Weak Form Efficiency in Sports Betting Markets

Thomas R. Robbins
East Carolina University

Betting on sports is increasingly popular, and legal in the United States. Many states have moved to legalize sports betting both in-person and on-line. In this paper we evaluate the sports betting market and assess its efficiency in the financial sense. Using a large dataset of betting odds and outcomes across a wide range of sports over an extended period, we evaluate the weak-form efficiency of the sports betting market. While we find some minor technical inefficiencies, overall, the markets are generally efficient, and no odds-based betting strategy will yield statistically significant long-term profits. But some bets are better than others. Slight underdog bets in professional and collegiate football and the UFC have had positive returns over an extended time frame, though they do not clear a statistical significance test. On the other hand, we find some bets clearly under perform. Longshot bets in college basketball are among the worst bets and longshot biases can be shown to exist in collegiate football and basketball as well as baseball.

Keywords: sports betting, market efficiency

INTRODUCTION

Gambling has been popular throughout human history, and gambling on sports has been popular as long as there have been sports. But the legality of sports betting in the United States has varied considerably over time. The Professional and Amateur Sports Protection Act of 1992, also known as PASPA or the Bradley Act, effectively outlawed betting on most sports throughout most of the US, making exceptions only for licensed sports pools in Nevada as well as lotteries in Oregon, Delaware and Montana. Excluded from the reach of PASPA were jai alai, as well as parimutuel horse and dog racing.

The situation changed dramatically in 2018 when the United States Supreme Court ruling in Murphy vs. NCAA struck down the PASPA law and returned the regulation of gambling to the states. In the years since many states have moved to legalize sports gambling, both in-person and on-line. Total betting numbers are uncertain, but in 2019 betting in the Vegas sportsbook alone exceeded $5 billion. In the first quarter of 2022 DraftKings Inc., one of the larger on-line sportsbooks, reported quarterly revenue of $417 million dollars, a 34% increase from the prior year (Jones 2022). Sports betting is now a large and growing financial market, increasingly legal and in the open.

In this paper we evaluate the sports betting market and assess its efficiency in the financial sense. Using a dataset of odds and results on over 155 thousand sporting contests across the major sports in North America that covers 16 seasons, we evaluate the accuracy and efficiency of the odds to assess if the markets can be considered weak-form efficient. Our analysis finds that technical inefficiencies exist in the odds to the degree that we conclude that some of the markets are not weak-form efficient. These inefficiencies vary from sport to sport but are reasonably consistent over time. However, the level of inefficiency is small.

Positive returns are present in some odds ranges over time, but the returns are small and not statistically significant. No abnormal positive returns exist for the bettor but returns in excess of the average book margin do exist for the bookmaker in some cases. From this we can conclude that, overall, the sports bettor cannot earn a positive profit by a betting system based on the moneyline odds for these major sports.

LITERATURE REVIEW

Capital Market Efficiency

The focus of our analysis is on the efficiency of the sports betting markets. Market Efficiency is a concept first developed in the economics and finance literature as defined by the efficient market hypothesis. (EMH). The efficient-market hypothesis (EMH) is a hypothesis in financial economics that states that asset prices *fully reflect* all available information. A direct implication is that it is impossible to "beat the market" consistently on a risk-adjusted basis since market prices should only react to new information (Wikipedia 2022).

A key review of the theoretical and empirical literature on the Empirical Market Hypothesis is provided in Fama (1970). Fama analyzes efficient markets relative to three board information sets. Weak form efficiency is based on the use of historical prices, semi-strong efficiency on publicly available information, and strong efficiency is based on all information public and private. In this framework the possibility of trading systems based on the relevant information set generating excess returns, returns in excess of equilibrium expected profits, are ruled out. Stated simply, excess profits are not possible from a trading system in a market that is efficient. The empirical analysis in this paper provides reasonably strong support for the weak, and semi-strong forms of market efficiency. The analysis however identified exceptions to the strong form of market efficiency whereby market makers and corporate insiders can exploit their monopolistic access to information to earn returns in excess of the expected risk-adjusted rate.

Sports Betting Market Efficiency

A large body of research published beginning in the 1980s and 90s examined efficiency in sports betting markets. Much of this early research focused on parimutuel and fixed odds systems in horse racing. A comprehensive review of this literature is provided in (Kuypers 2000). Kuypers reviews 5 papers that examine parimutuel systems, 6 papers on odds-based systems, and 4 papers on spread based systems. Seven of the reviewed papers assess weak form efficiency, while six examine semi-strong efficiency and two assess strong-form efficiency.

Kuypers uses the following definitions of efficiency in the sports betting context:
- Weak form: no abnormal returns, either to the bookmaker or the bettor, can be achieved solely from price information. An abnormal return is defined as a return different from the bookmaker's expected take.
- Semi-strong: no abnormal returns can be achieved from odds or any publicly available information.
- Strong: no abnormal returns can be achieved by any group in society incorporating odds publicly available and privately available information.

Our analysis will focus on weak form efficiency. The implication of weak form efficiency is that the return on bets in any odds range to a bettor will be negative, consistent across odds ranges, and equal to the bookmaker's average hold.

Kuyper tests weak-form efficiency in the betting market for UK football (soccer) analyzing 3,882 matches from 1993-95. He divides the bets into 20 bins and calculates the expected after-tax return from taking all bets in each bin and compares those returns to the expected after-tax return of -18.5% implied by the fixed hold. The analysis finds that all returns are negative. The best return is -3.13% in the odds bin where the mid-point implied probability is 49%, the slight underdog. His analysis concludes that while market inefficiencies exist, no formula based simply on betting an odds range will yield a positive return. He further concludes that there is no systematic bias in the odds by regressing the actual win probabilities

against the implied win probabilities for each group and failing to reject the null hypothesis that the slope is equal to one.

A more recent examination of English Football is performed in Deschamps and Gergaud (2007). They analyze 8,377 matches between 2002 and 2006 with odds from six different bookmakers. They also find considerable variation across odds groups, but no positive returns. Another assessment of English football odds is provided in (Direr 2011). Direr evaluates 11 years of odds (200-2011) from 6-10 odds makers, for a total of nearly 80,00 games and 2.8 million betting opportunities. He finds that positive returns are available in the range of 2.8% for average odds, and 4.4% for best odds by betting on overwhelming favorites.

Other papers perform similar analysis on other sports. Levitt (2003) examines NFL games. (Hickman 2020) – looks at the NCAA "March Madness" basketball tournament. Gandar, Zuber et al. (2004) examines the National Hockey League (NHL) while Gandar, Zuber et al. (1988) looks at point spreads in NFL games. They implement two tests and come up with mixed results. A statistical test fails to reject rationality, while an economic test does reject rationality.

Longshot Bias

A specific type of inefficiency, and a frequent topic of analysis in betting markets, is the so-called longshot, or favorite-longshot, bias (FLB). An early review and assessment of this phenomenon was presented in the inaugural Anomalies series in the Journal of Economic Perspectives (Thaler and Ziemba 1988). This paper analyzed parimutuel betting and re-asserts the criteria that in a weekly efficient market no bets should have a positive expected value, and in a highly efficient market all bets have an expected value of $(1-t)$, where t is the racetrack's fixed take. The review demonstrates that the returns are systematically associated with the odds. Bets on favorites earn an above average return, while bets on longshots earn below average returns. Parimutuel odds are directly set by the amount bet so the longshot bias indicates that bettors systematically overestimate the probability that a longshot will pull off the upset. The longshot bias has at least two alternative explanations; risk seeking behavior by the bettor, or misestimation of the odds in extreme scenarios. Odds misperception is consistent with Prospect Theory's assertion that individuals overestimate the likelihood of rare events (Kahneman and Tversky 1979). A detailed comparison of these two possible explanations is presented in Snowberg and Wolfers (2010), who argue the data support the misperception hypothesis. A textbook level description of the phenomenon is provided in (Ottaviani and Sørensen 2008). They review the two explanations discussed above, as well as several others. A more recent review of the literature on the longshot bias is presented in Newall and Cortis (2021).

One additional explanation of the longshot bias is that some bettors possess private (inside) information. This approach, sometimes known as the Shin model, was developed by Hyun Song Shin in the early 1990s (Shin 1991, Shin 1992, Shin 1993). It has been further explored in subsequent papers (Cain, Law et al. 2003). Empirical analyses of the longshot bias have been published for sports such as UK football (Peel, Cain et al. 2000) and major league baseball (Gandar, Zuber et al. 2002).

THE DATA SET

Our data set includes odds and results on major professional and collegiate team sports as well as mixed martial odds contests from the Ultimate Fighting Championship (UFC). Data for the team sports has been collected from the website Sports Book Review (TopSportsbooks 2022). Odds are provided for professional football (NFL), college football (CFB) professional basketball (NBA), college basketball (CBB), major league baseball (MLB) and professional hockey (NHL). UFC Odds are collected from the web site BestFightOdds.com.

