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Essays in Sports Economics

Daniel Mark Chin
University of South Florida, daniel_m_chin@yahoo.com

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by

Daniel M. Chin

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Department of Economics
College of Arts and Sciences
University of South Florida

Co-Major Professor: Philip Porter, Ph.D.
Co-Major Professor: Bradley Kamp, Ph.D.
Beom Lee, Ph.D.
Patrick Kelly, Ph.D.

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ABSTRACT

The study of economics is based on key concepts such as incentives, efficiency, marginality and tradeoffs. Economic research has hypothesized and tested for how economic agents behave after taking each of these into account. In order for agents to meet their objectives it is sometimes the case that they intentionally keep their behaviors out of sight. However, economic theory can be used to search for patterns of observed behaviors from which the unobserved behaviors can be inferred. This dissertation performs this kind of analysis by observing the behavior of sports participants.

Chapter 1 is an application of Becker's (1968) economic model of crime by using an econometric model to search for the presence of National Basketball Association (NBA) referees who bet on NBA games. The placement of these bets is not observed since a referee who bets on a game does so illegally and therefore hides his betting activity to prevent detection. A referee who places a bet on a game he also officiates has an incentive to manipulate to improve his chances of winning the bet. At the same time he should also be mindful to manipulate in a way that lowers his chances of being detected. The referee's observed behaviors through detailed play-by-play data are used to look for patterns hypothesized to be consistent with manipulation. The results suggest that former NBA referee Tim Donaghy, who was found to have bet on NBA games, did behave in ways consistent with manipulation. One other referee also appears to engage in the same type of behavior but stops once Donaghy is detected.

Chapter 2 is an application of Fama's (1970) Efficient Market Hypothesis (EMH). Typically, the EMH is tested in the financial markets but some research tests for it in the sports betting markets so that the question becomes whether or not the betting market odds fully reflect all of the available relevant information. This chapter tests to see how completely National Football League (NFL) bettors use information called the circadian advantage. This occurs when a game is played in the evening, Eastern Time, between teams that are based on opposite coasts and always favors the better rested West Coast team. A regression model designed to test for market efficiency finds that the advantage is not fully reflected in the odds so that bets on the West Coast team are underpriced. In a majority of games that involve a circadian advantage most of the money is wagered on the overpriced East Coast team. A conclusion that ties these results together is that the bookmakers restrict the amount bet from informed bettors who tend to win their bets and who are aware of the circadian advantage, and adjust the odds just enough to bait uninformed bettors who are unaware of the circadian advantage into placing wagers on the team that is overpriced. Given these dynamics, it is the bookmakers who profit from the information contained in the circadian advantage.

Chapter 3 revisits the NFL betting market but instead estimates the extent to which bettors place wagers based on sentiment for a team that is unrelated to relevant measures of relative performance along the lines of speculative investment outlined by Graham and Dodd in 1934 (2009). The results show that more bets tend to be placed on teams for which bettors have high sentiment and fewer bets are placed on teams for which bettors have low sentiment. However, the market odds appear to be using sentiment unbiasedly, leading to the conclusion that contrarian bettors place wagers opposite the sentimental bettors. While the market as a whole is efficient in the use of sentiment, losers tend to be bettors who wager with sentiment and winners tend to be bettors who wager against sentiment.

CHAPTER 1: A MODEL TO DETECT IF REFEREES MANIPULATE GAMES FOR BETTING PURPOSES

1.1 Introduction

With the seminal work of Becker (1968), the occurrence of illicit behavior began to be analyzed in a theoretical economic framework. Since then, as computer technology has become more powerful and accessible, researchers have been able to process voluminous data into useful information and to robustly test hypotheses derived from economic theory through many different applications. The common strand among the research has been the specification of the marginal benefits versus the marginal costs from either society's or the offenders' perspectives. Modeled as typical economic agents, persons engaging in illicit behavior will do so as long as the additional benefits exceed the costs. To maximize their net benefits, they will seek to lower their costs by cloaking their behavior in order to decrease their chances of detection.

Sports have become a relatively new application of these theories due to the growing abundance of game-competition data that can be used to test for illicit behavior. These behaviors are akin to the principal-agent problem. Agents such as players or coaches are hired to either win a competition or, in the case of referees, to enforce the rules. Given their ability to influence the outcome of the competition, these agents may pursue a conflicting agenda for their personal financial gain, such as by a bet placed on the game. For example, a player may underperform in order to allow the opposing team to win, or a referee may unfairly officiate to allow the team bet on to win.

The purpose of this study is to test for game manipulation by National Basketball Association (NBA) referees. In this chapter, manipulation is defined to be the officiating of a game that unevenly enforces the rules between the opposing teams. If referees bet on games they officiate, then they clearly have an incentive to manipulate. Such manipulations, however, do come with costs and may be detected given their amounts or contexts within a game. Given the penalties they suffer if they are detected, referees who manipulate should seek to conceal their behavior so that the manipulation is not obvious. In this chapter, micro game data at the play-by-play level is used to look for patterns in game officiating consistent with referee manipulation.

The case this chapter revolves around is based on former NBA referee Tim Donaghy. On June 21, 2007, NBA Commissioner David Stern announced that the FBI had evidence that Donaghy engaged in betting activity on NBA games, some of which he also officiated.[1] The primary concern was whether Donaghy's ability to properly enforce game rules was compromised by his financial interests to win bets placed on the same games. Both the FBI and the NBA believe that Donaghy did not manipulate games[2] however Donaghy provided a back door admission by agreeing that his "…personal interest might have subconsciously affected his on-court performance."[3]

[1] Pedowitz (2008), pg. 2
[2] Ibid., pg. 16 & pg. 19
[3] Ibid., pg. 15

Donaghy has admitted to gambling-related behavior on NBA games from 2003 to 2007, a period over which he refereed in about 250 games.[4] His officiating was regularly observed by several thousand witnesses from several different perspectives each game: players, coaches, paying spectators, sports media, as well as the other two referees in his game crew. Could manipulation have been so subtle as to repeatedly evade detection from all of these witnesses? While there has been considerable interest among the sporting and sports betting communities in the answer to this question, there has been to date no academic research on this topic. This chapter develops an econometric model that is based on the assumed behavior of potential manipulators consistent with economic theory.[5] Donaghy's conduct is used as a reality check against the model.

Section 2 of this chapter reviews the relevant academic literature. Section 3 presents the theoretical framework of game manipulation on the part of referees. Section 4 lists the key assumptions as well as the hypothesized behavior of manipulation. Section 5 describes and summarizes the data that is used, and Section 6 discusses the basic empirical model. Section 7 describes the results, and Section 8 lists the conclusions.

1.2 Relevant Literature

Becker (1968) is the first to publish an economic theory applied to the study of crime. Criminals follow incentives to commit criminal activity and society expends resources to create disincentives that make it more costly for criminals to commit crimes. Rose-

[4] Ibid., pg. 11

[5] This was proposed by a number of academics shortly after the allegations against Donaghy were first announced including Ayres (2007) and Reese (from quotes in "Could a Statistical Model Detect Cheating NBA Ref?" downloaded from http://www.deseretnews.com/article/1,5143,695201262,00.html)

Ackerman (1975) expands on Becker's work by using economic theory to study the impact incentives and disincentives have on bribes during the bidding process for government contracts.

Perhaps the first empirical research within the area of detection for illicit behavior is Angoff's (1974) statistical model to search for cheating among standardized test takers. A set of indices is constructed that measures the covariance of answers among all pairs of test takers within the same room. A subset of the indices is found to be better at identifying known cheaters and is eventually used in practice by the Educational Testing Service. Jacob and Levitt (2003) investigate the degree of after-test answer changing among teachers who proctor their own students' standardized tests. Certain patterns in a classroom's answers consistent with the assumed objective of manipulatively raising test scores in a covert manner is specified and found to be effective in identifying known instances of teacher manipulation.

Slemrod (1985) and Feinstein (1991) develop models to detect aggregate tax evasion. Slemrod confirms his hypothesis, through individual tax return data, that the distribution of declared taxable income tends to clump at the upper end of tax brackets as taxpayers underreport from the next higher bracket. Feinstein regresses underreported taxable income on a number of hypothesized relevant taxpayer characteristics and finds that taxpayers who own their own businesses or are farmers, where more detailed forms could make detection more difficult, tend to underreport more than the typical taxpayer.

A number of empirical studies have been published that investigate the impact of corruption at the macroeconomic level. Mauro (1995) finds that corruption, as measured by a business survey, lowers economic growth through lower investment. Fisman (2001) estimates that rumors of then-President Suharto's ill-health had a larger effect on the stock price of publicly traded Indonesian companies that had closer ownership ties to the Suharto regime than companies with more distant, or non-existent, relations. Mocan (2008) makes use of polling data from several countries to measure the occurrence of government corruption where the characteristics of those polled is observed. Among other conclusions, he finds that males and respondents with higher income or who live in larger cities experience more interactions with corrupt government officials.

