Behavioural Biases and Irrational Decision-Making in Sports Betting by Nathaniel Bier

Abstract

Irrationality and behavioural biases are an almost ubiquitous part of decision-making processes and inevitably contribute to suboptimal outcomes, whether operating consciously or subconsciously. In no circumstances are these displayed more clearly than in financial markets, where all factors are optimised towards a single goal of maximising financial gain; however, the complex nature of modern financial markets makes conducting analyses on the decision-making process inherently challenging. By contrast, the distinct resolutions in sports betting markets of either success or failure make them an ideal laboratory to study irrational decision-making and the reasoning behind it. As such, this study was conducted by comparing the differences between expected returns implied by pre-match odds and actual returns from 1,900 football/soccer matches across five Premier League seasons. The results of this study supported the existence of several biases present amongst sports betting markets, including the favourite-longshot bias, confirmation bias and overconfidence bias, as well as the Efficient Market Hypothesis, with almost all betting patterns proving unsuccessful over a large sample size. Future research could expand the analysis to include a broader dataset of more matches, leagues and sportsbooks, possibly considering other sports and alternative betting markets.

Keywords: *Behavioural Biases, Irrational Decision-Making, Sports Betting Markets, Efficient Market Hypothesis, Favourite-Longshot Bias, Confirmation Bias, Overconfidence Bias*

1. Introduction

Legal sports betting markets are a large and rapidly growing sector. In 2024, 149.90 billion USD of sports bets were placed in America, producing a total economic impact of 328.6 billion USD, as per the American Gaming Association. Over half of all global betting volume involves football matches, totaling over 800 billion USD in 2023 alone (Statista Research Department). Approximate extrapolations based on viewership data suggest that 40-45% of all football bets are placed on Premier League matches, making the Premier League a sufficiently high-volume sample.

Decision-making processes in financial markets and sports betting markets are closely linked. Not only do ideal investors in each market operate in almost identical fashion, but retail investors in both markets consistently fall into a similar set of behavioural biases, positioning such demographics at a notable disadvantage. The difference between commercial fund returns and retail investor returns, known as the “behaviour gap”, stands at 1.7% annually in the United States (LaMonica).

This positions sports betting markets as a natural laboratory to conduct an experiment on behavioural economics. The outcomes in sports betting are fundamentally binary; either a bet will return the investor with its projected payout, or the investor will lose their capital, making analysis of the expected value (EV) and actual value of a bet straightforward and objective.

Sports betting markets operate on the premise that the odds offered by sportsbooks are optimised to maximise return on investment (ROI) while minimising exposure on either side

of a bet. This strategy is largely, but not perfectly, aligned with the mathematically optimised probabilities of real event occurrence. As market volumes increase, the market will naturally become more efficient as bettors will balance out each other's inaccuracies on aggregate; therefore, the alignment of mathematical probabilities and sportsbook odds will converge. This implies that in smaller markets, there is a possibility of a positive delta between mathematical probabilities and odds offered on bets that are comparatively unpopular to a large proportion of bettors.

Several behavioural biases are particularly useful in understanding the reasoning behind why some bettors continue to place unfavourable bets despite discouraging returns. The favourite-longshot bias can attract bettors to bets involving higher payouts but significantly inferior odds (Winkelmann et al.); the overconfidence bias can lead to bettors making misinformed and inaccurate decisions due to an overestimation of their own knowledge (Snow and Murray); the confirmation bias can cause those bettors who research their bets to focus exclusively on evidence and statistics which support their ideal outcome or their pre-empted conclusions of the match result (Murray). Whether working in tandem or individually, these biases will undoubtedly have a nontrivial impact on the thought process and eventual outcomes of bets when analysing them over a long period of time.

