	5.00	2.38	2.10	1.67	1.73	2.63	14.77	3.75	3.20	3.30
Player 11	3.50	4.20	1.83	5.50	1.62	2.38	3.00	1.80	2.70	2.63
Player 12	5.00	2.38	2.38	2.60	1.83	2.25	5.71	4.14	2.80	2.50
Player 13	12.00	5.50	1.60	1.83	1.73	1.88	1.67	3.51	1.13	2.35
Player 14	19.67	22.26	20.43	23.53	23.97	25.63	59.98	17.01	20.32	37.39
Player 15	9.00	4.50	4.00	4.00	3.50	3.50	4.20	3.50	5.25	12.22
Player 16	1.33	1.20	1.14	1.30	1.25	1.36	1.29	1.22	1.25	1.50
Player 17	3.50	3.30	3.50	3.25	3.40	3.30	3.30	3.40	3.40	3.40
Player 18	2.95	5.02	3.75	4.43	4.78	5.00	12.09	4.09	13.19	3.59
Player 19	1.20	67.16	3.23	61.33	34.61	31.81	14.49	245.57	1.18	1.17
Player 20	1.44	1.62	3.60	1.10	10.81	4.33	4.34	2.43	8.29	10.86
Player 21	386.40	28.93	20.48	23.21	8.35	10.05	30.10	12.38	38.93	8.29
Player 22	1.03	1.03	1.36	1.67	3.60	1.67	3.60	1.01	1.01	1.01
Player 23	3.50	5.50	3.25	5.00	3.00	2.20	4.33	3.00	6 235 125.50	152.07
Player 24	17.41	9.63	13.08	41.33	4.43	9.34	2.22	2.40	2.81	8.27
Player 25	27.05	7.86	7.65	1.44	21.99	24.46	37.84	7.64	18.38	10.57

Winnings

cust_id	1	2	3	4	5	6	7	8	9	10
Player 1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	146.67	0.00
Player 2	15.50	0.00	16.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Player 3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	25.60	0.00	0.00
Player 4	12.60	0.00	0.00	0.00	5.58	10.36	0.00	0.00	0.00	0.00
Player 5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	359.18	0.00	0.00
Player 6	0.00	0.00	0.00	0.00	10.27	0.00	0.00	0.00	0.00	22.00
Player 7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Player 8	0.00	0.00	0.00	0.00	0.00	65.00	0.00	0.00	26.67	31.54
Player 9	1.80	2.10	0.00	3.30	0.00	1.25	0.00	2.25	0.00	1.80
Player 10	50.00	0.00	42.00	0.00	0.00	0.00	0.00	0.00	16.00	0.00
Player 11	0.00	0.00	18.33	0.00	16.15	0.00	0.00	90.00	27.00	0.00
Player 12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	14.00	0.00
Player 13	0.00	27.50	32.00	0.00	34.55	0.00	0.00	0.00	5.63	0.00
Player 14	0.00	111.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Player 15	0.00	0.00	0.00	0.00	7.00	0.00	0.00	0.00	0.00	0.00
Player 16	2.00	2.40	5.71	0.00	6.25	6.82	6.53	0.00	6.25	0.00
Player 17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.70	1.70	0.00
Player 18	0.00	0.00	0.00	0.00	96.38	0.00	0.00	0.00	0.00	0.00
Player 19	12.00	0.00	32.30	0.00	0.00	0.00	0.00	0.00	11.82	14.00
Player 20	0.87	0.00	2.16	0.66	0.00	2.90	1.73	0.34	0.00	0.00
Player 21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	41.42
Player 22	1.24	1.24	0.00	2.33	0.00	2.35	0.00	2.53	12.12	25.25
Player 23	0.00	5.50	3.25	0.00	0.00	2.20	0.00	3.00	0.00	0.00
Player 24	87.80	0.00	0.00	0.00	0.00	0.00	0.00	48.19	56.33	0.00
Player 25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	763.64	460.64	1 058.40

