AGAINST THE ODDS: THE PROFITABILITY OF CONTRARIAN BETTING IN THE NFL

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Abstract

This study explores the (predictably significant) relationships between both projected win percentages (as per ESPN and FiveThirtyEight) and listed odds, available at the time of betting (per OddsPortal.com), and the success rate of NFL betting slips over the past five seasons (2015-16 to 2019-20) and how that relationship can be applied (in nominal terms) to increase the actual returns accumulated on aforementioned betting slips to produce returns that rival returns achievable via passive investment in the stock market.

KEYWORDS: Sports, Gambling, Investing
JEL CODE: L83, Z20, Z23

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED ANY UNAUTHORIZED AID ON THIS THESIS

Signature

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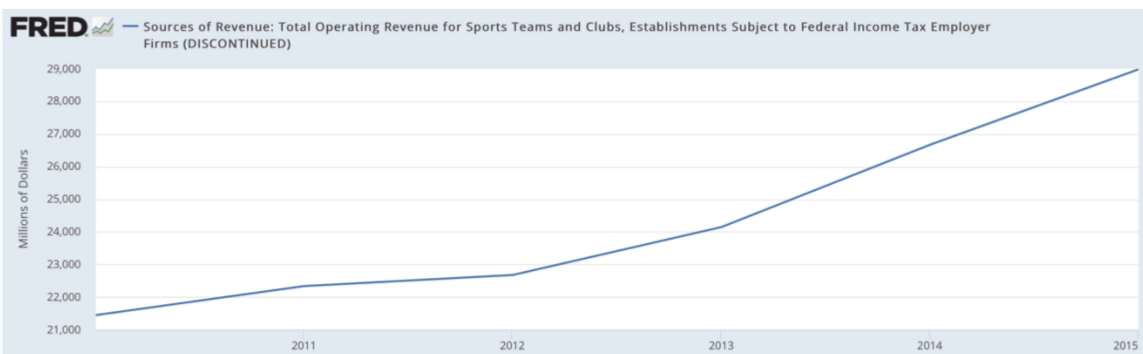
Introduction

The world as we knew it was changed when the Utah Jazz announced, on March 11, 2020, that Rudy Gobert had tested positive for COVID-19. While the overwhelming majority of our country (including our nation's leadership and Gobert himself) had not taken what would become a global pandemic seriously up until that point, the reality of the situation began to sink in at that moment in time. The importance of our nation's favorite athletes' and superstars' popularity and their influence on an impressionable youth had never been even more evident. This emphasis can be extrapolated across the older subsets of the population as well that (similarly) look to them [our athletes] as a source of distraction, release, and relief. Just looking at data from 2010 to 2015, total

Figure 1:



Source: U.S. Census Bureau (2010-2015), courtesy of the St. Louis Federal Reserve

operating revenue for teams (Federal Income Tax Employers) in the United States increased 35.28% from roughly \$21.442 billion to \$28.979 billion. It can be difficult to decipher the true volume of sports betting markets because of the competition amongst

Figure 2:

Source: U.S. Census Bureau (1929-2019), courtesy of the St. Louis Federal Reserve