Sport Book Review provides a single file for each sport for each season. The type of data varies from sport to sport and even season to season, and the data is not without issue. Considerable effort was required to merge and clean the data. UFC odds are provided for virtually every fight across multiple odds makers. After eliminating records without the required odds we were left with the following data set.

TABLE 1
DATA SET SUMMARY

League	From	To	Contests	Seasons Beg	End	Num	Participants
CBB	2007-11-05	2023-01-09	62,106	2007-08	2022-23	16	388
CFB	2007-08-30	2023-01-09	13,797	2007-08	2022-23	16	268
MLB	2010-04-04	2022-11-05	30,010	2010	2022	16	31
NBA	2007-10-30	2023-01-09	19,708	2007-08	2022-23	16	30
NFL	2007-09-06	2023-01-08	4,296	2007-08	2022-23	16	32
NHL	2007-09-29	2023-01-09	19,456	2007-08	2022-23	16	33
UFC	2007-06-16	2022-12-17	6,190	2007	2022	16	2,021
Total	**2007-06-19**	**2023-01-09**	**155,563**				**2,803**

The data set includes 155,563 contests from June 2007 through early January 2023. Participants represent individual fighters for the UFC and teams for the other sports. Contests represent games in the team sports and individual fights for the UFC. The UFC does not have seasons per se, so we treat each calendar year as a season. The data is current as of January 9, 2023, so it includes the end of the NFL 2023 regular season, and partial 2022-23 seasons for CBB, NBA and NHL.

BETTING ODDS AND PROBABILITIES

The menu of bets that can be made on sports is very large. Bets can be placed on almost anything related to a game, a team, or even individual performances of players. With minor variations from sport to sport, the main betting options have three different components: totals, spreads and moneyline.
- Totals: the total, or over/under, is a bet on the total points scored in the game. Bettors can bet the total points will be over, or under the stated line.
- Spreads: a bet on a team to win by a certain margin. The underdog is bet with plus points, the favored with negative points.
- Moneyline: a straight bet on what team or participant will win the game. Moneyline bets are made with differential payouts such that a bet on a favorite will risk more than can be won, while a bet on an underdog will return more than the amount risked.

Note that both totals and spread bets are quoted along with moneyline odds so that the payout to a winner is less than the amount risked. Odds are stated in different equivalent formats in different locations and different settings. In the United States odds are most often quoted in American Odds format.

In the American format the odds can be expressed as either a positive number or a negative number. A positive number shows the profit a successful wager will return on a $100 bet. So, for example, a bettor who wagers $100 at +110 odds and wins, will earn a profit of $110, plus the original wager of $100 for a total payout of $210. Positive odds typically imply the team is an underdog. Conversely, negative odds show how much a bettor must risk to earn a $100 profit. So, for example if a bet is made for $120 at -120 odds, the successful bettor will receive a profit of $100, plus the original wager of $120 for a total payout of $220. The favorite team is given negative odds, but in some evenly matched games both teams may have negative odds. More formally the Payout P to a wager of stake S, at odds M are given by equation (1).

$$P = \begin{cases} S \times \frac{M}{100} + S & \text{for M} > 0 \\ \frac{S}{-M/100} + S & \text{for M} \leq 0 \end{cases} \tag{1}$$

Odds of +100- and -100 are equivalent. In practice M is always quoted as a number with an absolute value greater than or equal to 100. So, while odds of -125 and +80 would both return a profit of $80 on a $100 bet, the odds are always quoted as -125.

Moneyline odds carry an implied probability of success. The implied probability is the probability at which a bettor is indifferent to taking either side of the bet. The probability calculation in the American odds format again depends on whether the odds are positive or negative. So, for a bet with odds M, the implied probability p is given by equation (2)

$$p = \begin{cases} \frac{100}{M+100} & \text{for } M > 0 \\ \frac{-M}{-M+100} & \text{for } M \leq 0 \end{cases} \tag{2}$$

While equation (2) gives the odds on one side of a bet, the bookmaker quotes odds in pairs. So, for example, a bookmaker might quote odds of -120 for a favorite and +110 for the underdog. Converting each of these to implied probabilities gives probabilities of 54.5% and 47.6%. These odds are not fair in the sense that they add up to more than 100%. The excess probability, in this example 2.1%, is the booksum (k), sometimes referred to as the *vig* or the *juice*. The book margin exists so that the bookmaker is guaranteed a profit as long as bets are made in the appropriate proportion. Book margins in the range of 3%-5% are common.

In order to convert the bookmaker's odds into meaningful probability estimates the odds must be converted to consistent probabilities. Draws are rare in the sports we are evaluating. So, if the contest ends in a draw all win-lose bets are effectively cancelled, and bettors are returned their original stake. The most common way to convert the implied probabilities is a simple normalization process. So, for a contest with implied probabilities of p_1 and p_2, the normalized probability that team 1 will win the game and bets will pay is given in equation (3)

$$p_{1_n} = \frac{p_1}{p_1+p_2} \tag{3}$$

The Sportsbook's Margin

Because the implied odds are unfair, they add up to more than one, the sports book has a built-in advantage. The excess probability gives the sportsbook a built-in margin, appropriately allocated bets on either side will guarantee the book a profit. The sportsbook's profit margin is proportional to the book sum, the excess implied probability in the stated odds. If we have a two-way bet with implied odds p_1 and p_2, then the booksum k, is given in equation (4)

$$k = p_1 + p_2 - 1 \tag{4}$$

The bookmaker's margin (m), also known as the *hold*, is the sportsbook's average profit and can be shown to be

$$m = \frac{k}{k+1} \tag{5}$$

The booksum and hold varies from game to game, and league to league, but typically averages in the 3% range. Summary metrics for our dataset by league are shown in Table 2.

TABLE 2
AVERAGE MARGIN

Booksum and Margin by League 2002–2022		
League	K	M
CBB	3.69%	3.56%
CFB	3.51%	3.39%
MLB	2.85%	2.77%
NBA	3.77%	3.63%
NFL	3.77%	3.63%
NHL	3.40%	3.28%
UFC	4.60%	4.40%

The Bookmaker's Decision

A bookmaker will publish odds on a game for each team and accept bets on either outcome. The bookmaker competes with other bookmakers to secure bets. In order to attract bettors, they need to post odds that are competitive in terms of the odds and the book margin included. Over the long term, the bookmaker seeks to maximize their expected profit on similar bets, as well as minimizing the potential risk on any individual contest. Since each game is a single event where a team wins or loses, the concept of probability is necessarily a belief probability rather than a frequency probability, and the notion of expected value takes on a somewhat different conceptual meaning.

To eliminate this issue for the time being, let us consider a slightly more abstract model. Consider a bookmaker that takes bets on a digital coin toss that is executed repeatedly. The bookmaker states odds that apply to all tosses over a given period, but bets are made on each individual toss. Assume the digital coin is fair and that the probability of heads is 50%, in terms of frequency in the long term. The expected payout for the bookmaker is a function of the stated odds, M_H and M_T, the probability of a head or tail, p_H and p_T, and the bets placed on each outcome, B_H and B_T. The expected profit (G) for the bookmaker is the total amount wagered less the expected payout, or

$$E(G) = B_H + B_T - \left[p_{HT} \left(\frac{B_H M_H}{100} + B_H \right) + p_{TT} \left(\frac{B_T M_T}{100} + B_T \right) \right] \tag{6}$$

The expected profit is an average over a large number of bets. The bookmaker is also concerned with their individual transaction *risk*, the potential loss on any individual trial, or in the sports case the potential loss on any individual game. Assume that for a particular trial the outcome is heads, the loss on this trial is equal to the payout on heads less the amount wagered on tails. The a priori *risk* is the worst-case outcome based on the amount wagered on each possible outcome.

The risk is given by equation (7)

$$r = max \left[\frac{B_H M_H}{100} + B_H \quad , \quad \frac{B_T M_T}{100} + B_T \right] \tag{7}$$

In our simple example of a digital coin toss, the bookmaker knows the true probability is 50% for each outcome. Assume odds are set as -120 for each outcome. These odds give an implied probability of 54.5% for each outcome and a book margin of approximately 9.1%. From equation (6) the bookmaker's expected profit is 8.3% of the total money wagered. The risk varies based on the proportion of money wagered on each outcome. The payoffs to the bookmaker are shown in the following graph.

