Efficiency and the Disposition Effect in NFL Prediction Markets

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January 2012

Abstract: This paper examines $20.7 million of betting contracts on NFL games at Tradesports.com, an online prediction market. We find mispricing consistent with the disposition effect, where investors are more likely to close out profitable positions than losing positions. Prices are too low when teams are ahead and too high when teams are behind. Tradesports.com offers an ideal place to examine the impact and underlying cause of the disposition effect as market participants have a common stable reference price, the price before kick-off. These results do not appear driven by a lack of participation in the market, as games with more money gambled actually exhibit more mispricing. Further, team loyalty does not appear to impact trading behavior. Finding the disposition effect in a negative expected return gambling market calls into question the standard explanations for the disposition effect, a belief in mean reversion or prospect theory. It is consistent with cognitive dissonance, and models with time-inconsistent behavior. Implications for companies implementing prediction markets are discussed.

Keywords: Disposition Effect, Prediction Markets, Behavioral Finance, Behavioral Decision Theory

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1. Introduction

Online gambling is a large global market that has expanded from an estimated $14 billion in 2007 to $21 billion in 2011 and is forecast to grow to more than $30 billion in 2012 (ECB report (2009) and KPMG report (2010)). We study gambling at the consumer market Tradesports.com, a gambling website structured as a prediction market. Prediction markets are a specific sector of online gambling that is structured similarly to a typical financial market (such as the New York Stock Exchange). In this market, the price of a contract indicates the market's estimate of the probability a given event will occur. Contracts are bought and sold by traders (people gambling in the market) with no intermediary, at prices determined by the best bid or ask price offered. Thus, this market structure yields a clear benchmark of efficiency, the probability of an outcome, against which the price impact of behavioral biases of traders can be examined.

In addition to reflecting behavior in an expanding consumer market, Tradesports is an interesting middle ground with much higher stakes than the lab, and much cleaner benchmarks than a typical financial market. We study contracts traded during football games lasting only a few hours, which allows us to examine price efficiency without the need to model complexities important in traditional financial markets, such as how macroeconomic risks are priced. Thus this market does not suffer from the joint hypothesis problem, where one cannot test whether a given market is efficient without also assuming a model of security returns (Fama (1970)), which plagues the study of traditional financial markets. Further, studying this market instead of using a laboratory allows us to examine voluntary participants who wager more than $20 million of their own money.

In this paper we examine 525 similarly structured contracts on NFL football games from Tradesports.com. The contracts pay out $10 if the team in question wins the game and $0 otherwise. Because the outcome of the event is unrelated to economic risks that the investors care about, the price of this security must equal ten times the probability of the team winning (Wolfers and Zitzewitz (2006)). For example, suppose the Bears are playing the Giants and there is a contract for the Bears to win. If the contract is trading at \$6, the market's implied estimate of the probability of the Bears beating the Giants at that time is 60%.

We study the existence of the disposition effect , the tendency of investors to close out trading positions when they are at a profit, and hold on to them when they are at a loss (Shefrin and Statman (1985)). The existence of the disposition effect has been documented extensively, in individual investors (Odean (1998), Feng and Seasholes (2005)), mutual fund managers (Wermers (2003), Frazzini (2006)), E-trading environments (Lee, Park, Lee and Wyers (2008)) and futures traders (Locke and Mann (2000)). While there is strong evidence for the disposition effect as a description of traders' behavior, two important questions remain - first, whether the disposition effect impacts prices, and second what the underlying cause of it is. We provide evidence on both of these questions.

We find significant price inefficiencies that are consistent with the disposition effect. When we compare observed prices with the ex-post probability of the team winning, there are significant deviations in the pattern of an 'S-shape'. At prices greater than approximately \$6 the contract is underpriced relative to the ex-post probability of winning; i.e., for trades during game time, trades between \$6.50 and \$7.50 won roughly 80-90% of the time. Meanwhile at prices less than approximately \$4 the contract is overpriced; i.e., for trades during game time, trades between \$2.50 and \$3.50 won roughly 10-20% of the time (Figure 2).

Tradesports allows us to examine the price impact of the disposition effect much more cleanly than other papers have been able to, because the benchmark of efficiency is so clear. If prices deviate from ex-post probabilities of winning, this is evidence of mispricing. By contrast, existing papers that show that the disposition effect impacts prices in equity markets (e.g. Grinblatt and Han (2005), Frazzini (2006), Scherbina and Jin (2008), Goetzmann and Massa (2008), Kaustia (2004)) require stronger assumptions about the process driving equilibrium expected returns, as the joint hypothesis problem is a larger concern (Fama (1970)).

Our results also have implications for understanding the causes of the disposition effect. The most frequently cited explanation of the effect is based on prospect theory (Kahneman and Tversky (1979), Barberis and Xiong (2009)). Odean (1998) argues that the disposition effect could be caused by investors having an unjustified belief in mean-reversion of stock performance. Finally, Zuchel (2001) gives an explanation based on cognitive dissonance, whereby traders are reluctant to realize losses because this means admitting the mistake of their earlier investment.

As we discuss in section 2.1, the nature of this market helps distinguish between these explanations. In particular, Tradesports is a negative expected return gambling market, whereas most evidence on the disposition effect comes from positive expected return assets. This suggests that a parsimonious model of the disposition effect needs to account for its existence in situations where investor behavior is locally risk-seeking. Standard implementations of prospect theory predict that investors are unlikely to enter a market without positive expected returns, a point emphasized by Barberis and Xiong (2009). Further, if the disposition effect in stock markets is driven by belief in mean reversion, it is unclear why this implies a belief about mean reversion of outcomes in a football game, where one team must win at the final whistle. The finding of a strong disposition effect in this market supports models such as cognitive dissonance or time inconsistent prospect theory investors (Barberis (2010)).

The disposition effect is unusually strong in this market because many investors share a common reference point for gains and losses. Roughly a third of volume occurs during the low-news period before kickoff, as investors establish either a long or short position, usually at a price of around \$5-\$7. If a positive news event pushes prices above their pre-game level, the disposition effect predicts that those who initially bought the contract will be eager to sell (to realize their gain), while those who initially sold short will be reluctant to buy (to realize their loss). This creates net selling pressure which pushes prices below their correct level. Corresponding effects for negative shocks make prices too high when they are below the pre-game level, hence the ‘S-shape’.

When prices are above the pre-game level, a positive shock will thus create negative short-term returns (from the initial selling pressure) and positive long-term returns (when the mispricing eventually corrects). By contrast, consider the case of a positive news event when the price is *below* the pre-game level. There is less reason to expect disposition-related selling, because those who initially bought the contract still face a loss. Similar predictions are made for negative price changes.

To test this explanation specifically, we examine reaction to news events during the game, similar to Frazzini (2006). Consistent with the disposition effect, we find that if the price is above the pre-game price, a positive shock to price results in significant short term reversals – there are negative price changes between -$0.09 and -$0.28 from 4 to 16 minutes after the shock. This negative short-term price pressure is reversed over the remainder of the game. Specifically, positive shocks above the pre-game price show significantly positive price changes of $0.33 from 16 minutes after the shock until the end of the game. Corresponding patterns also exist for negative shocks to price.

Conversely, if the same positive shock occurs when the price is below the pre-game price, the returns pattern is very different. We observe no statistically significant short-term reversal, and rather than long term momentum we observe long-term reversal. These trends are strong evidence for the disposition effect.

We also consider a number of alternative theories that may explain our empirical results - a time-based drift in prices (Gil and Levitt (2007), Croxson and Reade (2008)), the favorite-longshot bias in horse betting (Vaughan Williams and Paton (1997), Snowberg and Wolfers (2007)), investor preferences for certain types of bets (Rosett (1965), and investors making mistakes in estimating probabilities (Schmidt and Berri (2001), Snowberg and Wolfers (2007))

We find that the disposition effect is the only theory which explains all of our empirical findings. Many of these alternatives predict that price movements are related to price *levels*, (which measure the probability of the gamble, the payoff distribution, investor beliefs etc.). The disposition effect is unique in predicting that price movements depend not on price levels per se, but the interaction of price and pre-game price, as this measures the gains and losses of investors. To test this, we examine price changes after news events while controlling for the time in the game, and the price level, and see if the price/pre-game price effect survives. Adding time controls leaves both the short term and long term returns patterns virtually unchanged. Adding price controls makes the patterns in short term returns significantly stronger, while for the longer term returns it reduces the significance of the results, although they are still directionally correct.

We also examine whether the S-shape of prices over the course of the game is driven by a lack of market participation (insufficient market liquidity as in Tetlock (2008)) or team loyalty (non-financial reasons for trade as in Tetlock (2004)). We measure liquidity using high-volume Monday Night games, and the total population of the two cities playing. Team loyalty is examined using proxies for levels of support for the teams playing, which may affect prices if investors bet mainly to support a favored team. We use variables for whether teams were in the top 10 of NFL merchandise sales, and the ratio of the two city populations. We find that these commonly-cited explanations for mispricing in prediction markets do not explain pricing errors. Variables associated with higher levels of trader participation on average actually *increase* the mispricing, while measures of team-support do not explain mispricing at all.