Sports have recently become a new application of the economic theory of crime and corruption. Preston and Szymanski (2003) create a theoretical model of corruption where the players are susceptible to bribes from bettors. Their results confirm basic intuition that corruption is most likely to occur for low wage players in environments where punishment is light. Duggan and Levitt (2002) analyze sumo wrestling tournament results and find evidence that opposing wrestlers fix matches when one wrestler has a much larger financial return to winning than the other. The fixed loser is then compensated for the loss by becoming the fixed winner in a future rematch so that both wrestlers essentially maximize joint profits. Price and Wolfers (2007) look at NBA box score data and conclude that referees tend to officiate more leniently towards players of the same race.

It is widely alleged that the 2002 NBA playoff series between the Sacramento Kings and the Los Angeles Lakers was manipulated in favor of the Lakers. At one point during the series the Kings had won three games to the Lakers two (four wins were needed to advance to the next round). Before the start of game six, Donaghy alleges:

> *…the league office sent down word that certain calls – calls that would benefit the Lakers – were being missed by the referees. This was the type of not-so-subtle information that I and other referees were left to interpret.* (NBA referee) *Bavetta openly talked about the fact that the league wanted a Game 7.*[6]

After the game ended with the Lakers winning, noted sports columnist Michael Wilbon was highly critical of the referees:

> *When Pollard* (a player on the Kings), *on his sixth and final foul, didn't as much as touch Shaq* (a player on the Lakers)*. Didn't touch any part of him. You could see it on TV, see it at courtside. It wasn't a foul in any league in the world. And Divac* (a player on the Kings), *on his fifth foul, didn't foul Shaq. They weren't subjective or borderline or debatable. And these fouls not only resulted in free throws, they helped disqualify Sacramento's two low-post defenders.*[7]

Two studies lend support to the belief that manipulation occurred. Price, Remer and Stone (2009) analyze play-by-play game data and conclude that NBA referees tend to officiate in ways that favor game conditions that are more compelling for spectators to watch, or to extend playoff series. Presumably, these are ploys to increase league revenues although the authors find no evidence of an NBA management mandate to do so. Zimmer and Kuethe (2009) find that after controlling for playoff seeding, teams from larger cities tend to advance in the playoffs more often than expected. They also suggest this as evidence of referee behavior designed to advance teams with larger fan bases and hence larger revenue streams.

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[6] Donaghy (2009), pg. 96.
[7] http://www.leagueoffans.org/sternletter.html, accessed on June 13, 2012.

1.3 Theory

Assuming a referee has placed a bet on a game that he also officiates, the decision to manipulate at some point in time during the game is based on the following objective function to maximize:

$$P_t^w(m_t, S_t^{f-a})cB - [1 - P_t^w(m_t, S_t^{f-a})]B - P_t^d(M_t, m_t)L \tag{1}$$

t is the elapsed game time. $P_t^w(m_t, S_t^{f-a})$ is the probability that the referee will win the bet given the number of times he believes he will manipulate as of t (m_t), and the current score of the game between the team bet for (f) minus the team bet against (a) compared to the point spread (S_t^{f-a}).[8] Without loss of generality in this section, it is safe to let the point spread equal zero so that only the difference in the score matters. c is the proportion of the amount won net of commission fees. B is the amount bet. Assuming even odds are offered, if a bet in the amount of B wins, then the bettor realizes a net gain of cB. $P_t^d(M_t, m_t)$ is the probability of detection given the amount of previous manipulation in the game (M_t) and the planned amount of manipulation over the rest of the game. L is the monetary value of the penalty if manipulation is detected, and could include lost wages from job termination, or imprisonment as well as fines.[9]

[8] The *point spread* is the predicted amount the team that is predicted to win the game (*the favorite*) will defeat its opponent (*the underdog*) by which a bet on the favorite wins if the favorite wins by an amount greater than the spread, otherwise a bet on the underdog wins.

[9] Donaghy was sentenced to 15 months in prison and ordered to share in the repayment of $217,000 to the NBA [Pedowitz (2008), pg. 15]

To summarize the objective, the first term is the expected winnings from placing a bet, the second term is the expected losses from placing a bet, and the third term is the expected losses from manipulation that is detected and from punishment that follows.

The first order necessary condition is:

$$\frac{\partial P^w}{\partial m_t}[B(c+1)] = \frac{\partial P^d}{\partial m_t} L \tag{2}$$

where $\frac{\partial P^w}{\partial m_t}$ and $\frac{\partial P^d}{\partial m_t}$ are both greater than zero so that an additional act of manipulation not only increases the chance of winning the bet but also of getting detected. The left side of the equation corresponds to the marginal benefit from an additional manipulation and the right side to the marginal cost.

The ratio of the response of the probability of winning the bet to an additional manipulation to that of the probability of detection is:

$$\left.\frac{\partial P^w}{\partial m_t}\middle/\frac{\partial P^d}{\partial m_t}\right. = L/[B(c+1)] \tag{3}$$

Assuming that L is much larger than B, then optimally an additional manipulation should increase the probability of winning the bet far more than increasing the probability of detection. Equation (3) is also written in terms similar to the marginal rate of transformation in that manipulation is used to "produce" P^w and P^d. Figure 1.1 shows graphically how the optimal amount of manipulation is chosen.

The second order sufficient condition,

$$\frac{\partial^2 P^w}{\partial m_t^2}[B(c+1)] - \frac{\partial^2 P^d}{\partial m_t^2} L < 0 \tag{4}$$

is satisfied if $\frac{\partial^2 P^w}{\partial m_t^2} < 0$ and $\frac{\partial^2 P^d}{\partial m_t^2} \geq 0$. There are diminishing returns to manipulation and the probability of detection increases at a constant or an increasing rate.

From the betting referee's perspective, the marginal increase in the probability of winning a bet given an additional manipulation can change given a change in the context of the game. For one, the return to manipulation increases as elapsed game time, *t*, progresses. Therefore, as *t* increases it becomes more attractive to manipulate:

$$\frac{\partial\left(\frac{\partial P^w}{\partial m_t}\right)}{\partial t} \geq 0 \Rightarrow \frac{\partial m_t}{\partial t} \geq 0 \tag{5a, 5b}$$

The return to manipulation also increases as S_t^{f-a}, the difference in the opposing teams' scores compared to the spread, gets smaller. Therefore, as S_t^{f-a} decreases it also becomes more attractive to manipulate:

$$\frac{\partial\left(\frac{\partial P^d}{\partial m_t}\right)}{\partial S_t^{f-a}} \leq 0 \Rightarrow \frac{\partial m_t}{\partial S_t^{f-a}} \leq 0 \tag{6a, 6b}$$

Everything else the same, Equations (6a) and (6b) lead to an increase in the MRT outlined in Equation (3) which then leads to an increase in manipulation. Figure 1.2 shows graphically how manipulation increases in this case. If the MRT is small enough then a corner solution exists and no manipulation occurs.

While Donaghy is still an NBA referee, the NBA appears to monitor the referees for officiating quality only and not for manipulative behavior:

> *Since the 2003 – 2004 season, the League has been collecting data on calls and non-calls for each of its referees. Although this system was developed for training and developmental purposes, we have worked…to develop a…system for screening games in an effort to detect* data patterns *that warrant further investigation.*[10]

Given the above quote, it is possible that while the NBA may fire a referee who is in fact manipulating, the manipulation would instead be seen by the NBA as low quality officiating so that $\frac{\partial P^d}{\partial m_t}$ is a constant in that it does not depend on t or S_t^{f-a}. That is, if the NBA does not detect for manipulation, then the context of the game when a "questionable" call is made is irrelevant from the NBA's perspective. Since $\frac{\partial P^d}{\partial m_t}$, L, B, and c are constant, it follows from Equation (3) that if $\frac{\partial P^w}{\partial m_t}$ increases because elapsed game time increases or the difference in the scores decreases, then a corruptible referee is more likely to manipulate or, having already committed to a strategy of manipulation, will manipulate more.

[10] Ibid., pg. ES 6

1.4 Key Assumptions and Hypothesized Behavior

Two broad assumptions are made in this chapter about what is bet and how manipulation takes place. First, it is assumed that some referees might place bets against the point spread.[11] If the market's predictions are unbiased, then a bet against the spread, absent inside information or the ability to manipulate, amounts to a coin flip.