Separate, isolated legal markets along with the existence of a fairly prosperous illegal market. The habits of clientele can also be inconsistent and unpredictable since some clients tend to bet small while others prefer to bet significant portions of their income or savings. However, we do know that personal consumption expenditures on gambling have increased an impressive 117.62% just over the period from 2000-2019 and it would make sense that expenditures on sports betting would respect a similar trajectory over that same period. The implied growth in this segment of the entertainment industry paired with a recent shift in attitudes, at the federal level, concerning the legality of sports betting presents an opportunity to explore many attributes and facets of this particular market that may not have been accessible or observable prior. That being said, I benefit greatly from the substantial time and effort put in by the many that have examined the many avenues of this field before me. Previous attempts to assess the psyche driving fellow market participants' actions have examined the relationship between consumption and investment (Ignatin, 1984), the addictive properties of betting (Klemko, 2012), the variance in attitudes toward risk among economic agents (Paton et al., 2009), the attractiveness of certain offers given a participant's preferred level of risk (Woodland & Woodland, 1991), and the role that sentiment plays in establishing certain betting patterns (Franck et al., 2011). Additionally, past studies have touched on the logic behind price-setting mechanisms in the market by exploring the business models of betting exchanges (Ignatin, 1984), the pricing out of certain strategies and biases (Sinkey & Logan, 2014), the effects of legalization efforts in creating a more efficient and competitive market (Gupta, 2013), and sound evidence against corruption of outcomes at the collegiate and professional levels (Borghesi, 2008). A plethora of literature also recounts the efficacy of strategies previously trialed in hopes of exploiting certain biases within the market: these have included the likelihood of favorites and home teams to cover the spread (Gray & Gray, 1997), the derivation of final scores drawn from scoring indices (Jackson, 1994), mispricing within the win-totals market (Woodland & Woodland, 2015), investing in notorious past over- and under-performers (Kochman et al., 2015), price volatility preceding the events of the sample in question (Summers, 2008), the profitiability of underdogs against the spread (Vergin & Scriabin, 1978), and the replicability of strategies across time (Badarinathi & Kochman, 1996). I am fortunate that the wealth of past discovery enables me to approach my own research into the industry with an informed and conglomerated outlook on such a nuanced market. Ultimately, sports are a business. You cannot go to your broker and place commission-free trades on fractional shares and actually acquire equity in teams in most cases (unless we assume one has access to a substantial source of capital or knows the right people) as the majority of teams, especially in the United States are privately owned. However, the growing popularity of sports and prevalence of legal betting exchanges ensures that a speculative market is readily available for users to try and profit from whilst also allowing them to feel like they are part of the action. Just as an increase in access to financial markets may debatably lead to less-efficiently priced equities and investment vehicles, the same could hold equally true for sports betting markets priced primarily by investor sentiment. This could possibly increase the profitability of some strategies, pave the way for entirely new strategies, or disable strategies that might have enjoyed some degree of success in the past. And while there are plenty of similarities between these two kinds of markets there are also plenty of notable differences; the range of possible returns on investment are stated explicitly beforehand at the cost of more obscured probabilities of those returns, the timeframes on these financial contracts make them a far more volatile form of investment, and there is generally an even amount of capital thrown behind exactly opposite outcomes. I hope to prove that a speculative sports market is just as navigable as any speculative financial markets and that by providing even the slightest bit of additional guidance in a market commonly shrouded in uncertainty one can achieve access to the very generous returns of this particular market compared to its alternatives. If, upon observing the relationship between expected returns on individual events and their actual realized returns, we can utilize the nature of that relationship (treating success rate as second-tier and instead focusing on increased exposure the most favorable payouts) to achieve a significant upward trend for accumulated returns as a function of time and, in doing so, find a strategy that is capable of generating reliable yields as a sort of premium for the sheer unpredictability of this market.

Literature Review

It would be unwise to dive headfirst into a market that is not understood, although experience is generally a requirement for learning the ins and outs of almost any market. What I believe this means is that you must understand who you are betting against, how that affects the prices of betting slips, and what previous strategies have been employed and/or successful with resulting statistical significance. As I will discuss briefly, the price-setters in this industry prefer to assume a risk-neutral position so understanding the sentiments of fellow bettors, the patterns that result from those sentiments, and what has and has not worked taking those factors into consideration is even more important.

Psychology of Market Participants. To better understand your position within the market it is beneficial to understand the motivations that drive fellow bettors as well as determining those of the betting exchanges that are listing the odds. It is expected that gamblers fall into two main classes: a class that gambles to increase their wealth holdings (investment) and a class that gambles for the thrill and the additional utility that having a stake in a game, series, or season provides (consumption). The growing popularity of "parlays" or combinations of bets supports a dominant aspect of consumption as bettors rely on incredibly unlikely series of outcomes in hopes of slam dunk pay-outs. Although, economists consider the practice of betting on spreads to be irrational as you are always risking more than you are capable of winning (Ignatin, 1984). Aspects of addiction are also present as literature has claimed, in 2012, that "legal wagering on the NFL is up 20-25% from 2011" and we learn that bettors are not discouraged from skewed officiating in certain games so long as they feel the benefits of poor refereeing are dispersed somewhat evenly among competition over the course of the season (Klemko, 2012). The betting exchanges themselves seek to avoid relying on certain outcomes and instead seek to adopt a neutral, but profitable, position if possible. An increased customer base increases the variance of target prices on bets but also increase the incentivization to be informed when placing bets and this is largely due to the fact that because of the nature of the field a majority of customers are going to be risk-seeking individuals (Paton et al., 2009). Certain heuristic observations compiled over the last fifty years would indicate that bettors tend to overreact, become overconfident, and ignore the tendency of performance to regress to the mean and that this kind of trading is fuelled more by sentiment than sound fundamentals (Woodland & Woodland, 2015). Ironically, it is risk-aversion that drives many to prefer point spreads as opposed to odds/straight bets even though economists would suggest that this aversion is directing them towards irrational investment (Woodland & Woodland, 1991). Ultimately though, like in any competitive market, it is the actions of your fellow participants that determine the prices that will be available to you.