We also show that the mispricing is economically significant. Simple price-based trading strategies, trading for only 10 minutes per game, generate Sharpe Ratios (net of maximum expenses) of 1.064 and profits of $16,400 from roughly 20% of the sample games. Broader strategies create Sharpe Ratios of 0.284 and profits of $65,300 (based on a maximum total investment of $533,500), from roughly 60% of games.

The results in this paper extend the literature on prediction markets. The perceived accuracy of prediction markets, for example in predicting presidential elections, along with their relatively low cost has caused a number of companies to implement internal prediction markets to aggregate the information from employees (Cowgill, Wolfers and Zitzewitz (2009)). Such markets are seen as efficient ways of answering questions such as will product X be successful, or how many users will project Y have? A more thorough understanding of prediction markets and their predictable deviations from the efficient, true probability, will allow companies to better utilize them.

Wolfers and Zitzewitz (2004) summarizes the main papers in this field. A number of papers focus on price efficiency, in terms of arbitrage opportunities (Oliven and Reitz (2004)) and price reactions to news (Leigh, Wolfers and Zitzewitz (2003), Berg and Reitz (2003), Gil and Levitt (2007)). Most similar to the current paper is Tetlock (2004), who examines mispricing in sporting and financial contracts on Tradesports. To our knowledge, we are the first paper to directly test whether team support impacts prices in these markets, and we find that they do not.

The paper is organized as follows: Section 2 describes explanations of the disposition effect, and the requirements for price efficiency. Section 3 briefly describes the data and the Tradesports market structure. Section 4 presents the main results, Section 5 examines alternative explanations, Section 6 examines the profitability of trading strategies, and Section 7 concludes

2. The Disposition Effect and Market Efficiency

2.1 The Disposition Effect

The disposition effect, coined by Shefrin and Statman (1985), refers to the tendency of investors to sell winning stocks and hold losing stocks. In a stock market setting, it is at odds with optimal tax loss selling, and produces lower returns due to the momentum effect (Jegadeesh and Titman (1993)). More generally, the disposition effect represents uninformed trading based on personal gains and losses, not private information. This poses a challenge to market efficiency if it impacts market prices.

While evidence for the existence of the disposition effect is strong, the underlying cause for it remains unclear. Explanations based on standard economic models of rationality have found limited empirical support. Private information seems unlikely, as Odean (1998) shows the winning stocks sold early have higher returns over the subsequent year than losing stocks that are retained. Another possibility is portfolio rebalancing, where traders sell winning stocks to avoid being overweighted in their portfolio. Odean (1998) also casts doubt on this, as traders also exhibit the disposition effect when considering sales of the individual's entire holding of a stock.

More common explanations have focused on behavioral models. Initial explanations focused on prospect theory and mental accounting (Kahneman and Tversky (1979) and Thaler (1985)). Under this theory, an investor at a loss becomes risk-seeking in order to avoid the loss now, whereas the same investor at a gain becomes risk-averse in order to preserve the gain (Weber and Camerer (1998), Grinblatt and Han (2005), Frazzini (2006)). The other leading explanation (from Odean (1998)) is based on an unjustified belief in mean-reversion of stock prices, so disposition-related trading is due to mistaken estimates of future price movements.

Zuchel (2001) argues that cognitive dissonance may cause the effect (Festinger 1957)). Cognitive dissonance arises when individuals attempt to hold two contradictory ideas simultaneously, particularly those associated with the individual's self-concept. Investors likely have beliefs such as 'I am a clever trader' or 'my investing strategy will generate superior returns'. Kaustia (2010) puts forward a similar argument based on self-justification and regret avoidance. In both cases, when faced with a paper loss, investors may be reluctant to realize the loss as this means admitting to the mistake of investing in the first place.

Recently, Barberis and Xiong (2009) and Hens and Vlcek (2005) have questioned whether prospect theory preferences alone can produce a disposition effect. Barberis and Xiong (2009) argue that the disposition effect in stock markets is more consistent with prospect theory preferences based on *realized* losses rather than annual (paper) losses. These preferences are able to produce disposition effect behavior; however their model emphasizes the importance of including the investor's decision to buy the security in the first place. As Barberis and Xiong (2009) put it, "[S]ince the investor is loss averse, the expected return on the stock needs to be reasonably high for him to buy it at all at time 0."

In the current market, the expected returns for an uninformed investor are *negative*. This implies that most prospect theory investors who view this as a one-off gamble will be unlikely to enter, as will the investors in Barberis and Xiong (2009). Hence our results are problematic for basic prospect theory explanations of the disposition effect, as we show its existence in a market that prospect theory traders are unlikely to enter. This complements the findings in Kaustia (2010), where the propensity to sell is impacted by the existence of gains and losses, but roughly constant as gains and losses increase (again, inconsistent with prospect theory).

Our results are however consistent with models of time-inconsistent behavior, such as in Barberis (2010)'s model of casino gambling. In this setup, investors have prospect theory preferences, but are willing to enter a zero or negative expected return gamble because they intend to leave once they start losing, thus skewing their payoff distribution to be more positive. However, because of time-inconsistency, they instead continue gambling when they are losing, and leave the casino once they are winning, similar to a disposition effect.

The explanation of the disposition effect in Tradesports seems unlikely to be driven by other factors specific to this market. Support for particular teams does not appear to drive our results, as variables related to team support have no explanatory power over prices. If the disposition effect is driven by a mistaken belief in mean reversion like Odean (1998), there is little reason to predict it in this setting. Grinblatt and Keloharju (2001) show that the disposition effect in equity markets persists even after controlling for past returns, and hence does not appear to be driven by mean reversion. Even if it were, it is unclear why a mistaken belief in the mean reversion of stock prices implies a belief about mean reversion of outcomes in a football game. To see the disposition effect in this setting would require that investors have a pervasive belief in mean reversion across a wide range of securities and underlying events, an assumption that does not seem to have much empirical support. This is particularly relevant since one team must eventually win at the final whistle, so prices cannot mean-revert forever.

A cognitive dissonance explanation is also consistent with the disposition effect in this setting. It merely requires that Tradesports investors have some self-esteem tied up in the concept that they are clever gamblers able to predict positive returns, which is consistent with Barber and Odean (2001)'s findings that traders are overconfident, Strahilevitz, Odean and Barber (2011)'s finding that investors are reluctant to repurchase stocks sold at a loss that subsequently rise in price, and Summers and Duxbury (2007)'s finding that in an experimental market the disposition effect disappears when participants are not responsible for choosing their own portfolio. It is also consistent with the literature demonstrating the impact of emotion on choice under uncertainty (for example Bell (1982), Fong, and Wyer (2003), Mellers, Schwartz, and Ritov (1999)).

2.2 Prediction Markets and Price Efficiency

In this paper, we rely on the argument that for a binary outcome contract to be correctly priced, the price of a $1 contract must equal the probability of the event occurring. This requires minimal assumptions about investor preferences. Since the underlying event is a football game means that it is too brief for intertemporal substitution and discount rates to be significant factors in price determination. Also, for most investors the outcome of the game does not vary in a meaningful way with their consumption or wealth. Hence the price must equal the true probability of the event occurring. Thus if prices in the market are efficient in the sense argued by Fama (1970), we obtain three central predictions of rational asset pricing in this context:

1. At any point in time, the price should equal the true probability of the event occurring.
2. Other than the price, no information available at the time should have significant explanatory power over the probability of a team winning.
3. No trading strategy should be able to generate positive expected returns.

3. Data

The data in this paper comes from the online exchange Tradesports.com, an online exchange that operated from 2000 until closing in 2008. Tradesports allowed trades 23 hours a day, allowed short sales, and was a limit-order driven market, meaning that traders submitted buy and sell orders that executed against other traders. While it had no centralized bookmaker or specialist/market-maker setting prices, Gil and Levitt (2007) document that it had several large traders that in effect served as market-makers, although these did not appear to affect price. The data we have includes each time-stamped transaction price for each individual contract for professional football games during the 2003-04, 2004-05 and 2005-06 seasons. We use 'money-line' contracts where the payoff is based on a favorite winning or losing.

Before the initiation of trading, Tradesports chose whether the contract was for Team A to win (Team A is the Tradesports pick) or Team B to win (Team B is the Tradesports pick). Tradesports picks are based on the favored team from the Vegas betting odds when the contract starts trading, usually a few days before the game. If a buyer and seller agree on a price p and the Tradesports pick wins, then at expiry the contract purchaser receives \$10 and the seller receives \$0, giving a total payoff to the buyer of \$(10-p) and a total payoff to the seller of \$(p-10). If the Tradesports pick loses then at expiry the contract purchaser receives \$0 and the seller receives \$0, giving a total payoff of -\$$p$ to the buyer and \$$p$ to the seller. Positions may also be closed out prior to the end of the game by taking an opposing position.