FIGURE 1
BOOKMAKER EXPECTED PROFIT AND RISK
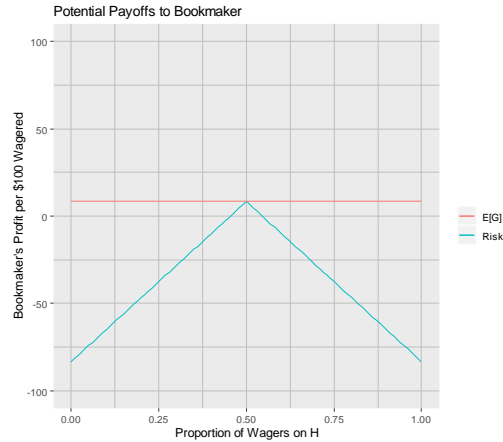
This graph shows that the expected payout is constant, regardless of the wager allocations. Over the long run the book maker will earn the expected profit per $100 bet on average. But the risk varies based on how much is wagered on each outcome. It can be shown that the expected profit is equal to

$$E(G) = B_H + B_T - \left[\frac{p_{HT}}{p_{HI}} B_H + \frac{p_{TT}}{p_{TI}} B_T \right] \tag{8}$$

where p_{HT} and p_{TT} are the true probabilities and p_{HI} and p_{TI} are the probabilities implied by the odds. The point of minimal risk occurs where the wagers are allocated in the same proportion as the true odds. There is in fact a risk-free region that occurs when wagers are allocated close to the same proportion as the implied odds. The risk-free zone occurs when the amount wagered on each outcome is between the implied and normalized probabilities.

Equation (8) also illustrates an important concept. The bookmaker's expected profit will be positive when the implied probabilities (p_{HI}, p_{TI}) are greater than the true probabilities (p_{HT}, p_{TT}). Conversely, a bettor will have a positive expected profit if they wager on a set of bets where the true probability is greater than the implied betting probability.

Now let us consider a second example. Here, instead of betting on a virtual coin flip, we will bet on a virtual draw of integers from one to five. Let us assume that the bookmaker is taking bets on the draw being a one. Again, the bookmaker states odds that apply to all draws over a given period, but bets are made on each individual draw. The probability that the draw comes up one is 20%. Assume out bookmaker states odds of -535 for a draw of one, and +375 which applies at least approximately the correct probabilities. The bookmaker's payoff is shown in (8).

FIGURE 2
BOOKMAKER EXPECTED PROFIT AND RISK ON NON-EVEN ODDS

Potential Payoffs to Bookmaker
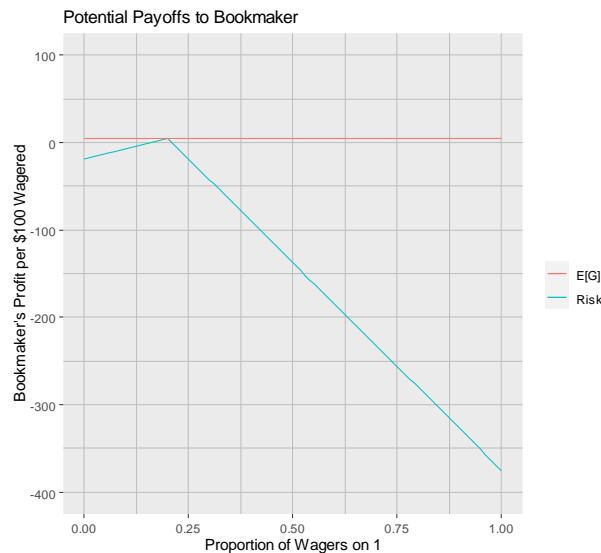
The bookmaker's potential payoff curve looks very different now. The expected payoff is again approximately constant, but the risk profile is no longer symmetrical. The no risk zone now occurs when the proportion of wagers on the low probability event are at or near 20%. Risk increases dramatically as more wagers are placed on the low probability event. With + 375 odds the bookmaker has the potential to lose 3.75 times the amount wagered if all bets are on the low probability event, and that event occurs.

Now let us consider one last scenario. We maintain the one in five chance for the event to occur, but assume the bookmaker misstates the odds. For our example the misstatement is significant, and the bookmaker quotes even odds of -120 on each outcome.

The bookmaker's risk profile is the same as in the true 50-50 case, but the expected profit curve is now significantly different. This occurs because the ratios of true to implied odds in equation (8) are now mis-calibrated. In this example the ratio of the true probability to the implied probability for event T is 8/5. If bettors are more likely to bet on the high probability, undervalued outcome, perhaps because they have better insight into the true probability than the bookmaker does, a high proportion of bets will be on the outcome T and the expected payoff to the bookmaker will be negative.

The impact of misstated odds is a major consideration in our real-world scenario of setting odds on a sporting contest. While the probabilities for a coin flip, or a number draw, are known, the true probabilities for a sporting event are unknown, and unknowable. Since the sports event is in fact a one-time event, the probabilities are belief probabilities with no long-term frequency analogy. But bookmakers don't only set odds on single games, they set odds on a large number of games occurring over an extended time frame. The implication of the expected profit curve is that if the bookmaker systematically offers biased odds, or more specifically, if the bettors are better at judging the probabilities than the bookmaker, the bookmaker will face expected losses on those bets.

The general consensus has been that odds makers set odds so as to attract the appropriate level of bets on either side. This has been documented in the literature since the late 1960s (Pankoff 1968). But in the early two thousands, an alternative theory was put forward in (Levitt 2004). Levitt analyzed a data set of contest bets in which he identified a bias for bettors to pick home team favorites and favorites in general. He hypothesized that bookmakers exploited that bias to mis-state odds so as to increase their profit. He effectively argues that sportsbooks purposely implement a risk-return curve similar to FIGURE 3 hoping to attract bets skewed to the right side of graph and earn a higher expected profit. Additional empirical support for this position has been documented (Paul and Weinbach 2012, Paul and Weinbach 2014).

FIGURE 3
BOOKMAKER EXPECTED PROFIT AND RISK ON MIS-STATED ODDS

Potential Payoffs to Bookmaker
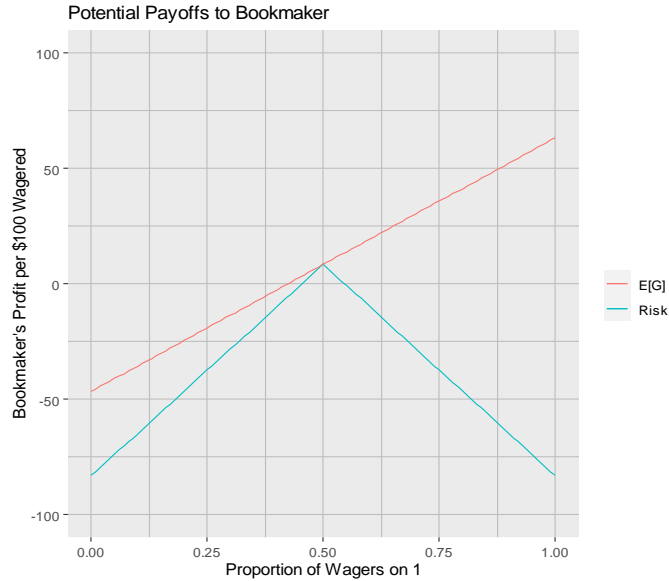
EMPIRICAL ODDS DISTRIBUTIONS

Before we investigate efficiency in detail, let us examine the distribution of odds for each major sport. The following graphs represent the normalized odds for each sport, plotted as a density graph using the ggplot library in R. Not that each graph is by design symmetrical since each game is represented by the normalized odds of the favorite and the underdog which by definition must add to one. Figure 4 shows the density plot for football, both professional and collegiate.

