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Betting Against Efficiency: Behavioral Finance in an NFL Gambling Exchange

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Abstract

Although it may be a stretch to claim that the efficient markets hypothesis of Eugene Fama (1970) has been toppled, recent work has uncovered both empirical and theoretical opposition to Fama's pillar of financial theory. Much of this substantial body of research has focused on the world's financial markets. The explosion of internet-based betting exchanges and information markets, however, provides a rich and simple dataset with which to examine market behavior. These markets provide an especially interesting environment under which to study pricing behavior because the fundamental value is always revealed at the close of each contract, unlike stock prices that merely provide repeated estimations of fundamental value. Concentrating on trading in contracts with the outcomes of National Football League (NFL) games as the underlying event, this paper first revisits two of behavioral finance's major theories: overreaction and underreaction. These behavioral theories make somewhat conflicting predictions about investor activities, and I determine what evidence of each theory exists in NFL gambling markets. The paper then focuses on two hypothesized anomalies that are more specific to NFL wagering. These contradictions to the weak and semi-strong form of the efficient markets hypothesis in the NFL market I label "implication ignorance" and "improper normal curve pricing." Implication ignorance involves the mispricing of contracts that depend on multiple distinct events. This analysis examines the prices of parlay contracts with an eye toward the behavioral work of Tversky and Kahneman (1974). Improper normal curve pricing investigates the prices of different point spread contracts in the context of Stern's (1991) normal curve approximation of the margin of victory distribution. Though no evidence of overreaction or underreaction in NFL trading is found, there is strong evidence of implication ignorance and marginal evidence of improper normal curve pricing.

1. Introduction

Prediction markets and behavioral finance are two burgeoning topics of economic interest. This paper will attempt to use empirical evidence from the former, along with findings from the latter, to examine a third topic that has dominated the financial literature since its introduction 35 years ago: the efficient markets hypothesis, or the EMH. In 1970, Eugene Fama defined an efficient market as one in which security prices accurately aggregated all public information. The EMH takes three forms. The weak form states that knowledge of past prices and returns will not lead to superior risk-adjusted returns. The semi-strong form posits that no publicly available information can be used to generate excess returns. Strong form EMH states that even "insider" information will not help an investor earn superior returns. Most studies have concentrated on the first two forms (Shleifer 2000). Fama (1970) went on to state that real financial markets appeared to satisfy the semi-strong definition of efficient markets. Since then, economists have produced a vast array of evidence supporting the EMH (Shleifer 2000).

In the past twenty years, however, a new framework known as behavioral finance has challenged the EMH in an attempt to better explain the reality of financial markets (Shleifer 2000). Even more recently, another innovation has generated a great deal of interest in economic journals. A search for the phrase "information markets" on Google Scholar, an online search engine devoted to scholarly literature, retrieves an average of just under thirteen articles a year written between 1980 and 2000, while it locates an average of over seventy per year between 2000 and 2005 (scholar.google.com 2005). Wolfers and Zitzewitz (2004) call prediction markets "a new – and emerging – form of financial market." Prediction markets (also known as betting exchanges, event futures, or information markets) have even entered the general public's awareness.[1] TradeSports, a part of the privately owned, Ireland-based "Trade Exchange Network," proudly boasts mention in *The New York Times*, *Time Magazine*, *Bloomberg*, *Reuters*,

[1] Ates (2004) differentiates between betting and gambling by defining betting as a subset of gambling that is "justified by sports knowledge of the bettor." Removing myself from the semantics of the terms, I refer to any commitment of capital in which the payoff depends on the outcome of future events as gambling, betting, or wagering. Although these terms have acquired a negative connotation, there is little intellectual difference between "betting" that the Jets will lose and selling pork belly futures with the hope that prices fall. As Swensen (2000) notes, the security selection of any active manager is a zero-sum game, implying that the manager who engages in it believes s/he holds knowledge about the future superior to the rest of the market.

Fortune, *The New Yorker*, *Esquire Magazine*, the *Wall Street Journal*, *Islamic Republic News Agency*, and many more (tradesports.com 2005a).

The existence of prediction markets provides researchers yet another opportunity to study market activity with an eye toward the debate between the EMH and behavioral finance. A better understanding of investor behavior could provide an informed party the opportunity to earn abnormal returns by exploiting documented irrationalities. Given the amount of energy that humans deploy in other attempts to achieve this goal, the demand for further study of markets is very high. Although, as I discuss later, the jump from betting exchange research to financial markets is not immediate, the growing popularity and size of event futures markets make them interesting in their own right. Saporito (2005) reports that Prof. Justin Wolfers at the University of Pennsylvania's Wharton School believes that individuals will eventually be able to use prediction markets to hedge "everything." If that forecast comes to fruition, it will certainly be important to understand how efficient these markets are as well as when they fail to produce efficiency.

After providing some background on information markets and a comparison with present-day financial markets, I turn briefly to the dataset under consideration before introducing the overreaction and underreaction biases documented in behavioral finance studies. I evaluate the existence of short-term overreaction to winning streaks and briefly consider the possibility that the NFL betting market on TradeSports is underreacting to these signals. I then investigate possible violations of the weak form and semi-strong form EMH for reasons more specific to sports prediction.

"Implication ignorance" hypothesizes that market participants do not price related contracts appropriately. In particular, psychological studies have shown that people systematically overestimate the probability of conjunctive events. This leads to an analysis of NFL parlay contracts. Although possible explanations for the observed mispricing are similar to those posited for the existence of the long shot bias in gambling research, I demonstrate that these are not satisfactory. "Improper normal curve pricing" evaluates the different spread contracts available on TradeSports for internal consistency and agreement with the findings of "On the Probability of Winning a Football Game" (Stern 1991). I conclude with mention of the difficulties encountered in the research and suggestions for future work.

2. NFL Wagering and Prediction Markets

2.1 Background

Wolfers and Zitzewitz (2004) define prediction markets as those in which members buy and sell contracts whose future payout is dependent on unknown future events. Sports contests are perfect examples of such events and their outcomes have been wagered on for centuries (Ates 2004). Saporito (2005) reports an ever-expanding array of events – from the capture of al-Qaeda leaders to party nominations – upon which people can bet. Though betting on the outcomes of sporting events, particularly the NFL, is nothing new, the structure of the "bet" on sites like TradeSports is markedly different.

Boyle and Videbeck (2005) report that all-or-nothing contracts, which pay some positive sum if and only if some event occurs, are the most common type of contract on information markets. TradeSports contracts expire at 100 "ticks" (each tick is worth $0.10) if the event occurs, and zero otherwise. Therefore, at any point in time the price of the contract approximates the market's estimation of the probability that the event will occur.[2] The approximation is exact if both the riskless interest rate and the risk premium are zero (Boyle and Videbeck 2005). Traditional NFL wagers have similar terms, but they have a fixed price set by a bookie.[3] Most of the traditional betting done on the outcomes of individual NFL games uses a spread system where the odds (and hence payoffs) on both sides of the bet are identical, but a specified number of points is added to one team's total before determining the winner (Woodland and Woodland 2000). In contrast, TradeSports utilizes multiple fixed spreads for each game. The exchange facilitates trade of these contracts so that the price of each contract dynamically adjusts to

[2] The relationship between the money line, odds, price, and probability is detailed in Appendix B.
[3] For a definition of bookie and other betting terminology, please see Appendix A.

demand. All of TradeSports' NFL contracts are offered via a continuous double auction that matches buyers' bids with sellers' asks if there is a mutually agreeable price (Wolfers and Zitzewitz 2004).