These contracts can be bought (a long position created) or sold (a short position created). Transaction costs are low. There are no fees for execution of limit order, where traders specify a maximum purchase price or minimum sale price that they are willing to transact at. Traders pay \$0.04 per \$10 contract for executing a market order (when they issue an order to buy or sell at the best possible price, transacting against an existing limit order), and a further fee of \$0.04 for whoever is paid out at the termination of the contract.

We choose to study football contracts as they were the most actively traded contracts of a recurring nature on Tradesports. We have data on 525 games, comprising 151,853 separate trades, 2,068,807 total contracts traded and \$20.7 million in dollar volume. Summary statistics are presented in Table I. We obtain city MSA populations from the 2000 census, and data from http://www.nfl.com about game length, quarter-by-quarter scores[1], and team merchandise sales.

4. Main Results

4.1 Tests of Mispricing

First, we test proposition 1 in section 2.2, namely *that the contract price at any time should represent an unbiased estimate of the true probability of the event occurring.* We test this using the ex-post proportion of contracts that win at each contract price. For each trade we generate a dummy variable, Win_i, that equals 1 if the Tradesports pick wins the game and 0 if the Tradesports pick loses. We then take the volume-weighted average value of *Win* over all trades at a particular price level to give the ex-post proportion of contracts that win for a given price. Figure 1 plots this proportion versus price for in-game trading of all of the games in the sample.

Figure 1 shows one of the consistent trends of contract prices in this market – an 'S-Shape', where the probability of winning is higher than expected for prices above about \$6 (contracts are undervalued), and the probability of winning is less than expected for prices below about \$4 (contracts are overvalued). It also shows the result of fitting a curved functional form to the data (with Price/10). Specifically, we use non-linear least squares to fit a model of the form:

$$P(win) = \frac{\delta Price^{\gamma}}{\delta Price^{\gamma} + (1 - Price)^{\gamma}}$$

When δ=1 and γ=1 the function is linear. γ controls the curvature, and δ controls the elevation (roughly speaking, where the curve intersects the 45° line). We choose this particular functional form (used in Tversky and Fox (1995)) because it allows for different levels of curvature and elevation, while allowing formal test of deviations of the parameter estimates from their values under linearity.

[1] We obtain from http://www.nfl.com/ calendar times for kickoff and the end of the game, but point scores are given in terms of game time, not calendar time. To estimate quarter-, half- and three-quarter-time, we take the total playing time, subtract 15 minutes for the half time break, and divide the remaining period into quarters. Prices listed as 'quarter time' are the volume-weighted average price during the 10-minute period surrounding the designated period

When we fit this function to the data, we find that the estimated γ is 1.37, representing the S-shape in the fitted values, and the estimated δ is 0.849, indicating that the S-shape intercepts the 45° line to the right of \$5, at a value of about \$6.

Using a smaller sample of the quarter-time, half-time and three quarter-time prices per game (giving a total of 1023 observations), we can thus test whether the non-linearity is statistically significant. We find that the estimated values are γ=1.32 (with a t-statistic of 2.95 for the null that γ=1) and δ=0.96 (with a t-statistic of –0.56 for the null that δ=1). For in-game trading, the relationship between the price and the probability of winning is significantly non-linear, violating market efficiency. Kickoff prices, on the other hand, are a function of the betting odds in Vegas (the main US sports betting market) on a team winning. They demonstrate a different pricing pattern where we cannot reject the assumption of linearity: γ =0.95 (t=0.2) and δ=1.248 (t=1.1). This is consistent with the disposition effect, because the stability of prices before the game means that few investors face meaningful gains or losses, upon which the disposition effect relies. The simplest interpretation of this S-Shape is that the contracts are overvalued for prices below \$4, and undervalued for prices above \$6 (though not for prices above \$9.50[2]). Equivalently, the market views games as more uncertain than they actually are. When the Tradesports pick gets ahead, the market views the non-pick team as having a greater likelihood of coming back to win, and thus underprices the Tradesports pick, and vice versa.

4.2 Reactions to News Events

To further examine whether the disposition effect is driving the S-shape, we examine the returns available after event-driven price changes (i.e., price changes which may occur due to events like touchdowns, intercepts, etc). 41.3% of total contracts are traded before kickoff, and prices are

[2] The mispricing around \$9.50 is possibly due to the unusual incentives created by the Tradesports fee structure at these prices - traders have an incentive to close out positions in order to avoid the 4c fee for holding the contract at the end of the game.

very stable – the standard deviation of pre-game prices[3] is 12.1¢, versus $1.524 for in-game prices. Because the security is in zero net supply, at the start of the game an equal number of contracts were bought and sold short at the pre-game price. If the disposition effect after positive news events causes an excess supply of contracts – eager sellers and reluctant buyers – then the price must fall and we should observe that after positive news short-term returns are negative, while longer term returns are positive as the price is eventually corrected as the game approaches its conclusion. This creates a pattern of initial overreaction and subsequent underreaction that is difficult to reconcile with other stories.

We predict that when the price is above the pre-game price and there is favorable news pushing up the price, there will be an excess disposition-related supply at the current price, causing short-term negative returns due to selling pressure and prices being pushed below their fundamental value. This will be followed by positive long-term returns as prices return to their true equilibrium probability. On the other hand, if the same positive shock occurs when the price is below the pre-game price, then this reduces the gains to short traders and losses to long traders, and there is no reason to predict an increase in disposition-related trading. Similarly, a negative shock pushing down the price when the price is already below the pre-game price will produce an excess disposition-related buying pressure, resulting prices being pushed above their fundamental value. This will be followed by long-term negative returns as the price returns to its true equilibrium probability. Finally, a negative shock above the pre-game price similarly does not predict these disposition driven patterns.

In Table II, we test these predictions and find evidence supporting all of them. Table II examines price changes following shocks or large price changes. We calculate volume-weighted prices for each 3-minute period of the game. Price shocks are defined as a price change from the

[3] 'Pre-game price' refers to the volume weighted average price from the start of trading to one hour before kickoff.

previous period greater than 50¢, excluding certain defined cases.[4] We find that after the exclusions, 50¢ changes occur roughly four times per game. We split shocks into positive and negative price changes, and according to whether the price in the period before the shock was above or below the pre-game price.

Consider *t* to index the start of a three-minute period in which the price shock occurs. If the average price during period (*t*-3, *t*) is at least 50c different from the average price during period (*t*, *t*+3) then the event is presumed to occur sometime before t+3 (most likely between *t* and *t*+3, although it is possible it occurred slightly before *t*). We then skip a minute (to eliminate the effect of the bid-ask bounce) and examine the change in price between the average price in the period subsequent to the shock (*t*+4, *t*+7) and the average price two, three and four periods subsequent to the shock (for 3 minute periods starting at *t*+7, *t*+10 and *t*+13). We also examine price changes between those latter three periods and the end of game price (which must be either $0 or $10 depending on which team won).

Table II presents the results of these tests. Consistent with our predictions, positive shocks when the price is above the pre-game price and negative shocks when the price is below the pre-game price both demonstrate short term price reversals, and long-term price momentum. After a positive shock of 50¢ when the price is above the pre-game price, prices decrease by -$0.09, -$0.15 and -$0.28 in two, three and four periods after the shock, statistically significant at a 5% or 1% level. Positive shocks when the price is below the pre-game price exhibit no significant reversal. Similarly, negative shocks when the price is below the pre-game price exhibit significant subsequent reversal in the following three periods, of $0.08, $0.12 and $0.12 in two, three and four periods after the shock. Negative shocks when the price is above the pre-game price exhibit no significant reversal.

[4] In order to exclude price changes right at the end of games, and trades based on the fee-induced effects at very high and very low prices, we eliminate shocks that occur at prices less than $0.50 or more than $9.50, and those that occur less than 15 minutes before the end of the game.

Corresponding patterns of subsequent momentum are observed for price changes to the end of the game. Positive shocks above the pre-game price show significant positive price changes to the end of the game for prices in the (t+13, t+16) period (i.e., four periods after the shock), of \$0.33. For negative shocks below the pre-game price, price changes to from periods two, three and four to the end of the game are -\$0.30, -\$0.35 and -\$0.32 respectively, significant at a 5% level in 2 cases and 10% level in one. Positive shocks below the pre-game price actually show long-term reversals, rather than positive momentum.

These results strongly support the predictions that prices will exhibit initial reversals and subsequent momentum, depending on the price relative to the pre-game price. For negative shocks, the disposition-related buying appears to be largely confined to the second 3-minute period, as the total price change post-shock does not vary much after that. For positive shocks above the pre-game price, the subsequent selling seems to occur for a longer period. Periods with larger reversals also exhibit larger subsequent momentum, suggesting that the reversal is indeed pushing prices beyond efficient levels. The results in Table II indicate that investors reverse too much of their initial response to news, leading to an ultimate continuation in returns.