FIGURE 4
FOOTBALL ODDS

Implied Win Probability - Professional and NCAA Football
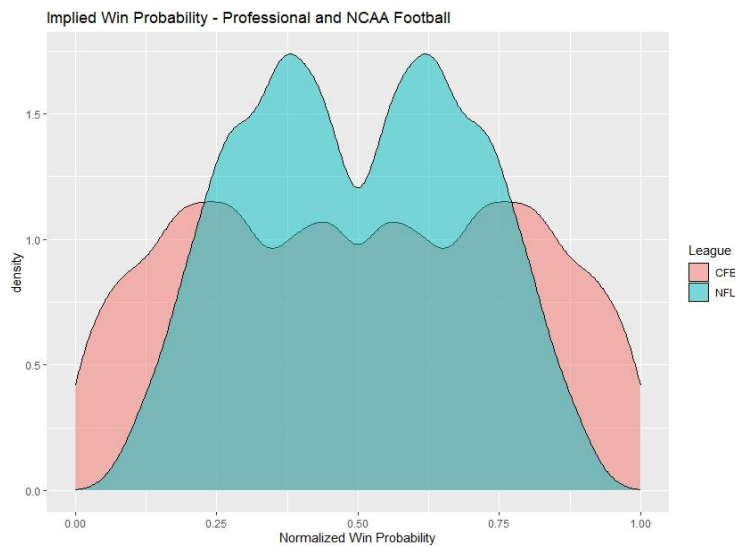
This graph reveals a few interesting properties of this data. First the odds for college football are more lopsided than for the NFL implying a higher level of parity at the professional level. Secondly, slight favorite-underdog matchups are more common than even (pick'em) odds. The NFL odds are bimodal with a peak around 65%, and due to symmetry, a corresponding peak near 35%. The modal odds for NFL underdogs is +170, corresponding to an implied probability of 37%. The density drops of sharply with a trough at 50%. Only 1.19% of NFL games are true even money bets with 50-50 odds. If we expand the range to near even money, probabilities in the range [.49,51] we still have only 1.28% of games. Even money bets are even less common in college football at 0.71% of all games, near even bets are 0.74%. It appears the odds are defined so that having one team as a small favorite is more common than an even-money bet. This bias away from even-money bets is consistent with Levitt's hypothesis that odds makers shade the odds, shifting even games to slight favorite/underdog games.
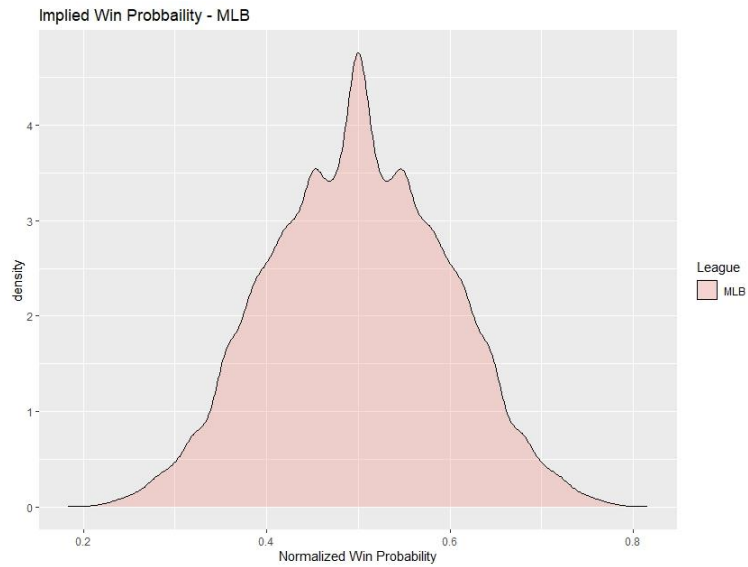
FIGURE 5
BASKETBALL ODDS
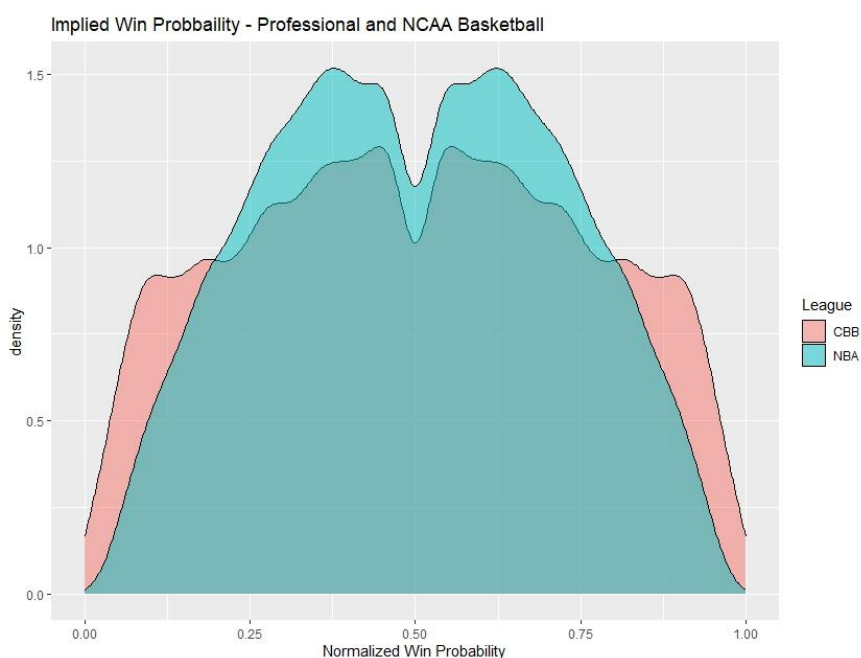
Odds for professional and college basketball have a similar distribution to football. College odds are more dispersed, and the slight favored effect is in place for both leagues. A similar trough exists for both basketball leagues with even money odds being less popular than slight favorite matchups. Even odds are quoted in 0.99% of NBA games, while near even odds are stated in 1.15% of games. In college basketball the figures are 1.07% for even money and 1.11% for near even money.

Odds for professional baseball (MLB) appear quite different. The even money trough is absent and even or near even odds are common. There is in fact a small bump in the distribution near the 50% level. Strictly even odds are offered in 2.94% of games and near even odds in 10.4% of games. Extreme odds are also much less common. Whereas football and basketball both had extreme probabilities, at or near 100%, odds greater than 75% appear quite rare in MLB.

FIGURE 6
MLB ODDS

Implied Win Probbaility - MLB

FIGURE 7
NHL ODDS

Implied Win Probbaility - NHL
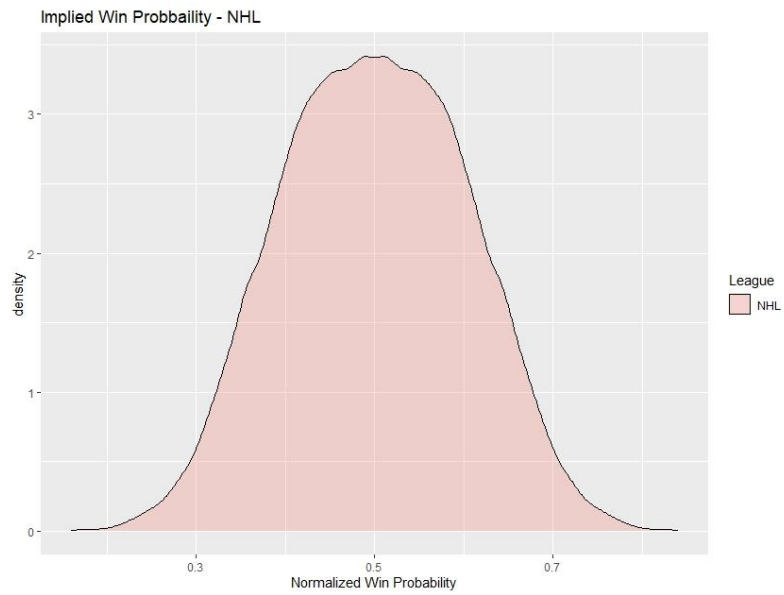
The odds for professional hockey are similar to baseball, but with a pronounced peak near parity. Odds can be a little more extreme in hockey with the density extending to nearly 80%. Strictly even odds are offered in 2.29% of games and near even odds in 4.59% of games.

FIGURE 8
UFC

Implied Win Probbaility - UFC
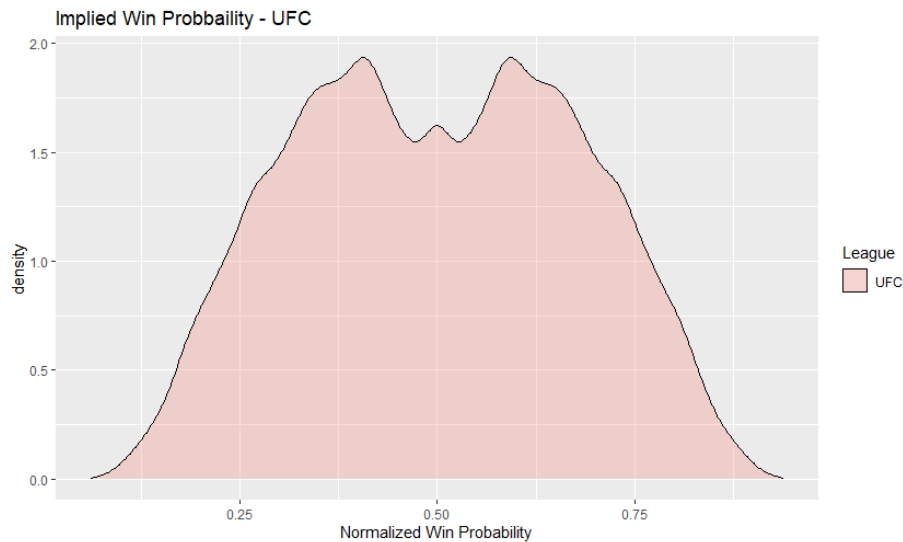
The odds for the UFC have a similar distribution to football and basketball, with a bi-modal distribution of slight favorites and underdogs. Pick'em odds are relatively rare, although there is a small minor bump at even odds. Of all the odds quoted, 2.08% are at even money and 2.70% are at near even money.