In addition to single game contracts, TradeSports lists parlays for multiple teams to win in one week. Both kinds of contracts are examined extensively throughout the rest of this paper. Longer term contracts on which team will win the Super Bowl, conference championship, and division also are offered on the TradeSports.com and considered in the suggestions for future work. Also mentioned in the discussion of future work is "index" betting, distinct from all-or-nothing contracts, in which the payout varies depending on the number of games that a team wins during the regular season. This paper does not analyze over/under bets on single game point totals or contracts on individual performance, both of which TradeSports offers.

Although the purpose of my work is not to study the predictive powers of information markets, it is worth noting the success that they have had and how likely it is that NFL markets will duplicate that success. Wolfers and Zitzewitz (2004) observe that the Iowa Electronic Markets have produced accurate election predictions and outperformed most polls, while other event futures markets have done as well or better than expert opinions on topics that range from the removal of Saddam Hussein from power to who will be awarded an Oscar.[4] For a prediction market to be successful, it requires clear, easily adjudicated contracts, motivation to trade, and the existence of useful intelligence to aggregate (Wolfers and Zitzewitz 2004). NFL contracts obviously possess stark clarity, just as the outcomes of NFL games do. The "thrill of pitting one's judgment against others" and widespread disagreement over the likely outcome of games produces motivation to trade, even before considering the financial incentive (Wolfers and Zitzewitz 2004). Lastly, the games themselves, reams of statistics available on NFL.com, and "expert" analyses of various media prognosticators provide numerous sources of worthwhile information on which to trade.

[4] One should not forget the complication that expert opinions are often well-publicized and may affect market behavior. The interested reader is referred to Geyser's 2004 research on the influence of expert opinions – specifically college football and basketball rankings – on bettors.

2.2 Arbitrage and Its Limits

Many of the limits to arbitrage in traditional markets do not exist in prediction markets. Barberis and Thaler (2003) list fundamental risk, noise trader risk, and implementation costs as the three theoretical impediments to arbitrage. Unlike the stock market, where the economy could influence the returns of virtually all stocks, the aggregate result of each NFL game is constant and known with certainty: one team will win and the other will lose.[5] Since systematic risk is essentially zero, an arbitrageur in the NFL market does not need to identify a substitute security with which to hedge his or her "market" risk. Thus, fundamental risk in the arbitrage is minimal. Likewise, noise trader risk is very limited because NFL contracts must expire at fundamental value at some finite point in time. Better still, the time horizon is usually quite small for these contracts and never more than a year in the dataset at hand.

Short-sale constraints are a major component of implementation costs, further limiting arbitrage in real financial markets. Prediction markets, TradeSports included, have no such constraints on shorting securities. The transaction costs of trading are discussed in section 3.2. Barberis and Thaler (2003) mention three other implementation costs that I choose not to address. These are the bid-ask spread, the price impact of trading, and the cost of learning about the mispricing. The smaller scale of the market also makes it less likely that participants will be capital-constrained (Wolfers and Zitzewitz 2004).

Though Wolfers and Zitzewitz (2004) conclude that prediction markets present very few arbitrage opportunities, they point out two distinct forms that an arbitrage could take. Investors could arbitrage similar contracts across different exchanges, or identify deviations from rationality on the part of other traders. Wolfers and Zitzewitz claim that the former is almost nonexistent, but Ben Marshall (2005) finds that sizeable profits can be earned from exactly this strategy, popularly known as "sports arbitrage."[6] Sports arbitrage involves, for example, wagering $10 on the Cowboys to defeat the Giants at even odds

[5] Technically, ties are possible in NFL regular season games, but they are very rare.
[6] This depends on one's definition of "sizeable." Sports arbitrageur Alan Seymour reports earning between approximately $45,000 to $65,000 a year exploiting these arbitrages (sportsarbitragereview.co.uk 2006). Based on the number of hours he works finding the arbitrages, this equates to an hourly wage of roughly $50 – comfortable, but hardly a path to unbridled riches.

(50 ticks) on one sportsbook and \$6.67 on the Giants at 2/1 odds (33 ticks) on another. If the Giants win, the first bet loses \$10 but the second bet wins \$13.33 (2 x \$6.67). If the Cowboys win, the first bet wins \$10 while the second loses \$6.67. Regardless of which team is victorious, the total outcome of both bets is a riskless gain of \$3.33. Hausch and Ziemba (1990) documented a similar phenomenon at racetracks, where riskless arbitrage was possible by betting on the same horse at different tracks.

The research in this paper will explore the other method of arbitrage proposed by Wolfers and Zitzewitz (2004): the possibility of identifying persistent deviations from rationality in market participants. Since there is no systematic risk in most NFL contracts, all of the risk is idiosyncratic. If bettors are acting irrationally in certain instances, then statistical arbitrageurs should realize excess returns from exploiting these behavioral biases, even though the strategy may not be an arbitrage in the purest sense of the word.

3. The TradeSports Exchange and Traditional Financial Markets

3.1 Mechanics

Unlike most financial exchanges, TradeSports requires traders to have enough funds in their account to meet the maximum loss on a trade. The maximum possible loss is frozen in the trader's account, i.e. it cannot be withdrawn or used to trade, until the contract expires. There is some trading on margin permitted, but the majority of traders are bound to the aforementioned strict margin requirement. While there is no restriction on short selling, the proceeds from a sale are not credited to the trader's account until the contract expires. Commissions, on the other hand, are paid immediately.

Tetlock (2003) reports that almost 90% of the contracts listed on TradeSports expire within one week. To minimize the opportunity cost of freezing money for longer term trading, TradeSports pays 1% annual interest on a quarterly basis for all account balances that are greater than \$20,000 for the entire quarter. Frozen funds are included in the account balance calculation. The short duration for most of these contracts makes the time value of money immaterial and assuming a risk-free interest rate of zero is a close approximation to reality.[7]

3.2 Commissions

Each contract lot is worth $10 upon "successful" expiry, making each tick on TradeSports' 0 to 100 scale equivalent to ten cents. With the exception of contracts priced above 95 or below 5, $0.04 commission is charged to buy or sell any contract. Liquidation at expiry incurs a further $0.04 charge, making the total commission 0.8% of the maximum contract price. These transaction costs are much smaller than traditional sportsbooks, which typically take almost 10% of the winner's net profit on each wager. Thus, the average return net of fees from betting at a traditional sports book is -5%, while it is -1.6% on TradeSports. Though small, these fees produce a real limit to arbitrage. Anecdotally, on December 4, 2005, it would have been possible to sell the contracts of 18 NFL teams to win the Super Bowl for a combined price of 101.70. Since at most one contract could avoid expiring at zero, this would ensure a seventeen cent profit before commissions – but that profit quickly turns into a loss of $1.27 once the costs of selling 18 contracts are considered.

3.3 Market Characterization

World financial markets operate on a vastly different scale than that of the TradeSports exchange. In October 2003, Tetlock estimated that on the NYSE approximately 100 million participants have invested close to $10 trillion. TradeSports claims to have traded almost $1 billion between 30,000 members over the past three years (tradesports.com 2005b). Although this study is confined to wagers made on TradeSports, the scope of the gambling industry as a whole bears mentioning. Bettors legally risk nearly $1 billion per year on NFL games (Borghesi 2004), and Vergin (2001) estimates illegal wagers

[7] If one assumes a generous 5% risk-free interest rate, then the frozen funds staked in TradeSports wagers have an opportunity cost of 4% per year. Given that the average contract duration is much less than one week, taking a position that risks $100 implies an opportunity cost for the money staked in that bet of less than eight cents.

on sporting events may be as much as ten times as large. Even if that estimated illegal volume is included in the analysis, the betting exchange market is orders of magnitude smaller than world financial markets.