	Bet time									
Cust. ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Player 1	2009-09-05 14:39	2009-09-05 14:42	2009-09-05 17:25	2009-09-05 18:31	2009-09-05 20:11	2009-09-06 14:23	2009-09-09 16:20	2009-09-09 16:21	2009-09-09 16:22	2009-09-09 21:57
Player 2	2009-10-01 20:11	2009-10-02 23:47	2009-10-03 11:12	2009-10-03 13:09	2009-10-03 14:44	2009-10-03 14:44	2009-10-03 17:58	2009-10-04 11:16	2009-10-04 14:56	2009-10-04 14:56
Player 3	2009-10-20 19:30	2009-10-20 22:14	2009-10-20 22:14	2009-10-20 22:15	2009-10-21 15:07	2009-10-21 19:11	2009-10-21 21:46	2009-10-22 17:17	2009-10-22 17:20	2009-10-22 19:59
Player 4	2009-10-04 16:03	2009-10-04 16:03	2009-10-04 20:49	2009-10-05 18:39	2009-10-06 18:27	2009-10-06 18:30	2009-10-10 10:49	2009-10-17 14:41	2009-10-17 15:35	2009-10-17 17:13
Player 5	2009-08-26 10:21	2009-08-26 10:25	2009-08-26 18:16	2009-08-26 18:17	2009-08-26 18:18	2009-08-26 19:44	2009-08-28 14:40	2009-08-29 07:56	2009-08-29 17:07	2009-08-29 17:09
Player 6	2009-12-05 14:47	2009-12-05 14:47	2009-12-05 14:48	2009-12-05 14:48	2009-12-05 14:58	2009-12-05 14:59	2009-12-05 17:09	2009-12-05 20:22	2009-12-05 20:23	2009-12-05 20:58
Player 7	2009-11-29 13:24	2009-11-29 15:45	2009-11-29 18:32	2009-11-29 18:35	2009-11-30 18:38	2009-12-01 12:37	2009-12-02 10:35	2009-12-03 15:06	2009-12-03 17:20	2009-12-03 19:21
Player 8	2009-08-25 16:38	2009-08-26 14:48	2009-08-26 14:49	2009-08-27 10:46	2009-08-27 17:21	2009-08-27 19:56	2009-08-28 08:33	2009-08-28 08:33	2009-08-28 08:35	2009-08-29 10:12
Player 9	2009-10-04 10:31	2009-10-04 10:32	2009-10-04 10:32	2009-10-04 10:33	2009-10-04 10:33	2009-10-04 10:34	2009-10-04 10:34	2009-10-10 13:56	2009-10-10 13:58	2009-10-10 13:59
Player 10	2009-10-17 11:45	2009-10-17 15:40	2009-10-17 19:30	2009-10-17 20:34	2009-10-18 15:26	2009-10-18 19:51	2009-10-20 18:08	2009-10-21 20:04	2009-10-22 16:22	2009-10-22 16:22
Player 11	2010-01-03 11:12	2010-01-03 11:12	2010-01-03 11:12	2010-01-03 11:12	2010-01-03 11:12	2010-01-03 11:32	2010-01-03 11:32	2010-01-03 17:08	2010-01-05 19:05	2010-01-05 19:05
Player 12	2009-10-03 20:57	2009-10-04 19:59	2009-10-05 19:04	2009-10-05 19:04	2009-10-06 18:50	2009-10-06 19:30	2009-10-06 19:30	2009-10-07 19:51	2009-10-07 19:51	2009-10-07 19:51
Player 13	2009-09-12 09:39	2009-09-12 09:39	2009-09-13 09:43	2009-09-13 09:44	2009-09-13 20:03	2009-09-13 20:03	2009-09-14 22:19	2009-09-14 22:20	2009-09-15 22:17	2009-09-15 22:23
Player 14	2009-10-24 09:44	2009-10-24 09:45	2009-10-24 09:46	2009-10-24 09:47	2009-10-24 09:47	2009-10-24 09:48	2009-10-24 11:23	2009-10-24 11:23	2009-10-24 11:27	2009-10-24 17:46
Player 15	2009-12-01 19:43	2009-12-04 20:45	2009-12-04 20:45	2009-12-04 20:45	2009-12-04 20:45	2009-12-04 20:45	2009-12-04 20:45	2009-12-04 20:45	2009-12-12 08:15	2009-12-12 08:15
Player 16	2009-11-25 21:52	2009-11-26 21:32	2009-11-27 21:32	2009-11-28 14:00	2009-11-28 14:01	2009-11-28 14:02	2009-11-28 17:02	2009-11-28 17:19	2009-11-28 17:20	2009-11-28 17:21
Player 17	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51	2009-09-19 11:51
Player 18	2009-08-23 16:01	2009-08-23 18:05	2009-08-24 17:55	2009-08-24 18:21	2009-08-24 20:35	2009-08-24 20:55	2009-08-25 19:21	2009-08-27 18:03	2009-08-28 21:23	2009-08-29 09:48
Player 19	2009-10-03 16:46	2009-10-03 16:56	2009-10-03 19:51	2009-10-03 23:44	2009-10-03 23:45	2009-10-06 15:35	2009-10-06 15:37	2009-10-06 15:38	2009-10-06 17:17	2009-10-06 20:45
Player 20	2009-07-25 18:00	2009-07-25 18:00	2009-07-25 18:00	2009-07-25 18:00	2009-07-26 09:15	2009-07-29 18:35	2009-07-30 07:50	2009-07-31 09:13	2009-07-31 15:47	2009-08-01 15:55
Player 21	2009-09-16 17:47	2009-09-16 22:09	2009-09-17 17:32	2009-09-17 17:33	2009-09-17 17:35	2009-09-17 17:36	2009-09-17 17:38	2009-09-17 17:39	2009-09-17 17:42	2009-09-17 23:00
Player 22	2009-12-28 16:45	2009-12-28 16:45	2009-12-28 17:12	2009-12-28 19:45	2009-12-28 19:45	2009-12-28 19:46	2009-12-28 19:46	2009-12-28 21:16	2009-12-28 21:17	2009-12-28 21:19
Player 23	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:10	2010-01-31 12:14
Player 24	2009-10-12 20:20	2009-10-12 21:09	2009-10-12 21:14	2009-10-13 08:45	2009-10-13 08:46	2009-10-13 08:47	2009-10-13 17:47	2009-10-13 18:09	2009-10-13 21:00	2009-10-14 12:22
Player 25	2009-12-05 00:50	2009-12-06 11:43	2009-12-06 11:46	2009-12-06 21:15	2009-12-08 00:39	2009-12-08 00:42	2009-12-08 00:45	2009-12-09 01:18	2009-12-09 01:30	2009-12-09 01:40