Price-Setting Methodology. To invest in such an unpredictable market, it helps to know what you're investing in and what the probabilities of each individual outcome is which is something most probably consider subconsciously (and briefly) but probably only in the context of individual events and not in terms of a bigger picture. Exchanges like to take their profits before the game even starts (to be independent of the outcome) and do so in the form of a "vigorish" or "juice" making it so that one has to perform above a 52.4% success rate on their investments to profit on bets like point spreads where neither side is likely to return more than is risked and by the difference in available returns on straight bets or moneylines. It is expected that increased popularity will lead to increased revenues for these exchanges and that, so long as they get their cut, they will remain indifferent to the actualized outcomes of any individual event (Ignatin, 1984). My study will focus on primarily straight bets (or moneylines) as opposed to more consistently priced spreads, for margins of victory and point totals, that have been the focus of much of the cited literature. Interestingly though, because a lot of bettors may have some concept of strategy, it doesn't seem possible that exchanges could remain completely neutral if one side of their consumer base utilizes a strategy to win significantly more than the other side. However, based on the extent of research completed prior to this, we can assume that there are not a lot of bettors capable of winning consistently and significantly through the use of such strategies. In fact, it is believed that "betting houses (will) deliberately inflate the betting lines to account for previous strong performances," and they do this to protect themselves from certain biases and strategies that arise and achieve prevalence within their consumer bases (Sinkey & Logan, 2014). We also find that legalization of such practices will lead to the consolidation of isolated markets and provide more competitive prices for the consumer as they must compete for customers else risk losing them to other betting exchanges and missing out on critical revenue (Gupta, 2013). Exchanges will also inflate lines to take advantage of bettors with particularly strong convictions whether it be in a strong favorite on any given weekend or out of a sentimental obligation to one's favorite teams (Borghesi, 2008).

Previously Tested Strategies. So what can we do with this information? Beat writers with ample knowledge of the sports they cover can pick outright winners with 60-65% accuracy (Ignatin, 1984). Unfortunately, the organization of the odds market means that some of those winners may have been expected and, thus, your rewards for going with the flow are minimal. This has led to a plethora of creative strategies from many looking to exploit the biases present in this market. Examples of tested strategies include betting on just the favorites, just the underdogs, just the home teams, just the away teams, combinations of those two factors, and isolating your sample to exclude games outside of certain probability ranges (Gray & Gray, 1997). Strategies have included a lesser explored "season win totals" market that may be more exploitable but suffers from the volume of realistic applicability as well as observed implicit biases on betting the "under" for point totals as your competition is likely to inflate the value due to the utility that comes with seeing more points (Woodland & Woodland, 2015). Betting on the best- and worst-performers of current seasons is likely to lead to significant profits but relies on an element of hindsight rather than being a strategy one could implement in the moment and we also learn that most strategies are doomed in the long run as if they are profitable and employed by enough bettors, betting exchanges will shift their price-setting priorities to shield themselves from new biases in the market (Kochman et al., 2015). This is corroborated by findings that, upon retesting strategies profitable over the 1969-74 seasons, only one was replicable in its profitability when observed over a timespan from 1984-1994 and even then it is possible that it was only because of the increased range in available prices caused by the commonality of isolated markets because large, widely available betting exchanges would not have been common at the time (Badarinathi & Kochman, 1996). Profitable strategies have existed though, betting on underdogs to cover the spread would have been profitable in some seasons, but the majority of strategies seek to exploit recent and over-accounted for biases begging the question of whether they are just leading the pack in an inevitable cycle of bias and readjustment. Indeed, the dangers of publishing your findings are made well-known at least without having a good idea of what possible changes you could expect to the landscape of the industry and having a good idea of what biases might be exploitable thereafter (Vergin & Scriabin, 1978). Research also indicates that there are no significant profits to be made from index betting and using point spreads to uncover implied scores and winners (Jackson, 1994). Additionally, we learn that lines fluctuate in the week before an event (once following a sort of IPO model where insiders got first access before betting exchanges became more prevalent) and that using these fluctuations when betting on point spreads makes it possible to incur an overlap on spreads allowing you to possibly win two bets on two outcomes in the same game if the final score-line dictates as “simple strategies of only betting on one of those categories… did not prove profitable” but also opening up a unique niche in the market due to the fact that “a strategy of betting on both teams might not be terribly exciting to a typical nonprofessional bettor” There has been a lot of research conducted up until this point but a lot of it fails to prove significant profits after accounting for transaction costs and considering the timeframes required. Most previous work however has dealt with spreads and have treated the success rate of bets as an independent variable rather than by prioritizing profits over rate of success, however. Perhaps the limited downside and generous upside of select offers is enough to craft a strategy that wins nominally even with a minority of successful engagements.