3.4 The Value of Prediction Markets in Financial Research

NFL wagering provides a simpler market in which to test the EMH than stock markets (Woodland and Woodland 2000; Vergin 2001). In equity markets, it is difficult to determine whether or not investor reaction to some piece of news was justified because fundamental values are typically not revealed. In NFL betting markets, on the other hand, fundamental value is always revealed at the expiry of the contract in the form of game outcomes (Borghesi 2004). Also, as mentioned above, the absence of non-diversifiable risk in NFL contracts implies that risk premiums should not be present in prices, removing yet another complexity found in traditional markets. At the same time, the data from information markets is less artificial than that generated by economic experiments (Boyle and Videbeck 2005). Tetlock (2003) provides an excellent summary:

> Many features of the TradeSports exchange recommend its use as a "natural laboratory" for testing asset pricing theory. It is easy to determine the fundamental value of the contracts on the exchange that are only exposed to idiosyncratic risk. Because events on TradeSports tend to be widely publicized, the assumption that all traders can costlessly acquire information about these fundamental values is probably not a bad approximation.
>
> Moreover, if prices ever stray from fundamental values, experienced traders from real financial markets have excellent opportunities to identify and eliminate arbitrage opportunities on the TradeSports exchange. Prospective arbitrageurs face minimal hurdles to entering the market, near-zero transactions costs, and very few regulations on their trading behavior. If at least some of these arbitrageurs have rational expectations and access to sufficient capital, they will prevent substantial mispricings on the TradeSports exchange.

Tetlock urges caution, however, in attempting to generalize tests of the EMH in prediction markets to real financial markets, a point to which I will return later.

3.4 The NFL Dataset

Sinead Kelliher of TradeSports provided all of the NFL market data analyzed in this paper.[8] The dataset included trades made on long-term contracts for the 2003, 2004, and 2005 NFL seasons. It also included individual games for all available spreads and parlay trading for the entire 2003 and 2004 season and the first seven weeks of the 2005 season. Note that for individual games, shorting one team is equivalent to betting on the other team to win. Consider, for example, the Jets at Patriots game. A contract that gave the Jets 3.5 points would be specified as either "Patriots-3.5" or "Jets+3.5."[9] Buying the Patriots-3.5 contract is equivalent to betting the Patriots to cover, or shorting the Jets+3.5 contract. Shorting the Patriots-3.5 contract means placing a bet on the Jets to win (or lose by less than four points).

Lastly, the dataset included index trading on the number of wins in a season for 2004 and 2005. I inserted the raw data into a Microsoft Access database after cleaning it with a Python script and used SQL expressions to manipulate it. I wrote another Python script to scrape historical scores from NFL.com and inserted this as another table in the database. This scraper retrieved the quarter and final scores of all 855 games from 2002 week 3 to 2005 week 10. Most of the data analysis and chart creation was done using Microsoft Excel.

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[8] Other online event futures exchanges exist that are not considered in this paper, including betfair.com and wsex.com. TradeSports is indisputably amongst the most prominent.

[9] Please see the definition of "Point Spread" in Appendix A. In this example, someone who wagered on the Jets would win the bet if the Jets lost by less than 3.5 points. Therefore, the bet would payoff if the Jets lost by 3, 2, or 1 points, tied, or won the game.

	Games	Long-term	Parlays	Wins Index**	Wins O/U
# of contracts	2,171	192	335	64	96
total volume*	$59.44 MM	$12.54 MM	$63.3 K	$1.52 MM	$1.07 MM
total volume (in lots)	5,944,475	2,507,756	12,655	304,072	213,529
# of trades	380,245	62,669	1,199	1,588	6,454
avg. lots per trade	15.6	40.0	10.6	191.5	33.1
avg. lots traded per contract	2,738.1	13,061.2	37.8	4,751.1	2,224.3
avg. trades per contract	175.1	326.4	3.6	24.8	67.2

Table 1.

* Exactly $10 is at stake in each trade of a contract, though the proportion of the risk that lies with the buyer and seller differs for each transaction.
** Win index contracts expire between 0 and 16, with every point equivalent to $1. Hence, the average contract is worth $8, whereas all the other contracts have an average value of $5. I adjusted the volume by multiplying it by 8/5 to reflect the increased capital at stake.

4. Overreaction and Underreaction

4.1 Literature Review

In their landmark paper "Judgment under Uncertainty: Heuristics and Biases," Tversky and Kahneman (1974) identify two heuristics people use in answering probabilistic questions. The first, representativeness, states that people judge an event's likelihood by how representative it is of a class and that people expect local sequences of a pattern to be representative of the pattern as a whole. The second, known as adjustment and anchoring, or conservatism, finds that people adjust their estimates from an initial value, but these adjustments are usually insufficient.

These biases make strong statements about the kind of behavior that might be observed in markets. Notably, these statements are contradictory in their predictions. The representativeness heuristic would lead investors to extrapolate a pattern of good earnings growth, assume that it is representative of the company's future prospects, and overvalue the corporation (Barberis, Shleifer, and Vishny 1998). Conservatism, on the other hand, would cause individuals to cling to prior beliefs even in the face of important news about a company – so good news would not be fully incorporated into the price, and the stock would be undervalued following a positive announcement (Barberis, Shleifer, and Vishny 1998). There seems to be a contradiction – good news causes both overreaction that leads to overvaluation *and* underreaction that leads to undervaluation – yet empirical evidence of both has been found in financial markets. Most studies distinguish between the two phenomena by their timeframes or different circumstances.[10] Underreaction occurs in response to isolated informational shocks, whereas overreaction is caused by longer-term patterns of information. De Bondt and Thaler (1985) find that portfolios composed of stocks with poor previous three year returns outperform those portfolios composed of stocks with high returns over the same period, suggesting that the market is correcting for previous overreaction to good (and bad) news. Cutler, Poterba, and Summers (1991) find evidence of both underreaction in the short term and overreaction over longer periods.

Overreaction seems particularly likely in sports betting markets given unfounded, but widespread, fan belief in the "hot hand" (Barberis and Thaler 2003). Accordingly, researchers have not neglected gambling markets in their search for confirmation or dismissal of overreaction. The results have been mixed. Vergin (2001) tested betting strategies on NFL point spread wagers for the seasons 1981-1995. He found that "bettors tend to overweigh outstanding positive performance when measured over the previous game, over the previous two to five games or over the previous season…the more outstanding the performance, the greater the overreaction." Tetlock (2003) finds a very slight positive return to betting on price reversals in sports contests, indicating that sports traders exhibit overreaction, but concludes that it is small enough to be attributable to chance. Woodland and Woodland (2000) find that NFL point spread betting is highly efficient with little overreaction.

[10] Barberis, Shleifer, and Vishny (1998) produce a model of investor sentiment capable of generating results consistent with both overreaction and underreaction. This is a good effort at producing a unifying theory, something that has been distinctly absent from the literature. The first two sections of the article – "Introduction" and "The evidence" – also provide an excellent review of past empirical work demonstrating the two phenomena.