Number of games

Cust. ID	1	2	3	4	5	6	7	8	9	10
Player 1	8	9	3	11	1	4	5	3	5	5
Player 2	1	1	1	1	1	2	1	1	1	2
Player 3	4	4	3	3	3	3	3	4	5	3
Player 4	1	1	1	1	2	1	1	1	1	1
Player 5	6	17	5	10	5	2	3	2	5	7
Player 6	2	2	2	2	2	2	2	2	2	1
Player 7	9	4	3	2	5	7	3	10	3	3
Player 8	3	4	4	4	1	1	1	1	1	1
Player 9	1	1	1	1	1	1	1	1	1	1
Player 10	1	1	1	1	1	1	4	1	1	1
Player 11	1	1	1	1	1	1	1	1	1	1
Player 12	1	1	1	1	2	1	2	2	1	1
Player 13	1	1	1	2	1	2	1	3	1	2
Player 14	8	9	7	8	8	10	4	3	4	8
Player 15	1	1	1	1	1	1	1	1	2	7
Player 16	1	1	1	1	1	1	1	1	1	1
Player 17	1	1	1	1	1	1	1	1	1	1
Player 18	4	5	4	3	5	1	7	5	4	5
Player 19	1	7	3	7	6	6	4	7	1	1
Player 20	1	1	1	1	5	1	2	2	3	2
Player 21	10	5	4	4	4	4	5	5	5	4
Player 22	1	1	1	1	1	1	1	1	1	1
Player 23	1	1	1	1	1	1	1	1	12	12
Player 24	7	2	5	11	7	4	3	2	3	12
Player 25	4	6	3	1	4	4	5	5	5	7