A large body of literature on behavioural biases originally designed with financial markets in mind can be applied to sports betting markets with varying levels of accuracy. The Efficient Market Hypothesis postulates that asset prices fully reflect all available information, leaving no room for investors to generate consistent alpha (Fama). Just as the price of equities or bonds ought to reflect and internalise the relative values and risks of the assets they represent, initial betting odds would represent the collation and assessment of all relevant information, such as match location and conditions, team form, historical data, roster information (Chesir). Following this, as a self-regulating market, any odds offered should eventually converge on the mathematically optimal probabilities of outcomes as market volume increases and an increasing number of informed bettors provide information on which selections are favourable and unfavourable based on how they place their bets (Ramirez et al.).

The favourite-longshot bias, initially observed in the context of sports betting markets, diverges from the Efficient Market Hypothesis as to how informed investors and bettors are in the markets they engage with and subsequently how they contribute to the accuracy of those markets. It posits that a disproportionately large segment of bettors tend to select longshot outcomes over favourite outcomes despite longshot markets typically providing less favourable odds than the alternative (Williams). In the example of horse racing, more data would naturally be available on horses favoured to win than those considered longshots, allowing sportsbooks to deflate the odds offered on longshot horses without losing significant volume on longshots due to bettors having incomplete information. Prior literature has also hypothesised bettors' willingness to gamble on longshots as being due to risk-loving behaviour or inaccurate calculations (Sobel and Raines), despite the widely accessible odds-to-probabilities converters such as Shin, Power and Goto_Conversion (Goto and Yamada; Štrumbelj). This bias is particularly relevant in the mispricing of certain events in sports betting markets by sportsbooks.

A dataset on match results and pre-match odds was aggregated from 1,900 Premier

League matches across the last five seasons. Subsequently, the deltas between actual returns of each betting pattern relative to their expected values, assumed to be neither positive nor negative, were collated across each season and across the five seasons, all of which displayed largely negative returns. Several substudies were taken from the larger dataset and confined to betting on a reasoned subset of teams, some of which supported different hypotheses, including the Efficient Market Hypothesis, the favourite-longshot bias, the confirmation bias and the overconfidence bias. However, all studies aligned with the notion that the consistent adoption of any one betting philosophy would produce overall negative returns.

2. Methodology

2.1 Aim

This study aims to gain insight into behavioural biases and the role they play in irrational decision-making, in the context of financial markets as well as in other areas. Sports betting was selected as a laboratory due to its inherently binary nature of market resolution, leaving no ambiguity as to the outcomes in any scenario, while also remaining self-regulating, allowing bettors to have an impact on the odds and prices of the markets they place bets on and maintaining the integrity of the market.

2.2 Data Collection

Data was collected from Football-Data.co.uk, which has publicly available and downloadable spreadsheets containing the full-time results of each Premier League match as well as the pre-match home, away and draw odds from bet365, amongst a broad range of additional statistics. The data for each match in the five Premier League seasons between 2020/2021 and 2024/2025 inclusive was collated in a spreadsheet, with a separate tab for each season.

2.3 Data Analysis

For each match, the pre-match odds were manipulated to be considered as favourites and longshots instead of as home and away teams. From here, the return for each selection (favourite, longshot or draw) was calculated based on the full-time result, assuming a bet of one unit for each selection. The returns were then averaged across each season and across all five seasons. Several analyses of subsets were also conducted with the intention of isolating a specific hypothesis in each substudy. The first substudy involved only matches involving teams who had finished in the top five places in the previous season, the second involved only matches involving teams considered in the traditional Premier League “Big Six” (Arsenal, Chelsea, Liverpool, Manchester City, Manchester United and Tottenham Hotspur), the third involved only matches involving teams considered “major favourites” (with odds of winning more than 1.00 greater than their opponent, regardless of whether they were playing at home or away) and the fourth involved only matches considered “close” (with the favourite’s odds of winning less than 0.50 greater than their opponent). A separate study was also conducted on the total over/under tally at a benchmark of 2.5 goals and the aggregated returns across each season and across all five seasons.