4.2 Discussion

The analyses of Vergin (2001) and the Woodlands (2000) suffer from their use of point spread contracts. News on game outcomes is not necessarily correlated with changes in the fundamental value of bets. Generally, the outright winner of the game receives the most publicity, not the winner based on the spread. According to Tetlock (2003), "the behavioral theory of overreaction based on salience suggests price reversals should be greatest in events with a lot of media coverage." NFL contests receive a vast amount of media attention in the U.S. and it seems likely that if overreaction were to occur in the NFL betting market, it would be due to voluminous media reports on previous game winners, not bet winners.[11] In fact, Woodland and Woodland (2000) admit that there is "weak evidence that bettors overreact when a team wins or loses a game outright." Furthermore, both studies assume that bookmakers try to find a spread that balances the betting on both sides, but there is evidence that bookies purposefully take positions (by having an unbalanced book) to exploit bettor biases (Levitt 2004 and Strumpf 2003). This means that the spread is *not* the market-clearing price, as both papers assume. In short, examining traditional spread bets adds a layer of complexity to the research that makes it more difficult to interpret.

Tetlock (2003) avoids the pitfalls of unbalanced sportsbooks by using TradeSports contracts, whose price is guaranteed to be market-clearing since TradeSports does not take a position in any of its contracts. It is difficult, however, to draw conclusions specifically about NFL betting from Tetlock's broad study of contracts on TradeSports because he does not separate contracts from different sports, nor does he distinguish between the different types of NFL contracts that exist. Tetlock wisely uses a brief timeframe given the limited duration of the vast majority of the contracts in his dataset. His trading strategy purchases (sells) contracts that experienced poor (good) returns in the past thirty minutes. While Tetlock demonstrates overreaction in sports contracts, the thirty-minute period used precludes a test of the overreaction Barberis, Shleifer, and Vishny (1998) suggest might occur after a *consistent pattern* of good or bad returns. Furthermore, by not considering the underlying event and looking only at past price

[11] NFL.com (2003) reports that NFL games were the top rated shows in their respective markets almost 70% of the time in 2002. In addition to the games themselves, entire radio stations and cable channels (most notably ESPN) are devoted to analyzing the NFL and other sporting events.

movements, the reasoning is somewhat circular. It assumes that large price movements were caused by reaction to news, but speculative trading, for example, could also cause these price movements.

4.3 Analysis of TradeSports Data

My test attempts to avoid these difficulties and to extend Tetlock's excellent demonstration of overreaction in sports contracts. To that end, the test examines only non-spread contracts for games in which one team enters with a winning streak. Note that if the trend of wins continues, it will directly affect the fundamental value of the contract for the game in question. The test requires a pattern of results – not an isolated event – because financial markets and psychological research have shown that patterns, not one-time events, are what generally produce overreaction. The trading strategy is simple: bet against teams that have won at least three games in a row.[12] If market participants do overreact and become overly optimistic about the team's chances in games played while on a winning streak, betting against that team should generate excess returns on average.

Note that the hypothesis makes no statements about when during pre-game trading the overreaction might occur. It merely conjectures that the market has a predictable bias when estimating a team's chances of winning while riding a winning streak. Hence, I use the weighted by volume average price of all trades prior to the game in reporting the returns of the trading strategy. The strategy sells short one contract for the team with the win streak to win the game and holds this short position until expiry, incurring round-trip commissions of $0.08. Table 2 reveals the results of following the strategy from the start of the 2003 season through week 7 of 2005. The table is split into bets that are placed on the home team (when the away team is riding a winning streak) and those placed on the away team (when the home team is riding a winning streak).

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[12] If the other team has won two or more games in a row, no trade is made to avoid overreaction effects cancelling each other out. For the purposes of the trading strategy, a bye-week ends a streak.

	On home team	On away team	Combined
Positions taken	52	31	83
Average return, before fees	-2.9%	-66.1%	-26.5%
Std. Dev. of returns	134.6%	92.2%	123.8%
t-statistic (assuming zero mean)	-0.16	-4.00	-1.95
Average return, after fees	-5.1%	-68.8%	-32.5%

Table 2.

The data soundly rejects the hypothesis of overreaction to win streaks. Based on the average contract prices and the actual results during the same period, the market believed that visiting teams on a win streak would win 55.4% of the time; they won 59.6% of the time. Home teams on a win streak were priced to win 67.2% of the time; they won a staggering 87.1% of the time.

Perhaps the win streak used was too short, so that the pattern of returns was not consistent enough to have produced overreaction. It would have been preferable to use teams on five or six game win streaks, but that would have reduced an already small sample to one less than a fifth of the size used. It is tempting to conclude that, rather than overreaction, market participants are underreacting to positive signals about a team's quality. Kahneman and Tversky (1974) document the "gambler's fallacy," in which bettors believe that deviations in one direction are "corrected" by deviations in the other. This would help explain unwillingness to bet on teams that have had recent success.

However, both explanations suggest that similar – though perhaps not as strong – underreaction to single game winning streaks should be present. It is not. In fact, away teams that won their last game facing home teams that lost their previous contest are significantly[13] overvalued, as overreaction would predict (home teams that won their last game are slightly undervalued, in line with underreaction). In short, my analysis of non-spread NFL event futures produces no conclusive evidence of either overreaction or underreaction. This result highlights the fact that most of behavioral finance's current theories of overreaction and underreaction are not much more than observations of how markets have behaved over different timeframes.

[13] A strategy of choosing the home team against the "streaking" away team produces 16.8% average returns with a t-statistic of 2.05 against the assumed population mean of zero.

5. Implication Ignorance and Overconfidence

5.1 Literature Review

Again, the review of the literature begins with Tversky and Kahneman (1974). They find that "people tend to overestimate the probability of conjunctive events," which they attribute to the anchoring heuristic. After developing a beginning estimate of a value, people typically make insufficient adjustments to that initial value. Consider the conjunctive event that events A and B *both* occur. The probability of one of the events (either A or B) occurring is a natural starting point for the estimation of the conjunctive event. Since the probability of the conjunctive event must be lower than both the probabilities of the two elementary events, and because adjustments are usually insufficient, the final probability assigned to the conjunctive event is too high. The reverse bias – probability estimates for disjunctive events are typically too low – appears for similar reasons. Because TradeSports does not offer disjunctive NFL contracts, I omit discussion of this phenomenon.

Since parlays in which the bettor must pick the winner of both games are less likely to win compared to most single game contracts, they can be characterized as "long shots." This raises an alternative explanation for the mispricing of conjunctive contracts. There is a well-known long shot anomaly observed at racetracks that expected returns to wagers decrease with reductions in the probability of winning (Golec and Tamarkin 1995).[14] It is therefore important to distinguish between behavior that might be due to a preference for long shots and that which is due to improper conjunctive probability estimation. Wolfers and Zitzewitz (2004) write that "prediction markets do seem to display some of the deviations from perfect rationality that appear in other financial markets. There is substantial evidence from psychology and economics suggesting that people tend to overvalue small probabilities and undervalue near certainties." This contradicts the assumption that bettors are both risk neutral and

[14] See, for example, Richard Thaler and William Ziemba's 1988 "Anomalies: Parimutuel Betting Markets: Racetracks and Lotteries" in the *Journal of Economic Perspectives*, Vol. 2 No. 2:161–174.

rational.[15] Golec and Tamarkin (1995) hypothesize that bettors are either risk-loving or overconfident in their ability to reduce the risk of these riskier wagers. After examining bets made on NFL parlays and "teasers," they conclude that the latter reasoning better explains their data.

Other researchers have also found substantial evidence that people, bettors in particular, are overconfident. Sociologists determined that one of the main motivations to begin betting is an overestimation of one's knowledge or luck in predicting sports games (Ates 2004). According to Barberis and Thaler (2002), "extensive evidence shows that people are overconfident in their judgments." Golec and Tamarkin (1995) suggest that this could help explain the long shot anomaly because bettors may perceive that their "expertise" can produce greater risk reduction in higher risk bets.