5. Potential Alternative Explanations of Results

5.1.1 Time-based drift in prices

One possible explanation for the results is a time-based drift in prices, with information such as scoring events being slow to be incorporated into price. (Gil and Levitt (2007), Croxson and Reade (2008)). A time-based drift could conceivably produce the S-shape, due to certain prices being more or less likely after different amounts of time have elapsed. We test this by examining whether time-based drift is affecting the reversals and momentum in Table II. If these patterns in price changes are simply a time-based drift, then there should be no difference between the categories of shock once the effects of game time are controlled for.

5.1.2 Favorite-Longshot Bias, Preferences over gambles, mistaken estimates of probability

These three explanations are related to each other, and make similar predictions. The favorite-longshot bias in horse betting is an empirical result where bets on horses with lower odds of winning have lower expected returns than horses with higher odds of winning. (Vaughan Williams and Paton (1997), Snowberg and Wolfers (2007)). The S-shape in prices resembles this pattern, with low-odds teams having lower expected returns than high odds teams. There are two broad classes of explanations for the favorite-longshot bias that are relevant here, as discussed in Snowberg and Wolfers (2007). The first is investors having preferences for certain types of bets, such as in prospect theory. Investors are more sensitive to losses than to gains. Investors pay a premium for longshots and their expected returns are lower, while requiring a discount to purchase favorites thereby pushing their expected returns higher. Second, investors may view games as more uncertain than they actually are. (Schmidt and Berri (2001), Smith et al (2006), Sobel and Raines (2003)). When a team gets ahead, investors may think it has a lower probability of winning than it actually does, and returns are higher than the price indicates.)

These three explanations make similar predictions. They would most clearly predict the S-shape, which resembles the prospect theory value function. It may also predict longer term momentum after large price movements, if price *shocks* are proxying for price *levels*. Specifically, positive shocks are more likely to result in prices above $5, where subsequent returns will be high, whereas negative returns are more likely to result in prices below $5, where returns will be low. These explanations do not seem to predict both short term reversals and long term momentum, however – returns for a given price level may be high or low based on investor preferences or mistakes, but it is not clear why they would be too high in the short term and too low in the long term. If any of these explanations are causing our results, then controlling for the price level should eliminate the apparent effects of price shocks on subsequent returns.

5.1.3 Non-Financial reasons for trade

Investors may bet on particular teams based on their support of the team. Supporters of a particular team might bet against the team to hedge against their disappointment if the team loses, or bet in favor of their team due to optimism about their chances of winning. To impact prices, there must be an imbalance of support for one team, as otherwise the two sides could simply hedge each other's preferences. This would predict that team support is related to overall returns. We test whether imbalances of support for a particular team affect prices in section 5.3.

5.2 Regression Tests of Price changes After Price Shocks

We control for the above possibilities in Table III using a regression setting. Table II examined whether the price changes in each category were significantly different from zero. In Table III, we examine determine whether the price changes in these categories are significantly different from each other, controlling for price and time effects as discussed above. The observations are the price changes after the same price shocks in Table II. The regression is:

$$\Delta Price = \alpha + \sum_{s=1}^{3}\left[\beta_{PA,s} * PosAbove_s + \beta_{NA,s} * NegAbove_s + \beta_{NB,s} * NegBelow_s\right]$$
$$+ \sum_{s=2}^{3}\left[\beta_{PB,s} * PosBelow_s\right] + \sum_{i=1}^{9}\gamma_i * PriceDum_i + \sum_{i=1}^{15}\delta_i * TimeDum_i$$

Essentially, this regression determines whether the price changes after scoring events vary according to the shock direction, price level, and time after the shock. The main variables of interest are $PosAbove_s$, $PosBelow_s$, $NegAbove_s$, $NegBelow_s$. These are dummy variables for positive shocks with price above the pre-game price, positive shocks with price below the pre-game price, negative shocks with price above the pre-game price, and negative shocks with price below the pre-game price respectively. The subscript *s* indicates the period from which the price change is calculated from. s=1 is associated with (t+7, t+10), s=2 is associated with (t+10, t+13) and $s=3$ is associated with (t+13, t+16). The *PosBelow* dummy is in the separate summation sign because we need to omit one category, and so the omitted dummy variable is a positive shock below the base price at (t+7, t+10).

In terms of control variables, $PriceDum_{1\text{-}9}$ are dummy variables for the dollar level of the post-shock price (e.g. $PriceDum_1$ equals 1 if the price was between $0 and $0.99, $PriceDum_2$ equals 1 if the price was between $1.00 and $1.99, etc.) with the dummy for prices between $6 and $6.99 omitted. $TimeDum_{1\text{-}15}$ are dummy variables for the number of fifteen minute periods until the end of the game.

Table III presents the results of these regressions. In Panel A, the price changes are short term changes, based on price changes from (*t*+4, *t*+7) to 3 minute periods starting in *t*+7, *t*+10 and *t*+13 as indicated. In Panel B, the changes are based on holding until the end of the game, based again on prices starting in *t*+7, *t*+10 or *t*+13 as indicated. In each panel, the rows show regressions using controls based on no controls, price level controls, time controls, and both price and time controls respectively.

As in Table II, our predictions are that there should be short term reversals and long term momentum for positive shocks where price is below above the pre-game price, and for negative shocks where price is below the pre-game price. In other words, for short term price changes, we predict *PosAbove* to have a negative coefficient and *NegBelow* to have a positive coefficient. For longer term price changes to the end of the game, we predict *PosAbove* to have a positive coefficient and *NegBelow* to have a negative coefficient.

Panel A shows that the results for short term returns survive controlling for both price and time. The price changes after *PosAbove* shocks are negative and significant in all four specifications (significant at all time intervals with both specifications with price controls, and significant only for *t*+13 in other specifications), and the price changes after *NegBelow* shocks are positive and significant. In both cases, the effects are not greatly changed by adding time controls, and get stronger in magnitude and significance when adding price controls. For example, looking at *t*+13, , *PosAbove* goes from a coefficient of -0.19 and a t-statistic of -2.048 with no controls, to a value of -0.95 and a t-statistic of -10.71 with full controls. *NegBelow* goes from a value of 0.20 and a t-statistic of 2.343 with no controls, to a coefficient of 0.38 and a t-statistic of 5.020 with full controls.

Panel B shows that for returns holding until the end of the game, the results are directionally correct but weaker. For *PosAbove,* the *t*+13 coefficient is 0.62 and t-statistic is 2.186 without controls, compared with a coefficient of 0.28 and a t-statistic of 0.914 with full controls. For *NegBelow,* the base effects are weaker – a coefficient of -0.03 and t-statistic of -0.125 without controls, compared with a coefficient of -0.06 and t-statistic of -0.235 with full controls. In other words, the results lose significance with the extra controls, but are still directionally correct. The effects get stronger as more time elapses after the shock, consistent with accumulated disposition trading after the shock increasing the mispricing.

Overall, these results show that the main effects survive the additional controls. In all cases, they retain the correct direction, and for short term returns, become stronger after controlling for price and time. This suggests that time-based drift and the favorite-longshot bias do not appear to be driving our results. The role of disposition-related variables is strong evidence of the disposition effect as the driver of these patterns in returns.

5.3 Regression Tests of Efficiency Around Game Quarters

In this section we test the second proposition implied by pricing efficiency, namely that *no information other than the price should have significant explanatory power over the probability of a team winning*. Whereas Table III examined alternative causes for the Table II price changes after news events, we next examine alternative causes for the S-shape in Figure 2. The observations here are again those taken at the end of each quarter, which allows us to incorporate information such as game scores for which we have observations only at the end of each quarter. It also serves as a robustness check for questions related to the sampling of games involved in Table II and III, such as the timing of shocks and their distribution across games.

We examine other explanations that may account for the observed mispricing, such as investors trading for non-financial reasons, or mispricing due to insufficient liquidity, or investors failing to incorporate specific fundamental information about a game. We take the cross section of prices at the end of each quarter and use linear probability and logistic regressions to determine if the price is able to completely explain variation in $Win_{i,}$ a dummy variable that equals 1 if the Tradesports pick wins game i, and 0 otherwise. For each game at time t¸ (where t is either quarter time, half time, or three quarter time) we estimate the panel linear probability regression[5]:

$$Win_i = c + \beta_1 Price_{i,t} + \beta_2 (Controls)_i + \beta_3 (TimeFE) + \varepsilon_i$$

where the main explanatory variable $Price_{i,t}$ is the average price divided by 10 (so as to lie on an interval between 0 and 1) for game i for the 10 minutes around time t. In an alternative specification, we estimate a logistic regression using the same variables. We include a number of control variables, designed to test for variation in liquidity, non-financial reasons for trade, and fundamental information. Under the null hypothesis of market efficiency, we should observe that c=0, β_1= 1 β_2= 0, and β_3= 0. Table IV presents the results of series of regressions for variables related to Liquidity (Panel A), Non-Financial Reasons for Trade (Panel B) and Fundamental Information (Panel C). Table V shows the marginal impacts of non-price variables from Table IV. All tables use heteroskedasticity-robust standard errors.