2.4 Statistical Tools

The statistical tools used in data collection and formatting were calculation of expected values, calculation of actual returns based on results and largely filtering of teams based on whether they met the aforementioned criteria for various subanalyses. For the data analysis itself, return-on-investment analysis of various betting patterns was conducted, as well as probability calibrations as to whether sportsbooks' statistics reflected actual odds and descriptive statistics calculating averages and other macro conclusions.

2.5 Softwares

The primary software used was Google Sheets and its built-in formulas in order to filter for particular matches when analysing subsets and calculate averages of expected and actual returns.

2.6 Ethics

While collecting and analysing data, no actual bets were placed or advertised; this paper serves not to promote gambling or betting in any form, but rather to analyse sports betting markets from an academic viewpoint and shed light on why existing bettors often make suboptimal and uninformed decisions. Although inquiries were made to previous researchers who were able to access and utilise restricted data directly from sportsbooks, all data collected and software used for this paper are publicly accessible.

3. Results

The following results were obtained after collating a dataset of 1,900 matches across five Premier League seasons and analysing the average returns for specific betting patterns: betting consistently on teams considered favourites by sportsbooks (i.e. teams with the "shorter" odds or smaller payout in the event of a successful bet, or simply the team which is deemed more likely to win the match), betting consistently on teams considered longshots by sportsbooks (i.e. teams with the "longer" odds or larger payout in the event of a successful bet, or simply the team which is deemed less likely to win the match), and betting consistently on the outcome being a draw, where neither team wins the match.

Table 1: Average returns for every Premier League match from season 2020/2021 to season 2024/2025

Season	Favourite Return	Longshot Return	Draw Return
2020/2021	-0.0877	0.2089	-0.1229
2021/2022	0.0179	-0.1659	-0.0877
2022/2023	-0.0087	-0.0727	-0.0920
2023/2024	0.0001	-0.1992	-0.1154
2024/2025	-0.0676	-0.1182	0.0108
Total	-0.0292	-0.0694	-0.0814

Table 1 shows that across all five seasons, all three of the aforementioned betting

patterns would have yielded negative results. Betting on favourites yielded a return of -0.0292 units per unit bet, longshots yielded an inferior return of -0.0694 units per unit bet, and draws yielded the worst return of -0.0814 units per unit bet. No betting pattern would have yielded positive returns for more than two out of the five seasons, and almost all positive returns were marginal in comparison to the negative returns. Notably, betting on longshots in the 2020/2021 season would have provided a markedly positive return, 0.2089, compared to any other betting pattern in any other season.

Table 2: Average returns for every Premier League match involving at least one team that finished in the top five places in the previous season from season 2020/2021 to season 2024/2025

Season	Favourite Return	Longshot Return	Draw Return
2020/2021	-0.1009	0.2804	0.0456
2021/2022	-0.0819	-0.1136	0.0827
2022/2023	-0.0623	0.0915	-0.0837
2023/2024	-0.0428	-0.1374	-0.2487
2024/2025	-0.0675	-0.3299	0.0982
Total	-0.0711	-0.0418	-0.0212

Table 2 shows that across all seasons, all three betting patterns would have yielded negative results. Betting on favourites yielded a return of -0.0711 units per unit bet, betting on longshots yielded a slightly superior return of -0.0418 units per unit bet, and betting on draws yielded the best return of -0.0212 units per unit bet, although still a negative return. Betting on favourites would have yielded negative returns across each of the previous five seasons, supporting the presence of the overconfidence bias in some sports betting markets, whereas betting on longshots or draws would have had mixed results across seasons, with positive returns coming in two out of five and three out of five of the seasons for longshot and draw betting patterns respectively. With a much smaller dataset of 420 matches, the results also showed much greater variance across seasons, with longshot betting specifically yielding returns of 0.2804 units per unit bet in the 2020/2021 season and -0.3299 units per unit bet in the 2024/2025 season.