5.2 Discussion

I start by examining the notion that traders are risk-loving. Assume that all contracts are priced correctly – i.e. a contract selling for x ticks will happen exactly x% of the time. Expected returns are zero (ignoring transaction costs) in all cases. The variance in returns is given by (100-x)/x. Taking variance as a measure of risk, then risk is strictly decreasing in the price of contracts for the buyer. But for the person that sells that contract at x, expected returns are also zero and variance in returns is given by x/(100-x). For the seller, risk is strictly increasing in price. If gamblers (both buyers and sellers) are risk-loving, buyers would be willing to pay a premium for the increased risk of low probability events and buy them for more than fundamental value, while sellers would be willing to pay a premium for the increased risk of high probability events and sell them for less than fundamental value. The least risky events would demand a "certainty" premium because their lower risk makes them less attractive to risk lovers. Buyers would only buy high probability events for less than their fundamental value, and sellers would only sell low probability events for more than their fundamental value. Assume that TradeSports traders are all risk-loving – a reasonable hypothesis since they are choosing to engage in a negative-sum activity. Then,

[15] Kahneman and Tversky explore systematic violations of expected utility maximization in much greater detail than is possible here. For an alternative proposal to expected utility theory, the interested reader is referred to their 1979 article, "Prospect Theory: An Analysis of Decision Under Risk," in *Econometrica*, Vol. 47:263–91.

in general, betting on low probability events (for which buyers must pay premiums for the increased risk and sellers demand premiums for the decreased risk) would generate subpar returns. Betting on high probability events (for which buyers demand discounts for the decreased risk and sellers will sell at discounts because of the increased risk it gives them) would earn excess returns. This phenomenon should not be restricted to parlays, as the risk characteristics exist unchanged in all contracts.

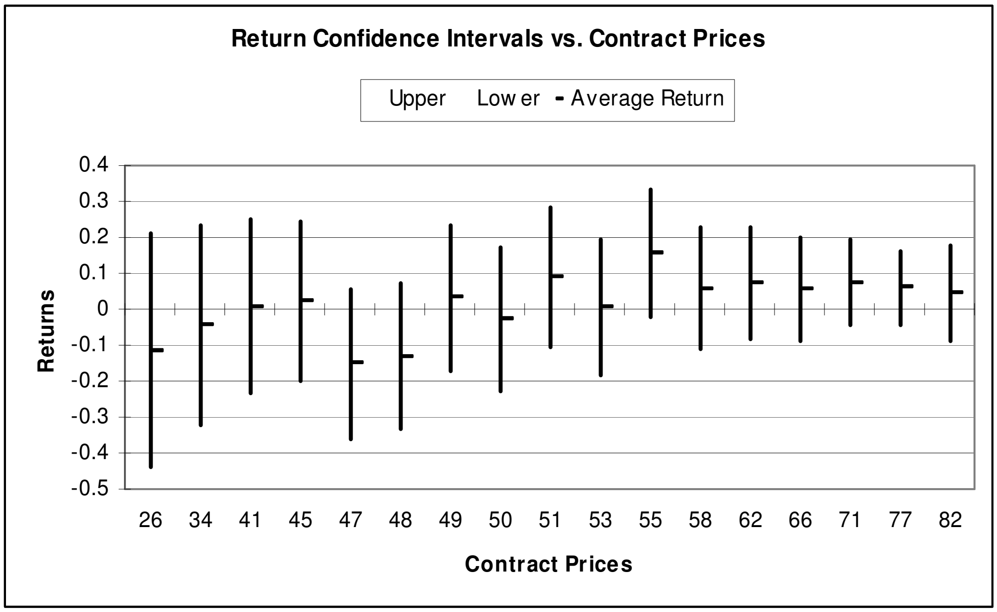

Figure 1.

Of the 1643 single game contracts that had ten or more lots traded before the day of the game, I sorted them by their volume weighted average price and then split them into 16 groups of 100 and a residual group of 43. The above graph shows the average return and 95% confidence interval on that return from purchasing the lowest group, second lowest group, third lowest group, etc. The values along the horizontal axis are the average prices of the contracts in each of the 17 groups. Indeed, all negative returns occur in the lower priced half, while the higher returns are found mostly in the higher priced contracts. But only one of the return groups has an average return that is statistically different from zero at a 10% significance level, and none are significant at the 5% level. Moreover, if traders are risk-loving then returns should increase monotonically with the probability of winning. This is clearly not the case in the given sample, as Figure 1 demonstrates.[16]

5.3 Analysis of TradeSports data

TradeSports sometimes offers parlay contracts in which two or more teams must win their game that week for the contract to expire at 100. Bets of this nature are conjunctive events, so Tversky and Kahneman's (1974) results make a clear prediction about what to expect in trading behavior: parlays will be overpriced. Note that the wording of the contracts specifies them as conjunctive events, e.g. "Cowboys and Jets to win" rather than "At least one of the Cowboys and Jets will lose." The experimental portfolio consists of all doubles and trebles traded on the exchange from 2003 through week 7 of 2005. Believing that these contracts will be systematically overpriced, the trading strategy sells each contract at the volume weighted average price. This strategy is designed to exploit a hypothesized human bias that causes people to overestimate the probability of conjunctive events, perhaps because traders are overconfident in their abilities.[17]

	Doubles	Trebles	Combined
Positions taken	223	62	285
Average return, before fees	20.6%	21.7%	20.8%
Std. Dev. of returns	152.9%	76.1%	139.7%
t-statistic (assuming zero mean)	2.01	2.26	2.52
Average return, after fees	19.2%	20.4%	19.4%

Table 3.

The results indicate that statistically significant excess returns are possible by following a strategy of betting against parlays. It must be noted, however, that the market for parlays on TradeSports is extremely thin. Over the roughly two and a half year period studied, only 9676 lots of double and treble contracts were transacted. Even if over that timeframe a statistical arbitrageur had managed to sell every

[16] This analysis suffers from a lack of extremely priced contracts. The behavior of contracts that are priced above 95 ticks or below 5 ticks might be far more influenced by the long shot bias than contracts not at either pole of the price spectrum.
[17] N.B.: The positions taken are decidedly *not* independent. Many of the contracts are based on the same underlying game with a different team winning. Others duplicate a game outcome over two or more different contracts.

single lot at the weighted average price for that contract, net profit after fees would have been only $6,667.

These results are in line with the well-documented “long shot bias” that betting against less-likely events generates superior returns, but, like Golec and Tamarkin (1995), I find that risk-preferences are insufficient to explain the anomaly. First, the average double and treble price in the dataset was 41.9 and 41.6, respectively, which hardly makes the bets “long shots.” The very fact that the two average prices are so close suggests that bettors are not sufficiently reducing their overall probability predictions when estimating the chances of three teams all winning, as opposed to just two. Second, single game contracts do not indicate a similar preference for lower probability events, as witness Figure 1 of section 5.2. In fact, similarly priced single games returned almost exactly zero (see the third contract grouping in Figure 1).