RETURNS BY ODDS GROUPS

We now examine the return on bets made at different odds ranges. To do this we take the entire data set of games in each sport sorted by the implied probability from low to high. Note once again this implies each contest is represented by two records, one for each team. But, unlike the normalized odds this data is not symmetric since we are using the quoted odds which includes the bookmaker's margin. For the purpose of this analysis, we divide the odds into twenty bins of approximately equal count. We assume we bet $100 on every contest and determine the average profit earned on those bets. Recall that in a weak-form efficient market the returns on all these bets would be negative, equal to each other, and equal to the bookmaker's average hold. If a longshot bias exists, we would expect to see higher returns for the favorites and lower returns for the underdogs.

National Football League

In Figure 9 we see the returns for bets on NFL games. Recall that this is based on a data set of over 4,000 games over 16 seasons. The graph reveals several issues that nominally support the notion of inefficiencies in the market.

- The return on bets made in each group does not appear to be constant by group.
- The return on bets in some odds categories is positive.
- While not readily apparent from the graph, the average return across all bets is -4.20% which is lower than the expected profit of -3.63% indicated by the average hold.

The graph does seem to indicate a longshot bias, returns on bets on the lower probability teams have lower returns than bets on the highly favored teams.

FIGURE 9
NFL RETURNS

Return on Bets by Odds Group - NFL
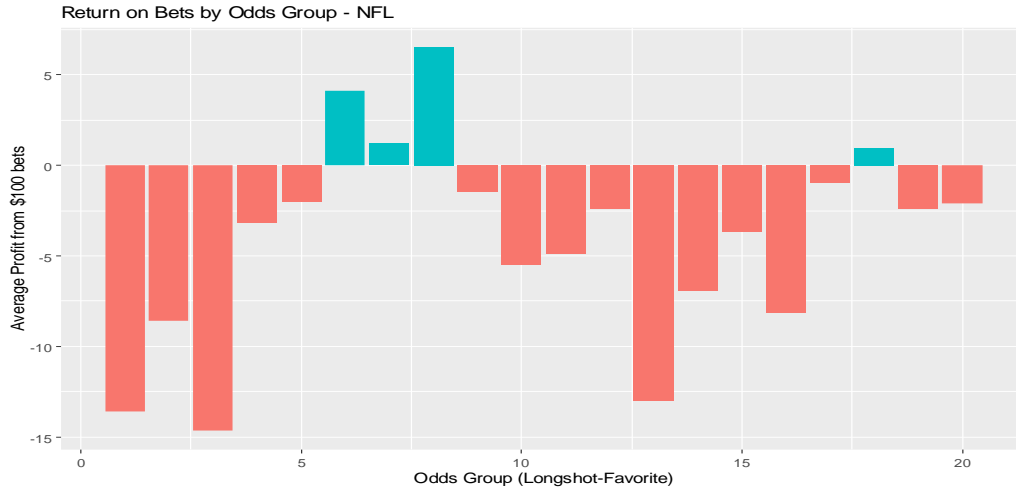
The odds group with the strongest positive returns corresponds to a bin 8 where odds range from +125 to +144, corresponding to implied win probabilities of 41% to 44%. The two bins below that level also offer a very small positive return. It is worth noting that these games correspond roughly to the bump in the density of implied probabilities in Figure 4. This higher rate of return on slight underdog bets is again consistent with Levitt's hypothesis that bookmakers systematically shade the odds. If bookmakers shift the odds on true pick-'em games to slightly favor one team and attract a disproportionate share of bets on the favorite, it would stand to reason that betting the underdog team would be a higher expected value bet.

In Table 3, we examine the consistency of these returns over time.

TABLE 3
RETURNS ON NFL BETS BY SEASON

Season	[+160, +178]	[+145, +159]	[+125, +144]
2007-08	3.5%	–31.0%	43.8%
2008-09	–46.2%	15.4%	12.6%
2009-10	13.2%	12.7%	20.5%
2010-11	3.4%	20.0%	3.2%
2011-12	–6.7%	–5.0%	10.7%
2012-13	37.2%	19.8%	5.0%
2013-14	–25.7%	–61.1%	–13.0%
2014-15	–24.5%	–8.3%	29.0%
2015-16	–11.4%	10.4%	–22.1%
2016-17	19.5%	–49.0%	3.9%
2017-18	–19.9%	–28.8%	5.9%
2018-19	3.9%	5.5%	–11.9%
2019-20	26.4%	19.1%	24.9%
2020-21	18.6%	25.6%	7.8%
2021-22	16.9%	25.5%	35.0%
2022-23	17.9%	19.6%	–34.5%
Total	4.1%	1.2%	6.5%

The returns in these 3 bins, representing 30% of the games in each season, vary considerably. Each bin has positive returns in some seasons, and negative returns in others. Bin 8, odds in the range of [+125-+144] has the highest long-term return and the most consistently positive returns; 12 out of 16 seasons, and an overall return of 6.5%.

While the odds appear to indicate inefficiencies, the statistical validity of inefficiency is marginal. As a test of a systematic bias as per Kuypers we regress the predicted win probability in each bin against the actual win probability. This test failed to reject the null hypothesis that the slope of that line is one; the 95% confidence interval is [.920, 1.03]. So, we cannot conclude that there is a systematic bias across the range of odds. While the returns appear different across the bins, an ANOVA test of the null hypothesis that the returns are the same for each bin, has a p-value of .322, so our ability to reject the hypothesis of equal returns is marginal at best. If we examine the return on the most profitable bin, bin 8 with odds of [+125,+144], and test the null hypothesis that these returns are negative, we obtain a p-value of 0.108 and we cannot reject that hypothesis using a standard cutoff of 5%. We cannot reject the null hypothesis for negative returns on bin 6, the p-value is .249. The p-values on the other nominally positive returns are also well above the cutoff value. The p value on bin 7 is 0.427, and the p value on bin 18 is 0.366. If we compare the actual return on all bets to the bookmaker's average hold we are unable to reject the null hypothesis that they are equal with a p-value of 0.65.

Finally, to perform a more formal test of the longshot bias we perform a two-sample hypothesis test on the returns in bin 1 and bin 20, the biggest underdogs and biggest favorites. While there appears to be a strong difference in the graph, the p-value of this test is .257; again, too high to confidently reject the null hypothesis with confidence.

In summary there is evidence that would suggest that the odds for NFL games are weak form inefficient. While there appears to be a variation in return against different odds groups and heavy longshot bets have historically performed the worst, but these conclusions are tentative due to the variable state of the returns. Slight underdog bets appear to be the best option for NFL games and they have earned a small positive return over the 16 seasons in our data set, those returns are highly variable and we cannot reject the null hypothesis that they are negative. While we can observe some anomalies from the strict requirements of weak-form efficiency, we cannot reject any hypothesis that would invalidate weak form efficiency.

College Football

In Figure 10 we see the graph for college football. The CFB graph is similar to the NFL graph; returns are uneven, heavy longshots yield very low returns relative to other groups. There is also a set of profitable bets in the slight underdog range, in the case of CFB those odds are in the range of +285 to +150. These represent implied win probabilities of about 26% to 40%.

FIGURE 10
CFB RETURNS
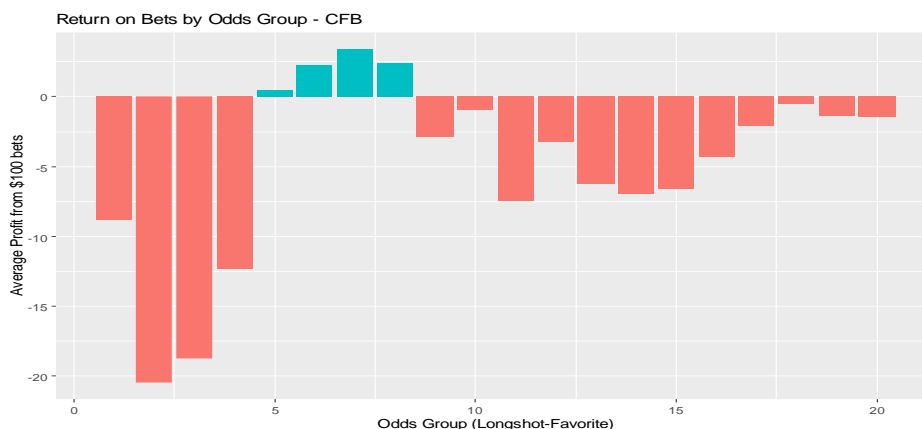
As was the case with professional football, the returns in these bins are sometimes positive and sometimes negative over the course of a season, though there is less consistency than there was for the NFL.

