Efficiency in the NFL spread betting market

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Abstract: This thesis examines the efficiency of the NFL spread betting market, specifically focusing on its statistical and economic efficiency within the context of the Efficient Market Hypothesis (EMH). The research question explores whether it is possible to consistently profit from betting strategies based on historical data, thus assessing the weak form of market efficiency in NFL betting. The motivation for this study stems from the significant growth in the NFL betting market, driven by the option given for US states to legalize sports betting since 2018 and the global expansion of online sports betting, with estimates suggesting $35 billion will be wagered on the NFL during the 2025 season in the United States alone. The study incorporates behavioral economics, utilizing cognitive biases to better understand bettors' decision-making processes. Statistical efficiency is first examined through probit regression analysis, while economic efficiency is assessed through both in-sample and out-of-sample testing. The findings indicate that the NFL spread betting market exhibits clear economic efficiency, with no substantial opportunity for consistent profit based on historical data. However, the statistical efficiency remains somewhat unclear, with potential inefficiencies identified. A key contribution of this study is the discovery that bookmakers, using advanced techniques, can effectively neutralize any potentially profitable strategies in new higher level, highlighting their sophisticated understanding and sharp countermeasures that render the market nearly impossible to beat when relying on historical data.

Keywords: NFL spread betting, Efficient market hypothesis, Behavioral economics, sports betting, American football

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" Good teams win, great teams cover."

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1 INTRODUCTION

The Efficient Market Hypothesis (EMH) is a foundational concept in finance and economics that posits financial markets are efficient, meaning that asset prices fully and instantly reflect all available information. Introduced by Eugene Fama (1970), EMH suggests that in an efficient market, it is impossible for investors to consistently achieve returns above the market average by exploiting historical data. This hypothesis is critical to understanding the dynamics of stock market or in our case betting markets, such as those in the National Football League (NFL), where participants continuously process and act upon publicly available information. The EMH is often tested through analyses of pricing anomalies, predictive modeling, and profitability assessments to determine whether any consistent patterns can be identified and exploited for economic gain. This thesis builds on the EMH framework to evaluate the efficiency of NFL betting markets, integrating statistical and economic assessments to explore the extent to which market outcomes align with the principles of efficiency. By examining both predictive performance and profitability, this work contributes to the ongoing discourse on market behavior, shedding light on whether opportunities for systematic gains exist within these contexts in recent data.

1.1 Sports betting vocabulary and terms

The point spread is a betting line used to level the playing field between two teams of differing skill levels. It represents the margin by which the favored team is expected to win. For example, if a team is a 7-point favorite, it must win by more than 7 points for a bet on that team to succeed. Conversely, the underdog can lose by up to 7 points (or win outright) for a bet on them to pay out.

Favorite is the team that is seen as more likely participant to win the game, meaning that they have smaller betting odds.

Underdog is the team that is seen as not the favorite and they are more likely to lose the game, meaning they have larger betting odds.

Public/dumb money refers to wagers placed by inexperienced or casual bettors who lack deep understanding, analysis, or strategy when making their bets. These bettors often rely on intuition, emotions, or popular sentiment, such as betting on their favorite team or following media hype, rather than using data-driven or analytical approaches.

Sharps or pros are individuals or groups who consistently place calculated, data-driven wagers with the aim of securing long-term profits. Unlike casual bettors, sharps rely on in-depth analysis, statistical modeling, and a thorough understanding of the sports or events they bet on.

Moneyline refers to a wager on which team will win a game or event outright, without considering point spreads. This format simplifies betting by focusing solely on the outcome rather than the margin of victory.

Key numbers in NFL spread betting are the most common margins of victory, primarily 3 and 7, reflecting the structure of football scoring through field goals (3 points) and touchdowns (6 points + PAT 1 point). These numbers are critical because they significantly influence the setting and movement of betting lines, as games often end with these point differentials

Cover or covering the spread refers to a team outperforming the point spread set by oddsmakers, meaning who won game spread wise.

Push is a situation where the outcome of a game matches the spread exactly, resulting in no win or loss for bettors, initial bet is refunded to the bettor.

Vig refers to the commission or fee charged by bookmakers for accepting bets. This is typically expressed as a percentage of the wager and is designed to ensure profitability for the bookmaker, regardless of the outcome of the event. Same things as bookmakers margin.

Line movement refers to the changes in the point spread from when a bet is first posted (**the opening line**) until just before the game starts, when it reaches **the closing line**. The opening line is typically released several days before the game and may fluctuate due to factors like team news, betting patterns, and sharp money. As more bets are placed, bookmakers adjust the line to balance action and manage risk. The final spread just before the game begins is considered the closing line, which reflects the most current market view of the game's outcome.

1.2 Problem statement

The aim of this thesis is to examine the efficiency of the NFL spread betting market from both statistical and economic perspectives. The analysis of statistical efficiency serves as a foundational step toward evaluating economic efficiency, as it assesses whether consistent profitability is achievable based on historical data. Thesis answers to questions:

Statistical Efficiency: Does the NFL spread betting market exhibit statistical efficiency, meaning that past data cannot be used to predict future outcomes?

Economic Efficiency: Does the NFL spread betting market demonstrate economic efficiency, meaning that it is not possible to consistently profit from betting strategies based on historical data?

1.3 Motivation

The rapid growth of sports betting, driven by advancements in online platforms and legislative changes, has transformed the global and U.S. markets, presenting juicy opportunities for research into market behavior. The legalization of sports betting across numerous U.S. states following the 2018 Supreme Court decision has not only expanded the betting landscape but also intensified interest in the efficiency of these markets. Among the various sports, the National Football League (NFL) holds a particularly prominent place, given its widespread popularity and the substantial volume of betting activity it generates, for 2025 season it has been estimated that only in USA 35 billion dollars will be betted in the NFL (Purdum, 2024). This makes the NFL spread betting market a compelling case study for examining the principles of the Efficient Market Hypothesis (EMH). Betting markets share key characteristics with financial markets, such as aggregating public information to forecast uncertain outcomes, but they also offer distinct advantages for efficiency analysis due to their structured payoff mechanisms and shorter timeframes and clear end point when the game ends compared to stocks where time frame is essentially infinite. By focusing on the NFL spread market, this study seeks to evaluate the extent to which this market adheres to EMH principles and to explore whether it offers opportunities for systematic profits. This investigation not only contributes to the broader understanding of market efficiency but also sheds light on the evolving dynamics of the sports betting industry in the context of increasing accessibility and participation.

Throughout the history of sports betting, individuals and groups have continually sought to develop strategies to outwit bookmakers and gain a competitive edge. These efforts have ranged from analyzing historical performance data to identifying patterns in betting behavior, all aimed at predicting outcomes more accurately than the odds set by bookmakers. Early studies, such as those by Pankoff (1968) and Ziemba et al. (1988), delved into the possibility of exploiting inefficiencies in betting markets, offering hope to bettors that systematic approaches could yield profits. However, bookmakers possess a significant advantage due to their expertise, access to vast datasets, and advanced analytical tools for setting odds, which often neutralize any exploitable edge identified by bettors. Furthermore, the bookmaker's margin, or vigorish, adds an additional layer of difficulty for bettors aiming to achieve consistent profitability. Despite these challenges, researchers such as Golec & Tamarkin (1991), Gray & Gray (1997) and Shank (2017) have argued that inefficiencies may still exist under certain conditions, enabling informed bettors to achieve modest profits. This persistent tension between bettors seeking exploitable strategies and bookmakers aiming to maintain market efficiency has become a defining feature of sports betting markets, driving continued interest and innovation in the field.

Sports betting historically has been a popular way to make sporting events more exciting and because of expansion of online betting and loosened regulation in many countries it is extremely easy in today's environment to bet games. This has led more casual players entering in the market, injecting more dumb money to the market. Bookmakers also acknowledge this and evolvement of the betting market and methods to analyze bettors has created new opportunities to bookmakers as well as for players (Levitt, 2004).

1.4 Purpose

This thesis aims to evaluate the presence of weak form market efficiency within the NFL spread betting market. In the context of NFL spread market statistically weak form efficiency suggests that the point spread serve as an unbiased predictor of outcomes. Economically, this form of efficiency indicates that bettors cannot consistently achieve profits by utilizing past information, as the spreads already reflect all available historical data. I examine how past researchers' models, like Golec & Tamarkin (1991) and Gray & Gray (1997) home underdogs fair in this new data set. After that I'm using my own models.

1.5 Outline

This thesis is structured as follows: Chapter 2 provides a comprehensive overview of the general concepts surrounding sports betting, exploring key topics such as the mechanics of betting markets. Additionally, this chapter presents an examination of the sports betting market, including its structure and the characteristics. Chapter 3 delves into the theoretical foundations of the study, focusing on the Efficient Market Hypothesis (EMH) and its application to sports betting, alongside an exploration of behavioral economics theory. This chapter provides the theoretical framework necessary to understand following chapters. Chapter 4 reviews the existing body of research on the NFL spread betting market, synthesizing studies that have examined its efficiency and those that have explored human behavior in betting contexts. This chapter serves to contextualize the study within the broader literature. Chapter 5 presents the empirical analysis, detailing the data used in the study, the hypotheses tested, and the models applied. It further outlines the methodology, including the probit model regressions, in-sample and out-of-sample testing, and a discussion of the results. Finally, Chapter 6 concludes the thesis, summarizing the key findings, discussing their implications, and suggesting areas for future research.

1.6 AI used

I have used an AI tool called ChatGPT (OpenAI, 2024) to structure my work alongside grammatical and coherence assistance. I wrote my own paragraphs and then inputted them to ChatGPT to correct grammatical errors and make text more fluent. I reviewed texts and declined versions that changed crucial information. I accepted parts that kept my own original idea but made it more fluent with only slight modifications to structure. ChatGPT was only used following Hanken AI guidelines to assist me.