The best evidence that bettors overprice parlays because of conjunctive overestimation comes from examining the prices of the two underlying games of each parlay contract on two teams. Since the outcomes of two separate football games are nearly, if not perfectly, independent, the probability of a parlay paying off is the product of the probabilities of each bet on the individual teams in the parlay paying off. Consider, for example, a parlay on the Jets and the Cowboys. In an efficient market, with the very reasonable assumption of independence between the two games, the following must hold:

$$Price_{parlay} = 100 \bullet \Pr(\text{both teams win}) = 100 \bullet \Pr(\text{Jets win}) \bullet \Pr(\text{Cowboys win})$$

and because $Price_x = 100 \bullet \Pr(\text{x wins})$

$$\therefore Price_{parlay} = 100 \bullet \frac{Price_{Jets}}{100} \bullet \frac{Price_{Cowboys}}{100} = \frac{Price_{Jets} \bullet Price_{Cowboys}}{100}$$

In an efficient market, the "implied price" of a parlay on both x and y to win is

$$Price_{x\,and\,y} = \frac{Price_x \bullet Price_y}{100} = \Psi$$

The TradeSports data demonstrates that this is definitively not the case. I restricted attention to the 86 cases of doubles in which a minimum of ten lots were traded on each of the parlay and single game contracts. Using Ψ to denote the “implied” price, the observed prices of the parlay were significantly greater than their corresponding Ψ values. That means that parlay contracts were priced to win more often than they would pay off according to the prices for the underlying single game contracts.[18] Only 16.3% of the parlays in the sample were underpriced (observed price < Ψ). On average, Ψ was 7.84 ticks less than the observed price and the difference between the observed price and Ψ had standard deviation of 12.23. If the TradeSports market was truly efficient, then this difference should be zero. Assuming the difference population follows a normal distribution with mean zero, the 86 TradeSports observations represent almost a six standard deviation event. I conclude that irrational bettor behavior – overestimation of conjunctive probabilities and, perhaps, the bettor's overconfidence in his or her ability to improve the wager's odds by betting on more than one game – is responsible for the results.

5.4 Examples of Applications

The observed overvaluation of double and treble contracts confirms Tversky and Kahneman's (1974) findings and has any number of important implications. A two-worker family considering disability insurance may overestimate the likelihood of both workers being simultaneously disabled and purchase more than the efficient quantity of insurance. Similarly, take the example of a manufacturer deciding whether to construct a new plant. He or she might identify the two primary risks to the future profitability of the plant as rising labor costs and falling demand, though in this case these are probably not strictly independent. The manufacturer determines that the business could avoid bankruptcy in either case, but not if both misfortunes were to strike at once. Overestimating that conjunctive probability might cause the manufacturer to misperceive the risk of bankruptcy and fail to make a worthwhile investment into the construction of the new plant.

[18] I used the volume weighted average price of trades made prior to the game for the single game contracts and the doubles. This admits the possibility of an inconsistency because the parlays and individual games were traded asynchronously. If all of the doubles trading took place before a high-volume, large change in the prices of the single game contracts, it would be misleading to use those prices in determining an implied price of the double to compare against its observed price. In practice, this is unlikely to be an issue because trading usually occurs in a relatively short timeframe and because all trades included in the sample were made prior to the day of the game. Therefore, in most cases, the trades occurred at times when approximately the same information was available.

6. Improper Normal Curve Pricing

6.1 Literature Review

Statistics professor Hal Stern (1991) studied NFL game outcomes and spreads from the 1981, 1983, and 1984 seasons. Stern finds that the margin of victory over the point spread is approximately normally distributed with mean zero and standard deviation 13.861. Results collected in 1985 and 1986 also support Stern's conclusion that "the normal cumulative distribution function can be used to compute the probability that the favored team wins a football game" given the even money point spread.

Because sportsbooks have traditionally offered only one line on each game, it has been impossible to measure the market's perception of the entire margin of victory distribution. If bet takers maintained a balance book – a situation that, as discussed in section 4.2, only approximates reality – then a traditional spread bet reveals only the market's estimate of the median margin of victory (Wolfers and Zitzewitz 2004). The family of spread contracts offered by TradeSports provides a unique opportunity to observe a number of data points on the probability distribution over victory margins implied by market expectations (Wolfers and Zitzewitz 2004).

6.2 A Statistical Arbitrage Strategy

Though not mentioned in section 2.2, there is another form of sports-related arbitrage. Paul and Weinbach (2002) note the possibility of taking a "middle" position in spread betting. This position exploits differing spreads to win both wagers if the score falls in between the two spreads, risking only the vigorish if it does not. For example, such a bet is made by betting on the favorite at minus 6.5 points and on the underdog at plus 7.5 points. If the favorite wins by exactly seven points then both bets win. For all other outcomes of the game, one bet wins and the other loses, offsetting all losses other than transaction costs. In practice, it is sometimes, but rarely, possible to implement this strategy by betting with sportsbooks that are offering differing spreads on the same contest.

Traditional sportsbooks take bets for football games on one "line" that may be adjusted slightly throughout the betting. TradeSports, on the other hand, usually offers contracts with a number of different unchanging lines for each game. In a well-functioning market, these do not present middle positions because the market price for each will differ. The more points the favored team gives in a contract, the more cheaply a bettor can buy that contract on the favorite to win. However, a *statistical* arbitrage between the two spreads may still exist. For example, if a contract on the Jets giving 6.5 points sells for 45 and another contract on the Jets giving 7.5 points sells for 52, then the market is estimating that there is a 7% chance that the Jets will win by exactly 7 points. If the true probability were more than 7%, then a statistical arbitrageur would buy positions in the Jets-6.5 contract and sell positions in the Jets-7.5 contract. With a true probability less than 7%, one would reverse those positions, going long the Jets-7.5 and shorting the Jets-6.5.

6.3 Analysis of TradeSports Data

Assume, as Stern (1991) suggested, that the victory margin is normally distributed with standard deviation of 13.861. Then, given the price and the spread for that particular contract, it is possible to determine the mean of the hypothetical distribution. The mean is the μ that satisfies the following equation:

$\int_{-\infty}^{s} \frac{1}{13.861 \cdot \sqrt{2\Pi}} \cdot e^{-\frac{(x-\mu)^2}{2 \cdot 13.861^2}} \partial x = \frac{p}{100}$, where p is the price of the TradeSports contract on the underdog to win and s is the spread being given to the underdog on that contract.

This mean is the even money spread implied by the contract's current price. For example, a contract on the 49ers that receives 7.5 points and trades for 33 implies an even money spread of 13.6 points. A contract on the same game giving the 49ers 11.5 points and trading at 47 implies an even money spread of 12.6 points. Using Excel's Solver add-in and a self-constructed macro, I calculated the implied even money spread for all 1643 single game contracts based on the volume weighted average price of trades occurring up to and including the day before the game. If two contracts in the same family (i.e. for the same game) imply markedly different even money spreads, then, presumably, at least one of the contracts is mispriced. The implied even money spread is used as a proxy for the relative value of the two contracts. If contract A implies an even money spread giving 13.6 points to the 49ers, and contract B implies an even money spread giving 12.6 points to the 49ers, then betting on the 49ers via A is "cheaper" than via B. This is because the implied even money spread of each contract means a bettor who takes the 49ers receives more "implied" points under A than B.

The trading strategy determines the two contracts in a single family that differ the most in their implied spreads. If this difference exceeds a specified threshold, the hypothetical portfolio buys the contract that gives away (receives) fewer (more) points in the implied spread and sells that which gives away (receives) more (less) points in the implied spread. The results of this strategy applied to the dataset using four different thresholds are presented in Table 4.

	> 0 pts.	> 1 pt.	> 2 pts.	> 3 pts.
Games that meet the threshold	587	353	167	78
Average difference in max and min implied spread	1.62	2.35	3.31	4.22
Average return, before fees	2.82%	3.41%	7.66%	1.97%
Std. Dev. of returns	46.9%	53.6%	61.3%	63.2%
t-statistic (assuming zero mean)	1.46	1.20	1.62	0.28
Average return, after fees	0.99%	1.46%	5.55%	-0.00%

Table 4.