5.3.1 Significance of Mispricing

In nearly every specification prices are found to be significantly inefficient. When comparing price and *Win* in the first column of panel A, β_{Price}=1.109 and the F-test of H_0: β_{Price}=1 gives a p-value of 0.028, while the constant is –0.059 with a t-statistic of –1.68. Similar results are obtained across

[5] All the following results are robust to using a logit specification.

the different specifications. While adding other variables may remove the residual mispricing, this does not resuscitate market efficiency, since in an efficient market price should be the only variable that explains the chance of a team winning.

5.3.2 Analysis of Changes in Liquidity

The regression results in Panel A of Table IV provide evidence that pricing accuracy is affected by variables related to market depth and liquidity. We are interested in variables that potentially cause an increase in market participation for reasons unrelated to game events. Variables like volume are not clean measures of liquidity because they might also increase with greater news (which under the disposition effect explanation can make mispricing worse). The variables instead are dummy variables for Monday night games (which are screened on TV nationally and are the focal NFL game that week), dummy variables for which season the game was in (as Tradesports as a whole became more liquid over the three seasons) and the log of the total population of the cities playing, as bettors may watch games involving teams that they personally follow. Pre-game volume is also a measure of liquidity largely unrelated to news. Other than pre-game volume, these variables show statistically significant effects on prices, although they do not eliminate the mispricing entirely.

To interpret whether greater liquidity is bringing prices closer to or further from efficient levels, Table V shows marginal effects and associated pricing errors of the significant variables in Table IV. We use the linear probability models, because according to economic theory price ought to enter linearly in its effect on outcome probability. The 25th, 50th and 75th percentiles of prices are \$5.00, \$7.00 and \$8.59., Table V shows that for Monday Night Games the pricing errors at these prices of \$1.204, \$0.956 and \$0.758, versus \$0.134, \$0.382 and \$0.580 for all other games. Thus the more liquid Monday Night Games exhibit greater mispricing across the interquartile range of prices than other games.

For the Season 2003 Dummy, a similar analysis shows that the mispricing is roughly symmetric – the low-volume 2003 season, when compared with the base high-volume 2005 season, is more accurate at the 25th percentile of price, roughly equally accurate at the 50th percentile, and less accurate at the 75th percentile. For Total Population, at the 25th, 50th and 75th percentile of price, the 25th Percentile of Total Population exhibits pricing errors of $0.314, $0.110 and $0.052 respectively, while the 75th percentile of Total Population exhibits pricing errors of $0.215, $0.419 and $0.581 respectively. Thus an interquartile increase in Total Population increases mispricing at the 50th and 75th percentile of prices, but somewhat decreases mispricing at the 25th percentile of prices.

5.3.3 Analysis of Non-Financial Motives For Trade

The regression results in Panel B of Table IV provide very little evidence that bettors are motivated in their trading decisions by non-financial motives. The coefficients that measure imbalance in the size of city populations, and Dummy Variables for which teams are popular in terms of merchandise sales, show no significant effect on the team's chances of winning (after price is considered). This evidence is inconsistent with Tetlock's (2004) explanation of sports prices being driven by non-financial motives for trade. Variables proxying for the most obvious non-financial motives relating to team loyalty do not show any effect.

5.3.4 Analysis of Fundamental Information

Panel C shows the effect of fundamental information. Both the difference in score between the two teams at that point in the game and whether the home team is an underdog (Levitt (2004)) both show no significant effect. The Period Quantity/Pre-game Quantity (proxying for the amount of news in that quarter) is insignificant. The Above Pre-Game Price Dummy (which equals 1 if the price is greater than the pre-game price, and 0 otherwise) is significant, which is not an indication of fundamental information, but is suggestive of a role for the pre-game price in terms of the disposition effect.

6. Profitability of Trading Strategies

Another more direct test of the economic impact of the disposition effect (and also the economic significance of the Tradesports mispricing generally) comes from testing proposition 3, namely that *trading strategies should not be able to generate positive expected returns.* In Table VI, we evaluate strategies (based on the results in section 4.1) that involve buying contracts for some range of prices above $5, and/or selling short contracts for some range of prices below $5. In Panel A we measure profitability using the Sharpe Ratio of the strategy, defined as the expected return divided by the standard deviation of returns, which captures some aspect of the risk-return trade-off in following the strategy.

The range of contract prices in question is given in the left two columns. Since these price ranges may not be available in all games, we report under each Sharpe Ratio the number of games in the sample (out of 525) that the strategy would have been available to be implemented. For the Sharpe Ratios, expected returns are given net of the maximum possible expenses incurred. In Panel B, we present the dollar profit that could have been obtained by taking every transaction observed in the given price range, and underneath give the total amount of money required to establish the positions.

In interpreting these numbers, we do not have data on spreads, and placing market orders will incur a spread cost. However, the prices given are all actual transaction prices, and the profits described were necessarily realized by some investors in the market. The second question is that of depth and market impact. The profits described are the actual profits to investors, but if additional demand or supply were introduced by arbitrageurs following this strategy, this would eventually impact prices.

The results in Table VI indicate that over the period in question there were significant profit opportunities from the mispricing. From a Sharpe Ratio standpoint, the most lucrative strategies involve shorting the contract at prices between $1 and $2 or between $4 and $5, and buying the contract between $8 and $9. The $1-2 short and $8-9 long strategy generates a Sharpe ratio of 1.064 at Three-Quarter time (in 107 games) and 0.447 at half time (in 98 games). The simplest strategy, of buying above $5 and selling below $5, generates a Sharpe Ratio of 0.284 at Three-Quarter time. To put these numbers into perspective, the stock market has a Sharpe Ratio of about 0.5, and the average bet on the NFL in Vegas has a Sharpe Ratio of between–0.03 and –0.1, depending on the size of the vigorish (that is, the negative expected return that the casino charges when setting odds). Panel B shows the dollar profits available from such strategies. A strategy based on buying for all prices greater than $5 and selling for all prices less than $5 would have generated profits of $65,300 on a maximum required investment of $533,500, based on trading for only 10 minutes per game. This strategy can be implemented in 326 out of 525 games (65% of the sample).

7. Conclusion

In this paper, we examine the efficiency of NFL betting markets at Tradesports.com and find significant evidence of mispricing consistent with the disposition effect. Prices do not reflect the true probability of a team winning, but instead follow an S-Shape, with contracts being overpriced for prices between $0 and $4, and underpriced for prices between $6 and $10. We examine the reaction to news events, and find patterns of apparent overreaction followed by underreaction that depend on whether the price is above or below the pre-game price. Moreover, these patterns broadly survive controlling for price levels, and for time until the end of the game, suggesting they are not driven by probability mistakes, investor preferences over particular gambles, or in-game drift in prices. This evidence is very difficult to reconcile with explanations other than the disposition effect.

Our current results also suggest other instances in finance where the impact of the disposition effect may be particularly large. In the current market, the fact that roughly 40% of trading volume occurs before kickoff at a stable price means that a large proportion of investors face the same gains and losses at a given time. This causes the disposition-related trading to be magnified, rather than different trades cancelling each other out. Any other instance where numerous investors buy or sell the security at a given price may be expected to show the same large effects. Some examples of this would be mergers, initial public offerings (IPOs, such as investigated in Kaustia (2004)), and seasoned equity offerings (SEOs), all of which involve a large group of investors purchasing or receiving shares at a single price.

Finally, the results in this paper help shed light on the underlying causes of the disposition effect. We find strong evidence for the disposition effect in a gambling market where the decision to enter appears roughly risk-seeking. This is difficult to reconcile with explanations based on an incorrect belief in mean-reversion, or simple prospect theory models. It is however consistent with explanations for the effect such as cognitive dissonance (which do not rely on particular attitudes to risk), or models with time-inconsistent preferences such as Barberis (2010) (which allow for locally risk-seeking behavior).

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Table I: Summary Statistics of Tradesports.com Contracts

	Number of Observations	Mean	Std Dev	Max	Min
Price (in $)	134282	6.1	2.3	10.0	0.1
Contracts per trade	134282	14.2	49.7	3900.0	1.0
Time from End of Game per trade	134282	2.34	20.55	271.00	0.00
Contracts traded per Game	294	6506	7930	53678	1193
Contracts traded during Game Time	294	4019	6499	42592	6
Game Length (hours)	294	3.23	0.27	4.10	2.60
Total Games	294				
Total Wins	202				
Games 2003-2004 Season	57				
Games 2004-2005 Season	82				
Games 2005-2006 Season	155				
Monday Night Games	53				
Total Contracts	1912773				
Total Trades	134282				
Earliest Game Date	9/5/2003				
Latest Game Date	1/15/2006				

This table contains summary statistics for trades of money-line contracts (i.e. “Team A to Win”) on tradesports.com during NFL games from the 2003, 2004 and 2005 seasons. Each contract is for a payoff of $10 if the team in question wins, and $0 if the team loses. In terms of the ‘Number of Observations’ column, the first 3 rows all give a single observation per trade (134282 in total), while the second three rows give a single observation per game (294 in total).