Table 3: Average returns for every Premier League match involving at least one team in the traditional "Big Six" (Arsenal, Chelsea, Liverpool, Manchester City, Manchester United, Tottenham Hotspur) from season 2020/2021 to season 2024/2025

Season	Favourite Return	Longshot Return	Draw Return
2020/2021	-0.0907	0.2401	-0.0063
2021/2022	-0.0109	-0.1963	-0.1207
2022/2023	-0.0264	-0.0418	-0.0875
2023/2024	-0.0296	-0.1220	-0.2614

2024/2025	-0.0676	-0.2468	0.0576
Total	-0.0450	-0.0734	-0.0836

Table 3 shows that across all seasons, all three betting patterns would have yielded negative results. Betting on favourites yielded a return of -0.0450 units per unit bet, betting on longshots yielded an inferior return of -0.0734 units per unit bet, and betting on draws yielded the worst return of -0.0836 units per unit bet. Amongst this subset, only two betting patterns across any of the five seasons would have yielded positive returns – betting on draws in the 2024/2025 season and betting on longshots in the 2020/2021 season, yielding returns of 0.0576 and 0.2401 units per unit bet respectively. With a much smaller dataset of 364 matches, the results also showed much greater variance, with longshot betting specifically yielding returns of 0.2401 units per unit bet in the 2020/2021 season and -0.2468 units per unit bet in the 2024/2025 season.

Table 4: Average returns for every Premier League match involving a clear "favourite" and "longshot", defined as when the favourite odds are more than 1.00 greater than the longshot odds from season 2020/2021 to season 2024/2025

Season	Favourite Return	Longshot Return	Draw Return
2020/2021	-0.1200	0.2845	-0.1092
2021/2022	-0.0133	-0.1324	-0.1075
2022/2023	-0.0445	-0.0487	-0.0798
2023/2024	0.0204	-0.2424	-0.1563
2024/2025	-0.0637	-0.1441	0.0319
Total	-0.0442	-0.0566	-0.0842

Table 4 shows that across all seasons, all three betting patterns would have yielded negative results. Betting on favourites yielded a return of -0.0442 units per unit bet, betting on longshots yielded an inferior return of -0.0566 units per unit bet, and betting on draws yielded the worst return of -0.0842 units per unit bet. Amongst this subset, only three betting patterns across any of the five seasons would have yielded positive returns – betting on draws in the 2024/2025 season, betting on favourites in the 2023/2024 season and betting on longshots in the 2020/2021 season, yielding returns of 0.0319, 0.0204 and 0.2845 units per unit bet respectively.

Table 5: Average returns for every Premier League match considered a "close game", defined as when the favourite odds are less than 0.50 greater than the longshot odds from season 2020/2021 to season 2024/2025

Season	Favourite Return	Longshot Return	Draw Return
2020/2021	-0.0828	0.0083	-0.0723
2021/2022	-0.1449	-0.0160	0.0533
2022/2023	0.3178	-0.2342	-0.3430

2023/2024	-0.0309	-0.1323	0.0617
2024/2025	-0.1125	0.0672	-0.1585
Total	-0.0106	-0.0614	-0.0918

Table 5 shows that across all seasons, all three betting patterns would have yielded negative results. Betting on favourites yielded a return of -0.0106 units per unit bet, betting on longshots yielded an inferior return of -0.0614 units per unit bet, and betting on draws yielded the worst return of -0.0918 units per unit bet. This subset of matches displayed notably positive returns for betting on favourites in the 2022/2023 season (0.3178) and negative results for longshots and draws in the same season (-0.2342 and -0.3430 respectively). This study also had the most negative returns for any betting pattern across all five seasons – in this case, betting on draws.