While suggestive of excess returns, the results are not statistically significant. Practically, this strategy also involves trading two separate contracts – making commissions a very real barrier. One must also remember that this is a joint test of Stern's (1991) normal distribution approximation and irrational behavior on the part of traders. If Stern's normal distribution is exact, then any difference in the implied spread is irrational behavior. However, since it is unlikely that the normal curve approximation perfectly duplicates reality, the strategy is really a test of whether Stern's approximation or trader perceptions are closer to the truth. While not conclusive, it appears that large deviations from Stern's normal curve approximation are usually not warranted. When these substantial differences in implied spread exist, a profitable trading opportunity for rational traders may exist.

7. Difficulties and Future Work

7.1 Problems During the Research

The first and most difficult problem in any study of this nature is data mining. It is always possible to devise a trading strategy that has generated historical excess returns. Without identifying reasons to support a cause and effect relationship, these discoveries are meaningless and can border on the ridiculous.[19] As Vergin (2001) writes, "unless there is some logical and reasonable aspect of human behavior explaining the patterns, the results should be viewed with skepticism." The sample size for this paper was such that performing out of sample tests was not a useful strategy. To guard against spurious results, however, I followed Vergin's example and reported the results of all tests that I conducted. Furthermore, the mechanics of each test were formulated before examining any of the data.

Anecdotal evidence indicates that bettors are most irrational during intra-game trading. One of TradeSports' selling points – both for gamblers and potential researchers – is that it permits such trading. Relatively less research has been conducted on this betting arena because it is a recent development that has accompanied the proliferation of online betting exchanges. I had hoped to explore this fertile ground, but could not devise a method for aligning the timestamps given for each trade with those recorded for events within NFL games themselves. Whereas the trading times are recorded in a standard format, the NFL generally does not provide the actual time something occurred; instead, it records the *game* time, e.g. 7:38 left in the second quarter. By accepting some loss of precision and the pain of manually identifying timestamps for each play, Hakes, Sauer, and Waller (2005) manage to overcome some of these difficulties in examining intra-game betting on baseball games.[20] A more scaleable solution for the NFL might be to write a program to scrape data from one of the live "Game Cast" feeds available online. With this information in hand, a researcher might be able to draw conclusions about price movements and their

[19] Until President George W. Bush defeated Senator John Kerry in 2004, people – some seriously, most not – regarded the outcome of the Washington Redskins final home game before the presidential election as a predictor of the coming vote. Since 1933, when the Boston Braves were renamed the Redskins, the incumbent party carried the election if and only if the Redskins had won their most recent home game (USA Today 2004).

[20] Their paper is incomplete and the authors requested that it not be cited without their permission. Attempts to contact the corresponding author failed, but it is my hope that this footnote will appropriately inform readers of the paper's status.

causes. Perhaps market participants are too quick to adjust their priors because of the salience of the current game score. If only because people have less time to make informed decisions, betting might be expected to be less rational during games than beforehand.

The last major difficulty to overcome is the temptation to immediately draw conclusions about world financial markets from research conducted on gambling exchanges. The general strategy of this paper has been to investigate documented biases in financial markets within the context of an NFL event futures markets. While the similarities are striking, the leap from one to the other should not be made casually. Tetlock's (2003) research uncovers important differences between financial and sports-related contracts on TradeSports. After separating all the contracts into the three categories of financial, sports-related, and other, he finds evidence of inefficiencies in sports-related contracts, but determines that these do not generalize to the financial contracts listed on TradeSports.

The motivation for trading sports event futures might be very different from that of financial trading. While it is plausible that die-hard fans want to hedge the risk of watching their favorite team suffer defeat, that risk does not seem as realistic as that of the manufacturer who buys oil futures to hedge against a rise in oil prices. In fact, it is likely that sports fans enjoy betting for non-monetary reasons, such as facilitating social interaction or providing increased interest in watching a game. The far larger size of financial markets is another potential reason for fundamental differences between them and exchanges like TradeSports. Lastly, professional traders account for a smaller portion of the trading volume on most sportsbooks than they do on financial exchanges (Tetlock 2003). Though Tetlock believes that many TradeSports participants are employed in more conventional trading positions as their day jobs, it is still the case that almost all betting is done by individuals trading for their own account, rather than institutions. As Tetlock concludes, despite trader overlap in sports and financial contracts, traders in sports-related contracts possess motivations other than pure profit or have irrational expectations.

7.2 Future Research Opportunities

Rather than provide a laundry list of areas for future study, I will highlight the more interesting possibilities discovered during the research. One natural extension is to conduct similar tests in other sports and college football. This would improve the sample size and provide evidence that the observed anomalies are due to some fundamental human trading behavior, not just NFL gambling.

Implication ignorance provides an especially rich set of future study paths. The tournament structure of NCAA “March Madness” produces a number of relationships between contracts that must hold in an efficient market. Future researchers might study how the price of a contract for Duke to win the national championship moves with the price of a contract for Duke to reach the Final Four. Playoffs in the National Basketball Association, Major League Baseball, National Hockey League, and NFL provide similar opportunities. Even if research is restricted to the NFL, much work remains to be done. Index contracts on the number of wins that a team will have for the season are intimately related to over-under contracts based on whether a team wins more or less than a specified number of games. A more complicated analysis might attempt to determine the relationship between money line trading on individual games and the aforementioned seasonal wins contracts.

One interesting financial anomaly that this paper did not explore is the existence of excess volatility in equity returns.[21] In other words, deviations in returns are more than can be explained by changes in dividend growth (Barberis and Thaler 2003). In NFL trading, relatively little relevant information is made public during the interim between games. Media “gurus” and – perhaps more importantly – “armchair quarterbacks” of the average public produce a staggering amount of analyses and predictions for these games. While salient, these additional analyses are usually not new information. Adjusting for injury news would be difficult, but it is my belief that it would be hard to justify the volatility in NFL contracts on the basis of changes in information concerning the fundamental quality of

[21] Robert Shiller of Yale University has studied excess volatility extensively. The interested reader is referred to “Stock prices, earnings and expected dividends,” which Shiller coauthored with John Campbell in the 43rd volume of the *Journal of Finance* (1988). Earlier work by Shiller includes “Do stock prices move too much to be justified by subsequent changes in dividends?” in the *American Economic Review*, Vol. 71 (1981).

either team. If measures of the volatility in these contracts were high, it would indicate that excess volatility also exists in the NFL futures trading environment and is not an isolated phenomenon of financial markets.

Lastly, examining availability biases in sports betting is particularly enticing. When teams play each other more than once in a season, their early meetings provide very salient, relevant memories for fans. Bettors might overweight these memories in judging the probability of one team winning the current game. Tversky and Kahneman (1974) report that recent and salient occurrences are more likely to be "available" in probabilistic computations, suggesting that a recent outcome could distort wagering on a particular game.

8. Conclusions

This paper attempts to use the relatively modern findings and methods of behavioral finance to investigate a longstanding pillar of financial theory, the efficient markets hypothesis, in the context of NFL prediction markets. Though I found no worthwhile evidence of overreaction or underreaction to winning streaks, other hypothesized anomalies were present. In accordance with past psychological research, bettors consistently overpaid for contracts based on conjunctive events. I also found marginal evidence of inefficient pricing of contracts offering different spreads on the same game.