Table II - Price Changes After Shocks

Top is Price Change in $ between the two time periods, Middle is t-stat, Bottom is total number of shocks

Shock Direction	Price Criteria	(t+4,t+7) to (t+7, t+10)	(t+7, t+10) to End of Game	(t+4,t+7) to (t+10, t+13)	(t+10, t+13) to End of Game	(t+4,t+7) to (t+13, t+16)	(t+13, t+16) to End of Game
Positive	**All**	**-0.09** **	**-0.09**	**-0.09** *	**-0.04**	**-0.13** **	**-0.02**
		(-2.65)	(-0.61)	(-1.82)	(-0.32)	(-2.19)	(-0.16)
		707	845	709	898	706	915
Positive	**Pre-shock Price > Pre-Game Price**	**-0.09** **	**0.09**	**-0.15** **	**0.27**	**-0.28** ***	**0.33** **
		(-2.56)	(0.47)	(-2.54)	(1.56)	(-3.59)	(2.00)
		359	448	364	486	357	495
Positive	**Pre-shock Price < Pre-Game Price**	**-0.08**	**-0.29**	**-0.02**	**-0.41** *	**0.02**	**-0.44** **
		(-1.46)	(-1.26)	(-0.31)	(-1.87)	(0.18)	(-2.04)
		348	397	345	412	349	420
Negative	**All**	**0.06** **	**-0.23**	**0.09** *	**-0.26** **	**0.06**	**-0.24** *
		(2.06)	(-1.62)	(1.91)	(-1.97)	(0.96)	(-1.86)
		758	913	756	956	750	986
Negative	**Pre-shock Price > Pre-Game Price**	**-0.04**	**0.09**	**-0.05**	**0.10**	**-0.25**	**0.11**
		(-0.59)	(0.28)	(-0.40)	(0.35)	(-1.59)	(0.38)
		130	173	130	180	124	184
Negative	**Pre-shock Price < Pre-Game Price**	**0.08** **	**-0.30** **	**0.12** **	**-0.35** **	**0.12** *	**-0.32** **
		(2.42)	(-1.93)	(2.38)	(-2.32)	(1.84)	(-2.22)
		628	740	626	776	626	802

This Table presents the price changes after a shock to the price for contracts on NFL games at Tradesports.com for the 2003, 2004 and 2005 seasons. A shock is defined as when a) the volume-weighted average price (VWAP) in one 3-minute period, designated the shock period, is at least 50c different from the VWAP in the previous 3-minute period, and b) at least one minute out of the three in the second period has a volume that is in the top half of volume per minute for that game. The first three columns show the price change (in $) between the VWAP in the 3-min period starting one minute after the end of the shock period, and the relevant subsequent VWAP listed in the heading. Columns 3 to 6 show the price change (in $) between each VWAP listed (with (t+4, t+7) being the period starting one minute after the end of the shock period) and the contract price at the end of the game. The top entry in bold is the price change in dollars, the middle entry is the t-statistic adjusted for heteroskedasticity, and the bottom entry is the number of shocks identified that met the criteria given (out of 525 games). *, ** and *** indicate significance at a 10%, 5% and 1% level.

Table III - Price Changes After Shocks with Controls

Panel A - Period Returns

	Positive Shock Price > Pre-Game Price			Positive Shock Price < Pre-Game Price			Negative Shock Price > Pre-Game Price			Negative Shock Price < Pre-Game Price			
	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	CONSTAN
No Control	**-0.01**	**-0.07**	**-0.19****	**OMITTED**	**0.06**	**0.10**	**0.05**	**0.03**	**-0.16**	**0.16****	**0.20*****	**0.20****	**-0.08**
Obs. R^2	(-0.203)	(-0.845)	(-2.048)		(0.591)	(0.911)	(0.549)	(0.220)	(-1.004)	(2.504)	(2.672)	(2.343)	(-1.461)
4,386 0.01													
Price Control	**-0.84*****	**-0.88*****	**-0.97*****	**OMITTED**	**0.04**	**0.08**	**-0.55*****	**-0.58*****	**-0.71*****	**0.33*****	**0.37*****	**0.37*****	**0.43*****
Obs. R^2	(-11.95)	(-11.05)	(-11.10)		(0.447)	(0.879)	(-6.629)	(-5.082)	(-5.330)	(5.191)	(5.270)	(4.946)	(6.466)
4,386 0.276													
Time Control	**-0.02**	**-0.08**	**-0.21****	**OMITTED**	**0.06**	**0.10**	**0.05**	**0.03**	**-0.17**	**0.16****	**0.19****	**0.19****	**-0.08**
Obs. R^2	(-0.370)	(-0.952)	(-2.135)		(0.605)	(0.918)	(0.545)	(0.215)	(-1.030)	(2.397)	(2.565)	(2.227)	(-1.377)
4,386 0.015													
Price+Time	**-0.83*****	**-0.87*****	**-0.95*****	**OMITTED**	**0.04**	**0.08**	**-0.55*****	**-0.57*****	**-0.70*****	**0.34*****	**0.38*****	**0.38*****	**0.44*****
Obs. R^2	(-11.65)	(-10.68)	(-10.71)		(0.461)	(0.895)	(-6.506)	(-5.015)	(-5.277)	(5.346)	(5.397)	(5.020)	(6.652)
4,386 0.285													

Panel B - Returns to End of Game

	Positive Shock Price > Pre-Game Price			Positive Shock Price < Pre-Game Price			Negative Shock Price > Pre-Game Price			Negative Shock Price < Pre-Game Price			
	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	(t+4) to (t+7)	(t+4) to (t+10)	(t+4) to (t+13)	CONSTAN
No Control	**0.38**	**0.56***	**0.62****	**OMITTED**	**-0.12**	**-0.15**	**0.38**	**0.39**	**0.40**	**-0.01**	**-0.06**	**-0.03**	**-0.29**
Obs. R^2	(1.273)	(1.943)	(2.186)		(-0.389)	(-0.466)	(0.964)	(1.049)	(1.082)	(-0.0432)	(-0.218)	(-0.125)	(-1.257)
5,513 0.004													
Price Control	**0.02**	**0.21**	**0.31**	**OMITTED**	**-0.11**	**-0.16**	**-0.02**	**0.06**	**0.07**	**-0.01**	**-0.07**	**-0.04**	**0.62****
Obs. R^2	(0.0792)	(0.694)	(1.045)		(-0.361)	(-0.502)	(-0.0389)	(0.147)	(0.199)	(-0.0199)	(-0.244)	(-0.139)	(2.186)
5,513 0.017													
Time Control	**0.30**	**0.48***	**0.56***	**OMITTED**	**-0.12**	**-0.15**	**0.31**	**0.32**	**0.34**	**-0.02**	**-0.07**	**-0.05**	**-0.26**
Obs. R^2	(1.012)	(1.677)	(1.954)		(-0.385)	(-0.475)	(0.788)	(0.865)	(0.928)	(-0.0759)	(-0.265)	(-0.179)	(-1.120)
5,513 0.014													
Price+Time	**-0.02**	**0.17**	**0.28**	**OMITTED**	**-0.12**	**-0.17**	**-0.06**	**0.00**	**0.04**	**-0.02**	**-0.09**	**-0.06**	**0.64****
Obs. R^2	(-0.0614)	(0.551)	(0.914)		(-0.363)	(-0.534)	(-0.144)	(0.00791)	(0.0946)	(-0.0780)	(-0.318)	(-0.235)	(2.238)
5,513 0.026													

This Table presents regression coefficients for the price changes after a shock for contracts on NFL games at Tradesports.com for the 2003, 2004 and 2005 seasons. The regressions include dummy variables for type of shock and for the time period after shocks. Regressions also include controls as indicated in the right hand column. Each time period (e.g. (t+4)) indicates a volume-weighted average price (VWAP) taken over a three minute period beginning with the time noted. So (t+4) is the VWAP between t+4 and t+6 inclusive. The period 't' indicates the period that the price shock occurs in. A shock is defined as when a) the volume-weighted average price (VWAP) in one 3-minute period, designated the shock period, is at least 50c different from the VWAP in the previous 3-minute period, and b) at least one minute out of the three in the second period has a volume that is in the top half of volume per minute for that game. 'Negative Shocks' involve negative price changes in the shock period, and 'Positive Shocks' involve positive price changes in the shock period. 'Price </> Pre-Game Price' indicates whether the price immediately before the shock was greater or less than the VWAP before the start of the game. Panel A shows the price change (in $) between the VWAP in the 3-min period starting one minute after the end of the shock period, and the relevant subsequent VWAP listed in the heading. Panel B shows the price change (in $) between each VWAP listed (with (t+4) (i.e. (t+4:t+6) being the period starting one minute after the end of the shock period) and the contract price at the end of the game. The top entry in is the coefficient, and the bottom entry is the t-statistic, adjusted for heteroskedasticity . *, ** and *** indicate significance at a 10%, 5% and 1% level.