2 GENERAL KNOWLEDGE OF SPORTS BETTING AND SPORTS BETTING MARKET

The sports betting industry represents a unique and multifaceted market characterized by its distinct participants, mechanics and vocabulary. Understanding this market requires a foundational grasp of key concepts and terminology, which provide the basis for analyzing its operational dynamics and strategic implications. Sports betting involves wagering on the outcomes of sporting events, with betting odds reflecting the implied probabilities of these outcomes. Participants in this market range from casual bettors, who engage for entertainment, to professional bettors, who utilize data-driven approaches to achieve long-term profitability. The interplay between these groups and bookmakers, who set odds and manage risk while ensuring their profitability through calculated margins, defines the market's ecosystem. Central to this market are numerical elements, including odds, expected value, and variance, which underpin the mathematical framework of betting. These components guide decision-making and strategy, emphasizing the importance of informed and disciplined approaches to wagering. In the context of NFL spread betting, the introduction of point spreads and the dynamic adjustment of betting lines illustrate how bookmakers balance market interests and integrate new information. Together, these aspects reveal the complexity of sports betting as both an economic activity and a recreational pursuit, laying the groundwork for deeper exploration of its efficiency and underlying market behaviors.

2.1 Sports betting market in general

Understanding the betting market and achieving success within it requires comprehensive knowledge of the characteristics and dynamics of this specific market. Sports betting can be divided into market participants and the numerical aspects. Market participants encompass both bookmakers, or betting companies, and bettors, who engage in wagering. The behavior of each party influences the movements of the other within the market. It is also crucial to recognize that there is unlikely to be a loss-making bookmaker, whereas the majority of bettors incur losses. For bettors, sports betting constitutes a negative-sum game; as a group, they tend to lose money, while betting companies consistently generate profits.

The numerical aspect of betting encompasses everything related to numbers and mathematics. A thorough understanding of odds, including their implications for probabilities and expected value, is a central skill. Additionally, managing one's bankroll and comprehending the principles of staking are essential for ensuring the sustainability of betting activities and avoiding financial ruin.

2.2 Bookmakers, marginal and RTP

Bookmakers are companies that facilitate betting by offering odds to sporting events, political elections or other events. Their role is to set odds that reflect the probability of different outcomes while ensuring their own profitability through calculated margins. Bookmakers manage risk by adjusting odds and margin depending what kind of event odds are calculated for. Their business thrives on their ability to attract customers while maintaining a consistent edge over the long term. Bookmakers are somewhat regulated, in example they can't take underaged customers but at the same time they have lots of power, in example they can limit any players betting limits or ban them without any reason, void bets because they offered "wrong" odds or any other maneuver they see necessary to exploit their customers.

Bookmakers margin is the built-in profit that a bookmaker includes in the odds they offer. This margin ensures that the bookmaker earns a profit regardless of the outcome of a games in the long run. It is calculated by adjusting the odds slightly in their favor so that the total implied probabilities of all potential outcomes exceed 100%. For bettors, this margin reduces the value of potential returns compared to the true odds, making it a critical factor in assessing whether a bet offers good value.

Return to Player (RTP), refers to the percentage of total wagered money that a bookmaker returns to players as winnings over time. For example, an RTP of 95% means that, on average, players will receive $95 in winnings for every $100 wagered. A higher RTP indicates better value for the bettor, while a lower RTP suggests a larger portion of the stakes is retained as the bookmaker's profit margin, making profitable betting harder.

2.3 Balanced book hypothesis

The original concept behind bookmakers odds setting was to collect a margin while acting as a 'neutral' intermediary in betting events. Theory of the balanced book hypothesis is that bookmakers set odds that attract as many bettors each side of the game, essentially making them as market makers and earning just the margin (Pankoff, 1968, Zuber et al., 1988). However, this role has evolved into a profit-maximizing mechanism that capitalizes on bettors' mistakes and cognitive biases Levitt, (2004). Bookmakers knows well before publishing the odds and lines which side will absorb majority of the action. This allows them to skew lines to their advantage (Levitt, 2004). Bookmakers are willing to take more risk in singular event to make more long run profits over the margin.

2.4 Odds, expected value, variance

Odds are numbers which tells bettor how many times the bet is returned if correct result is betted. In example if bettor bet 100 euros for team A to win the game with odds of 3.1, bettor receives initial bet 3.1 times, meaning 310 euros and 210 euros net profit. Odds represent essentially the likelihood of a particular outcome occurring and are central to determining potential payouts. Odds are calculated using mathematical models based on probability analysis, incorporating factors such as team strength, injuries, venue, weather conditions, and bettor behavior. However, as Young (2022) describes the process is not purely scientific it involves a degree of subjectivity, as the true probability of an event cannot be determined with absolute precision, bookmakers aim to set odds close to the forecasted probability.

Expected value (EV) is a key concept in betting that measures the potential profitability of a wager over the long term. It is calculated by multiplying the probability of each possible outcome by its corresponding payoff and summing the results. A positive expected value (+EV) indicates that the bet is profitable in the long run, while a negative expected value (-EV) suggests a loss over time. Expected value can be illustrated through a simple example of a coin flip, where the probability of either outcome (heads or tails) is 50%, or 0.5. Suppose a bookmaker offers odds of 2.1 for heads and you bet it with one euro.

$$\text{EV} = (\text{net profit x probability of heads}) - (\text{net loss x probability of tails}) \tag{1}$$

$$\text{EV} = (1.1 \text{ x } 0.5) - (1 \text{ x } 0.5) = 0.55 - 0.50 = 0.05 \tag{2}$$

This positive EV +0.05 indicates a profitable bet over time. Conversely, if the bookmaker offers odds of 1.9 for the same coin flip, this turns to negative EV bet:

$$\text{EV} = (0.9 \text{ x } 0.5) - (1 \text{ x } 0.5) = 0.45 - 0.5 = -0.05 \tag{3}$$

On average, you would lose money in the long term with such a wager because of EV -0.05. This example highlights the importance of identifying bets with positive expected value to maximize profitability. Understanding EV helps bettors assess whether a wager is worth the risk and ensures a more analytical approach to betting decisions.

Variance in betting refers to the natural fluctuations in outcomes over a series of wagers, reflecting the unpredictability inherent in probabilistic events. It quantifies how much the results of bets deviate from the expected value over time. For example, in a fair coin flip with a 50% probability of landing heads or tails, the expected value of a wager may suggest that, over a large number of flips, you will break even. However, due to variance, short-term results may deviate significantly. You might experience a streak of several consecutive wins or losses, even though the long-term probability remains balanced. This concept highlights that short-term outcomes are often influenced by randomness, and only over a sufficiently large sample does the actual result converge toward the expected probabilities. Managing variance is crucial for bettors, as it ensures that they maintain consistent strategies despite temporary swings.

2.5 11 to 10 rule

Under this rule, bettors are required to risk $11 to win $10 on an even-money bet, creating a built-in margin known as the "vig". This commission serves as the bookmaker’s compensation for facilitating bets, so this is the already mentioned bookmaker’s margin. For instance, if two opposing sides attract equal betting action, the bookmaker collects $110 from losing bets for every $100 paid out to winners, retaining a $10 profit. In this study, the 11-to-10 rule is employed because it has been used in prior research and represents a standard, widely accessible model for bettors. While some betting sites may offer lower margins, this rule is adopted here for consistency and because it is a commonly accepted baseline in the industry. Because of this rule, bettor need to correctly predict 52.38 percent of games to break even, this is the basis for the economic tests as well.

2.6 Spread betting

In NFL betting, the point spread is a popular wagering format designed to level the playing field between two teams of differing abilities. The spread assigns a hypothetical margin of victory that the favorite must exceed to cover the bet, while the underdog can either win outright or lose by fewer points than the spread to cover. For example, if a team is favored by -6.5 points, they must win by 7 or more for a bet on them to succeed, while a bet on the underdog would win if they lost by 6 points or fewer or win the game outright. The point spread adds complexity and balance to betting markets by encouraging action on both sides, as it is not only about who wins but by how much.

Bookmakers often adjust the spread to reflect team performance, injuries, and betting trends, aiming to rack up wagers on both sides of the line. Spread also moves throughout the time it is available for betting, common things to move the spread line is heavy betting for only one side or player injuries in example. Similarly to stocks and securities prices, at the end of trading, closing spreads are assumed to reflect all information, like in sports betting case weather, injuries etc., and perhaps, biases of the market participants. Opening spread line is more “clean” indication of bookmaker’s view about the probability of the game at opening time. Common odds in spread betting are usually between 1.8 and 2.05. Idea of the spread is to make game “even” and that is why the odds are similar to favorite and underdog.

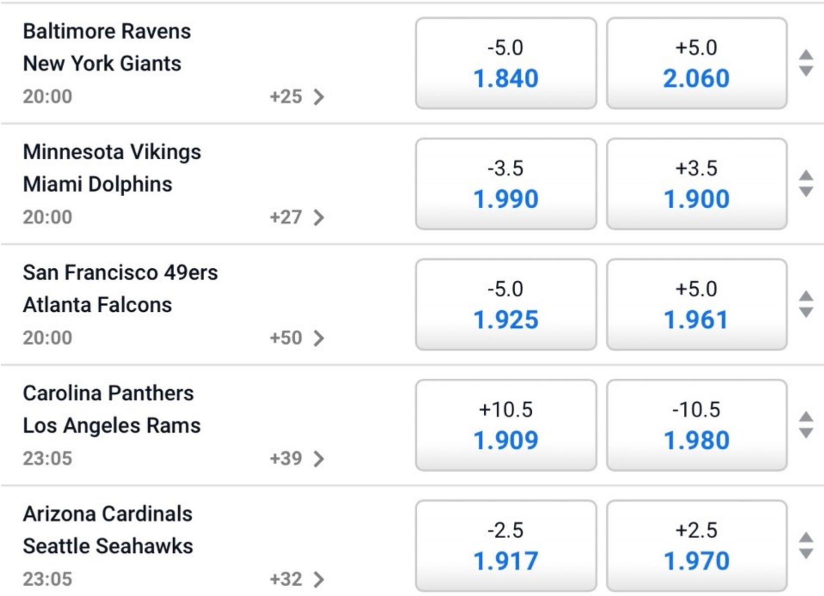

Figure 1. Typical spread lines and odds (pinnacle.com).