Second, it is assumed that the referee who manipulates has one tool at his disposal: foul calling.[12] In particular, fewer fouls will be called against the team bet on and more fouls will be called against the team bet against when there is manipulation. In this case, the chances of winning the bet will increase for two reasons. First, more free throws than normal will be awarded to the team bet on and fewer free throws than normal will be awarded to the team bet against thus favoring the team bet on. Second, the team bet against will be forced to play less aggressive defense in order to prevent more fouls from being called against them to the point of player disqualification while the team bet on will be able to continue to play aggressive defense with less fear of disqualification.[13] The lessened ability of the team bet against to play its normal defense compared to the team's bet on continued ability to play its normal defense once again favors the team bet on.

How referees officiate games can be categorized into two distinct refereeing philosophies. One philosophy advocates that referees should officiate "by the book" so that rules are enforced regardless of the context of the game. The other philosophy,

[11] There is no mention of over-under betting in Pedowitz (2008) or Donaghy (2009).
[12] Price *et al.* (2009) refer to foul calling as a more pertinent measure of referee behavior as opposed to other calls where the rules are less open to interpretation, such as a shot clock violation.
[13] A player who is called for his sixth personal foul is ejected from the game.

called the "Tower Philosophy," advocates that referees should have more latitude in how they officiate so as not to unduly interfere with the pace of the game.[14] Therefore, over the course of a game, a referee who manipulates can migrate between the two philosophies to legitimize or obfuscate the manipulations.

Four hypotheses based on strategies intended to increase the probability of winning a bet without being detected are jointly tested. That is, all four of the hypotheses listed below must be satisfied in order for manipulation to take place.

Hypothesis One (H1): Announcement of Donaghy's betting and punishment in the summer of 2007 deters other referees from officiating in ways that are consistent with manipulation beginning with the 2007 – 08 season as they perceive the cost of manipulation has risen. Figure 1.3 shows this graphically.

Hypothesis Two (H2): Given Price, Remer and Stone's (2009) findings that referees generate increased fan interest, thus revenues, by officiating games in ways to keep the game outcomes in doubt for a longer period of time, the referee is more likely to place bets on games with small spreads since the expectation is that these games may need to be manipulated. If manipulation under these circumstances is condoned by the NBA, as is alleged by Donaghy (2009), then this might provide cover for referees who place bets on these games.

Hypothesis Three (H3): From Equation (5b), manipulation is more likely to occur later in the game when the impact a manipulation has on the betting outcome is more certain.

[14] Pedowitz (2008), pp. 42-44

Early in the game, the amount of uncertainty over the betting outcome would lead the referee to not manipulate since there either could be a reasonable enough chance that he could win the bet without manipulation or the impact of a manipulation early in the game can more easily be offset by unanticipated changes in conditions throughout the rest of the game.

Hypothesis Four (H4): From Equation (6b), manipulation is more likely to occur if the difference in the score between the two teams is sufficiently close to the point spread. If the referee is winning a bet by a large enough margin then he is relatively certain he will win the bet without manipulation. Therefore, he will not manipulate since the marginal benefit is small and less than the marginal cost from the additional manipulation. If the referee is losing a bet by a large enough margin then he is relatively certain he will lose the bet even with manipulation. He will not manipulate since the amount of manipulation needed to reverse the betting outcome is large and more likely to be detected. In this case, the referee concedes that the bet is lost.

1.5 Data

The sample is from all NBA games played in regulation time from the eight regular seasons from 2003 – 04 to 2010 – 11. The first four seasons of the sample correspond to the period of Donaghy's betting activity on NBA games. The second four seasons are used to test for changes in the other referees' behaviors given that Donaghy's behavior is detected. Point spread data is from a sports betting website, www.covers.com, and game data is from play-by-play files on www.espn.com[15]. There are a total of 8,234 games in the sample excluding games with missing or bad data. Game data includes: the teams, the three referees in charge of calling the game, when during the game each foul is called, when during the game the score changes, and the score of the game. Although there are 86 referees in the sample, evaluations are performed on Donaghy and the 36 referees who officiate games over all eight seasons in the sample.

Figure 1.4 graphs the empirical probability that a bet on a randomly selected team will win given the context of the game, specifically what time during the game and how far the actual game score between the two teams is from the spread. There are two features of the graph that are consistent with the hypotheses that are tested. Hypothesis H3 can be seen in the increasing certainty in the outcome of the bet, win or lose, as game time elapses. Hence, the impact of one act of manipulation is greater closer to the end of the game. Hypothesis H4 can be seen in the increasing certainty in the outcome of the bet as the score between the two teams deviate further from the spread. The larger the deviation, the less likely manipulation will take place.

Towards the end of a game, teams that are losing often commit fouls intentionally in order to stop the game clock and allow them more time to try to overcome the deficit. Thus, a perfectly legal tactic on the part of the players can be confused for manipulative behavior on the part of the referees. Figure 1.5 shows the standard deviation across all games in fouls called during 4th quarters in 15 second intervals. The variation appears to be fairly constant until there are 75 seconds left when it spikes. Considering this extra noise, the last 75 seconds of all games are omitted from the sample.

[15] I am greatly indebted to Joseph MacDougald for creating the database.

There are unobservables that could complicate model estimation.

- The games Donaghy bet on has not been revealed by the FBI.[16]
- The kinds of bets Donaghy placed has not been made public. Point spreads can vary among the different bookmakers, legal or illegal, presumably by a small amount. The consensus spreads in the data sample, therefore, may match or approximate the actual spreads bet on.
- Although the play-by-play data records when fouls are called during the course of a game and the identity of the three man referee crew is known, which specific referee calls which specific foul is not known.[17]

1.6 The Model

The broad question this chapter addresses is whether NBA referees bet on NBA games. The occurrence of bets placed is unobserved, however, referees who bet have incentives to manipulate the games bet on in order to improve their chances of winning the bets. However, such manipulation increases the chance of detection. With this in mind, the referee crew's observed behavior from play-by-play data will instead serve as a proxy for the unobserved bets.

Any manipulation should be restricted to those parts of the game where the benefits from manipulation exceed the costs, as hypothesized in H1 through H4. If this is the case then how fouls are called between the two teams should differ over the parts of

[16] Donaghy (2009) lists 12 games he claims to have bet on.
[17] The NBA has developed a proprietary database of calls made at the individual referee level (Pedowitz, pp. 48-51)

the game when manipulation is more and less likely to occur. If no manipulation takes place, then there should be no change in how fouls are called against the two teams.

Let FH and FA be the number of fouls called against the home and away teams during some portion of a game so that the difference in fouls called is $FH – FA$. This forms the basis for the measure of the referee's behavior but in itself is not informative without some context. First, $FH – FA$ is tallied over two parts of a game, one where manipulation is more likely to occur (part M) and the other where manipulation is less likely to occur (part L). Second, $FH – FA$ is converted into a rate, V, by dividing it by the amount of time from the part of the game the fouls are tallied over. Let $V_M = [(FH – FA) / t]_M$ be the rate at which fouls are called against the home team compared to the away team per unit time over the part of the game when manipulation is more likely to occur and $V_L = [(FH – FA) / t]_L$ be the rate when manipulation is less likely to occur. V_M and V_L are used to construct the metric of referee behavior relevant to manipulation called the *change in foul calling index (CFCI).*

$$CFCI = |V_M - V_L| \tag{7}$$

It is the magnitude, not the direction, of the change that is relevant, hence the use of absolute values. Everything else the same, larger values are hypothesized to indicate behaviors consistent with manipulation. Smaller values indicate that the referee's behavior does not change even though the marginal benefits and costs from manipulation do, thus it is unlikely in this case that manipulation is occurring. According to Hypothesis H3, the $CFCI$ should be larger in the later period of a game if there is manipulation. This is especially the case, according to Hypothesis H4, when the manipulation is assumed to take place if the difference in the opposing teams' scores relative to the point spread is close.

The *CFCI* could be measured over the entire game however conditions that have nothing to do with manipulation could change as the game progresses. To hold these other conditions constant and thus focus on the factors that are relevant to manipulation, the *CFCI* is measured over subsamples of the game so that each subsample has a unique part *M* and part *L*. For each game the *CFCI* is measured in two dimensions. Across the first dimension it is measured in the first and the second half of a game. Across the second dimension it is measured when part *M* is assumed to occur when the opposing teams' scores relative to the point spread is within three points and then again within nine points. One half of a game is 24 minutes long and to improve measurement reliability, part *L* and part *M* are set to be at least six minutes along. Some observations are lost since there are some games where part *M* or part *L* does not exist with the given parameters. If both parts exist then four different observations of the CFCI are generated for each game. Figure 1.6 illustrates the subsamples the *CFCI* are measured over.

Figure 1.7 is an example of how the *CFCI* is computed over the second half of a game that Donaghy refereed. In this case, manipulation is assumed to be more likely once the difference in scores between the two teams falls within three points of the spread. Within this region, 446 seconds of playing time elapsed with team A and team B called for one and nine fouls respectively. The remainder of the half, 919 seconds in duration, saw team A and team B called for six and four fouls respectively. Given the hypothesized behavior, this could suggest that manipulation is done to favor team A by calling more fouls against team B over the period when manipulation is more likely.