Maximum odds

Cust. ID	1	2	3	4	5	6	7	8	9	10
Player 1	2.63	1.73	2.20	2.20	3.20	2.63	1.80	2.75	1.62	2.10
Player 2	3.10	2.63	3.30	2.25	1.91	2.10	1.62	2.75	1.57	3.30
Player 3	1.83	3.60	3.25	3.50	4.33	6.50	3.50	2.38	4.33	3.00
Player 4	2.10	2.20	3.50	2.75	1.73	1.73	6.00	2.10	4.00	2.00
Player 5	1.53	2.00	1.57	2.00	1.44	1.44	1.50	1.57	3.30	1.44
Player 6	2.20	1.80	2.50	1.67	1.83	1.83	1.73	2.60	3.00	1.57
Player 7	2.25	3.20	3.40	5.00	4.00	4.20	1.83	1.83	3.75	2.20
Player 8	1.44	1.30	1.57	1.44	1.40	1.44	1.73	1.40	1.33	1.57
Player 9	1.20	2.10	1.57	3.30	3.20	1.25	2.25	2.25	1.62	1.80
Player 10	5.00	2.38	2.10	1.67	1.73	2.63	2.10	3.75	3.20	3.30
Player 11	3.50	4.20	1.83	5.50	1.62	2.38	3.00	1.80	2.70	2.63
Player 12	5.00	2.38	2.38	2.60	1.50	2.25	2.40	2.30	2.80	2.50
Player 13	12.00	5.50	1.60	1.50	1.73	1.57	1.67	1.67	1.13	1.62
Player 14	1.65	1.60	1.62	1.62	1.62	1.62	3.40	3.75	2.80	2.00
Player 15	9.00	4.50	4.00	4.00	3.50	3.50	4.20	3.50	2.50	2.00
Player 16	1.33	1.20	1.14	1.30	1.25	1.36	1.29	1.22	1.25	1.50
Player 17	3.50	3.30	3.50	3.25	3.40	3.30	3.30	3.40	3.40	3.40
Player 18	1.44	1.53	1.44	1.83	1.57	5.00	1.83	1.44	2.20	1.91
Player 19	1.20	2.88	1.83	2.10	2.25	2.30	2.40	2.38	1.18	1.17
Player 20	1.44	1.62	3.60	1.10	3.60	4.33	2.60	1.62	2.60	6.50
Player 21	3.30	2.25	3.25	3.25	2.00	2.10	3.25	3.20	2.50	1.91
Player 22	1.03	1.03	1.36	1.67	3.60	1.67	3.60	1.01	1.01	1.01
Player 23	3.50	5.50	3.25	5.00	3.00	2.20	4.33	3.00	6.50	2.10
Player 24	3.60	3.50	1.83	1.83	1.62	1.83	1.62	1.57	1.50	1.67
Player 25	2.70	2.25	2.25	1.44	3.00	2.70	4.33	1.91	2.63	1.91