Figure 1: Average returns for betting on a total of over (blue) or under (red) 2.5 Goals per match from season 2020/2021 to season 2024/2025

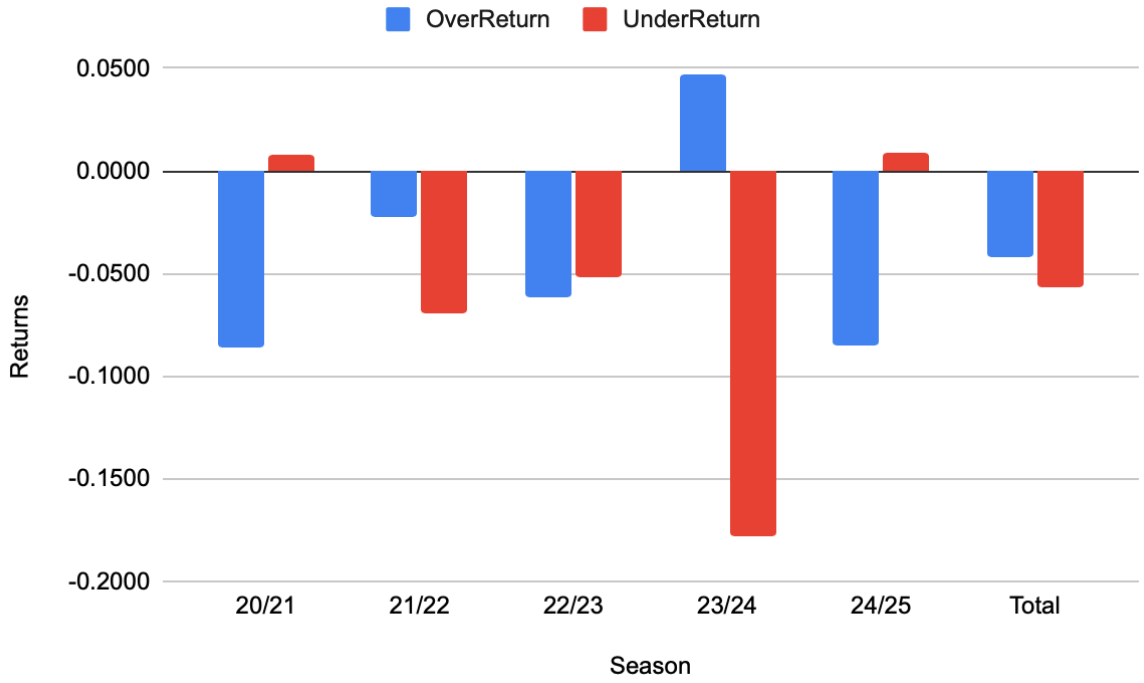


Figure 1 shows that across all seasons, betting on either over 2.5 goals or under 2.5 goals would have yielded negative results. There is natural variance throughout the seasons, particularly visible in the 2023/2024 season and the 2020/2021 season, but the chart is predominantly composed of negative returns. Positive returns were only achievable in three seasons – two of which were marginal – and the third of which is betting on over 2.5 goals in the 2023/2024 season.

4. Discussion

The results of this study strongly support the thesis that any simple pattern of selections on full-time outcomes of football matches is highly unlikely to produce consistently positive returns over an extended period of time. This is primarily due to the

"vig"; effectively the margins present in sports betting markets such that if one were to place equal bets on all outcomes of an event they would lose a marginal amount of money – or simply put, that the probabilities implied by sportsbook odds will always sum to a value greater than one (Clarke; Feddersen et al.). With this disadvantage already integrated for all bettors, the remaining deviations between comparatively successful and unsuccessful strategies exist largely because of behavioural biases, which can mitigate or amplify losses.

The wider results largely agree with the Efficient Market Hypothesis. All markets used in this study involved high-volume betting and adaptive odds based on bettor activity; as such, betting odds broadly reflect public perception of how likely each of the respective outcomes is to occur. The repeatedly negative returns derived from following any consistent betting pattern across all five seasons support this notion. Despite individual seasons of positive returns, the increase in sample size streamlined the market inefficiencies, balanced out and neutralised the various biases amongst bettors and therefore aligned the odds offered by sportsbooks with the underlying probabilities involved.