2.7 Sports bettors, bankroll

Sports bettors are commonly referred as professional bettors (pros, sharps) or amateur bettors (joes, casuals). Vuoksenmaa (1999) represents extended model where he divides players to four categories: casuals, hobbyist, semi-pro and professional bettors. Many criterions are used for grouping bettors to these groups, like time used in betting but also research and self-evaluation, how profitable betting is for longer periods of time and how risk – profit is understated alongside other skills.

Casual bettors wager primarily for entertainment, often placing bets on games they watch without much analysis or strategy. Hobbyists possess some understanding of betting principles and the characteristics of teams or players but frequently make errors due to behavioral biases or statistical oversights. Semi-professional bettors may achieve profitable streaks over extended periods, but their lack of consistent skills, advanced strategies, or disciplined bankroll management limits their long-term success. At the top are professional bettors, who operate with a calculated and systematic approach, relying on rigorous bankroll management, expected value (EV) analysis, and sophisticated modeling techniques to identify value bets and sustain profitability over time. These distinctions highlight the varying degrees of expertise and dedication within the betting community (Vuoksenmaa, 1999).

Bankroll management is a fundamental aspect of responsible and professional betting, referring to the allocation and control of the funds designated specifically for wagering. A bettor's bankroll represents the total amount of money they are willing to risk, and effective management ensures that they can sustain potential losses while pursuing long-term profitability. Key principles of bankroll management include setting a clear budget, dividing the bankroll into units (a percentage of the total, typically 1–5%), and placing bets accordingly to minimize the risk of significant losses. For example, a bettor with a 1000 euros bankroll might decide to wager 20 euros per bet (2% of their bankroll) to maintain consistency and avoid overextending during losing streaks. Proper bankroll management helps mitigate the impact of variance, encourages discipline, and prevents emotional decisions, ensuring a more sustainable and calculated approach to betting.

3 EFFICIENT MARKET HYPOTHESIS AND BEHAVIORAL ECONOMICS THEORY

This section of the thesis delves into the theoretical frameworks and behavioral dynamics relevant to understanding the NFL spread betting market. Aim is to explore the intersection of economic principles, market efficiency, and human behavior, contextualized through the lens of betting markets. The review begins with an examination of the Efficient Market Hypothesis (EMH), a cornerstone theory in economics that evaluates how information is reflected in prices and whether opportunities for consistent profit exist in financial and betting markets. Following this, the role of behavioral economics is introduced, highlighting how cognitive biases and psychological factors influence decision-making and contribute to observed inefficiencies in betting environments. Finally, the discussion extends to behavioral phenomena such as recency bias, gambler's fallacy, herd mentality, and the favorite-longshot bias, which uncover the nuanced ways in which human tendencies impact betting behaviors and market pricing.

3.1 Efficient market hypothesis

The efficient market hypothesis (EMH), as proposed by Eugene Fama (1970) in his groundbreaking paper, asserts that financial markets are informationally efficient, meaning that asset prices fully reflect all available information. EMH is viewed as one of the fundamental theories in Economics, and its elementary efficiency ideas extends as far as 16th century, but more recognized roots belong to 20th century. First efficiency was investigated in theoretic sense when Bachelier (1900) studied the movements of the stock exchange. Cowles (1933) deepened the theoretical robustness with first worthy empirical study. Research included analyses of the 45 professional agencies, who tried to forecast stock market in aggregate or pick certain stocks that could generate over average profits (Cowles, 1933). Cowles (1933) presented results that sided market efficiency and his famous badass line "the most successful records are little, if any, better than what might be expected to result from pure chance. There is some evidence, on the other hand, to indicate that the least successful records are worse than what could reasonably be attributed to chance.

The efficient market hypothesis gained widespread recognition through Fama's work (1970) in academic circles but after Malkiel (1973) published book "A Random Walk down Wall Street" the theory took off in professionals circles which cemented Famas (1970) paper in the history books (Shiller, 2003). Fama categorized market efficiency into three forms: weak, semi-strong, and strong. Weak efficiency suggests that historical price data cannot predict future prices, rendering technical analysis ineffective, essentially implying that prices should be following the random walk. Semi-strong efficiency posits that all publicly available information is already incorporated into market prices, making it futile to exploit new public disclosures for profit, debunking profitability of the fundamental analysis. Strong efficiency extends this notion, arguing that even private or insider information is reflected in market prices, meaning that it is even impossible to make profit with insider information which is absurd idea in reality making usual academic research focusing on weak-form efficiency or in some cases semi-strong efficiency (Fama, 1970).

The efficient market hypothesis (EMH) has faced lots of criticism and even Fama (1991) in his own later paper has questioned the EMH by presenting joint-hypothesis problem. He states that because of this market efficiency cannot be directly tested on its own; instead, it must be evaluated alongside an asset-pricing model that serves as a benchmark for equilibrium. Otherwise, when anomalies are observed in return patterns, it becomes unclear whether they stem from market inefficiency, flaws in the pricing model, or a combination of both, leaving the distinction ambiguous. Because of this is it even a hypothesis if it can't be proven to be true or false? Fama (1991) asks two interesting questions: "Does the fact that market efficiency must be tested jointly with an equilibrium-pricing model make empirical research on efficiency uninteresting?" and "Does the joint-hypothesis problem make empirical work on asset-pricing models uninteresting?" (Fama, 1991). His answer is no, arguing that the knowledge, views and practices have changed because of empirical work EMH has driven, praising its successfulness in empirical economics.

EMH has gathered critics also in other sides of the hypothesis. Shiller (2013) argue that the hypothesis is only partially accurate, as it cannot account for certain price patterns and anomalies in financial markets. Researchers has implied that it has theoretical problems that decreases its value, like the rationality of the market participants (Shleifer, 2000). This has led to the emergence of alternative theories, including behavioral finance, which emphasize psychological and irrational factors in market behavior. EMH has base assumption that the markets participants are rational, meaning that even if market participants act irrationally, it is random. This is not supported in behavioral economist's research and in actuality they have found that irrational market participants tend to act similarly to others, uncovering biases like recency bias, loss aversion bias and herd mentality (Kahneman & Trevsky, 1979, Black 1986, Shleifer 2000, Bodie et al. 2005).

Nonetheless, the EMH continues to offer valuable insights into the dynamics of information dissemination and price formation in financial markets like Fama argued, even though "market efficiency per se is not testable" because of "The empirical literature on efficiency and asset-pricing models passes the acid test of scientific usefulness." (Fama, 1991).

3.2 Behavioral economics

Behavioral economics is a field that blends insights from psychology and economics to explore how individuals make decisions, often deviating from the rational actor model traditionally assumed in classical economics (Pompian, 2012). This style of economics approaches situations by assuming that individuals are not flawless or fully rational in their decision-making and tend to fall in their biases. Their behavior and choices are often influenced by specific psychological factors and biases. Behavioral economics are relatively new viewpoint, and it started to gain ground in the field more in 1980s after Kahneman and Tversky's (1979) and Thalers (1980) papers. Although, ideas and intuitions go way back. Smith (1759) believed similar concepts that prospect theory offers regarding the loss aversion and insensitivity to opportunity cost versus out-of-pocket costs later offered. Earlier in the history significant economists and researchers seemed to favor leaving psychology out of the economic theories and basing them purely to mathematics and rational models (Bruni & Sugden, 2005).

Key concepts in behavioral economics include prospect theory (Kahneman & Trevsky, 1979), which describes how people perceive and evaluate gains and losses asymmetrically, 100 euros win doesn't feel as good as 100-euro loss, leading to loss aversion. Kahneman & Trevsky later in 1992 conducted money gambles through multiple choice tests backing the loss aversion theory. Odean (1998) applied this in the stock market finding the disposition effect in investors buying and selling behavior, meaning that people tend to sell stocks that has grew in stock price after the initial purchase and keep the stocks which price has gone down after the initial purchase, that way not booking the loss yet. Kahneman & Trevsky (1979) also found framing effect which is closely associated with prospect theory, which highlights that people evaluate potential losses and gains relative to a reference point, often influenced by how a choice is framed. For example, individuals may react differently to a surgery described as having a "90% survival rate" versus a "10% mortality rate," even though these descriptions convey the same statistical reality.

Another a cognitive bias is overconfidence in which individuals overestimate their knowledge, abilities, or the accuracy of their predictions. In behavioral economics, it is a significant factor influencing decision-making and market behavior, often leading individuals to make suboptimal choices. Overconfidence manifests in several ways, including overestimation (believing one's abilities are better than they are), over placement (believing one is better relative to others), and over precision (excessive certainty in the accuracy of one's beliefs or forecasts). People even think they can control random events through their abilities, indicating severe overconfidence (Cowley, et al., 2015). In financial markets, overconfident investors might trade excessively, believing they can consistently outperform the market, despite evidence showing that frequent trading often reduces returns (Odean, 1998). In economic contexts, overconfidence can lead to market inefficiencies, bubbles, and crashes, as overconfident behavior distorts price-setting and resource allocation.

3.3 Favorite-longshot bias

The "favorite longshot bias" is a psychological phenomenon where people tend to favor or support an individual, team, or entity that is perceived as an underdog, especially when they are up against a dominant or favored opponent (Ali, 1977). This bias can be explained by the work of behavioral economists Kahneman & Trevsky (1979), who studied how people make decisions under uncertainty. Their research reveals that individuals often favor low-risk, high-reward options, a pattern known as "prospect theory." In betting scenarios, this manifests as a preference for the underdog, as the potential for a large payout feels more appealing than smaller return (even thought more propable). Kahneman and Tversky (1979) also found that the value function is steeper for losses than for gains, meaning that people feel the pain of losses more intensely than the satisfaction of equivalent gains.