TABLE 4
RETURNS ON CFB BETS BY SEASON

Season	[+235, +289]	[+185, +234]	[+120, +149]
2007-08	–9.0%	–5.3%	4.2%
2008-09	26.2%	–34.7%	6.3%
2009-10	–9.7%	–7.6%	8.7%
2010-11	–3.3%	21.7%	7.2%
2011-12	8.2%	19.1%	18.0%
2012-13	–9.9%	13.5%	3.4%
2013-14	–10.4%	1.6%	–13.1%
2014-15	13.8%	–6.2%	18.7%
2015-16	3.3%	–5.2%	–41.0%
2016-17	27.6%	11.4%	–12.6%
2017-18	–6.1%	–3.9%	23.3%
2018-19	–0.2%	0.0%	15.3%
2019-20	–13.8%	12.1%	16.3%
2020-21	6.0%	20.4%	–17.5%
2021-22	15.5%	7.0%	–2.9%
2022-23	3.8%	7.4%	–4.5%
Total	2.3%	3.4%	2.4%

There is some weak evidence that there is a general difference across all bins, the ANOVA test has a p-value of 0.089. The regression test of actual win probability as a function of predicted win probability gives a slope with a 95% confidence interval of [.949, 1.01]. While the returns on bins 6-8 have been positive over an extended period of time, we have limited evidence that this is a statistically significant difference. If we test the null hypothesis that the returns are negative the p-values on these tests are 0.289, 0.428, and 0.108 respectfully. To test for a longshot bias we compare bins 2-19, and 3-18. For the bin 2-19 test we can safely reject the null hypothesis with a p-value of 0.0153. For the bin 3-18 test we can reject the null with a p-value of 0.0021. For the most extreme differences, bins 1 and 20, we cannot reject the null hypothesis as the p-value is 0.70. When we compare the actual return on all bets to the bookmaker's average hold we are unable to reject the null hypothesis that they are equal with a p-value of 0.24.

So, in summary we have some evidence to reject the weak form efficiency of CFB odds. The strongest evidence to reject efficiency is the longshot bias of bets on teams with odds in the range of [+480, +1495] have statistically significantly lower returns than betting the favorites in those contests at [-652, -3000]. While these are better bets, they have negative returns. The odds that do show positive returns are positive with questionable significance.

Professional Basketball
The returns for professional basketball are shown and **Error! Reference source not found.**. (Figure 10 shows the returns for college basketball.) These graphs are quite different from what we saw for football. Pro basketball returns are generally negative, with a very small positive return in bin 2, but the p-value of 0.417 provides very low confidence that this is a meaningfully positive return. The p-value for the ANOVA test of equal returns is 0.839. The largest difference in complementary bin profits is between bins 2 and 19, a potential reverse longshot bias, but the p-value here is .238. We can also reject the null hypothesis that the odds are unbiased. The slope of the regression line of actual win percentage to predicted win probability

is [.938, .978] which does not include 1. A slope less than indicates that the actual win probability increases slightly less than the win probability projected by the odds, those this difference is very minor. When we compare the actual return on all bets to the bookmaker's average hold we are unable to reject the null hypothesis that they are equal with a p-value of .0.96.

**FIGURE 11**
NBA RETURNS
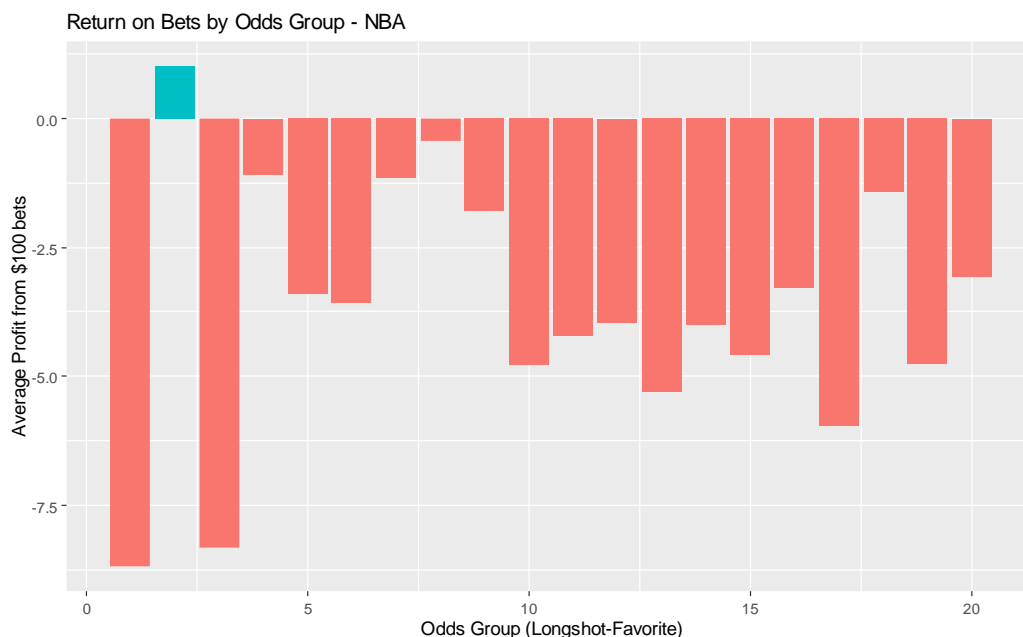
So, while the graph for NBA odds shows some variation, a small positive return for some bet ranges, and a modest longshot bias, none of these claims can be substantiated at a reasonable level of statistical significance. We therefore cannot conclude that NBA odds are not weak form efficient.

College Basketball

The returns on best in college basketball show significant variation. A formal ANOVA test confirms this with a p-value of less than 2E-16. College basketball returns also show the most significant longshot bias of all the sports examined in this paper. While returns are negative on all bins, the biggest longshot bin has a negative return of nearly 50%. Betting on the corresponding favorite has a return of -0.2%. The returns are different with a p-value of less than 2.2E-16. Recall that the odds are more lopsided in college vs. pro basketball and there are more mis-matches. Betting on the heavy underdog to pull of the big upset in college basketball is on average, the worst bet among the major sports. The longshot bias also holds for bins 2-19 (p-value 2.51 E-09), bins 3-18 (p-value 1.324E-07), bins 4-17 (p-value 2.74E-07), bins 5-16 (p-value 1.70E-06), bins 6 and 15 (p-value 0.0174), bins 7 and 14 (p-value 0.0045), and bins 8 and 13 (p-value 0.0086). For college basketball we can also reject the null hypothesis that the slope of the projected to actual win regression line has a slope of 1. The 95% confidence interval is [1.02, 1.03]. This slope slightly above one further confirms the long shot bias in CBB odds. When we compare the actual return on all bets to the bookmaker's average hold, we are able to reject the null hypothesis that they are equal with a p-value of effectively 0. The actual average return on college basketball bets is -7.71% vs. the average hold of -3.56%. The difference is due in large part to the very low returns on heavy underdogs.

FIGURE 12
**CBB RETURNS**

Return on Bets by Odds Group - CBB
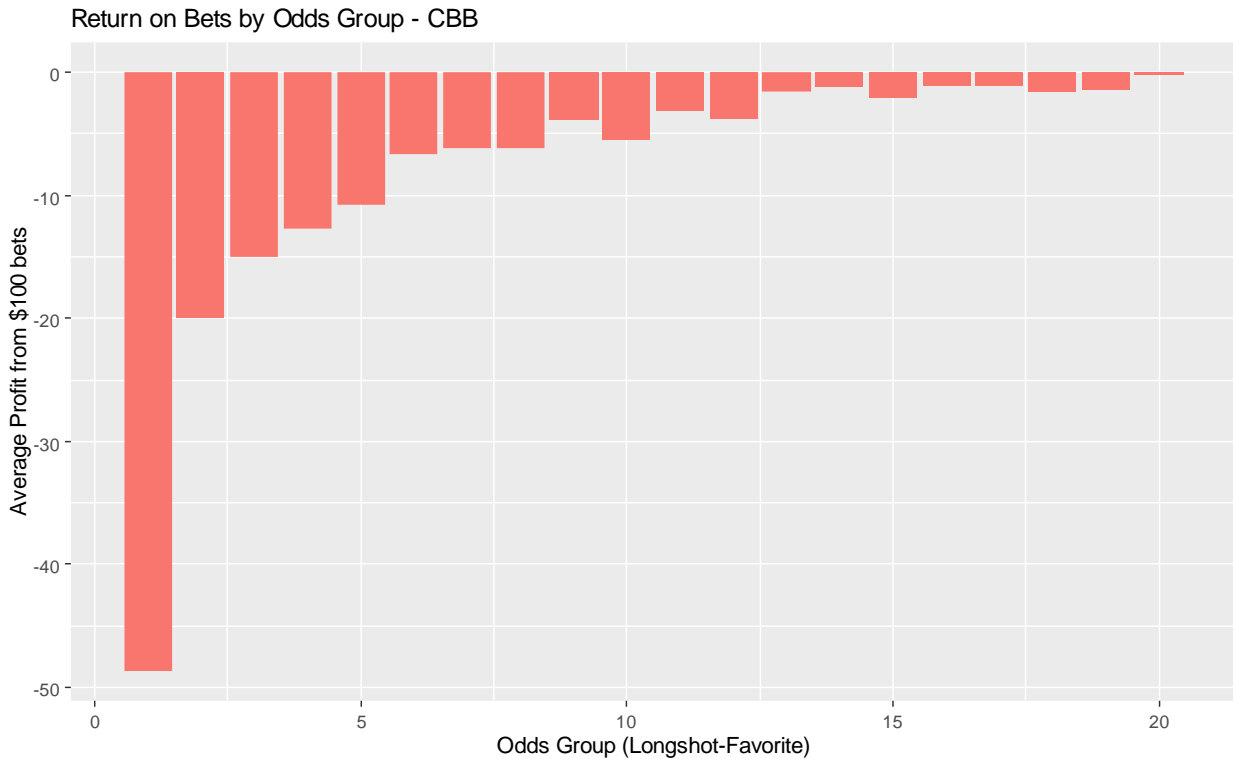
So, in conclusion, while all odds ranges in college basketball have negative returns there are some bets clearly worse than others. College basketball shows a very strong favorite-longshot bias. Bets on extreme underdogs have very poor returns, and in general bets on underdogs perform significantly worse than bets on favorites. So based on the inconsistency of returns on odds groups, and longshot bias we can reject the hypothesis that college basketball odds are strictly weak-form efficient. While CBB odds fail the strict weak form efficiency test, there are no profitable odds ranges available to the bettor.