If a manipulative foul is called, it is not possible to know if the referee or the player is the manipulator. That is, either the referee unfairly calls a foul or the referee fairly calls a foul on a manipulative player. There are two reasons to believe this may not be a problem. First, since the players are more highly compensated than the referees, they are less likely to engage in manipulation.[18] This point is consistent with Preston and Szymanski's (2003) findings. Second, Price and Wolfers (2007) quote the NBA as saying that referee assignments are "completely arbitrary." Therefore, if there are player(s) who manipulate, every referee is equally exposed to them.

In the data, the number of fouls called is reported for the crew, not the individual referee, so that the value of $CFCI_g$ for game g is the same for all three referees in the crew. One way to estimate the marginal behavior of one referee apart from the crew is to use a multivariate regression with dummy variables that indicate the presence of each of the three referees in each game. The problem with this kind of regression is that tests of significance depend on the referee that is held out and used to estimate the constant term. However, using the assumption that the composition of referee crews is arbitrary, every referee is not only equally exposed to player(s) but also to referee(s) who manipulate. Therefore, it is not necessary to account for the identities of the three referees in each game's referee crew. Equation (8) tests for hypotheses H1 through H4 individually, and is estimated separately for each of the k referees under evaluation.

[18] In 2007, the average salary for NBA referees is approximately $200,000 (http://www.cnbc.com/id/19876494, accessed on June 6, 2012) and for players it is approximately $4,300,000 (http://content.usatoday.com/sportsdata/basketball/nba/salaries/team/2007 accessed on June 6, 2012).

$$dCFCI_{gk} = \alpha_0 + \alpha_1\,\delta_{1gk} + \alpha_2\,\delta_{2gk} + \alpha_3\,\delta_{3gk} + \alpha_4\,\delta_{4gk} + \varepsilon_{gk} \tag{8}$$

$dCFCI_{gk}$ is a dummy variable that equals one if the value of $CFCI_{gk}$ is within the highest 50th percentile across the entire sample, zero otherwise. The choice of the percentile is based on not knowing what level of the *CFCI* is more likely to constitute manipulation. However, at a minimum it seems reasonable that such a level should be above average. δ_{1gk}, δ_{2gk}, δ_{3gk} and δ_{4gk} are dummy variables that are used to test for H1, H2, H3 and H4, respectively, and equal one under circumstances where manipulation is hypothesized to be more likely. δ_{g1} equals one if game g is played during the first four seasons of the sample when Donaghy is still officiating, zero otherwise. δ_{g2} equals one if the absolute value of the point spread on game g is less than or equal to three points, zero otherwise. δ_{g3} equals one if the *CFCI* is calculated over the second half of game g, zero otherwise. δ_{g4} equals one if the boundary that separates part L, the period of game g where manipulation is hypothesized to be less likely, and part M, the period of game g where manipulation is hypothesized to be more likely, is three points, zero if the boundary is nine points.

Appending interaction terms to Regression (8) gives:

$$dCFCI_{gk} = \alpha_0 + \alpha_1\,\delta_{1gk} + \alpha_2\,\delta_{2gk} + \alpha_3\,\delta_{3gk} + \alpha_4\,\delta_{4gk} +$$
$$\beta_{1k}\,\delta_{1gk}\,\delta_{2gk} + \beta_{2k}\,\delta_{1gk}\,\delta_{2gk}\,\delta_{3gk} + \beta_{3k}\,\delta_{1gk}\,\delta_{2gk}\,\delta_{3gk}\,\delta_{4gk} + \varepsilon_{gk} \tag{9}$$

The variable of interest is the interaction term $\delta_{1gk}\ \delta_{2gk}\ \delta_{3gk}\ \delta_{4gk}$ that equals one if all hypothesized conditions for manipulation to occur are met. The null hypothesis that a referee does not manipulate is $\beta_3 \leq 0$.

1.7 Results

Given the binary nature of the dependent variable, $dCFCI_{gk}$, probit modeling is used to estimate the regression coefficients. Table 1.1(a) records the occurrence of coefficients from Regressions (8) and (9) that reject the null hypothesis that β_3 is less than or equal to zero at the 5% level. The first column shows that several of the referees evaluated have likelihood ratio chi-squared tests that are significant. Therefore, it may help the explanatory power of the model to include these dummy variables individually.

Of the 37 referees under evaluation, Donaghy and three other referees (identified in this chapter as referees #16, #23, and #73) have β_3's that are significantly positive, thus suggesting that they are reacting to the hypothesized changes in game conditions by manipulating. However, there are two reasons to suspect that this count is too high. The first reason is that with 37 referees at the 5% level of significance approximately two referees can be identified merely by statistical chance. The second reason is that the choice of the *dCFCI* that identifies the highest 50% of the *CFCI* in the sample may be too liberal, thus increasing the chance of a type I error.

There are two other noticeable results from Table 1.1(a). First, there are seven α_1's from Regression (8) and six α_1's from Regression (9) that are significant suggesting that the corresponding referees are manipulating games at the same time Donaghy is betting on NBA games but they are doing it in ways not hypothesized. Second, there are ten α_3's from Regression (8) and seven α_3's from Regression (9) that are significant. These referees appear to be reacting to increasing returns to manipulation when the game progresses only, without regard to other hypothesized game conditions. This particular result may support Price, Remer, and Stone's (2009) findings that some manipulation is done to keep the scores close in order to generate fan interest given that the referees have a better idea which game is worth manipulating later in the game.

Table 1.1(b) presents the significantly positive coefficients estimated over the second half of the sample after Donaghy's betting is detected. The three referees besides Donaghy who have significant β_3's when Donaghy is betting on games lose their significance after Donaghy is detected. This is consistent with the hypothesis that Donaghy's detection and punishment deters further manipulation from these referees. However, the β_3's for three other referees (#21, #71, and #85) become significant after Donaghy is expelled. This result is unexpected since the deterrence that affects referees #21, #71, and #85 should affect all referees in the sample. Therefore, it is more likely that this is a Type I error for reasons discussed at the beginning of this section. Like Table 1.1(a), Table 1.1(b) shows that there are a number of referees who have significant values for α_3 so that even after Donaghy is penalized manipulation appears to take place later in games. This also supports Price, Remer, and Stone (2009) if an NBA mandate to manipulate games in order to keep the games close is always in effect.

1.8 Conclusion

By design, illicit behavior is often difficult to detect or not directly observable. According to economic theory, agents who commit such acts are mindful of the benefits and costs of their actions and will seek to maximize their expected net gains. Detection systems can use the theory to deduce the kinds of behaviors consistent with crime or corruption from observable data.

This chapter describes an application of such a system that is used to test for in-game behaviors of NBA referees that suggest manipulation of game results meant to increase the chance of winning a bet placed on the same game. A baseline measure of fouls called against the opposing teams are tallied during a part of a game when manipulation is hypothesized to be less likely to occur and compared to a tally over another part of the game when manipulation is hypothesized to be more likely to occur. Referees who are manipulating change how they officiate based on these conditions.

An econometric model designed with these concepts in mind finds that Tim Donaghy behaved in ways consistent with manipulation, however the model identifies three other referees, both during and after the period of time Donaghy bets on NBA games. Manipulation for betting purposes after Donaghy is identified does not follow from economic reasoning. Instead, it is more likely that a Type I error has occurred due to the design of the measure of manipulation. The model also identifies several referees who are exploiting the increasing returns to manipulation as game time elapses. In the absence of other hypothesized conditions, this result is consistent with the idea that manipulation is done for reasons unrelated to betting, such as to increase NBA profits.

If it is true that the Type I error is large then the model may need to be redesigned so that it is a better filter, although the level of complexity needed to accomplish this may require more than the information given in the play-by-play data. Other assumptions made in this chapter, such as only accounting for point spread betting, may be invalid. Relaxing these assumptions places additional demands on the model that may lie outside what it can do with the given data. However, it is encouraging that this model can be used to infer betting behavior from a known bettor.

CHAPTER 2: A TEST OF EFFICIENCY AND SPORTS BOOK PROFITS IN THE NFL POINT SPREAD BETTING MARKETS USING CIRCADIAN ADVANTAGE

2.1 Introduction

The Efficient Market Hypothesis (Fama 1970), or EMH, formalizes the concept that securities prices fully reflect all available information so that abnormal profits cannot be made. The EMH has gone through many tests in several financial markets. Additional tests have been conducted in the sports betting markets due to a number of shared characteristics with the financial markets. Sports bettors, making use of the relevant information on hand, place wagers on certain sporting outcomes occurring if they believe that the outcomes' odds are "underpriced" or "overpriced." Some of these tests have rejected the EMH. More recent research suggests that sports books who take wagers often offer odds that are perceived as underpriced to uninformed bettors but are, empirically speaking, overpriced. By restricting the amount informed bettors can wager, sports books can manage an unbalanced ledger with most of the amount wagered on what tends to be a losing bet. The surplus of betting amounts lost after the winning bets are paid off is retained by the sports books as profits in addition to commission fees.