Theory

The objective to investing, or in this case betting, is to make more than you lose. You have successfully invested in this market if you can say, rather than that a majority of your bets have been successful, that you have earned more than you have lost in terms of nominal dollars. What this means is that the most important measure of a bet for the purposes of profitability and this investigation is the actual return of a bet, or how much is won or lost, and so the goal is to identify variables that would be capable of providing even the slightest amount of insight amidst a very unpredictable market. A look at the effect average expected win probability (per ESPN and FiveThirtyEight) and available betting odds (per OddsPortal at time of event) have on the success rate of bets might also be useful in offering relevant insight. If significant relationships are discovered, how can these trends be monetized given the nature of the sports betting market? The economic models are then:

f(win) = (average projected win probability, odds) Equation 1

f(actual return) = (expected return) Equation 2

In Equation 1, win is a binary variable for whether a given bet was successful (1) or unsuccessful (0) and it is a function of odds and projected win probability. The win probabilities were collected from FiveThirtyEight and ESPN and averaged for each game although ESPN did not begin publishing probabilities until the 2016-2017 season and FiveThirtyEight does not publish statistics for pre-season games, so those matchups rely on slightly limited data. This variable would be some decimal value ranging from 0 to 1 and a positive coefficient would imply that your expected betting success rate goes up with increased projected win probabilities. Odds would refer to the returns or yields available in the market and could hypothetically range from near-zero to infinity. Odds of 1 would mean for every dollar you risk you can earn a dollar in return and a negative coefficient would mean the market is efficient at picking winners as well. Higher odds, like 1.5, would be available for outcomes the market is less optimistic about and lower odds, like 0.5, would be available for outcomes the market is more optimistic about. For Equation 2, actual return is the total gained or lost on a given bet and expected return is the combination of available yields and weighted probable outcomes. I would hypothesize a negative relationship ($h < 0$) between odds and wins because bets people think are more likely to land will have lower odds to balance the market. I hope to see a positive relationship ($h > 0$) between statistical forecasts and wins because being able to trust them would be greatly convenient. Then, depending on what Equation 2 reveals by having those two variables interact, that might allow you to formulate a profitable strategy to take advantage of the high yield returns of the sports betting industry.

Data and Methods

To put those equations into more quantifiable terms, the econometric models are then:

win = B0 + B1average win probability + B2odds + u Equation 3

actual return = B0 + B1expected return + u Equation 4

I would expect to see a positive correlation between average win probability and wins as well as expect to see a negative correlation between odds and wins. It's important to remember odds are centred around 1 and range from the lowest positive, non-zero values to whatever is being offered in the market. Actual return has the benefits of the upside from generous odds on unlikely events while losses on any wager are limited to just 100% of the wager but nothing in excess of that. Expected return is the averaged weighted probability of the two possible outcomes prior to an event. Say a team has 1.5 odds available and has a 50% chance of winning according to the experts at ESPN (45%) and FiveThirtyEight (55%). You would have a 50% chance of 1.5 returns and a 50% chance of -1.0 returns meaning your expected return for the bet would be 0.25. A positive expected return indicates the market is undervaluing a team's capability given what statistics have to say. This is not to say that statistics are always correct (the regression will show to what degree we can expect they might be) and there can be different reasons why this might occur. For one, the numbers might not be accounting for any late coaching or player developments so in some cases the market would know better than projections, but generous rewards would be available in the event that the market does not know better. Another might be that the market is mispriced, based on emotions, recent-form, or bettors just getting carried away until the price reflects a significantly different outlook than statistics would've predicted identifying bet candidates that are good for their worth if not entirely accurate. A negative expected return would indicate that the market is more optimistic about that outcome than statistics can justify and this can be because of bettor sentiment or because the market knows something the numbers don't like if a team has no desire to win or if a coaching scheme will have a certain effect in a game. For this study, actual return is equivalent to -100% of your wager in the event of a loss (when win = 0) and actual return is equal to you wager multiplied by your odds in the event of a successful bet (win = 1). Data for this study was collected for the time period beginning with the 2015-16 season and ending with the 2019-20 season. For purposes of including the expected return variable, readily available projected win probabilities were necessary, and ESPN began offering live probabilities for NFL games in the 2016-2017 season while FiveThirtyEight offers probabilities for the entire span of data but does not offer data on pre-season matchups. The result is 3,158 observable betting slips.