Major League Baseball

The returns on MLB bets in each odds group is shown in Figure 13. The p-value on the ANOVA test that all returns are equal is 0.066. Returns generally have a negative return over time, though there is a small positive return on bet in bin 14 corresponding to odds of [-125, -132] a slight favorite. The return is 1.48%, but the p-value associated with the test that it less than zero is 0.891. The slope of the predicted to actual win percentage line is in the interval [.963, 1.05] so no bias exists across the distribution. A longshot bias is clear with bets on the biggest underdogs yielding a return of -7.32, with the corresponding favorites yielding a -0.72% return. The returns are different with a p-value of 0.017. When we compare the actual return on all bets to the bookmaker's average hold, we are unable to reject the null hypothesis that they are equal with a p-value of 0.799.

FIGURE 13
**MLB RETURNS**

Return on Bets by Odds Group - MLB
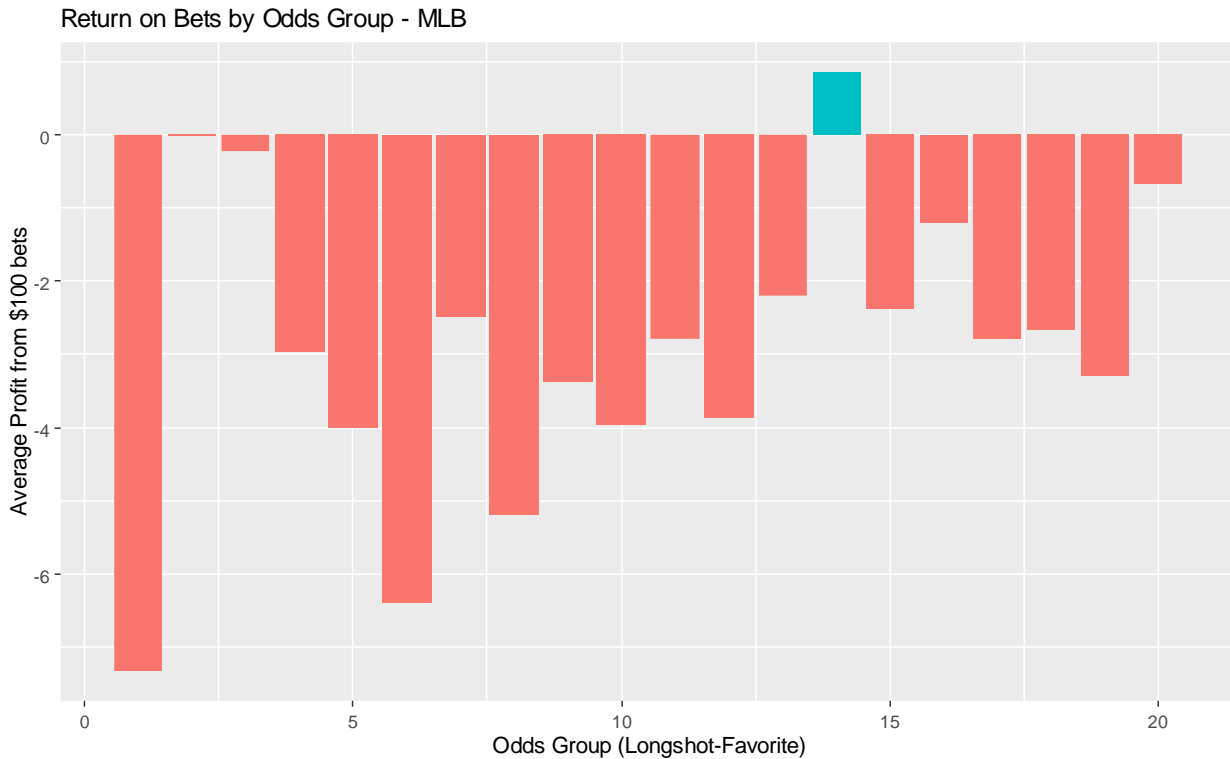
So, again we can reject the hypothesis that MLB odds are strictly weak form efficient. In this case the rejection is based on a statistically significant longshot bias. While one band of favorite odds has a nominally positive return, we cannot conclude that these returns are non-negative at a reasonable level of statistical significance.

Professional Hockey

Professional hockey returns are shown in Figure 14. They are similar to baseball in that they are all mostly negative and reasonably consistent. The p-value for an ANOVA test of the hypothesis that all returns are equal is 0.905, so we cannot reject the null hypothesis.

FIGURE 14
NHL RETURNS
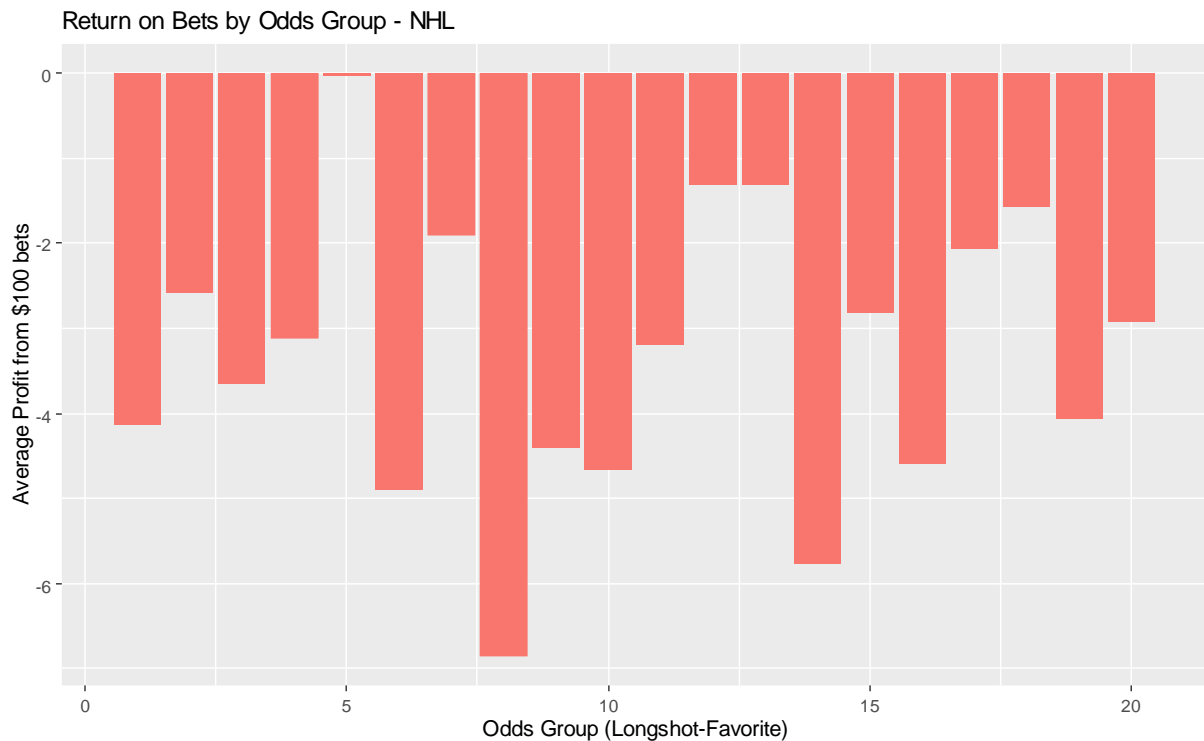
The returns in all bins is negative with the profit in bin 5 [+130, +139] being effectively zero at -0.003%. The p-value with associated with the hypothesis test that the returns are negative is 0.364, so we cannot reject the null hypothesis. There does not appear to be any clear longshot bias in the hockey odds. The return on the biggest longshots, bin 1 [+190, +505] are -4.13%, slightly worse than the returns on the complementary odds in bin 20 [-700, -219] which are -2.91%. We fail to reject the null hypothesis that these returns are different with a p-value of .546. The returns on the set of bins 2 and 19, show a nominal reverse longshot bias. Bin 2 returns are -2.19% and bin 19 returns are -3.28%, but the null hypotheses that these returns are different is 0.725%. The slope of the predicted to actual win percentage line is in the interval [.934, 1.01] so no bias exists across the distribution. When we compare the actual return on all bets to the bookmaker's average hold we are unable to reject the null hypothesis that they are equal with a p-value of .938.