As a result, bettors are more likely to lean toward bigger odds, chasing the excitement of a larger payout because they want to offset the psychological weight of smaller wins (even though more propable). This bias can cloud objective judgment, leading to irrational betting decisions where the underdog overvalued. Ali (1977) and later Thaler and Ziemba (1988) documented this bias in horse racing. They both came to the same conclusion that in the long run best expected value were achieved playing systematically favorites. In that time period bookmakers marginals were higher than in todays enviroinment and because of this Hausch and Ziemba (1990) conducted study that argumented that even though this bias exists it is almost impossible to make profits over the margin and preventing blindly betting favorites in horse racing.

One explaining factor is that bookmakers are aware of this tendency and adjust their margin in the odds to more in underdogs odds. For example, if the "fair" odds for a favorite are 1.20, bookmakers might lower them to 1.19, and for an underdog with "fair" odds of 6.00, they may offer 5.30 after adjusting for their margin. This strategy capitalizes on bettors' attraction to larger potential payouts, despite the lower likelihood of the underdog winning. The larger odds on the underdog often create an illusion of value, drawing bettors in with the idea that a big win is possible, even if the odds indicate expected value below 0, accounting as a losing bet in the long run.

However, spread betting introduces a twist to this bias, creating a reverse favorite longshot bias (Golec & Tmarkin, 1991, Gray & Gray, 1997, Shank, 2017). Unlike traditional betting, where bookmakers adjust the odds based on perceived likelihood, spread betting offers similar odds for both teams, simply there is no real “longshot” available to bet. The key difference lies in the spread line, which adjusts the expected margin of victory rather than the odds themselves. In this format, the favorite can have the same odds as the underdog, but bettors now have to consider the spread rather than just the moneyline. This can lead to a misinterpretation of value, as bettors often fail to fully grasp what is the real “price”. Although people understand the odds, they don’t fully appreciate how the spread works as a price adjustment and again, there is no big odds available. As a result, bettors in aggregate overvalue the favorite and underestimate the underdog, leading to biased betting decisions where favorites are backed more heavily than they should be (Golec & Tamarkin, 1991).

3.4 Recency bias and Gambler’s fallacy and hot hand

In the context of betting markets, recency bias occurs when bettors give undue weight to recent performances or outcomes, leading them to make decisions based on the most recent results rather than considering a broader perspective. For example, if a sports team has won several consecutive games, bettors might assume that the team is on a winning streak and is likely to continue performing well, disregarding factors such as the quality of their opponents or long-term trends (Gray & Gray, 1997). Similarly, bettors often forget or downplay irregular events that favor their opinion, like a lucky win or a fluke performance, treating them as regular occurrences. On the other hand, they might interpret regular events that contradict their views—such as a loss to a strong opponent or an off-game—as anomalies or outliers, masking these normal variations in performance. This selective focus can distort judgment, creating mispricing’s in the odds (Shank, 2017). Bettors who recognize and avoid recency bias can take advantage of these irrational trends, potentially profiting from market inefficiencies.

In the NFL, where there is typically a week between games, recency bias has the perfect conditions to flourish. The long gap allows bettors plenty of time to overreact to the outcome of the most recent game while forgetting or downplaying earlier games. If a team delivers a strong performance, bettors may overestimate their abilities and expect the same level of success in the following week. Conversely, a poor performance, especially against an underdog, can lead to an exaggerated negative outlook, causing bettors to unfairly downgrade a team's potential. With no immediate game to reassess or reset expectations, bettors often become fixated on the most recent result, which can cause them to ignore broader trends or past performances (Gray & Gray, 1997). This extended period provides ample time for emotions to influence decisions, allowing recency bias to distort betting judgments and create mispricing in the odds. Recognizing this bias can give more informed bettors an edge, as they can make decisions based on a more comprehensive analysis of a team’s overall performance.

Recency bias is also closely related to Gambler's fallacy. The gambler's fallacy, also known as the Monte Carlo fallacy, refers to the mistaken belief that past events in a random sequence influence future outcome, even though they are independent of each other (Kahneman & Trevsky, 1979). In simple terms, it's the idea that if something happens more frequently than usual, it's "due" to change, or if it happens less frequently, it's expected to occur soon. For example, if a roulette wheel lands on red several times in a row, someone might believe that black is "due" to hit, even though each spin is entirely independent of the previous ones, and the probabilities remain the same (Kahneman & Trevsky, 1979).

In the betting world, the gambler's fallacy can lead to poor decision-making. Bettors might believe that a team that has been losing repeatedly is "due" for a win, or conversely, that a team on a winning streak is bound to lose soon (Williams, 2004). In the NFL context, the gambler's fallacy can often lead to flawed betting strategies, as bettors mistakenly believe that past results influence future outcomes in a random, independent environment. For example, if a team has lost several games in a row, a bettor might fall into the trap of thinking that the team is "due" for a win, assuming their losing streak will end simply because it's perceived as unusual. Conversely, if a team has won several games in a row, bettors might assume they are "due" for a loss, expecting the streak to break. However, this line of thinking ignores the fact that each game is independent, with numerous variables at play, and there's no inherent force that causes a losing team to suddenly win or vice versa. The gambler's fallacy in NFL betting can result in bettors placing wagers based on skewed perceptions of randomness rather than analyzing the teams' true form, matchups, or other relevant factors. As a result, it can lead to irrational decisions and missed opportunities for more informed bettors who understand that past performance doesn't guarantee future results (Williams, 2004).

In contrary there also exists hot hand fallacy where people think that streaks will continue, ignoring, yet again all analysis and basing their decision to just hot streak (Gilovich et al. 1985). People mistakenly believe that a team experiencing a series of successes has a higher probability of continued success in subsequent events. The persistence of the hot hand fallacy highlights a fundamental human tendency to perceive patterns and assign causality in sequences governed by chance, revealing important implications for understanding decision-making and judgment under uncertainty (Gilovich et al. 1985).

This phenomenon has been studied long time in sports and Camerer (1989) and Brown & Sauer (1993) found that in NBA spread betting teams that were in the winning streaks were overvalued, they also found that four game winning streak meant larger overvaluation that two-game winning streak, backing the hot hand fallacy. Paul et al. (2012), in contrary to earlier studies, found that in the NFL spread betting teams in winning streaks received increase in bets in their favor, backing the hot hand assumption, although not that strong that sophisticated bettors could exploit this and earn consistent profit (Paul et al., 2012).

3.5 Herd mentality

Irrational behavior in financial markets has been explained partly due to humans' tendency to follow others in the decision making, generating theory behind herd mentality (Banerjee, 1992). Herd mentality in sports betting refers to the tendency of individuals to follow the actions or opinions of the majority, often without independent analysis or consideration of the underlying factors that influence outcomes (Wever & Aadland, 2012). This psychological bias can lead to a convergence of betting patterns, where bettors place wagers based on prevailing trends or the behavior of others, rather than on a thorough evaluation of the game's specifics or statistical data. This phenomenon is particularly evident in high-profile events/teams, where the collective enthusiasm or fear of missing out (FOMO) can drive irrational decision-making (Wever & Aadland, 2012).

The consequences of herd mentality in sports betting can include market inefficiencies, where odds become skewed due to large-scale, collective behaviors, creating opportunities for astute bettors who can identify mispriced odds or capitalize on public overreaction. Furthermore, the rise of social media has amplified this effect, as bettors increasingly share opinions, predictions, and betting tips through various platforms, creating a rapid spread of information—and misinformation—that influences betting decisions. Social media's ability to foster groupthink and instant validation of collective opinions has led to stronger, more immediate reactions in sports betting markets, making herd mentality even more pronounced in the modern era. Understanding this behavior is crucial for both bettors seeking an edge in the market and for researchers exploring the impact of psychological factors on decision-making in gambling environments. Wever and Aadland (2012) examined in their study elite highly publicized teams and found that large underdogs against these teams are underpriced, explained at least partly by herd behavior.

4 PREVIOUS RESEARCH

The integration of the efficient market hypothesis (EMH) with the NFL spread betting market and behavioral esomics are presented through a chronological literature review of seminal and modern studies. This review examines the foundational development of EMH in the context of spread betting, the methodologies employed to test its validity, and the evolving evidence of market inefficiencies. By exploring key contributions from early studies to recent advancements, the analysis provides insights into how theoretical constructs of market efficiency align or diverge from observed betting behaviors and outcomes.

4.1 Efficient market hypothesis in NFL spread betting market

Pankoff (1968) was the first person to expand the market efficiency research towards NFL betting market, drawing analogy between financial markets and sports betting. His elementary study of the NFL betting market, though simple, is widely regarded as foundational for the development of the efficient market hypothesis (EMH) in the context of spread betting market. Using historical data from the 1956–1965 NFL seasons, Pankoff analyzed whether the point spread market effectively priced outcomes. His methodology involved regressing actual game outcomes against the Las Vegas betting lines, which served as market predictions. Pankoff found that the spread market's predictions closely mirrored the actual outcomes and systematic market error patterns were too small to cover the bookmaker's margin. While these findings supported efficient market hypothesis strongly, Pankoff (1968) also identified potential evidence through random-walk theory of "superior analysts" (today referred as sharps), who might exploit nuanced inefficiencies which spread market struggles to incorporate in the prices.

Zuber, Gandar, O'Brien, and Russo (1988) tested NFL spread markets efficiency through market rationality with statistical and economical tests. "Statistical tests look at statistical properties of markets, such as price correlations. Economic tests attempt to detect unexploited profit opportunities" as Zuber et al. (1988) describes. Their statistical test couldn't reject the hypothesis that betting lines are unbiased predictors of actual game outcomes, same conclusion was reached with opening and closing lines, meaning that EMH once again stood tall. The economic tests in contrary suggested that assumption of a fully rational betting market is false. They tested the efficiency of betting lines as rational expectations of game outcomes by examining whether consistent technical or behavioral betting strategies could outperform the spread. Zuber et al. (1988) found that all three behavioural strategies were "decidedly profitable".

Behavioural strategies included: betting teams that became bigger underdogs, essentially betting against the public, bet against public after they have had winning week in previous week and the third strategy was to bet the underdogs when favourite covered the spread at least by 10 points in previous week (Zuber et al. 1988). These behavioural strategies were based on already known theories like recency bias, herd mentality and reverse favorite-underdog bias. Based on their research they concluded that markets are driven by dumb money and knowledge bettors are small fraction of the market participants. Yet again, efficient market hypothesis (EMH) was under the suspicion like Pankoff (1968) suggested with “superior analysts”, but statistical tests couldn’t reject it, leaving the Zuber et al. (1988) at “uncomfortable” conclusions.