The purpose of this chapter is twofold. First, to test the EMH by determining if the National Football League (NFL) point spread betting markets make use of the impact on relative performance between teams based three time zones apart due to differences in their circadian rhythms. The impact that travel across time zones has on athletic performance has been documented many times in the medical literature. Whether or not this piece of information is embedded in the NFL point spreads has not yet made its way into the economic literature. Second, this chapter examines betting patterns that can determine if sports books are profiting from this one piece of information.

Section 2 is a basic primer on sports betting terminology that will be used throughout the chapter. Section 3 reviews the relevant literature. Section 4 discusses the theoretical model. Section 5 describes and summarizes the data. Section 6 reports the results and Section 7 offers an interpretation of the results. Section 8 lists the conclusions.

2.2 Sports Betting Primer

The focus of this chapter is on wagers placed on National Football League (NFL) games. Given a game between two teams, the team that is predicted to win is called the *favorite*, and the team that is predicted to lose is called the *underdog*. The number of points that the favorite is predicted to score less that of the underdog is defined here to be the *point spread*, or *spread* for short, although the spread is usually defined to be the negative of what is used here.

A bettor who places a wager on the favorite to beat the spread wins the wager if the favorite beats the underdog by an amount greater than the spread. A bettor who places a wager on the underdog to beat the spread wins the wager if the underdog either loses by an amount less than the spread or unexpectedly beats the favorite. Games with spreads equal to zero are called *pick 'ems,* and games where the favorite wins by an amount equal to the spread are called *pushes*. In the event of a push all money is returned to the original bettors.

Determination of the favorite, underdog, and spread is initially made by a person called an *odds maker* who considers various factors that can, in general, explain the relative skill between the two teams. The odds maker transmits his product to *sports books* who take bets throughout Nevada, the only state in the United States where betting on NFL games is legal.[19] NFL games, for the most part, take place on Sundays and betting on those games begin on the previous Monday. Bettors pay a commission fee called a *vigorish,* or *vig* for short, to the sports book to place a wager. The vig typically follows an 11-for-10 standard such that a bettor who places an \$11 wager either returns \$10 for a win or −\$11 for a loss. Thus, the breakeven probability of winning a spread bet, *p,* is determined from:

$$p\ (\$10) + (1 - p)\ (-\$11) = 0 \tag{1}$$

So that *p* is approximately 52.4%.

The spread can change during the week prior to the game given the relative amounts wagered on both sides of the spread, as often occurs when new information

[19] I assume that the results of this chapter are not affected by illegal sports books.

about the two teams is made available to the betting market. Conventional thinking, and not necessarily what is practiced, is that the spread is adjusted throughout the week by the sports book such that the amounts bet on either side of the spread are equal to each other. If the sports book is able to achieve this, then the winning bets are paid off, dollar-for-dollar, by the losing bets with the sports book receiving the vig from all losing bettors. If the total winning amount exceeds the total losing amount, then the sports book may suffer a loss if the shortage it has to make up for on its own could exceed the vig it collects from all losing bettors. On the other hand, if the total losing amount exceeds the total winning amount, then the sports book enjoys a profit above the vig equal to the surplus.

In general, if equal amounts of money are beat on each team then the sports book initially collects an amount $2b(1 + v)$ where b is the amount bet on one team before paying the vig and v is the vig as a proportion of b. The winning bettors earn a total of $b(1 + v) + b$, thus leaving the sports book's absolute earnings at bv and earnings relative to the pot at $v / [2(1 + v)]$. Given the 11-for-10 vig, the sports books' return is approximately 4.5%.

2.3 Relevant Literature

Fama's (1970) semi-strong form efficient markets model hypothesizes that securities prices fully reflect all publicly available information. It is this form of the EMH that is the most relevant to this paper. Fama posits that while costless information is a sufficient condition for capital market efficiency, it is not necessary so that from an operational perspective capital market efficiency is possible even when there are information or transactions costs. Cornell and Roll (1981) expand on the definition by proposing that in an efficient market, while gross returns earned by informed investors may exceed that of uninformed investors, net returns between the two groups should be the same after taking into account costs the informed investors bear to acquire information.

The semi-strong form of the EMH has been tested many times. For instance, Ball and Brown (1968) find that stock returns of firms that report earnings that are different from market expectations experience a post-announcement "drift". In particular, stocks of companies that report earnings above expectations yield above average cumulative returns, and stocks of companies that report earnings below expectations yield below average cumulative returns for at least six months after the announcement is made. Basu (1977) finds that the risk-adjusted returns of portfolios made up of low price to earnings stocks tend to outperform the risk-adjusted returns of portfolios made up of high price to earnings stocks, although the difference becomes insignificant when transactions costs and taxes are accounted for. Banz (1981) finds that the risk-adjusted returns of small market capitalization stocks are significantly higher than the risk-adjusted returns of large market capitalization stocks, although he is not entirely willing to conclude that the EMH is violated. One possible explanation he offers is that investors may find it more difficult to estimate the true value of a small capitalization stock compared to a large capitalization stock, hence the investor would want to be compensated with higher expected returns. Roll (1984) finds that the price returns of orange juice futures contracts can predict some of the variation in temperature forecast errors made by the National Weather Service (NWS), hence the returns can be used to improve the accuracy of NWS forecasts. The amount of information transmitted, however, is muted by institutional limits that constrain how much prices can change.

Fama and French (1992) observe that stocks with high book-to-market ratios have risk-adjusted returns that tend to outperform stocks with low risk-adjusted book-to-market ratios, although Fama and French interpret book-to-market to be a proxy for risk and not a rejection of the EMH. On the other hand, Daniel and Titman (1995) find that the returns to book-to-market are independent of risk as measured by beta.

Brown and Hartzell (2001) study the behavior of stock prices for the Boston Celtics when information is publically announced. They find some results that are difficult to explain such as the asymmetric response of the stock price to the team's game performance: the stock price tends to fall after losses but also tends to show no reaction to wins. Brown and Hartzell also focus on two events and their impact on the Celtics' stock price. First, the stock price does not move appreciably on the news of a new stadium that ends up generating considerable profit. Second, the stock price increases more than 8% on heavy trading volume when a new head coach is announced.

Pankoff (1968) is the first to test for market efficiency in the NFL point spread betting markets. He evaluates betting strategies that make use of "expert" analysts' game predictions and finds that while they can be used to improve the chances of winning a bet versus the spread, it is not enough to profit net of transaction costs. Pankoff concludes that market efficiency cannot be rejected, at least in this case, although he also believes that it may be possible to make better use of the experts' predictions to create more profitable betting strategies.

Vergin and Scriabin (1978) uncover some simple betting strategies on NFL games, such as betting on large underdogs, during 1968-74 that are marginally profitable after accounting for commission fees bettors pay the sports books to place bets. Tryfos, Casey, Cook, Leger, and Pylypiak (1984) use 1975-81 as their sample period and find that three of 70 candidate strategies also evaluated by Vergin and Scriabin are profitable. They point out, however, that at the 5% level of significance roughly three strategies would be measured as profitable merely by chance so that in a statistical sense, there are no profitable strategies.

Golec and Tamarkin (1991) discover a modestly profitable NFL betting strategy that favors bets on teams that are home underdogs over a 1973-87 sample period although Gray and Gray (1997) find that the strategy loses its effectiveness over a later sample period. Dare and MacDonald (1996) address some econometric shortcomings from Golec and Tamarkin, as well as Gray and Gray, and find that the home underdog strategy does not profit in a statistically significant way. Dare and Holland (2004) further refine Dare and MacDonald's econometric model while also confirming their results. Borghesi (2007a) evaluates the home underdog strategy on a weekly basis and finds that it is more effective in games played later in the season.

Other tests of the EMH applied to the NFL betting markets include Vergin and Sosik's (1999) Monday Night Football and playoff game effects that demonstrate significant market underpricing of the home team, and Boulier, Stekler and Amundson's (2006) result that differences in stadium characteristics between the home and visiting teams does not add any profitable information. Borghesi (2007b) finds that bets placed on home teams that are based in colder climates tend to win when the visiting team is based in warm climates, thus the market underprices the impact of cold weather acclimitization.