Minimum odds

Cust. ID	1	2	3	4	5	6	7	8	9	10
Player 1	1.36	1.17	1.80	1.14	3.20	1.62	1.30	2.00	1.33	1.30
Player 2	3.10	2.63	3.30	2.25	1.91	1.91	1.62	2.75	1.57	1.57
Player 3	1.44	1.65	1.91	1.60	2.75	2.75	2.20	1.44	2.80	1.80
Player 4	2.10	2.20	3.50	2.75	1.62	1.73	6.00	2.10	4.00	2.00
Player 5	1.25	1.11	1.40	1.25	1.25	1.40	1.30	1.14	1.25	1.17
Player 6	1.91	1.80	1.67	1.44	1.40	1.50	1.33	1.62	1.62	1.57
Player 7	1.40	1.50	1.50	2.00	1.57	1.50	1.50	1.25	1.29	1.30
Player 8	1.40	1.22	1.40	1.22	1.40	1.44	1.73	1.40	1.33	1.57
Player 9	1.20	2.10	1.57	3.30	3.20	1.25	2.25	2.25	1.62	1.80
Player 10	5.00	2.38	2.10	1.67	1.73	2.63	1.83	3.75	3.20	3.30
Player 11	3.50	4.20	1.83	5.50	1.62	2.38	3.00	1.80	2.70	2.63
Player 12	5.00	2.38	2.38	2.60	1.22	2.25	2.38	1.80	2.80	2.50
Player 13	12.00	5.50	1.60	1.22	1.73	1.20	1.67	1.40	1.13	1.45
Player 14	1.08	1.20	1.44	1.14	1.33	1.20	1.62	1.62	1.44	1.29
Player 15	9.00	4.50	4.00	4.00	3.50	3.50	4.20	3.50	2.10	1.25
Player 16	1.33	1.20	1.14	1.30	1.25	1.36	1.29	1.22	1.25	1.50
Player 17	3.50	3.30	3.50	3.25	3.40	3.30	3.30	3.40	3.40	3.40
Player 18	1.22	1.29	1.33	1.40	1.20	5.00	1.20	1.22	1.57	1.06
Player 19	1.20	1.20	1.02	1.57	1.44	1.44	1.22	1.73	1.18	1.17
Player 20	1.44	1.62	3.60	1.10	1.10	4.33	1.67	1.50	1.67	1.67
Player 21	1.10	1.62	1.40	1.29	1.25	1.40	1.17	1.29	1.73	1.36
Player 22	1.03	1.03	1.36	1.67	3.60	1.67	3.60	1.01	1.01	1.01
Player 23	3.50	5.50	3.25	5.00	3.00	2.20	4.33	3.00	2.20	1.25
Player 24	1.11	2.75	1.40	1.02	1.02	1.67	1.06	1.53	1.30	1.01
Player 25	1.67	1.17	1.62	1.44	1.40	1.73	1.25	1.20	1.33	1.10

Customer information

Cust. ID	Gender	Age	Reg. Date	Membership Time (Days)	Stakes	Num. Bets	Num. Success
Player 1	Unknown		2000-08-10 19:35	3544	19 109.17	1 628.50	141
Player 2	Male	46	2001-06-02 23:21	3248	16 879.35	2 860.18	1013
Player 3	Unknown	33	2001-09-16 21:41	3142	3 077.04	1 799.96	141
Player 4	Unknown	54	2000-06-17 15:54	3598	9 346.29	2 100.30	707
Player 5	Unknown	40	2000-08-04 19:14	3550	190 299.43	1 485.83	327
Player 6	Male	41	2001-10-09 19:19	3119	25 720.25	3 973.75	942
Player 7	Unknown	41	2001-12-03 11:14	3064	15 772.77	2 244.25	258
Player 8	Male	62	2000-02-22 20:04	3714	30 403.09	1 435.50	693
Player 9	Male		2000-08-29 14:43	3518	17 824.90	3 565.50	1797
Player 10	Male	44	1997-03-09 00:00	4795	169 106.10	3 676.33	1229
Player 11	Male		2000-12-27 00:00	3406	91 065.49	3 569.00	1640
Player 12	Male		1999-11-17 00:00	3811	11 686.05	1 772.10	539
Player 13	Male		2000-02-08 00:00	3729	20 775.02	1 848.00	995
Player 14	Male		1999-10-03 00:00	3857	10 259.55	1 807.24	85
Player 15	Male	44	2001-12-26 12:43	3041	5 568.00	3 094.50	824
Player 16	Unknown	39	2002-01-02 19:36	3031	5 168.71	5 823.00	1597
Player 17	Unknown	48	2002-01-15 19:07	3013	927.37	634.00	208
Player 18	Unknown	36	2002-02-11 21:08	2994	49 218.86	1 840.89	374
Player 19	Unknown	46	2002-03-16 12:33	2961	29 690.88	2 756.38	358
Player 20	Male	49	2002-03-26 09:06	2950	2 081.66	2 273.00	765
Player 21	Male	34	2002-04-09 14:32	2923	4 172.01	1 436.15	238
Player 22	Unknown	33	2002-04-10 14:35	2936	193 946.27	6 607.36	5236
Player 23	Male	41	2002-06-15 12:19	2863	5 326.20	5 438.00	1317
Player 24	Male	55	2002-06-19 10:21	2866	15 721.15	1 453.45	121
Player 25	Male	58	2002-06-25 19:01	2860	70 973.57	1 006.15	132