Golec and Tamarkin (1991) advanced the analysis of market efficiency in football betting markets by addressing limitations in prior research, which primarily relied on simple regression models to test the efficient market hypothesis (Zuber, Gandar, O’Brien, and Russo, 1988). Their study incorporated data from the National Football League (NFL) as well as college football games over a 15-year period (1973–1987). Golec and Tamarkin (1991) made the argument that the model Zuber et al. (1988) built and tested based on Pankoffs (1968) research was not statistically strong enough.

Golec and Tamarkin (1991) probit model included new elements that brought more robust results compared to earlier. Two new dummy variables were used for one for home/away teams and another for favourites/underdogs. These variables allowed them to test whether these factors, which should theoretically already be reflected in the point spread under the efficient market hypothesis, contributed to systematic biases. Their findings revealed that the NFL betting market exhibited persistent inefficiencies, particularly an underestimation of underdog strength (which they concluded got even stronger) and a weaker but inconsistent bias against home teams (over time seemed to diminish). The strategy that prevailed best, was to bet home underdogs resulting winning percentage of 55.6%, which implied possibility of profitability and rejecting the efficient market hypothesis. Golec and Tamarkin (1991) also found that College football spread betting market was more efficient supporting the Zuber et al. (1988) claim that NFL spread betting market is driven by dumb money.

Gray and Gray (1997) conducted a study to test efficient market hypothesis in the NFL spread betting market that included games from 1976 to 1994. They argumented that OLS regression method in examining spread betting markets statistical efficiency, like earlier studies (Pankoff, 1968 and Zuber et al. 1988) was not the correct way to do it because particularly its sensitivity to extreme outliers, which can disproportionately influence results in betting contexts where all wins are equivalent regardless of margin. To lean back on this suggestion, Gray and Gray

(1997) used probit model, by treating all successful outcomes equally. They test Golec and Tamarkin (1991) home-underdog model and built on that their new model with additional variables analogous to those in financial and behavioral markets, such as a team's recent performance. Also, the research extended its focus to the economic efficiency of betting strategies, emphasizing that statistical biases in point spreads do not inherently signify inefficiency unless they can be systematically leveraged to generate profits.

Gray and Gray (1997) tested conditional betting rules in in-sample and out-of-sample to test the economic efficiency. They found that market overreacts strongly performed teams that are in bad recent form, resulting profitable strategy to bet on those teams blindly, displaying similar recency bias that earlier studies found (Zuber et al., 1988, Golec & Tamarkin, 1991). Also, similar to Golec and Tamarkin (1991) they found that home-underdogs strategy was profitable in total sample but was weakened towards end of the sample. Some strategies didn't produce positive returns out-of-sample even if they had potential in in-sample.

Levitt (2004) introduced new way of assessing NFL spread betting market efficiency by studying NFL betting contest where prizes were money. Spread lines followed real lines and through that Levitt (2004) introduced evidence that balanced-book hypothesis did not hold true. Bookmakers skewed the lines to their advantage and against bettors' behavioural biases, this way creating inefficiencies in the market and giving more proof to earlier studies findings of inefficiencies (Pankoff, 1968, Zuber et al., 1988, Golec & Tamarkin, 1991, Gray & Gray 1997). Levitt (2004) also offered answers why previous researchers statistical tests couldn't overrule the efficiency hypothesis. Bookmakers' skill to create better spread lines and adjusting them team by team, season by season differently depending on the specific biases bettors have, was far better than majority of pro bettors and public. Like Gray and Gray (1997) tests showed that home-underdog strategy seemed to perform well in total sample it was not returning profit steadily end of the studied period because bookmakers adjusted their strategy when creating lines.

In order to NFL spread betting market to be efficient, the timing of placing a wager should not influence betting strategies, as the spreads are expected to fully reflect all available information about the game, thereby eliminating the possibility of a profitable betting strategy hence the time. Paul and Weinbach (2011) analyzed last hour of the betting because major percentage of the bets are placed in the final hour before the game. Their analysis of last-hour betting trends revealed that bettors predominantly followed common strategies documented in the literature (Zuber et al., 1988, Golec & Tamarkin 1991, Gray & Gray, 1997) such as an example favoring favorites which align with the general public's betting behavior. Consequently, Paul and Weinbach (2011) findings suggest that the final hour of betting does not demonstrate evidence of informed trading and in fact, reflect uninformed behavior strengthening the evidence of dumb money driving the betting market like earlier findings (Zuber et al. 1988, Golec & Tamarkin, 1991). Paul and Weinbach (2011) found that in reality bettor could exploit this by betting on the underdog when spread moves away from them, resulting in a win rate exceeding 60%.

Spinosa (2014) and Shank (2017) both conducted statistical and economic efficiency test with newer data. Spinosa (2014) with massive dataset spanning from 1992 to 2012 and Shank (2017) from 2009 to 2017 to see the spread markets situation. Both found somewhat similar results. Spinosa (2014) found that while home teams and underdogs generally continue to perform better than away teams and favorites, the results suggest that market adjustments have rendered blanket strategies, such as betting on all underdogs or all home teams, unprofitable like Gray and Gray (1997) started to see in end of their data set concluding that aggregate market was efficient. But yet again when digging little deeper home underdogs that were getting seven points (touchdown + PAT) or more yielded 59.69 %-win rate which enormous in spread betting (Spinosa, 2014). Shank (2017) took the analysis even further into the detail and found that like Gray and Gray (1997) including team recent performance to model bettor could find and advantage. Inefficiency was found and large underdogs were more likely to cover the spread, and especially if they were in a losing streak (Shank, 2017). Mani (2018) also found that opening lines are more accurate predictor of game result than closing lines supporting arguments of skewing the lines and dumb money driving the market, especially in final moment before game time (Zuber et al. 1988, Levitt, 2004, Paul & Weinbach, 2011)

Literature regarding efficiency of NFL spread betting market seems to have research and studies both sides of the argument. But from the start (Pankoff, 1968) to recent days some kind of inefficiencies seem to always exist and still existing and that is supported by rejection of balanced book hypothesis (Levitt, 2004). Bookmakers are getting better each year and skewing the lines more precisely team by team and season by season based making pro bettors' job to exploit inefficiencies relatively hard. Still, some kind of home underdogs by straight up or with other variables seems to have persisted throughout the years but that also seems to go in cycles how good those strategies are season by season basis (Pankoff, 1968, Zuber et al., 1988, Golec & Tamarkin, 1991, Gray & Gray 1997, Levitt, 2004, Paul & Weinbach, 2011, Spinosa, 2014, Shank, 2017).

4.2 Behavioral economics and Betting

These observed market inefficiencies can be at least partly illuminated through the lens of behavioral economics, which studies how psychological factors influence economic decision-making, as mentioned (Kahneman & Trevsky, 1979). Bettors and gamblers behavior has many cognitive biases affecting the decision making but also how bettors analyze and view how they fared (Wagenaar, 1988). Illusion of control (IOC) is known obstacle which prevents bettors to keep up with their losses without precise bookkeeping and that way never evolving as a bettor.

Cowley et al. (2015) studied this IOC matter through simple coin toss game, where the test included 20 flips and series of betting where players chose heads or tails. After the test players was asked to assess how they fared and fill "control belief scale" questions to see how they thought about the controllability of the outcome in this random game. Cowley et al. (2015) found that gamblers exhibiting high levels of this IOC focused on isolated moments of success—such as a significant win during a game—even if they lost in totality. This kind of reactions create false feelings, clouding gamblers judgement of how the betting went, leaving them with positive feeling even though they lost in reality. Also, Cowley et al. (2015) found that even though coin toss is random game high IOC gamblers believe they can bet patterns profitable and "guaranteeing" next flips outcome, like after five heads, it must be tails.

Closely related concept of IOC is the near-miss effect that was studied by Reid (1986). The near-miss effect is the situation where bettor suffers a loss but was close to a win. A near miss—such as almost hitting a jackpot on a slot machine—creates a psychological response similar to that of an actual win (Griffiths, 1991). This effect exploits cognitive biases by triggering feelings of frustration and excitement simultaneously, reinforcing the belief that a win is imminent if they keep playing. The near-miss effect taps into the gambler's illusion of control leading them to overestimate their chances of future success. This phenomenon not only sustains prolonged gambling but can also escalate risky behavior, as players become more willing to bet larger amounts in pursuit of an anticipated win (Reid, 1986, Griffiths, 1991).

These psychological biases cause deviations from rational expectations, leading to mispriced odds and betting lines, as well as bettors' analysis of their own betting and behavior in the market. Understanding these behavioral underpinnings is crucial for developing betting strategies that can exploit the market's and bettors' systematic biases.

5 HYPOTHESES, EMPIRICAL EVALUATIONS AND DATA

We begin with a clear definition of the study's hypotheses, grounded in the established literature, focusing on statistical efficiency (the unbiasedness of spread lines as predictors) and economic efficiency (the absence of profitable betting strategies net of bookmaker margins). The following subsections detail the data, which spans ten NFL seasons from 2015 to 2024, encompassing 2,528 regular-season games, along with the methodological foundation rooted in prior works.

5.1 Hypotheses

This study includes two hypotheses like many other previous studies, statistical and economic efficiency tests (Gray & Gray, 1997, Spinosa, 2014, Shank, 2017). The concept of statistical weak form market efficiency suggests that all available information regarding future NFL game outcomes is already reflected in historical betting lines. Not only statistical but also, and especially, this study is interested in the economic efficiency, meaning that even if statistical inefficiencies are found hypothetical bettor could exploit the market with some betting strategy to earn profit over bookmakers' margin consistently. These focus points create two hypotheses in this study:

Hypothesis 1: The NFL spread betting markets spread lines are unbiased predictors of actual game outcomes, implying statistically efficient market (weak form).