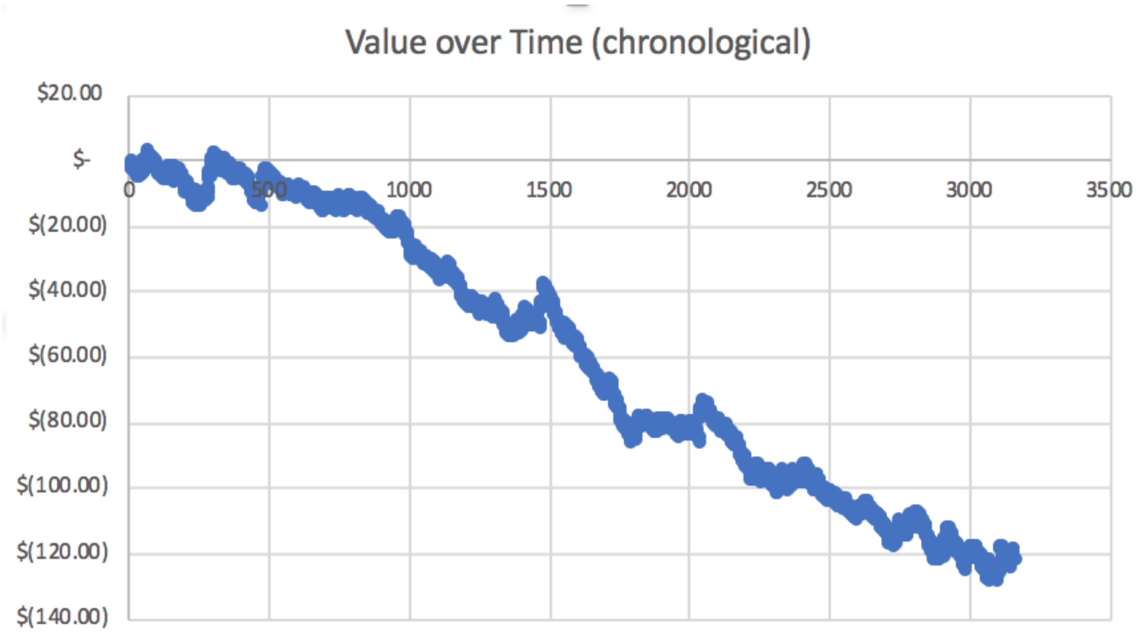
Figure 3:

Regression Results	wins (bet success rate)	actual return (nominal)
odds	-0.0473497	
odds (se)	0.0103444	
average win probability	0.696372	
average win probability (se)	0.0729393	
expected return		0.2364582
expected return (se)		0.0950104
constant	0.2126024	-0.0347319
constant (se)	0.047944	0.0199362
Observations	3,158	3,158
R-squared	0.1128	0.002
F	F(2, 3155) = 200.49	F(1, 3156) = 6.19