Some explanations have been offered to account for inefficiencies in the betting markets. Gandar, Zubar, O'Brien, and Russo (1988) and Golec and Tamarkin (1991) point out that wagers from informed bettors are outweighed by wagers from uninformed bettors, and Gandar, Zubar, and Russo (1993) write that Las Vegas sports books raise obstacles to restrict wagers from informed bettors.[20] Likewise, Borghesi (2007a) reasons that limits placed on arbitrageurs can explain why the late season home underdog bias has persisted over time.

Most of these studies assume, in the absence of empirical data, that point spreads are set and adjusted in order to equate the amounts wagered on each team. For instance, Vergin and Scriabin (1978) write that the intent of the sports book is to, "…assure that approximately equal amounts are bet on each side…," and Boulier *et al*. (2006) write, "The betting spread on NFL games is intended to balance the size of the bets placed on the home and visiting teams." However, Levitt (2004) observes from an online NFL point spread betting competition[21] that about half of the games played had at least two thirds of the money wagered placed on one team. In games involving a visiting favorite, an average of 68% of the betting amounts are on that team. Since bets on the home underdog tend to win, Levitt concludes that the bookmaker generates profits by knowing what kinds of biases bettors are prone to lean towards, and maintains point spreads to exploit these biases. One shortcoming with the data Levitt uses is that all bets are the

[20] Andrew Patterson, an odds maker at Las Vegas Sports Consultants, estimates that 20% of all bettors are informed. Konik (2006) chronicles sports books efforts to restrict wagers placed by a wealthy, informed sports bettor who tries to conceal his identity.

[21] Bettors compete against each other and wager equal amounts in every game bet. Therefore, the percent of bets placed on one team is the same as the percent of money wagered on one team.

same amount, a constraint that is not the norm. Paul and Weinbach (2007) make use of betting data without the constraint but do end up supporting Levitt's results.

This chapter tests for the use of information that comes from a field of medical research called chronobiology which deals with the cyclical nature of many basic psychophysiological functions. Winget, DeRoshia, and Holley (1985) summarize various studies that measure cognitive, neuromuscular, and cardiovascular functions, among others. Not surprisingly, the studies show that the human body's performance peaks during daylight and usually within late afternoon hours.

Jehue, Street, and Huizenga (1993) evaluate the performance of NFL teams by time zones the visiting teams travel to arrive at the home team site, and find that for games played at night Eastern Time (ET) between Pacific (henceforth WC for west coast) versus Eastern (henceforth EC for east coast) Time Zone teams during 1978-87, the WC teams win 69% of the time regardless of where the game is played. This is consistent with the hypothesis that the outcome of a game should favor the team whose players' circadian rhythms are closer to late afternoon. Jehue *et al*., however, do not account for the confounding effect that the WC teams could be better than the EC teams, time zone differences aside. Smith, Guilleminault, and Efron (1997) attempt to control for this by evaluating a simple betting strategy of always betting on the WC teams to beat the point spread versus EC teams during Monday Night Football games where the point spread can be thought of as the expected difference in quality between the opposing teams. Such a strategy wins 68% of the time over 1970-94. Smith *et al*. are not concerned about betting market inefficiency. Instead, they explain the profitable strategy as essentially being equal to what they dub the "circadian advantage".

2.4 Statistical Tests of Efficiency

Pankoff's (1968) model is implicitly based on rational expectations as formalized by Muth (1961):

$$ACT_{v\text{-}h} = \beta_0 + \beta_1\, SPR_{v\text{-}h} + \varepsilon \tag{2}$$

where $ACT_{v\text{-}h}$ is the actual difference in the points scored between the visiting team minus the home team and $SPR_{v\text{-}h}$ is the corresponding spread. $\beta_1 < 1$ means that bets on the home team to beat the spread tend to win, and for $\beta_1 > 1$ the same holds for the visiting team. Zubar, Gandar, and Bowers (1985) explicitly model Equation (2) and run an F-test on the joint null of $\beta_0 = 0$ and $\beta_1 = 1$ over the 1983 NFL season. They do not reject the null and thus conclude that the betting market is efficient.

Amoako-Adu, Marmer, and Yagil (1985) reverse Equation (2) so that *ACT* is used to explain the variation in *SPR*. They conclude that, "…there is very little connection between closing spreads and actual game outcome…" because the slope coefficient is only 0.04 over their sample period of the 1979 – 1981 NFL seasons. However, their model assumes that var(*SPR*) > var(*ACT*), something that is not evident in the data. Sauer (1998) points out that Amoako-Adu *et al.*'s findings are based only on the fact that the variance of *ACT* is much larger than that of *SPR*. The estimator for the slope coefficient in Equation (2) is cov(*SPR*,*ACT*) / var(*SPR*) and in Amoako-Adu *et al.*'s specification it is cov(*SPR*,*ACT*) / var(*ACT*). Figures 2.1(a) and (b) show the slope coefficient using Pankoff's (1968) specification is 1.0 and Amoako-Adu *et al.*'s specification is 0.17 over the sample data used in this chapter, thus var(*ACT*) is about six times greater than var(*SPR*).

While Equation (2) has an intuitive appeal, it has two main drawbacks. First, it is a weak test of efficiency. There are potentially many exploitable biases that have been omitted from the regression that could offset and, when aggregated, produce non-rejection of the null. Second, the relative nature of the scores between the opposing teams complicates model design and estimation. As Gandar *et al*. (1988) point out, a *home team difference* definition where the (implied) away team score is subtracted from that of the home team results in different regression estimates compared to a *favorite team difference* definition where the (implied) underdog team score is subtracted from that of the favorite.[22]

To address these shortcomings, Golec and Tamarkin (1991) design a more powerful test by including other potential biases into Equation (2):

$$ACT = \beta_0 + \beta_1\, HOME + \beta_2\, FAV + \beta_3\, SPR + \varepsilon \qquad (3)$$

where *HOME* and *FAV* are binary variables that equal one for the home and favorite teams, respectively, otherwise they equal zero. The joint null of efficiency becomes $\beta_0 = \beta_1 = \beta_2 = 0$ and $\beta_3 = 1$. Depending on the differencing definition used, however, either *HOME* or *FAV* will be a unit vector. This introduces a singularity that makes Equation (3) inestimable. Golec and Tamarkin seek to avoid this problem by randomly selecting the differencing definition across games so that roughly half of the sample is based on the home team difference and the rest on the favorite team difference, although in doing so

[22] Terminology from Dare and MacDonald (1996).

they generate different estimates each time the regression is run. In interpreting the regression results, they recognize that symmetric strategies, such as a bet on the favorite team versus a bet on the underdog team, have symmetric coefficients so the negative coefficient on *FAV* also means that a bet on the underdog tends to win.

Dare and MacDonald (1996) note that while Golec and Tamarkin (1991) are careful to apply the same differencing definition to *ACT* and *SPR* within the same game, they do not account for the fact that the same differencing definitions can affect the signs of the coefficients on *HOME* and *FAV* in different ways. For example, if a favorite team differencing definition is used for a certain game, and the away team is favored to win, then the coefficient on *HOME* should be multiplied by −1. This reasoning leads to the following from Dare and MacDonald:

$$ACT_{f\text{-}u} = \beta_0 + \beta_1 H + \beta_2 SPR_{f\text{-}u} + \varepsilon \tag{4}$$

where *ACT* and *SPR* are in terms of the difference between the favorite's (implied) score less that of the underdog. $H = 1$ if the home team is the favorite, and −1 if the visiting team is the favorite. If none of the games in the sample are pick 'ems, pushes, or played at a neutral site, then β_0 is the favorite team bias and β_1 is the home team bias. The use of H eliminates the singularities faced in Equation (3) so that Equation (4) is estimable with the use of one differencing definition across the entire sample.

Dare and Holland (2004) point out an unrealistic restriction that Dare and MacDonald (1996) implicitly make. The joint home/favorite and home/underdog biases, according to Equation (4), are:

$$\beta^{HF} = \beta_1 + \beta_0$$

$$\beta^{HU} = \beta_1 - \beta_0$$

which can be added together to form the overall home team bias:

$$\beta^{H} = (1/2)\,\beta^{HF} + (1/2)\,\beta^{HU} \tag{5}$$

However, empirically speaking, home teams are more often the favorite than the underdog. Dare and Holland's solution to this discrepancy is to treat the four home/visiting and favorite/underdog combinations as separate biases. Assuming a favorite team differencing, the model with favorite team differencing is:

$$ACT_{f\text{-}u} = \alpha^{HF}\,HF + \alpha^{VF}\,VF + \beta\,SPR_{f\text{-}u} + \varepsilon \tag{6}$$

where *HF* or *VF* equals one if the favorite team is the home or visiting team, respectively, and zero otherwise. α^{HF} is the joint home/favorite bias, the negative of which is the visiting/underdog bias, and α^{VF} is the joint visiting/favorite bias, the negative of which is the home/underdog bias.