Hypothesis 2: In the NFL spread betting market no betting strategy can generate consistent profit over time, implying economically efficient market (weak form).

5.2 Empirical evaluations

To empirically test the hypotheses, I employ five different probit models to assess the statistical efficiency tests. Two pre-registered models and three explorative models. To ensure transparency and mitigate potential biases in model selection, I pre-registered two primary empirical specifications before conducting the analysis. These pre-registered models were selected based on theoretical considerations and prior literature (Gray & Gray, 1997), ensuring that the empirical approach was not influenced by data-driven decisions. To further validate statistical findings, I employ the Likelihood Ratio Test (LRT) to compare nested models which allows to assess the models' overall significance.

To assess the predictive performance and practical applicability of the models in the context of economic efficiency, I employ in-sample and out-of-sample testing as in previous study of Gray & Gray (1997). In-sample testing evaluates how well the models explain historical data, capturing key relationships within the observed sample. However, since strong in-sample performance does not necessarily indicate real-world predictive accuracy, I conduct out-of-sample testing to assess how the models perform on new, unseen data.

5.3 Data

The data used in this research consist of NFL regular season games from 2015 season (started fall of 2014) to the end of the 2024 season. The data was obtained from aussportsbetting.com. The data has 2607 games, and I have excluded “void” bets, which means that game has ended exactly by point spread and there is no winner in terms of point spread, meaning wager would have been refunded back to the bettor. We are left with 2528 games as observations.

The data includes basic information of the game like date of the game and season where it belongs. Then game specifics like home team and their score, away team and their score. Also, betting related information like moneyline odds, spread line relative to home team and away team with the different categories of the opening line, max line and the closing line. Spread line relative to home and away team simply means that if home team is favorite spread is supposedly 3.5 then relative to home team spread is -3.5 and relative to away team +3.5.

This study’s empirical part uses Gray and Gray (1997) as a benchmark in the statistical and economical test’s structure. It also examines home underdogs similarly as Golec & Tamarkin (1991) and Gray & Gray (1997). This way we have directly comparable results from past and then new models explores data as well. The "team of record" refers to the team from whose perspective the spread and result are defined, and there are three different approaches we could use: favorite (or underdog), home team (or away team) and random team selection (Gray & Gray, 1997**)**. This study uses random selection in the pre-registered phase models which are registered before conducting research with data and in the exploratory phase models the “team of record” is home/away team.

Table 1 shows trends in today’s NFL as general numbers. Summary statistics of game scores and winning margins have changed little bit compared to Gray & Gray (1997) study from 1976 to 1994 data. Scoring has gone up for winning score and losing score which is expected through rule changes favoring offensive side of the ball in years past. Winning margin is marginally gone down from 11.73 to 11.47 but that is marginal change.

Statistic	Mean	Std.dev	Range
Winning score	28.46	8.48	6-70
Losing score	16.99	8.10	0-51
Winning margin	11.47	9.07	0-52

Table 1. NFL game summary statistics. Winning score refers to the team that won, regardless of the home/away team status. Losing score refers to the team that lost, regardless of the home/away team status. Winning margin means margin on victory: Winning score minus Losing score.

Table 2 presents summary statistics from point spread point of view and the columns are divided across three possible team of record options that were mentioned earlier (Gray & Gray, 1997). These results indicate that based on mean values favorites and home teams are both bit overvalued because forecasted values are larger than actual outcomes. Gray and Gray (1997) study showed similar bias towards favorites, but with larger difference (0.42 versus 0.22). Contrarian to Gray and Gray (1997) results, interesting development has happened in home team results, in their study home teams are undervalued (-0.43) compared to this study's results which indicate home team's overvaluation (0.09).

Parameter	Favorite	Home	Random
Point Spread			
Mean	5.24	1.85	0.06
Std.dev	3.44	5.98	6.26
Outcome			
Mean	5.02	1.76	0.22
Std.dev	13.74	14.52	14.62
Difference			
Mean	0.22	0.09	-0.16
Std.dev	13.17	13.17	15.92

Table 2. NFL spread and result summary statistics. The point spread shows average lines before the actual games are played, outcome shows numbers based on the real scores that games ended, and difference shows the difference between forecasted (point spread) versus actual (outcome).

6 METHODOLOGY AND THE MODELS

In this section the methodology for testing both, statistical and economic efficiency in NFL spread betting market are presented. After that section proceeds to present pre-registered and explorative models in detail.

6.1 Methodology for testing statistical efficiency

First, we conduct statistical efficiency tests and try to conclude if the NFL spread betting markets spread lines are unbiased predictors of actual game outcomes (hypotheses 1). NFL spread summary statistics seems to be fairly close between the forecasted mean compared to the actual outcome mean, but still showing little deviation. Averages do not strictly mean that there could or couldn't be systematic biases or inefficiencies in the market, because in spread betting we do not care if the team beat the spread by one point or with 20 points. This is a major point why this thesis investigates statistical market efficiency through the probit model (Gray & Gray, 1997), which is specifically designed for binary outcomes such as win or lose (covering the spread), rather than using Ordinary Least Squares (OLS) methodology (Gray & Gray, 1997). The binary nature of our interest—whether a team covers the spread or not—aligns naturally with the probit model's suitability. The OLS approach can disproportionately emphasize outliers, as its slope coefficient is influenced not only by the outcome of the game but also by the margin of victory. This means that games with large winning margins unduly affect the slope coefficient. We want to avoid that, since as mentioned, we only care winner not the amount. As a result, we employ a discrete choice variable as our dependent variable. For the market to be statistically efficient, no observable information should significantly predict the outcome variable Y (Gray & Gray, 1997).

6.2 Methodology for testing economic efficiency

Next, the thesis builds on the statistical examination moving on to evaluating the economic efficiency by examining the models in in-sample and out-of-sample context (Gray & Gray, 1997). The idea behind in-sample and out-of-sample tests is to evaluate the predictive performance and generalizability of a statistical models, to further our knowledge about the market efficiency in economic sense. In-sample testing involves using a portion of the dataset (the in-sample data) to train and fit the models and out-of-sample testing involves evaluating the model's predictive performance on a separate portion of the dataset (the out-of-sample data) that was not used during model training (Gray & Gray, 1997). Models are typically used to make predictions on new data and out-of-sample testing simulates this scenario. A potential weakness of the out-of-sample data sets in this thesis is the relatively small sample size, which may result in some scenarios occurring only limited amount of the times.

6.3 Pre-registered and explorative models

I have constructed five different models to test the market efficiecny. I have pre-registered models 1 and 2 to enhance transparency and credibility before examining the data. Models 3, 4 and 5 are explorative models which are assembled after the first two models were ran. These models build upon the pre-registered models by introducing additional analyses, contributing to a more comprehensive understanding of the economic efficiecny state in the NFL betting market. Table 3 includes all the variables explanations.

Model (1) $Y = b0 + b1HOME + b2FAV + e$

Model (2) $Y = b0 + b1HOME + b2FAV + b3L2 + b4L3 + b5W2 + b6W3 + e$.

Model (3) $Y = b0 + b1homelostwo + e$

Model (4) $Y = b0 + b1AwayWonTwo + e$

Model (5) $Y = b0 + b1HomeLostMore + b2SpreadIncreased + b3BigSpread + e$

Variable	**Explanation**
HOME	Team of record is playing home
FAV	Team of record favorite
L2	Team of record current losing streak exactly two in a row spread wise
L3	Team of record current losing streak three or more games in the row spread wise
W2	Team of record current winning streak exactly two in a row spread wise
W3	Team of record current winning streak three or more games in the row spread wise
homelosttwo	Home team current losing streak exactly two games spread wise
AwayWonTwo	Away team current winning streak exactly two games spread wise
HomeLostMore	Home team current losing streak three or more games spread wise
SpreadIncreased	Underdogs spread increased from opening line to closing line

BigSpread	Spread of seven or more points

Table 3. Explanations of variables. If explanation is true, value of 1, otherwise value of 0.

7 RESULTS

This chapter provides a comprehensive framework for evaluating the efficiency of the NFL spread betting market through both statistical and economic lenses. Statistical models, inspired by Gray & Gray (1997) and extended with new variables reflecting contemporary betting trends, are systematically applied to test for potential inefficiencies. This is followed by economic tests which include in-sample and out-of-sample testing.

The results of the statistical tests are discussed in depth, highlighting patterns such as the undervaluation of teams on losing streaks and overvaluation of visiting teams on winning streaks. These findings suggest possible biases in market pricing, though not all models achieve statistical significance. This section then transitions to economic efficiency tests, evaluating the real-world applicability of the identified patterns through in-sample and out-of-sample analyses. While in-sample tests show marginal profitability in certain strategies, the out-of-sample results reveal substantial declines, underscoring the challenges of achieving consistent profits in a market adjusted to counteract systematic bettor advantage by bookmakers.

7.1 Statistical efficiency results of pre-registered models

In this section we go through the pre-register models (1-2) statistical probit regressions. Team of record is chosen by random selection, and it is defined as follows:

$$Y = 1 \text{ if the team of the record beat the spread, otherwise } 0 \tag{4}$$

First, we start to examine the home underdog bias which is found and mentioned in the literature earlier (Zuber et al. 1988, Golec & Tamarkin, 1991, Shank, 2017). We use same probit model that Gray & Gray (1997) used in their study:

$$Y = b0 + b1HOME + b2FAV + e \tag{5}$$

Team of record (Y) is defined by random selection and Y is defined like above, HOME and FAV variables are defining as follows: HOME = 1 if the team of record is playing home, 0 otherwise and FAV = 1 if the team of record is the favorite, 0 otherwise. In table 3 one can find results to this probit model.