key	color
p<0.01	
p<0.05	
p<0.10	
standard error	

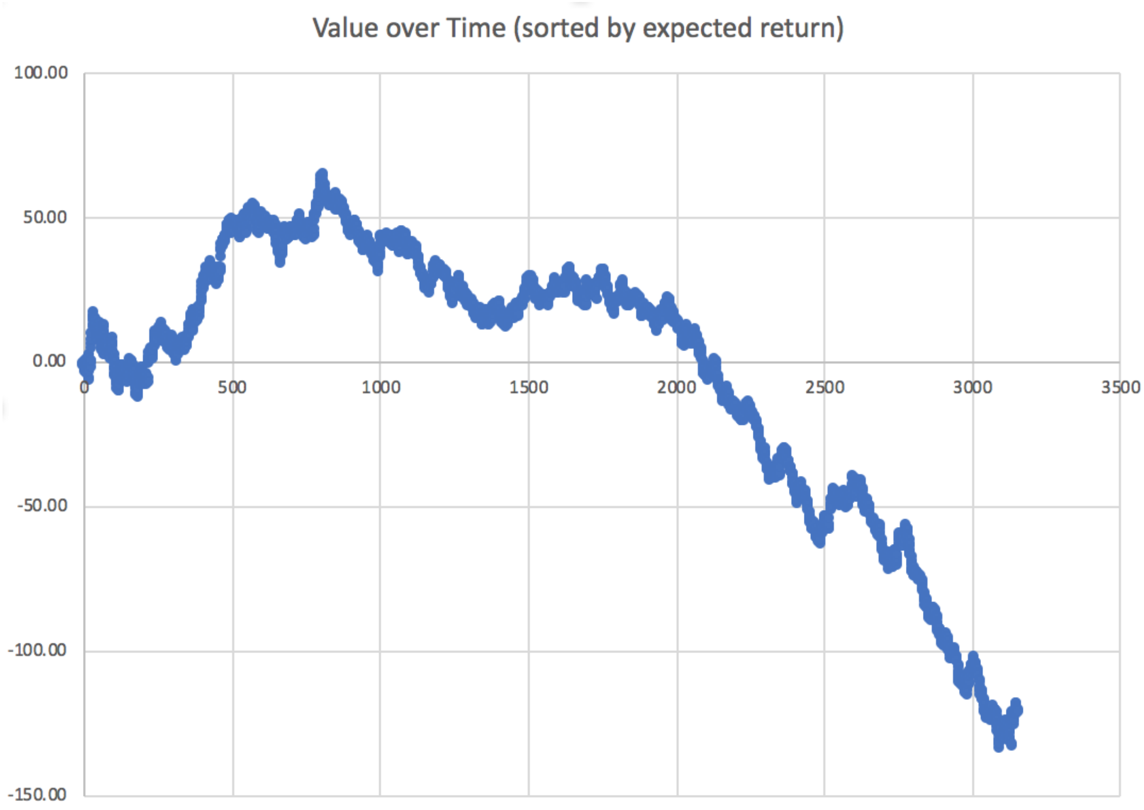
As we see in the linear probability from the figure above (Figure 3), odds do share a negative correlation (-0.0472) with a bet's success albeit with a weaker coefficient than its counterpart, average win probability, with its positive coefficient (0.6972). This indicates that the market is generally above average when it comes to pricing outcomes but that the market might be more efficient if priced by the numbers rather than by investor sentiment (although that might take away some aspect of consumption). More interestingly though, is that by allowing odds to be weighted with projected win probabilities (combining the two above independent variables) leads to a positive coefficient (of 0.2365) for the expected return variable in terms of nominal returns. The profitability of any ensuing strategies can then be tested by plotting value against time (number of events bet on). For the sake of this experiment, every betting slip will have an assumed, constant wager of 1 unit. Figures charting value over time will have an initial value of 0 so using percentages to gauge returns without understanding how much of the underlying value was actually necessary for liquidity purposes becomes a more difficult task. If you simply bet on every available offer over each of the five

Figure 4:



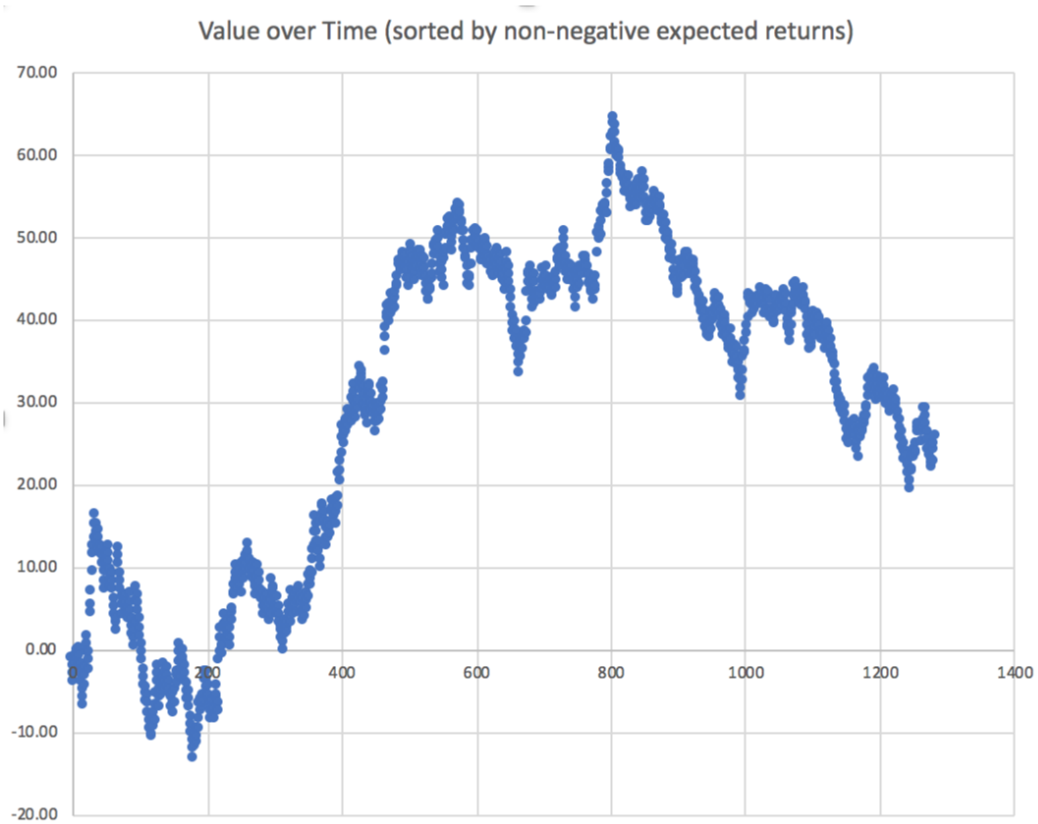
seasons, then your value over time would look something like this. This model would have a success rate of exactly .500 and results in a loss of over 120 units. There are some spikes and peaks in that downtrend though and we know that win probabilities are supposedly better indicators than market prices and events where win probabilities are comparatively profitable to the market are more profitable in their returns so what if we then sort that same the sample by greatest expected return to the least greatest expected return?

Figure 5:



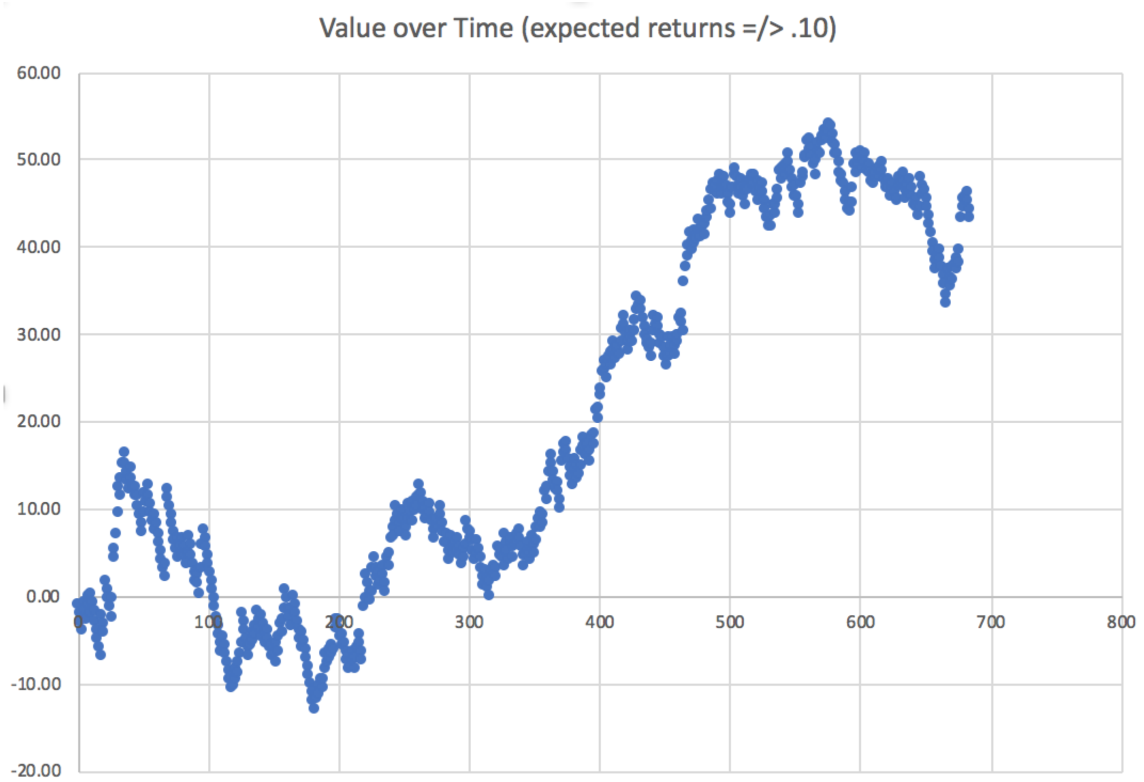
Given that we know expected return has the slightest of positive effects on actual returns, it makes sense that if we then reorganize the previous depiction of data in this order, we might be able to isolate more of the upward movement over the trend. In fact, when only using positive values of expected return, and then by further isolating the employed positive values to only include expected returns greater than 0.10, it then becomes:

Figure 6:



We actually find that, by limiting the observable sample to incorporate solely positive values for expected return, we finally end up with a net positive return on the strategy. Additionally, by further splicing our selected sample to only include values for expected return that are equal to .10, or 10% of your wager, we isolate even more of the uptrend and get a steeper slope on the positive trendline over time.

Figure 7:



To give a heavily conservative calculation concerning liquidity and returns: the minimum value (~15 units) + 20 more units on hand for liquidity = initial value of 40 units to be safe; so with a safe estimate of 40 units for the final value, there is a 100% increase in the value of one's invested capital over five seasons (~50 units/125% increase expected from 12.05229 +.0917356t). Given that this information spans across five seasons and the conservative growth rate we have calculated, the final value would have benefited from around a ~14.85% annualized rate of return generating returns that rival what investors have come to expect from passive investment in the S&P 500 and other indices. For comparison, from September 18, 2015 through February 7, 2020 (the observed window of games) the S&P 500 went (+69.97%). The Dow Jones Industrial Average returned (+72.46) over a similar period ending January 31, 2020.

Limitations and Future Research

Prior to this study, I had a few hypotheses about how to approach sports betting profitably. I had entertained ideas contrary to my findings here by assuming that the house knows best more often than not and that if you ended up taking bets where you could expect to lose more than you would make (if the bet were successful) you would get more correct than you did incorrect because the house always wins. And while those bets were successful more often than not, they only delivered enough returns to break-even although this was based on a very small post-COVID sample size. This was before understanding how lines are actually set though and knowing how that is done makes the observed relationship easier to justify. I also thought it might be profitable to just hedge your bets by betting the same amount on both teams in every game over five seasons and hoping your winners paid more than your losers. Maybe not so broadly applicable, but the premise was amendable. In this study, I was hoping to give a little more explanation into why some games might be more, or less, predictable based on the time of season, time of day, television audience, or a team's recent form. As a result, many variables were tested but ultimately came up very with very insignificant and inconclusive results, so they were excluded from the final analysis (such whether a game was pre-, post-, or regular season, prime-time, and how an average of how a team had performed over their previous five games). The observed coefficients leave much to be desired and that does leave room for future research. These findings might not work for other sports or competitions, like college football, due to the nature of competition and the ranges of straight bet odds available but it hasn't been tested to its entirely possible. This means that future research can be targeted either further into the NFL in an attempt to uncover more of what might explain actual return econometrically or in other fields (sports/competitions) with different levels of unpredictability and randomness so that these kinds of returns don’t have to be limited to just their seasons, or day of the week, but can be applied at a higher volume for even more generous returns throughout a given year.

Conclusion

As previously mentioned, the observed coefficients leave much to be desired (in terms of explanatory power) and that does leave room for future research but it’s also possible that sports betting is, for the most part, a random walk and perhaps that’s what we should expect for what is perceived, by a majority, as a truly competitive market. And perhaps that’s not a bad thing, a random walk is really what we’re hoping for if our current findings hold true because then we know the market is not perfectly competitive because we have observed that it is not, even if imperfectly so. To recapitulate, a bet’s success rate is improved by a decrease, or cut, in odds and an increase in a team’s projected win probabilities per the experts at ESPN and FiveThirtyEight. As mentioned before, this means you can try to bet on teams that are “likely to win” if your idea is winning a singular bet but the numbers show that just winning bets isn’t enough, you want to be winning bets with returns that allow for sustainable reinvestment and that’s where actual return comes in. In essence, it is the bet’s success rate quantified in nominal terms, the terms that matter for this particular field. Upon that shift in measurement, the only variable with some semblance of significance was the expected return variable, if only just (coefficient: 0.24 | p-value = 0.013). And while it’s worth noting the remainder of unexplained variance of actual returns and what this means in terms of this study’s statistical significance and future research it’s also helpful to display the efficacy of the economic significance to show what is being explained by the variable, expected return and why it might be worth it to consider what else may contributes to the predictability of actual return.

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