Equation (6) can be restated in terms of the betting market's forecast error by subtracting *SPR* from both sides:

$$ACT_{f\text{-}u} - SPR_{f\text{-}u} = \alpha^{HF}\,HF + \alpha^{VF}\,VF + (\beta - 1)\,SPR_{f\text{-}u} + \varepsilon \tag{7}$$

However, the more relevant variable to study is not necessarily the magnitude of the forecast error, but whether or not a bet wins, as reasoned by Gray and Gray (1997). Letting W_f be a binary variable that equals one for a winning bet on the favorite against the spread and zero otherwise, Dare and Holland's (2004) model becomes:

$$W_f = \alpha^{HF} HF + \alpha^{VF} VF + (\beta - 1)\, SPR_{f\text{-}u} + \varepsilon \qquad (8)$$

If the market is unbiased, then HF, VF and $SPR_{f\text{-}u}$ should have no ability to explain variations in the occurrence of a winning bet. The null hypothesis is, therefore, $\alpha^{HF} = \alpha^{VF} = \beta - 1 = 0$.

To account for Borghesi's (2007a) finding of the late season home underdog bias, binary variable δ equals one for games played after week 14 and zero for all other weeks.

$$W_f = (\alpha^{HF} + \gamma^{HF} \delta)\, HF + (\alpha^{VF} + \gamma^{VF} \delta)\, VF + (\beta - 1)\, SPR_{f\text{-}u} + \varepsilon \qquad (9)$$

where γ^{HF} and γ^{VF} are the changes in the home/favorite and visiting/favorite bias, respectively, during late season games. If the home underdog bias exists throughout the NFL season then $\alpha^{VF} < 0$ and $\gamma^{VF} = 0$, and if the bias exists only late in the season then $\alpha^{VF} = 0$ and $\gamma^{VF} < 0$.

To properly estimate the circadian advantage bias, other potential biases should be accounted for at the same time, thus the use of Equation (9) as a foundation to which the circadian advantage strategies are added. One strategy involves betting on games played in the evening (ET), as identified by Smith *et al*. (1997). A second strategy involves betting on games played in the late afternoon (ET). In this case, and regardless of the game's location, the EC team has the circadian advantage since its players' circadian rhythms are at the late afternoon peak compared to the players from the opposing WC team whose circadian rhythms are three hours before peak. A third strategy involves betting on games played in the early afternoon (ET) where, regardless of the game's location, the EC team has the circadian advantage, at least in a relative sense, since its players' circadian rhythms are three hours closer to the late afternoon peak than the WC team's players' circadian rhythms. These strategies can be summarized like so:

S_1: bet on WC team for games played in the evening (ET)

S_2: bet on EC team for games played in the late afternoon (ET)

S_3: bet on EC team for games played in the early afternoon (ET)

Considering the favorite team differencing used here, the circadian advantage strategies can also be stated as the following:

S_1: For evening games (ET):

bet the favorite if the favorite is a WC team (S_{1F}).

bet the underdog if the favorite is an EC team (S_{1U}).

S_2: For late afternoon games (ET):

bet the favorite if the favorite is an EC team (S_{2F}).

bet the underdog if the favorite is a WC team (S_{2U}).

S_3: For early afternoon games (ET):

bet the favorite if the favorite is an EC team (S_{3F}).

bet the underdog if the favorite is a WC team (S_{3U}).

Letting S_i, S_{iF}, and S_{iU} for i = 1, 2 or 3, be binary variables that equal one if one of the above sub-strategies is used, and zero otherwise, each pair of sub-strategies is combined by making the following restrictions for strategy i: For games involving a circadian advantage, $S_i = 1$ if $S_{iF} = 1$ and $S_i = -1$ if $S_{iU} = 1$. If no circadian advantage exists then $S_i = 0$. These circadian advantage strategy variables are then added to Equation (9):

$$W_f = (\alpha^{HF} + \gamma^H \delta)\ HF + (\alpha^{VF} + \gamma^V \delta)\ VF + (\beta - 1)\ SPR_{f\text{-}u} + \rho_1 S_1 + \rho_2 S_2 + \rho_3 S_3 + \varepsilon \quad (10)$$

The joint null hypothesis of market efficiency is that all of the regression coefficients in Equation (10) equal zero.

2.5 Data

Game data including point spreads is downloaded from covers.com, and the start time for each game is downloaded from pro-football-reference.com. The sample period is the 22 NFL regular seasons from 1988 – 2009. There are a total of 5,096 observations after excluding games with missing data, 10 neutral site games, 46 pick 'ems, and 147 pushes.[23] I account for the end of Daylight Savings Time which usually occurs around the middle of the NFL season. In addition, I also account for the nonobservance of Daylight Savings by the team based in Arizona throughout the sample period, as well as the team based in Indianapolis until the 2006 season.

Most NFL games begin at one of three different times; approximately 1:00, 4:00, and 9:00 p.m. ET. Table 2.1 presents the start time intervals used in this chapter, as well as the number of observations, for each circadian advantage betting strategy. Four hundred sixty-one games, or approximately 1% of the sample, involve a form of circadian advantage as defined in the previous section.

Data compiled by Sportsinsights.com is used to look for patterns in the proportion of money bet on each side of the spread, like Paul and Weinbach (2007), that involve games with a circadian advantage. The compiled data is drawn from six online betting sites. It is assumed that the bettors' behaviors as well as the spreads offered on these sites are not significantly different from other sports books like those in Nevada. The data includes the three NFL regular seasons from 2005 – 2007 for a total of 739 observations excluding those that are missing. Sixty-eight of these observations involve games where a circadian advantage exists.

[23] Since the regression is in terms of home/visitor and favorite/underdog, neutral site games, pick 'ems, and pushes are excluded since these would show up in the constant term. Excluding these slightly simplifies the model without loss of information.

2.6 Results

2.6.1 Statistical Test of Circadian Advantage Unbiasedness

Given that W_f is a binary variable, a probit model is used to estimate the regression coefficients as do Gray and Gray (1997). The estimates for Equation (10), with *p*-values in brackets, are:

$$W_f = \underset{[0.617]}{(0.0078} + \underset{[0.637]}{0.0104} \, \delta) \, HF + \underset{[0.422]}{(0.0135} - \underset{[0.032]}{0.0672} \, \delta) \, VF - \underset{[0.049]}{0.0040} \, SPR_{f\text{-}u} +$$

$$\underset{[0.015]}{0.1580} \, S_1 + \underset{[0.463]}{0.0223} \, S_2 + \underset{[0.872]}{0.0076} \, S_3 \qquad (11)$$

The likelihood ratio chi-squared statistic for the test of joint exclusion is 20.62 which has a *p*-value of 0.008, thus the null hypothesis of betting market efficiency can safely be rejected. The estimated coefficient on late season *VF* is statistically significant at the 5% level, and supports Borghesi's (2007a) finding that the home underdog bias is a late season phenomenon. While the estimated coefficient on *SPR* is also statistically significant at the 5% level, its magnitude is not of any economic significance. As for the circadian advantage coefficients, only the evening strategy S_1 is statistically significant at the 5% level. The insignificance of the afternoon strategies S_2 and S_3 could mean that either these circadian advantages exist and are correctly priced by the market, or they do not exist, although it is unlikely that if they do exist that the market would unbiasedly incorporate them into the spread in the afternoon and not in the evening. Instead, this could be taken as evidence that the circadian advantage is asymmetric in that the disadvantaged team that plays in the afternoon (ET) suffers significantly less than the disadvantaged team that plays in the evening (ET).

Given other covariates that are at their means, there are two marginal impacts that are economically significant. The late season home underdog strategy has a marginal effect of decreasing the probability of winning a bet placed on the favorite by approximately seven percentage points. The marginal effect of using the evening circadian advantage strategy on the probability of winning a bet on the favorite is an increase of 16 percentage points.

2.6.2 Effectiveness of the Evening Circadian Advantage Strategy

Table 2.2 shows the yearly record of the strategy. The success rate of 0.651 for the strategy over the entire sample period is similar to those found in Smith *et al.*'s (1997) 1970 – 1994 sample. Assuming that the results from Smith *et al*. are unknown to the betting market before its publication, the publication of their study appears not to have diminished the effectiveness of the strategy. A Wilcoxon signed-ranks test is applied to the results in Table 2.2 to test the hypothesis that the observed winning percentage does not exceed breakeven on a year-by-year basis, and yields a Z-score of 1.8 which is significant at the 5% level.

2.6.3 Evening Circadian Advantage Betting Patterns

For the sports books to profit from the evening circadian advantage bias, more money would have to be bet on the EC team than on the WC team. Since bets on the WC team tend to win, there would be a surplus of money from the losing bets placed on the EC team that is then retained by the sports books. The data from Sportsinsights.com can be used to see if this is happening.