Table IV - Panel Regressions of Win/Loss Dummy on Price									
Panel A - Variables associated with Changes in Liquidity									
Dependent Variable is a Dummy Variable that equals 1 if the team won the game, and 0 otherwise									
								All Variables, All Panels	
	LPM	LPM	LPM	LPM	LPM	LPM	Logit	LPM	Logit
Price	**1.109 *****	**1.097 *****	**1.104 *****	**1.124 *****	**1.110 *****	**1.108 *****	**6.617 *****	**1.030 *****	**6.400 *****
	(22.30)	(22.05)	(22.24)	(22.69)	(22.29)	(22.33)	(15.15)	(12.63)	(9.75)
Constant	**-0.059 ***	**-0.021**	**-0.100 *****	**-0.049**	**-0.056**	**-0.064**		**-0.953 *****	
	(1.68)	(-0.55)	(-2.64)	(-1.40)	(-1.53)	(-1.50)		(-3.33)	
Season 2003		**-0.097 *****				**-0.073 ****	**-0.464** **	**-0.094 *****	**-0.646 *****
		(-3.06)				(-2.19)	(-2.09)	(-2.70)	(-2.69)
Season 2004		**-0.035**				**-0.031**	**-0.222**	**-0.031**	**-0.239**
		(-1.26)				(-1.12)	(-1.13)	(-1.07)	(-1.13)
Log Total Population			**0.004 *****			**0.004 ****	**0.353** ***	**0.058 *****	**0.421 *****
			(2.69)			(2.46)	(2.87)	(3.26)	(3.23)
Monday Night Game				**-0.134 *****		**-0.121 *****	**-0.828** ***	**-0.119 *****	**-0.818 *****
				(-3.94)		(-3.31)	(-3.30)	(-3.22)	(-3.14)
Pre-Game Volume					**-0.001**	**0.003**	**0.028**	**-0.001**	**0.001**
(in 1000s)					(-0.25)	(0.49)	(0.64)	(-0.14)	(0.01)
R2 / Pseduo R2	**0.328**	**0.334**	**0.333**	**0.338**	**0.328**	**0.346**	**0.310**	**0.360**	**0.328**
Obs	**1023**	**1023**	**1023**	**1023**	**1023**	**1023**	**1023**	**956**	**956**
F Stat for H0:									
Beta(Price) = 1	**4.83**	**3.81**	**4.37**	**6.27**	**4.85**	**4.73**		**0.14**	
p-value	**0.028**	**0.051**	**0.037**	**0.012**	**0.028**	**0.03**		**0.780**	
Quarter Fixed Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

This table presents panel linear probability regressions for tradesports.com contracts on NFL games from the 2003, 2004 and 2005 seasons. ‘LPM’ indicates a Linear Probability Model regression, while ‘Logit’ indicates a Logistic regression. The Dependent variable in each regression is a Dummy variable that equals 1 if the Tradesports pick team wins and 0 if the team loses. ‘Price’ is the price for a $10 contract (divided by 10) for three observations per game, taken as the average for the 10 minutes surrounding the quarter-time, half-time, and three-quarter-time in each game. Panel A presents variables associated with different levels of liquidity: Dummy variables for which season the game is in (Season [ ]), variables for the log of the combined metropolitan population as reported in the 2000 census of the two cities that the teams are from (Total Population), a dummy variable for whether the game was played on Monday night (Monday Night Game) and the number of contracts traded between the opening of trade and one hour before kickoff (Pre-Game Volume). Panel B presents variables associated with non-financial reasons for trade: the ratio of the populations of the two cities (Favorite Population/ Non-Favorite Population), and dummy variables for whether the favorite, underdog, or both were in the top 10 merchandise sales of NFL teams in the previous season (Favorite in Merchandise Top 10, Non-Favorite in Merchandise Top 10, Both in Merchandise Top 10). Panel C presents variables associated with fundamental information: the difference between the team scores at each time (Point Differential), a dummy variable for whether the home team is favored to win before the game (Home Underdog), a dummy variable for whether the period price is greater than the average price before kickoff (Price Above Pre-Game Price) and the volume in the previous quarter divided by the volume before kickoff (Volume/Pre-game Volume). In each row, the top entry in bold is the coefficient, the bottom entry in parentheses is t-statistic adjusted for heteroskedasticity for that estimate. *, ** and *** denote significance at a 10%, 5% and 1% level respectively.

Panel B - Variables associated with Non-Financial Reasons for Trade								
							All Variables, All Panels	
	LPM	LPM	LPM	LPM	LPM	Logit	LPM	Logit
Price	**1.110 *****	**1.108 *****	**1.110 *****	**1.109 *****	**1.108 *****	**6.418 *****	**1.030 *****	**6.400 *****
	(22.31)	(22.24)	(22.29)	(22.29)	(22.21)	(15.20)	(12.63)	(9.75)
Constant	**-0.065 ***	**-0.065 ***	**-0.062 ***	**-0.060 ***	**-0.077 ****		**-0.953 *****	
	(-1.85)	(-1.81)	(-1.73)	(-1.70)	(-2.02)		(-3.33)	
Favourite Population / Non-Favourite Population	**0.003**				**0.003**	**0.021**	**0.002**	**0.014**
	(1.13)				(1.07)	(1.12)	(0.77)	(0.74)
Favourite in Mechandise Top 10		**0.018**			**0.026**	**0.151**	**0.043**	**0.279**
		(0.73)			(0.88)	(0.76)	(1.42)	(1.26)
Non-Favourite in Mechandise Top 10			**0.011**		**0.019**	**0.087**	**0.047**	**0.304**
			(0.41)		(0.56)	(0.38)	(1.32)	(1.20)
Both in Mechandise Top 10				**0.009**	**-0.033**	**-0.227**	**-0.078**	**-0.587**
				(0.23)	(-0.62)	(-0.63)	(-1.43)	(-1.50)
R2 / Pseduo R2	**0.329**	**0.329**	**0.328**	**0.328**	**0.330**	**0.288**	**0.360**	**0.328**
Obs	**1023**	**1023**	**1023**	**1023**	**1023**	**1023**	**956**	**956**
F Stat for H0: Beta(Price) = 1	**4.87**	**4.68**	**4.86**	**4.84**	**4.66**		**0.14**	
p-value	**0.028**	**0.031**	**0.028**	**0.028**	**0.031**		**0.780**	
Quarter Fixed Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Panel C - Variables associated with Fundamental Information and the Disposition Effect								
							All Variables, All Panels	
	LPM	LPM	LPM	LPM	LPM	Logit	LPM	Logit
Price	**1.098 *****	**1.113 *****	**0.987 *****	**1.121 *****	**1.049 *****	**6.229 *****	**1.030 *****	**6.400 *****
	(17.83)	(22.35)	(13.19)	(21.85)	(12.76)	(9.99)	(12.63)	(9.75)
Constant	**-0.052**				**-0.056**		**-0.953 *****	
	(-1.29)				(-1.20)		(-3.33)	
Point Differential	**0.001**				**0.000**	**0.004**	**0.000**	**0.007**
	(0.32)				(0.03)	(0.29)	(0.16)	(0.46)
Home Underdog		**0.037**			**0.031**	**0.268**	**0.027**	**0.244**
		(1.39)			(1.11)	(1.38)	(0.98)	(1.20)
Price Above Pre-Game Price			**0.079 ****		**0.047**	**0.168**	**0.051**	**0.177**
			(2.18)		(1.22)	(0.70)	(1.33)	(0.70)
Volume/Pre-Grame Volume				**0.048**	**0.053**	**0.421**	**0.070**	**0.586**
				(0.49)	(0.53)	(0.65)	(0.71)	(0.87)
R2 / Pseduo R2	**0.328**	**0.329**	**0.331**	**0.336**	**0.338**	**0.296**	**0.360**	**0.328**
Obs	**1023**	**1023**	**1023**	**956**	**956**	**956**	**956**	**956**
F Stat for H0: Beta(Price) = 1	**2.52**	**5.11**	**0.03**	**5.55**	**0.36**		**0.14**	
p-value	**0.112**	**0.024**	**0.864**	**0.019**	**0.550**		**0.780**	
Quarter Fixed Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Table V - Marginal Effects of Statistically Significant Variables from Linear Probability Regressions

Pctile of Price Price ($)	25th 5.00	50th 7.00	75th 8.59	25th 5.00	50th 7.00	75th 8.59
	Estimated Prob(win)			Implied Pricing Error (in $)		
Total Population (mil.)						
Min = 1.33	0.457	0.678	0.853	0.429	0.221	0.056
25th Pctile = 4.93	0.472	0.693	0.869	0.276	0.069	0.097
Median = 8.43	0.487	0.708	0.883	0.128	0.080	0.245
75th Pctile = 12.10	0.503	0.724	0.899	0.028	0.236	0.401
Max = 42.40	0.631	0.852	1.028	1.313	1.520	1.685
Monday Night Game						
Min = 0	0.513	0.738	0.917	0.134	0.382	0.580
Max = 1	0.380	0.604	0.783	1.204	0.956	0.758
Season 2003						
Min = 0	0.528	0.747	0.922	0.028	0.047	0.063
Max = 1	0.431	0.651	0.825	0.069	0.049	0.034
Price Above Base Price						
Min = 0	0.473	0.670	0.827	0.027	0.030	0.032
Max = 1	0.552	0.750	0.907	0.052	0.050	0.048

This Table presents the fitted values of the linear probability regressions in Table III and the pricing errors implied by such values, for tradesports.com contracts on NFL games from the 2003, 2004 and 2005 seasons. In each case, the coefficients are taken from the regression in Table III of a dummy of whether the team won the game on Price and the Independent Variable listed at the left. Columns titled 'Estimated Prob(win)' are the fitted values of the regression using the price listed at the top of the column at the value of the independent variable at the left of that row. The columns titled 'Implied Pricing Error' equals 10*|Price/10 - Estimated Prob(win)| , equal to the difference between the actual price and the efficient price.