The overconfidence bias is evident through the consistently negative returns of selecting favourites. This indicates that bettors overestimate the probability of favourites winning and therefore place a disproportionately large percentage of bets on favourites to win; subsequently, sportsbooks react by adjusting their odds accordingly to make bets placed on favourites less favourable in their returns. Considering that this pattern is most visible in Table 2, where each unit bet would have resulted in a mean loss of 0.0711 units, this notion aligns clearly with the overconfidence bias, as bettors may have been placing undue weight on historical results and performances from previous seasons (Brown, Grasley & Guido). The favourite-longshot bias is also visibly supported by these results, as bettors are naturally attracted to the greater potential payout without regard for the low probabilities implied by the odds, as shown in Table 4.

Although this study analyses sports betting on Premier League matches, the behavioural biases observed can be applied to a wide range of circumstances outside of this area. In financial markets, retail investors exercise the overconfidence bias by overestimating their understanding of price movements and macroeconomic trends, often coming to conclusions which are based on insufficient or inaccurate data. The favourite-longshot bias is also prevalent amongst retail investors, many of whom choose to invest in penny stocks to stand a chance of earning significant ROI despite the underlying stocks often not meeting the fundamentals and criteria necessary to make it a worthwhile investment. Within professional circles, venture capital and entrepreneurial activities can display signs of the favourite-longshot bias in action, where even tenured and experienced businesspeople become attracted to high-reward but low-probability opportunities.

Understanding these biases more clearly could provide a greater degree of equity to sports betting markets and in broader financial markets. Mandatory educational programs and warnings of cognitive biases could help to level the playing field between bettors and sportsbooks and between retail and professional investors.

5. Conclusion

5.1 Summary

This study aimed to understand and further investigate the key drivers of irrational

decision-making and used sports betting markets as a laboratory to do so. After conducting six separate analyses using a dataset of 1,900 football matches across five Premier League seasons, results largely aligned with the notion that no consistent betting strategy would yield positive long-term returns. In addition to the built-in margins found in all sportsbooks, the results supported the existence of several behavioural biases hypothesised to impact sports betting markets; namely the favourite-longshot bias, the overconfidence bias and the confirmation bias, all of which are also applicable to wider financial markets and various other areas of critical decision-making.

5.2 Limitations

The scope of this study was limited in some respects, particularly with regard to data collection and breadth of analysis, due to the commitment to source all data exclusively from publicly available databases. Although 1,900 matches were included in the analysis, the dataset was confined solely to football matches within the last five full Premier League seasons and only included pre-match betting odds from a single sportsbook (bet365), whereas a broader dataset across multiple leagues, sports and sportsbooks could have provided a greater degree of confidence and reliability to the results and conclusion of the study. Furthermore, the analysis did not include any alternative betting markets (e.g. individual player props) or more advanced betting strategies such as hedging, variable bet sizing or selective betting. These limitations somewhat restricted the applicability of the findings across different leagues, sports and markets.

5.3 Future Work

Future research could build on this study by addressing the limitations and expanding the scope of the analysis. Inclusion of multiple leagues, sports and sportsbooks would further test the validity and reliability of behavioural biases in sports betting markets. Analysis of live betting markets, where beliefs such as the recency bias and the hot-hand fallacy can be observed, may open the door to further understanding of irrational decision-making. Comparative analysis of bettor activity based on bet sizing and timing to distinguish between retail bettors and professional bettors could aid in clarification of how expertise and utilisation of algorithms can either mitigate or amplify biases. This could also shed light on which biases are due to human conditions such as tribalism and other social-identity effects, and which are due to misinterpretation of data. Finally, integrating psychological survey-based data alongside the previous quantitative analysis may provide insight into the deeper drivers and reasoning behind irrational decision-making, allowing for a broader application of conclusions drawn in a sports betting laboratory to broader behavioural economic theory and decision analysis. Finally, the quantitative component of this study could also be coupled with a psychological aspect, surveying sports bettors and non-bettors to understand the differences in their respective decision-making processes and how sports betting impacts decision-making outside of financial markets.

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