Whether or not these conclusions generalize to financial markets, the increasing importance of prediction markets is enough to make them valuable.[22] As section 5.4 illustrated, overestimation of conjunctive probabilities could distort a number of important economic choices in people's lives. While I could make no definitive conclusion about mispricings with respect to the distribution of victory margins, such a potential bias might point to poor calibration in estimating percentiles, other than the median, of an unknown distribution. That is, typical spread bets only test the bettor's ability to judge the median value

[22] Mark Cuban, billionaire owner of the NBA's Dallas Mavericks, proposed a sports arbitrage hedge fund in his blog in 2004. Its legality may be at issue and finding enough volume to support a large fund will be problematic, but a number of experts (some cited in this paper) believe it is feasible (Bialik 2004). If Cuban's proposal is successful, the study of inefficiencies in gambling exchanges could even have substantial monetary worth.

associated with future states of the world; people may not be as adept at determining the sixty-fifth percentile because that type of estimate is less relevant to every day life. Even the “non-results” related to overreaction and underreaction are worthwhile, as they highlight the absence of an accepted behavioral finance theory that could simultaneously test for both effects without making an arbitrary decision of what time horizon to consider.

In addition to being a potentially worthwhile tool for hedging risk and generating predictions, information markets provide a valuable research resource. Applying the findings of behavioral finance to data gathered in event futures exchanges could add support to empirical discoveries in financial markets. Though all of the inefficiencies discovered in prediction markets may not generalize to financial markets, their study is still capable of yielding important insights into market behavior and irrational biases in human estimations. While this paper succeeded in demonstrating the manifestation of one such bias in trading activity (overestimation of conjunctive probabilities), there are many remaining opportunities for further research of this vein. Prediction markets like TradeSports are a perfect place from which to draw the data for this work.

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Appendix A

This glossary and the definitions given are adapted from Ates (2000), who provides an extended version.

Bookie/bookmaker – Person (or firm) that accepts and pays off bets.

Cover – Winning as defined by the point spread. A 7.5 point underdog that loses by 7 still covers, whereas a 7.5 favorite that wins by 7 does not cover.

Double – A parlay bet requiring the bettor to correctly select both winners of two different games.

Even money – A bet with even odds, i.e. each bettor stands to lose or gain the same amount (less the vigorish). On a 0-100 scale (see Appendix B), this bet would sell at 50.

Favorite – Team that, according to the odds in the betting market, is the stronger (or strongest) in a given matchup.

Handle – Total amount of money in wagers accepted by a sportsbook.

Intra-game trading – Betting that occurs while the game is in progress.

Line – The point spread or odds on a game or event.

Long shot – Bet that has a low chance of winning.

Middle – Situation in which one bets both sides on a game at two different spreads. If the margin of victory falls in between the two spreads, both bets win. Otherwise, only the vigorish is lost.

Money line – The odds on a team winning a game outright, regardless of the point spread. This is equivalent to a game with a zero point spread. This is also a method of specifying odds (see Appendix B).

Over/under, or **Totals** – Bet on whether a score or result will go over or under a given number.

Parlay – A bet in which two or more events must happen in order to win. This is a bet on a conjunctive event.

Point spread, or just **Spread** – The number of points added to or subtracted from a team's actual score before determining the game's winner for betting purposes.

Sportsbook – The part of a casino that accepts and pays off bets on athletic contests. Also a sports betting firm, or bookie.

Underdog – Team that, according to the odds in the betting market, is the weaker (or weakest) in a given matchup.

Treble – A parlay bet requiring the bettor to correctly select all three winners of three different games.

Vigorish – The commission charged by the bookmaker.

Appendix B

Odds, the effective prices on contracts, are specified in a number of different formats. The most common are digital, money line, fractional, and 0 to 100 (the form used by TradeSports and in this paper). The 0 to 100 form is useful because it facilitates perception of the bet as a futures contract. Furthermore, the price gives the market's estimate of the probability of the wager paying off (in all-or-nothing contracts). If the event trades at x and it occurs in y% of the future states of the world, then a risk neutral investor would buy the event's contract if $x<y$ and sell it if $x>y$.

Digital odds specify the proportion of your money that you will win if the bet is successful. If the money line is proceeded by a + it means the team is the underdog and a winning bet of $100 will return that amount of dollars. A - prefix means the team is the favorite and one must bet that much money in order to win $100. Fractional odds of the form x/y indicate the amount of profit (x) possible for the amount staked (y). The table on the following page, from tradesports.com, provides conversions for these different formats.

Conversion Table

0 to 100	*Digital*	*Money Line*	*Fractional*	*0 to 100*	*Digital*	*Money Line*	*Fractional*
1	100	+9900	99/1	50	2.00	EVEN	1/1
2	50	+4900	49/1	51	1.96	-104	20/21
3	33	+3230	33/1	52	1.92	-108	10/11
4	25	+2400	24/1	53	1.89	-113	10/11
5	20	+1900	19/1	54	1.85	-117	6/7
6	16.7	+1570	16/1	55	1.82	-122	5/6
7	14.3	+1330	13/1	56	1.78	-127	4/5
8	12.5	+1150	11/1	57	1.75	-133	3/4
9	11.1	+1010	10/1	58	1.72	-138	5/7
10	10.0	+900	9/1	59	1.70	-144	20/29
11	9.1	+810	8/1	60	1.66	-150	2/3
12	8.3	+730	15/2	61	1.63	-160	5/8
13	7.7	+670	13/2	62	1.61	-160	8/13
14	7.1	+610	6/1	63	1.59	-170	10/17
15	6.7	+570	11/2	64	1.56	-180	5/9
16	6.2	+530	16/3	65	1.54	-190	20/37
17	5.9	+490	5/1	66	1.51	-190	1/2
18	5.5	+460	9/2	67	1.49	-200	1/2
19	5.2	+430	13/3	68	1.47	-210	8/17
20	5.0	+400	4/1	69	1.45	-220	5/11
21	4.7	+380	15/4	70	1.43	-230	3/7
22	4.5	+350	7/2	71	1.41	-240	2/5
23	4.3	+330	10/3	72	1.39	-260	5/13
24	4.2	+320	16/5	73	1.37	-270	4/11
25	4.0	+300	3/1	74	1.35	-280	5/14
26	3.8	+280	14/5	75	1.33	-300	1/3
27	3.7	+270	11/4	76	1.31	-320	5/16
28	3.6	+260	13/5	77	1.30	-330	3/10
29	3.4	+240	5/2	78	1.28	-350	2/7
30	3.3	+230	7/3	79	1.26	-380	4/15
31	3.2	+220	11/5	80	1.25	-400	¼
32	3.1	+210	17/8	81	1.23	-430	3/13
33	3.0	+200	2/1	82	1.22	-460	2/9
34	2.9	+190	2/1	83	1.20	-490	1/5
35	2.85	+190	37/20	84	1.19	-530	3/16
36	2.8	+180	9/5	85	1.18	-570	2/11
37	2.7	+170	17/10	86	1.16	-610	1/6
38	2.63	+160	13/8	87	1.15	-670	2/13
39	2.56	+160	8/5	88	1.14	-730	2/15
40	2.50	+150	3/2	89	1.12	-810	1/8
41	2.43	+144	29/20	90	1.11	-900	1/9
42	2.38	+138	7/5	91	1.10	-1010	1/10
43	2.32	+133	4/3	92	1.09	-1150	1/11
44	2.27	+127	5/4	93	1.07	-1330	1/13
45	2.22	+122	6/5	94	1.06	-1570	1/16
46	2.17	+117	7/6	95	1.05	-1900	1/19
47	2.13	+113	11/10	96	1.04	-2400	1/24
48	2.08	+108	11/10	97	1.03	-3230	1/32
49	2.04	+104	21/20	98	1.02	-4900	1/49
50	2.00	EVEN	1/1	99	1.01	-9900	1/99