Parameter	*Estimate*
b0	*0.0834**
	(0.0405)
b1Home	*-0.0524*
	(0.0517)
b2FAV	*-0.0685*
	(0.0517)
Correct predictions	*51.98 %*

*Table 4. Probit model (1) Y = b0 + b1HOME + b2FAV + e. Standard errors in the parentheses. **0.05 significance, *0.10 significance.*

The results for this probit model indicate that away teams and underdogs are marginally more likely to beat the spread than home favorites, although not significant (except intercept). This differs from results from Gray & Gray, (1997) where home underdogs were more likely to cover the spread. When ran through models' prediction accuracy, this probit model predicts correctly 51.98 % of the games. As mentioned earlier, 52.38 % is the breakeven point due to bookmaker's margin. Statistically it seems that this strategy could not beat the market, not to even mention the home underdog strategy suggested earlier (Golec & Tamarkin, 1991).

Next, we extend the model and add winning streak variables as well as losing streak variables. These additions are based on the earlier findings that indicate streaks playing the part of how the spreads (essentially prices) are formed, in example poor recent performance effecting the possibility of covering spread positively (Gray & Gray, 1997, Shank, 2017). New variables addition to home and favorite are L2, which is 1 if the team of record is on exactly in two game losing streak and 0 otherwise, L3 takes value of 1 if the team is on three game or more losing streak and 0 otherwise, W2 takes value of 1 if the team is on exactly two game winning streak and 0 otherwise and lastly W3 takes value of 1 if the team is on three or more game winning streak and 0 otherwise.

In this model we get new addition besides favoring away and underdog, the indication that one should bet with streaks. Both losing streaks variables generate positive coefficients and three or more games winning streak as well. Exactly two game winning streak coefficient is negative indicating that it would not be profitable betting with these kinds of teams. This model correctly predicts 52.61 % of games which indicates statistical inefficiency, although this model is bit hard to put in practice because of the nature of the streak variables, suggesting that siding with teams that are visiting underdogs and in any kind of losing streak or three or more winning streak. It seems that market overreacts especially in recent losing streaks similarly like Gray & Gray (1997) and Shank (2017) found in the earlier studies, evidence regarding winning streaks seems to favor betting teams that are in three or more games winning streak, giving indication that market seems to fall in the gamblers fallacy (Williams, 2004) and undervalue teams that are in longer winning streaks thinking maybe team is "due" to a loss. Although this model is not statistically significant.

Parameter	***Estimate***
b0	*0.0723*
	(0.0462)
b1HOME	*-0.0515*
	(0.0518)
b2FAV	*-0.0684*
	(0.0522)
b3L2	*0.0604*
	(0.0784)
b4L3	*0.0100*
	(0.0848)
b5W2	*-0.0266*
	(0.0803)
b6W3	*0.0532*
	(0.0871)
Correct predictions	*52.61 %*

*Table 5. Probit model (2) Y = b0 + b1HOME + b2FAV + b3L2 + b4L3 + b5W2 + b6W3 + e. Standard errors in the parentheses. **0.05 significance, *0.10 significance.*

7.2 Statistical efficiency results of explorative models

Then explorative model, where we use the team of record as home team similarly like earlier studies (Gray & Gray, 1997, Spinosa, 2014, Shank, 2017), meaning that our dependent variable Y is now 1 if home team covers the spread and 0 otherwise.

In the first model, we have home team that lost last two games against spread exactly in a row (b1) as a independent variable, meaning that our strategy is to bet home teams that are in two game losing streak. This model was chosen because Gray & Gray (1997) and Shank (2017) found that recent bad performances seem to indicate market overreaction and offering value for the team in slide. Similar evidence was noticed in the pre-registered model that was examined in this paper. Also, the intuition behind the fact that home team has better change to bounce back than visiting team. This model seems to back our earlier results as well as earlier studies (Gray & Gray, 1997, Shank, 2017), by showing positive coefficient in b1 indicating the undervaluation of home teams in the two-game losing streak spread wise. The model predicts 52.29 % of the game's outcomes correctly, which is well over 50 %, this model is very simple to put practice if economic efficiency is also found. Model is significant at the 0.10 level and just slightly no tin 0.05.

Parameter	***Estimate***
b0	*-0.0519**
	(0.0265)
b1homelosttwo	*0.1547***
	(0.0794)
Correct predictions	*52.29 %*

*Table 6. Probit model (3) Y = b0 + b1homelostwo + e. Standard errors in the parentheses. **0.05 significance, *0.10 significance.*

Next model in our explorative phase is the model that has visiting team on exactly two game winning streak as independent variable (b1), and dependent variable Y stays as home team covers 1, 0 otherwise. Reasoning behind choosing the b1 variable is that our second pre-registered model showed that there could be bias towards teams that are in the two-game winning streak, showing the hot hand phenomenon as Paul et al. (2012) found in their study. Also, we add the intuition that visiting team would suffer the "feel good" syndrome more easily than home team, and in combination the visiting team would be overvalued. B1 return positive coefficient meaning that betting against the away team in two game winning streak seems to be the right path and indicating our suspicions that visiting team overvaluation. The model predicts 52.41 % of game outcomes correctly landing just over the break-even point of 52.38 %. The model is significant in all levels.

Parameter	*Estimate*
b0	*-0.0656**
	(0.0297)
b1AwayWonTwo	*0.1879**
	(0.0140)
Correct predictions	*52.41 %*

*Table 7. Probit model (4) Y = b0 + b1AwayWonTwo + e. Standard errors in the parentheses. **0.05 significance, *0.10 significance.*

Lastly, we use only part of our sample when home teams are underdog (932) where we examine similar to Shank (2017) and Zuber et al. (1988), that how underdogs which are major underdogs of seven points or more (b3) and the spread moves further from opening line to closing line (b2) (essentially meaning that the home team gets more points, larger spread) and are in the losing streak of three or more games (b1).

All the coefficients of b1, b2 and b3 are positive indicating that all variables seem to better the probability of the home team covering the spread and reveling same kind of biases as Zuber et al. (1988) and Shank (2017) found. Although the model is not statistically significant. One reason is that the samples about the variables are getting pretty small in this model, which is using only part of the sample. This is known problem in the NFL studies because of only 16 (now 17) regular season games per team per season. The model still predicts 52.24 % of game outcomes correctly.

Parameter	***Estimate***
b0	*0.0509*
	(0.0968)
b1HomeLostMore	*0.0347*
	(0.1555)
b2SpreadIncreased	*0.1179*
	(0.1181)
b3BigSpread	*0.1081*
	(0.1495)
Correct predictions	*52.24 %*

*Table 8. Probit model (5) Y = b0 + b1HomeLostMore + b2SpreadIncreased + b3BigSpread + e. Standard errors in the parentheses. **0.05 significance, *0.10 significance.*

7.3 LRT tests

The Likelihood Ratio Tests (LRT) are employed to assess the overall significance of the models by determining whether the inclusion of predictors significantly improves the explanatory power relative to a baseline model. Gray and Gray (1997) used the same method in their earlier study.

In Model 1, the LRT does not show significance at either the 90% or 95% confidence levels, indicating that the predictors in this model do not significantly contribute to explaining the variation in the dependent variable. Similarly, in Model 2, the LRT also fails to show significance at either of these levels.

In Model 3, the LRT is significant at the 90% confidence level, indicating that the predictors in this model contribute significantly to explaining the variation in the dependent variable.. Moving to Model 4, the LRT shows significance at the 95% confidence level, providing strong evidence that the predictor in this model significantly contribute to explaining the dependent variable.

Finally, Model 5, the last model tested, does not show significance at either the 90% or 95% confidence levels, suggesting that the predictors in this model do not significantly explain the variation in the dependent variable.

In summary, the results indicate that Models 3 and 4 are significant at the 90% and 95% confidence levels, respectively, with their predictors demonstrating a meaningful contribution to explaining the variation in the dependent variable. In contrast, Models 1, 2, and 5 fail to reach significance at either the 90% or 95% confidence levels.

7.4 Recap of statistical efficiency findings

In conclusion, our statistical analysis employing probit models uncovers patterns indicative of potential statistical inefficiencies within the NFL spread betting market, although not strongly because of the statistical significance issues. While traditional biases like the home underdog effect did not come through in our study, we identified that teams on losing streaks are more likely to cover the spread. This suggests that the market may overreact to recent poor performances, undervaluing these teams. Conversely, betting against visiting teams on exactly two-game winning streaks also showed promise, hinting at possible overvaluation due to the "hot hand" fallacy. Although some of our models were not statistically significant, these findings align with earlier research and highlight areas where the market may not be fully efficient. These statistical inefficiencies form a basis for exploring whether they can be leveraged profitably. In the following section, we will examine the economic implications of our results, evaluating if these observed patterns can be translated into effective betting strategies when accounting for the bookmaker's margin and other real-world considerations.

7.5 Economic efficiency results

In the selection of in-sample and out-of-sample, random selection and chronological selection are chosen. In random selection 23.8 percent of the games (602) are moved in the out-of-sample category and remaining 1926 games to the in-sample. In chronological selection last two seasons (2023 and 2024) are put to out-of-sample dataset and first eight seasons (2015-2022) to in-sample. By using a chronological sample, we gain perspective on how someone running these same tests before the 2023 season would have fared in the next two season following these betting strategies.

First, we run how accurately models predict correct game outcome in in sample and out-of-sample similarly what we did in the statistical assessment part. Then the economic performance of the models was assessed through flat betting strategies, calculating the average returns for both in-sample and out-of-sample. Lastly, the predictive and economic performance of the models was further evaluated using significance tests based on a binomial distribution. For prediction accuracy, p = 0.5 was used as the benchmark, reflecting the random guessing. For profitability, p = 0.524 was applied, representing the success rate required to break even given typical sportsbook vigorish. The resulting p-value is the probability that a strategy of betting on a randomly selected team would yield a success rate higher than the observed success rate of the strategy.