Table VI: Sharpe Ratios and Profits Calculated For Various Trading Strategies

Panel A: Sharpe Ratios

(Sharpe Ratio net of maximum possible expenses above, Number of games for which strategy is possible below)

Short	Long	Kickoff			1st Quarter			Half Time			Third Quarter		
		S	L	S+L	S	L	S+L	S	L	S+L	S	L	S+L
P<5	**P>5**	**0.100**	**0.134**	**0.129**	**0.323**	**0.205**	**0.250**	**0.030**	**0.109**	**0.083**	**0.381**	**0.196**	**0.284**
		31	450	463	73	280	325	93	282	358	120	233	326
4<P<5	**5<P<6**	**0.087**	**0.288**	**0.226**	**0.225**	**0.255**	**0.239**	**0.295**	**-0.047**	**0.073**	**0.950**	**0.413**	**0.516**
		31	168	182	57	93	122	46	68	98	54	50	79
3<P<4	**6<P<7**		**0.047**	**0.055**	**0.272**	**0.282**	**0.278**	**-0.214**	**0.218**	**0.066**	**0.231**	**0.036**	**0.181**
			195	196	27	89	116	37	81	118	62	60	116
2<P<3	**7<P<8**		**0.173**	**0.173**	**0.873**	**0.454**	**0.620**	**-0.221**	**0.192**	**0.016**	**0.445**	**0.243**	**0.382**
			135	135	17	106	123	27	71	98	46	64	110
1<P<2	**8<P<9**		**-0.363**	**-0.363**	**17.644**	**-0.023**	**0.003**	**2.021**	**0.356**	**0.447**	**1.450**	**0.836**	**1.064**
			52	52	2	77	79	18	80	98	35	72	107
0<P<1	**9<P<10**		**0.870**	**0.870**		**0.326**	**0.326**	**-4.658**	**0.543**	**0.191**	**0.206**	**-0.168**	**-0.131**
			9	9		32	32	2	70	72	25	110	135

Panel B: Total Possible Profits

(Profit Net of Maximum Possible Expenses x $1000 above, Maximum amount of capital required to implement strategy below)

Short	Long	Kickoff S	Kickoff L	Kickoff S+L	1st Quarter S	1st Quarter L	1st Quarter S+L	Half Time S	Half Time L	Half Time S+L	Third Quarter S	Third Quarter L	Third Quarter S+L
P<5	**P>5**	**4.4**	**28.5**	**32.9**	**23.1**	**23.1**	**46.2**	**1.2**	**17.0**	**18.2**	**44.4**	**20.9**	**65.3**
		41.3	355.8	397.1	111.9	225.1	337.0	88.9	259.5	348.4	259.6	274.0	533.5
4<P<5	**5<P<6**	**3.9**	**22.1**	**26.0**	**7.7**	**8.8**	**16.5**	**6.8**	**-1.6**	**5.1**	**8.7**	**14.4**	**23.2**
		40.5	92.1	132.6	41.9	40.5	82.4	27.0	41.9	69.0	16.1	45.2	61.3
3<P<4	**6<P<7**	**0.5**	**3.8**	**4.3**	**3.2**	**5.7**	**8.9**	**-3.4**	**6.8**	**3.3**	**11.9**	**0.6**	**12.5**
		0.8	95.6	96.4	18.5	31.3	49.8	22.7	47.8	70.5	81.5	23.1	104.6
2<P<3	**7<P<8**		**10.8**	**10.8**	**11.4**	**7.5**	**19.0**	**-3.7**	**3.8**	**0.2**	**14.4**	**3.4**	**17.8**
			122.5	122.5	47.6	41.3	89.0	23.8	39.7	63.5	80.4	29.8	110.2
1<P<2	**8<P<9**		**-8.5**	**-8.5**	**0.8**	**-0.5**	**0.3**	**2.3**	**5.7**	**8.0**	**8.8**	**7.6**	**16.4**
			42.6	42.6	3.9	79.8	83.6	14.6	67.3	81.8	56.6	63.3	119.8
0<P<1	**9<P<10**		**0.2**	**0.2**		**1.5**	**1.5**	**-0.7**	**2.3**	**1.5**	**0.6**	**-5.1**	**-4.5**
			2.9	2.9		32.2	32.2	0.8	62.8	63.5	25.0	112.7	137.7

This table presents the Sharpe Ratios and Total Possible Profits for various trading strategies on Tradesports.com NFL contracts during the 2003, 2004 and 2005 seasons. The Sharpe Ratio is defined as E(R)/σ(R), where E(R) is the expected return from the strategy and σ(R) is the standard deviation of returns for the strategy. Sub-columns 'S' shorts the contract if the price criteria in the 'Short' column is met, Sub-column 'L' buys the contract if the criteria in 'Long' is met, and sub-column 'S+L' shorts the contract if the 'Short' criteria is met and buys the contract if the 'Long' criteria is met. The strategies are evaluated using all traded contracts during the 10-minute interval surrounding each of the time points given (kickoff, 1st Quarter, Half Time, and 3rd Quarter. In Panel A, in each row the top value in bold is the Sharpe Ratio of the strategy, the lower value is the number of contracts where the strategy was able to be implemented. In Panel B, the top value is the total amount of money possible from the strategy over that 10 minute period, and the bottom value is that maximum amount of money needed to establish the position under Tradesports.com's margin requirements.

Figure 1: Proportion of Contracts that Win Given Price

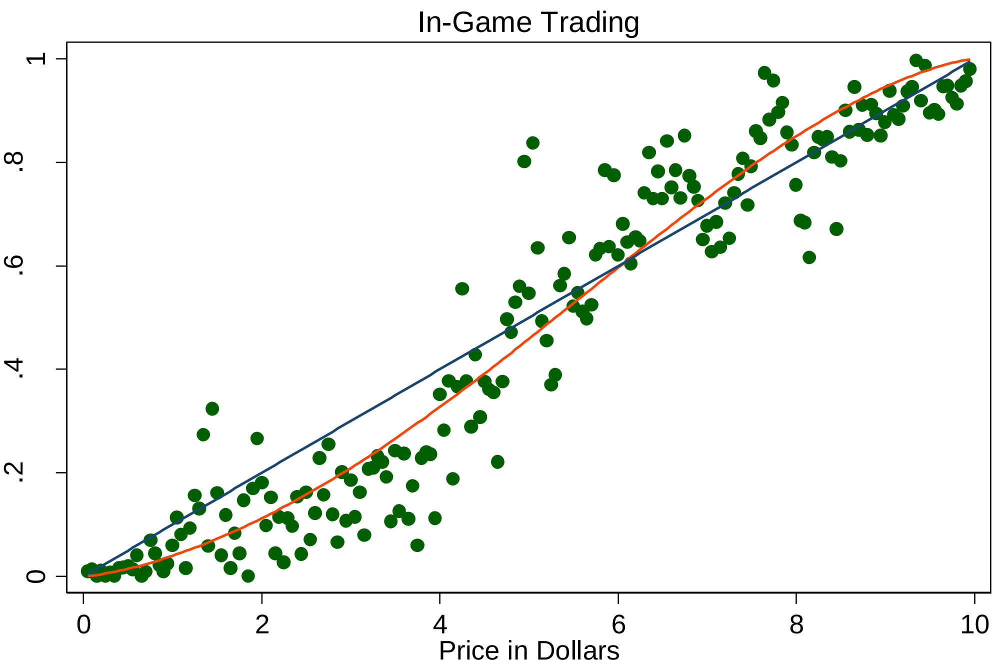

Figure 1 presents data Tradesports.com of contracts from the 2003, 2004 and 2005 seasons of NFL football of prices of all trades during game play. The plotted points are show for the price (in increments of 5c) on the x-axis vs. the fraction of cases at that price where the team actually won the game over all trades at the given price level on the y-axis (that is, the mean value of a dummy variable that equals 1 if the team in question won the game). The straight line is the 45° line, which is what prices should be under the null hypothesis of market efficiency. The curved line is the fitted values of a weighting function of the form $P(win) = \frac{\delta Price^{\gamma}}{\delta Price^{\gamma} + (1 - Price)^{\gamma}}$