NHL odds appear to be the most efficient of the odds set we have examined. While there are some nominal differences in the historical returns, all bins are negative and none of the differences can be shown to be the result of anything but statistical noise.

UFC

UFC returns are shown in Figure 15. These returns are similar in some ways to football, with a slight underdog profit. But they are also similar to basketball with what would appear to be a significant long shot bias. The long run profit is positive in bins 6 and 7 (2.44 and 2.49), but the p-values do not quite make the 5% threshold at 6.28% and 6.50%. The very small positive profits in bins 19 and 20 (.795 and .862) have p-values of 0.30 and 0.31. The UFC returns do show a significant difference across the odds distribution, the ANOVA test has an effectively 0 p-value (<2e-16). The p-value for a comparison between bins 1 and 20 is also <2e-16. Statistically significant differences exist between bins 2 and 19 (<2e-16), 3 and 18 (3.86e-07). The difference between bins 4 and 16 is not quite statistically significant with a p-vale of 0.063. The

slope of the predicted to actual win percentage line is in the interval [.983, 1.08] so no bias exists across the distribution. When we compare the actual return on all bets to the bookmaker's average hold, we are able to reject the null hypothesis that they are equal with a p-value of 1.04e-05. The average return on UFC bets is -5.82%, less than the average hold of -4.40%.

FIGURE 15
UFC RETURNS
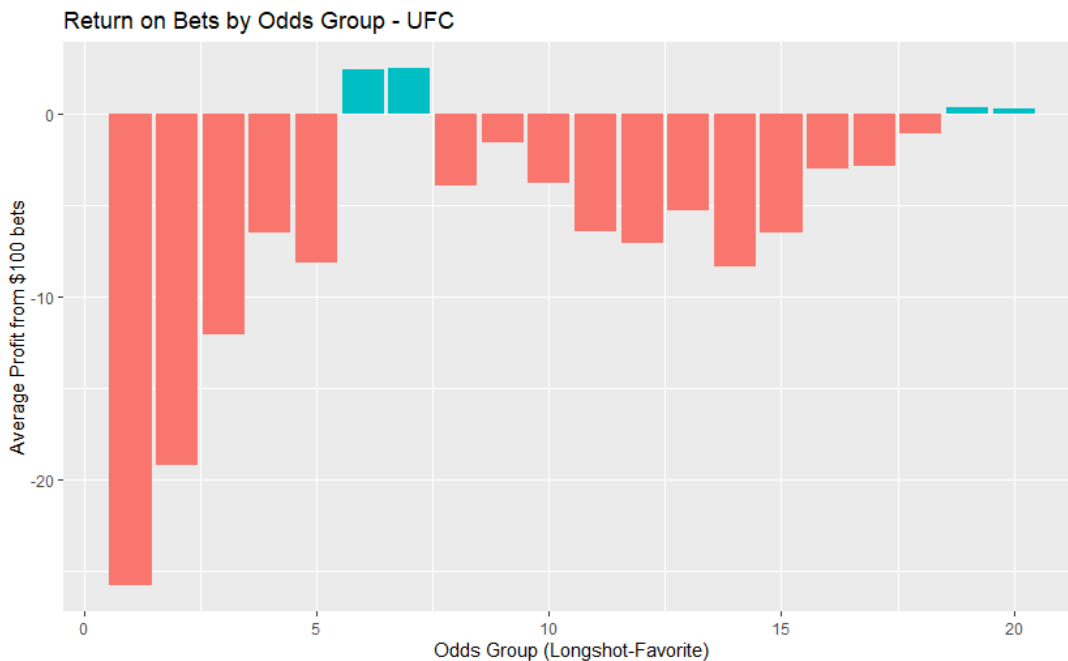
We can conclude that the UFC odds are not strictly weak form efficient as the results are not consistent across the odds distribution and a statistically significant longshot bias exists. Bets on slight underdogs are positive but only at the roughly 6% level.

CONCLUSION

Betting on sports is becoming increasingly popular, and legal, in the United States. Profitable betting is, however, very difficult. The sportsbook has several advantages, the most significant of which is their ability to offer unfair bets. These unfair bets create a margin for the book which allows them to profit regardless of the outcome as long as bets are placed in the appropriate proportion.

In our analysis we have performed several tests on the odds in each sport to evaluate the specific conditions for weak form market efficiency. A summary of our findings is presented in Table 5.

	NFL	CFB	NBA	CBB	MLB	NHL	UFC
Nominal Positive Return	X	X	X	-	X	-	X
Significant Pos Return	-	-	-	-	-	-	-
Abnormal Return to Hold	-	-	-	X	-	-	X
Consistent Return	-	-	-	X	-	-	X
Longshot Bias	-	X	-	X	X	-	X
Odds Bias	-	-	X	X	-	-	-

An X in this table exists where some form of inefficiency has been detected. So, over the long run positive average returns have been detected in five of seven sports. While these returns are positive over an extended period of time, they are not consistently positive and none of them can be confirmed as statistically significant.

While a strict interpretation of weak form efficiency dictates that the returns are equivalent in all odds ranges, and equal to the average hold, we do have evidence to indicate this is not always true. ANOVA tests for CBB and UFC indicate non-consistent returns across the full odds spectrum. A statistically significant longshot bias exists in both college sports, MLB, and the UFC. In two sports, CBB and UFC, the hypothesis that the average return to the bettor across all bet is negative and equal to the expected hold can be rejected. However, it is extremely important to note that the average returns are less than the average hold so the bettor does worse and the abnormal return accrues to the sportsbook. Finally, we can detect a statistically significant odds bias for professional and collegiate basketball; when we regress actual win probability to predicted win probability the 95% confidence interval for these sports does not contain 1. The NBA slope is slightly greater than 1, while the CFB slope is slightly below 1. While statistically significant, these discrepancies are quite small.

At the most basic level the returns on bets placed on different ranges of odds yield different returns. But many of these differences are statistically indistinguishable from random variation, while others are meaningful. Bets on slight underdogs in the NFL historically outperform bets in other odds ranges. Bets on extreme long shots in college basketball yield very poor returns while bets on corresponding heavy favorites in college basketball also yield negative returns, but these returns are significantly better. Our data indicates a statistically significant longshot bias in college basketball that extends over much of the odds range. Betting underdogs in general, and longshots in basketball is in general a losing proposition.

While our analysis shows that minor inefficiencies exist in some betting markets and confirms that making money betting on sports is difficult. Where positive returns exist, the pre-tax returns are small. And while they are positive over the long run, they are punctuated with long periods of negative returns. The strategy analyzed in this paper, bet on all opportunities in a certain odds range, is not recommended, nor is it likely to be profitable after tax in the short to medium term. But what our analysis does show is that some bets are better, or worse, then others. Betting on longshots in college basketball, is for example a strategy very unlikely to be successful. Bets on slight underdogs in football, on the other hand, are more likely to be successful.

A contribution of our paper is the breadth of its analysis. We examined bets across a wide range of sports over an extended time period with a very large data set. Our study does, however, have several limitations. First, we only looked at moneyline bets. We did not examine the other major markets of spreads and totals, not the more exotic markets of proposition bets. A further limitation of this paper is that we only analyzed a strategy of placing bets based on the odds, and therefore tested for weak form efficiency. An open issue, and an area for further research, is semi-strong efficiency. In a world of big data, AI, and machine learning, is it possible to build models that will predict outcomes successfully enough to overcome the sportsbook's hold and yield profitable results? While models may be very accurate in terms of predicting

outcome, the efficient market hypotheses suggests that the output of those models would be quickly reflected in the price of the bets and profitable opportunities would be removed.

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