Betting model	**Prediction rate**		**Average return**		**P = 0.5**		**P = 0.524**	
	R	C	R	C	R	C	R	C
Model 1								
In-sample	51.82 %	51.87 %	-1.08 %	-0.97 %	0.058	0.049	0.704	0.691
Out-of-sample	52.49 %	52.39 %	0.21 %	0.02 %	0.119	0.147	0.499	0.520
Model 2								
In-sample	51.92 %	52.57 %	-0.88 %	0.36 %	0.048	0.011	0.671	0.450
Out-of-sample	51.99 %	49.14 %	-0.74 %	-6.19 %	0.174	0.670	0.595	0.938
Model 3								
In-sample	51.92 %	52.92 %	-0.88 %	1.02 %	0.048	0.005	0.671	0.330
Out-of-sample	53.49 %	49.90 %	2.11 %	-4.73 %	0.047	0.535	0.311	0.882
Model 4								
In-sample	52.44 %	52.87 %	0.11 %	0.93 %	0.017	0.005	0.495	0.346
Out-of-sample	52.33 %	50.67 %	-0.11 %	-3.27 %	0.136	0.397	0.531	0.799
Model 5								
In-sample	52.44 %	52.46 %	0.11 %	0.15 %	0.196	0.187	0.516	0.512
Out-of-sample	51.69 %	50.50 %	-1.31 %	-3.60 %	0.391	0.500	0.597	0.686

Table 9. Economic tests for all probit models in random (R) and chronological (C) selection in in- sample and out-of-sample testing.

7.5.1 Random selection results

In the random selection approach, the prediction rates for in-sample testing ranged from 51.82% to 52.44%, indicating a modest improvement over the 50% baseline of random chance. Out-of-sample prediction rates in this approach remained slightly above the baseline, with values ranging from 51.99% to 53.49% across the five models. Only one of the models (model 3) prediction accuracy changed over one percent indicating that random selection test holds similarly in both samples. Notably, Model 3 demonstrated the highest prediction rate in the random out-of-sample testing at 53.49%, suggesting some degree of the possible profitability in capturing patterns from the in-sample data. Average returns yielded marginal results all over the board as expected after the prediction rates. Model 3 standing out as the most successful, yielding a positive return of 2.11 % in out-of-sample which is something.

In the random selection, in-sample prediction accuracy in P = 0.5 approached significance in some cases, such as in Models 2, 3 and 4. But this did only translate to the significant out-of-sample results in terms of the model 3, indicating robust predictive power of betting home teams that were in two game losing streak spread wise. Although, the model 3 profitability significance tests with P = 0.524 failed to yield compelling evidence, with p-values consistently above conventional significance thresholds. Similarly to model 3 all models in-sample and out-of-sample results were not significant in p = 0.524 tests.

7.5.2 Chronological selection results

In the chronological selection we start to see interesting results. Prediction rate test reveal larger dispersion between in sample and out-of-sample than in random election. Only the model 1 (betting on home underdogs) prediction rate of 51.87 % goes below break-even point of 52.4 % in in-sample. Other models range between 52.46 % and 52.92 %, indicating marginal profitability in average returns. The models 2-5 returns in average between 0.15 % and 1.02 %. In out-of-sample models 2-5 strategies prediction rates plummet drastically, between 49.14 % and 50.67 %. Because of these average returns yield negative results ranging between -3.27 % and -6.19 %. Model 1 has moved close to break-even point in out-of-sample.

The predictive and economic performance of the chronological models was further evaluated using significance tests based on a binomial distribution. In the chronological in-sample, the results were significant at p = 0.5 for all models except Model 5, consistent with the modestly above-random prediction rates observed. However, in the out-of-sample none of the models achieved statistical significance at p = 0.5 indicating their inability to fare effectively in recent data. Furthermore, when profitability was assessed using p = 0.524 the models performed poorly across both in-sample and out-of-sample periods. None of the models demonstrated significant profitability, and in the out-of-sample period, the results were particularly weak, with prediction and profitability outcomes falling to negative.

7.6 Recap of economic efficiency results

The results of the economic efficiency analysis indicate that while the statistical models demonstrate modest predictive accuracy above random guessing in in-sample tests, their out-of-sample performance reveals significant efficiency. All profitable models in the in-sample plummeted to negative suggesting systematic reaction by bookmakers to mitigate these inefficiencies, backing the efficient market. Under the random selection method, predictive accuracy for most models remained marginally above the 50% baseline, with Model 3 achieving the highest out-of-sample accuracy at 53.49% and a small positive return of 2.11%. However, statistical significance tests for profitability at p = 0.524 failed to provide compelling evidence of sustained economic efficiency, suggesting that these strategies are unlikely to yield consistent profits. The chronological selection method highlighted an even more pronounced decline in out-of-sample performance, with predictive accuracy falling below the break-even threshold for several models and average returns turning negative. These findings emphasize the challenges of leveraging historical data to predict outcomes and generate profits in the NFL betting market, supporting the hypothesis of market efficiency as well as bookmakers' skill to understand bettor behavior and adjusting accordingly to mitigate profitable strategies.

The significant deterioration in model performance in out-of-sample tests, particularly under chronological selection, underscores the difficulty of capturing stable patterns in this market, further suggesting that the NFL betting market operates close to an economically efficient state. Compared to Gray & Gray (1997) who conducted similar in sample and out-of-sample test from data ranging 1976 to 1994 seasons, I couldn't find strategy in chronological testing that would fare better in out-of-sample data than in in sample, like they did. Conversely, out-of-sample showing dramatic negative returns indicating intentional focus in mitigating marginally profitable strategies by bookmakers. Also, contradicting Shanks (2017) findings that large home underdogs in losing streaks could yield profitable strategy, it seems evident that not in my data.

The results of this study reveal new, heightened level of awareness among bookmakers in mitigating profitable betting strategies compared to earlier findings. While some earlier studies strategies have shown a decline in profitability over time, others persist, albeit less consistently, but not this study. This indicates that bookmakers are increasingly adept at adjusting their models and lines to neutralize exploitable inefficiencies, reflecting a more sophisticated response to market dynamics than previously observed.

8 CONCLUSION

Sports betting markets share notable similarities with financial markets, making them a compelling context for academic investigations into market efficiency. In some ways, they are even better suited for such studies, as sporting events have definitive outcomes, unlike the open-ended nature of financial instruments like stocks. The NFL spread betting market, in particular, provides a structured environment to analyze predictive accuracy and profitability through the lens of statistical and economic efficiency. This study contributes to the extensive body of literature by examining recent data and employing robust methodologies to assess whether these markets remain efficient in light of evolving bookmaker strategies and bettor behaviors.

The key finding of this paper lies in the contrast between in-sample and out-of-sample performance in a chronological review in economic test. Strategies that appeared marginally profitable in in-sample tests, such as those targeting undervalued teams on losing streaks or overvalued visiting teams on winning streaks, were rendered drastically unprofitable in out-of-sample tests. For instance, while models 2–5 demonstrated returns between 0.15% and 1.02% in in-sample data (spanning the first eight seasons), these same strategies produced significant losses ranging from -3.27% to -6.19% in out-of-sample tests (covering the last two seasons). This stark divergence highlights the adaptability of bookmakers, whose adjustments to betting lines effectively neutralize previously identified inefficiencies. These results align with the broader literature suggesting that bookmakers actively refine their methods to counteract patterns that sharp bettors exploit. Compared to earlier results these results indicate clear pattern by bookmakers to mitigate effictevily all profitable betting models and showing new level of efficiency in the NFL spread betting market. Earlier we have only seen some strategies, not all, to fall unprofitable (Gray & Gray, 1997).

Historically, strategies like betting on home underdogs provided evidence of both statistical and economic inefficiencies in the market (Golec & Tamarkin, 1991, Gray & Gray, 1997, Shank, 2017), allowing savvy bettors to achieve consistent profits. However, as this paper demonstrates, bookmakers have significantly improved their ability to detect and mitigate such vulnerabilities. The concept of line skewing—where bookmakers adjust point spreads based on anticipated bettor biases (Levitt, 2004)—has evolved into a highly sophisticated practice. Rather than applying blanket adjustments, bookmakers now tailor these modifications to specific teams, seasons, and known cognitive biases, such as recency bias, gambler's fallacy, and herd mentality. This evolution reflects a deeper understanding of bettor behavior, rendering straightforward betting strategies less effective (Gray & Gray, 1997, Mani, 2018).

The findings of this study also suggest that market participants, particularly casual bettors, continue to exhibit predictable psychological biases that bookmakers leverage to create skewed lines. Bettors tend to overreact to recent outcomes, undervalue teams on losing streaks, and overvalue teams on winning streaks, among other behavioral tendencies (Ziemba et. al, 1988, Gray & Gray, 1997, Shank, 2017) . Despite these biases being well-documented in both the academic literature and real-world betting contexts, this paper's results indicate that exploiting such inefficiencies has become increasingly difficult. Bookmakers' ability to adjust lines dynamically based on these biases ensures that any marginal advantage identified in historical data is unlikely to persist in real-world applications.

In light of these findings, this study supports the argument that the NFL spread betting market has approached very high level of efficiency that limits the profitability of simplistic betting strategies. However, this efficiency is not absolute. Behavioral tendencies among bettors and subtle inefficiencies still exist, but detecting and exploiting them requires far greater sophistication than in the past. Researchers must now employ more advanced methodologies, integrating comprehensive datasets with detailed modeling of team-specific and season-specific factors, as well as deeper analyses of public and bookmaker behaviors. Also, NFL season only containing 17 regular season games per team, per season, combined with fast changing patterns in the NFL and in betting, creates a complicated enviroinment to gather large enough sample which is up to date and offers robust results.

Moreover, the implications of this study extend beyond sports betting, as they offer insights into the broader dynamics of market efficiency. Like financial markets, where anomalies such as momentum or value effects emerge and dissipate over time, sports betting markets reveal a similar interplay between participants' behavior and market structures. The role of bookmakers as active market makers, deliberately introducing inefficiencies to maximize profits, parallels the actions of market participants in financial contexts who seek to capitalize on others' mistakes. In conclusion, this paper affirms that the NFL spread betting market remains a rich field for examining market efficiency, particularly as it evolves in response to advancements in data analytics and market behavior. While statistical inefficiencies can still be identified at some level, translating them into economic profitability is increasingly challenging due to bookmakers' growing sophistication in setting and adjusting lines. Now and in the future, studies will likely require not only rigorous analytical frameworks but also an interdisciplinary approach, combining insights from behavioral economics, data science, and traditional financial theories to unravel the complexities of this ever-adapting market.

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