For comparison's sake, Figure 2.2 is a benchmark distribution of the proportion of money bet on a randomly selected team over all games in the sample. As an example for how to interpret the graph, the middle bar shows that for about 17% of the games in the sample roughly half of the money bet is on the randomly selected team. Under these circumstances the sports book runs little risk of losing money. However, the tails of the distribution shows that there are some occasions when as little as approximately 10% or as much as approximately 90% of the money wagered is on the randomly selected team. In these cases, the sports book runs a large risk of losing money. As should be the case, no bias is evident as the distribution appears to be symmetric and its mean value is 0.487. Figure 2.3 is the distribution of the proportion of money bet on the visiting favorite. Given the well-documented bias in favor of the home underdog, the sports books profit by setting the spread such that most of the money wagered is on the visiting favorite. Such is the case here as the proportion of money bet is heavily skewed towards the visiting favorite with an average proportion of 0.633. This confirms findings from Levitt (2004) as well as Paul and Weinbach (2007).

If the sports books profit from the circadian advantage bias the same way it does from the visiting favorites then the same kind of skewness should show up in the direction of the EC team. Figure 2.4 is the distribution of the proportion of money bet on the EC team for games where an evening (ET) circadian advantage exists. There are only nine observations in the sample although none of them involve a game where a significant amount is bet on the WC team. The mean proportion of money bet on the EC team is 0.626 thus allowing for conditions where the sports books profit.

Perhaps Figure 2.4 does not illustrate a circadian advantage bias but instead a general bias skewed towards EC teams. Some of the EC teams are based in very large cities (such as the teams based in New York, Philadelphia and Atlanta) and perhaps have more fans who may place bets on their home teams out of reasons of sentiment. If this is true, then the skewness should also be present for the afternoon (ET) circadian advantage strategies. As Figure 2.5 shows, this turns out to not be the case since the distribution of the proportion of money bet on the EC team appears to be fairly symmetric with a mean value of 0.486.

To summarize the results, there is statistically significant evidence that the NFL point spread betting market inefficiently uses the information contained in the circadian advantage for games played in the evening (ET). The success of a bet based on the evening game circadian advantage wins at a rate that is statistically significantly greater than breakeven. Lastly, there is a tendency for the bulk of betting money to be placed on the disadvantaged EC teams.

2.7 Interpretation of Results

There appear to be informed bettors who are aware of the circadian advantage, as shown in these quotes from ESPN.com and covers.com, respectively:

> *What we've seen this season is the problem of West Coast teams playing at 1 p.m. on the East Coast. Body clocks of West Coast players have trouble adjusting in the East. They are playing games at an hour when they are normally leaving pregame meals or heading to stadium.*[24]

> *Performance on many cognitive and motor tasks peaks in late afternoon. Teams travelling west to east to play night games are playing with their biological clocks set earlier, close to the most favorable time, and teams traveling from east to west are playing at relatively later point in their biological "day," conferring a relative handicap.*[25]

However, the existence of a circadian advantage bias suggests that not all bettors are informed, such as perhaps those who rely on measures of sentiment described by Avery and Chevalier (1999). This also means that those who are informed are unable to arbitrage away the bias. These points are consistent with Gandar *et al*. (1988), Golec and Tamarkin (1991), Gandar *et al.* (1993), and Borghesi (2007a).[26]

Even though informed bettors who are aware of the circadian advantage may have lower betting limits than the uninformed bettors, they still send a signal, albeit a restricted one, to the sports books. The sports books do not have to know anything specific about the circadian advantage: They only need to know which team the informed bettors prefer.

[24] John Clayton (Oct 8, 2008), "Long trips force teams to try three-time-zone defense," http://sports.espn.go.com/nfl/columns/story?columnist=clayton_john&id=3632212 (accessed July 25, 2011).

[25] Paul Ingmundson, as quoted by Brian Covert, "Study says West coast teams have advantage," http://www.covers.com/articles/articles.aspx?theArt=81600&tid=25 (accessed July 25, 2011).

[26] Also Konik (2006) observes that sports books often have a good idea of who the informed bettors are, and cut their exposure to these bettors by either lowering their betting limits or by not allowing them to even place a bet.

In other words, the sports books are buying information at a low cost through their exposure to the informed bettors. Based on the incomplete signal, the sports books then partially adjust the point spread in the direction of the advantaged WC team. The adjusted spread does not reflect all of the information since the informed bettors are not allowed to wager unconstrained, hence the bias still exists. Wagers on the WC team are still underpriced or conversely wagers on the EC team are still overpriced.

The uninformed bettors who are unaware of the circadian advantage, however, believe that the movement in the spread makes a bet on the EC team underpriced. This perception entices more betting on the EC team relative to the WC team. This is shown in Figure 2.4.

2.8 Conclusions

I offer some evidence that the NFL point spread betting market is capital market inefficient by showing that a strategy of betting on the WC team to beat the point spread when it is playing against an EC team in the evening (ET), regardless of location, wins at a rate significantly above breakeven. Economic theory posits that in a competitive market the existence of betting profits on the WC team should encourage more WC team betting to the point where profits vanish. However, this does not appear to be the case here.

Instead, sports books may be acquiring a partial signal consistent with the circadian advantage from restricted wagers placed by bettors they know to be informed. The sports books then offer spreads that account for the partial signal to uninformed bettors who are unaware of the circadian advantage. From the perspective of the uninformed bettors, the offered spread makes wagers on the (unknowingly) disadvantaged team relatively cheap. From the sports books perspective, this encourages overbetting on what tends to be a losing wager. The surplus in the losing amount bet, after the winning bets are paid off, becomes the sports books profits above the vigorish.

CHAPTER 3: A TEST OF SENTIMENT IN THE NFL POINT SPREAD BETTING MARKETS

3.1 Introduction

In 1934, Graham and Dodd (2009) describe how it may be possible to profit from investing in the stock market by recognizing that part of a stock price is sometimes made up of speculative value that represents a "…strong psychological bias..." in addition to investment value that is "…justified by the facts." This chapter tests for these observations in the NFL betting markets. In this case there may be bettors who place wagers based partly on factors unrelated to the relative skills of the opposing teams or who incorrectly weight related factors. Based on Graham and Dodd, the hypothesis in this chapter is that bettors tend to profit when they place wagers opposite the "sentimental" bettors.

Similar research is done by Avery and Chevalier (1999) who find that the National Football League (NFL) betting markets' point spreads[27], which are somewhat analogous to stock market prices, move with various measures of sentiment derived from

[27] The *point spread* is the predicted difference in the score between the team expected to win the game (the favorite) and its opponent (the underdog). A bet on the favorite wins if the favorite wins the game by an amount greater than the point spread, otherwise a bet on the underdog wins.

the teams' past performances. They also find that a *contrarian* strategy, where bets are placed on the opponents of the sentimentally preferred teams, are marginally profitable. Avery and Chevalier's results are somewhat analogous to the superior performance of value stocks versus growth stocks if value (growth) stocks are treated as the equivalent of football teams with low (high) sentiment.

As in the previous chapter of this dissertation, I use the sports betting market as a platform to test for hypotheses usually made about the financial markets. I estimate the impact bettor sentiment has on betting odds, and if biases exist because of sentiment I investigate the extent of the biases and who stands to benefit. Assuming that sentiment is not necessarily entirely a function of on-field performance, I use a measure taken from surveys that ask respondents which teams are their favorites to follow. I also make use of the same database as in the previous chapter of this dissertation that records the percent of bets and money placed on each team to determine if sports books are profiting from bettor sentiment.

Section 2 is a review of the relevant literature. Section 3 discusses the theoretical model. Section 4 describes the data and the construction of the sentiment variable. Section 5 reports the results and Section 6 lists the conclusions.

3.2 Relevant Literature

There are a number of different definitions of sentiment. A conventional definition is, "an attitude, thought, or judgment prompted by feeling."[28] Baker and Wurgler's (2006) definition is, "propensity to speculate," and Avery and Chevalier's (1999) is, "…any

[28] *Webster's Ninth New Collegiate Dictionary* (1989)

nonmaximizing trading pattern among noise traders…" In any case, sentiment can lead to a biased estimate of the value of an asset.

A potential source of betting sentiment comes from teams who have won most of their games in the recent past. In this case, bettors develop a preference for recent winners in the belief that they will be more likely to beat the point spread in the next game. Camerer (1989) tests for this "hot hand" hypothesis in the National Basketball Association (NBA) betting market. He finds, instead, that bets on teams that have *lost* consecutive games against the point spread against teams that have *won* consecutive games against the point spread win at an above breakeven rate of 53.7%.[29]

Mispricings are also found in the horse racing betting market. In a sample of over 20,000 races, Ali (1977) compares subjective odds calculated from the betting pools placed on each horse with the objective, empirical odds and finds biases that underprice the favorites and overprice the long shots. In Ali's sample, favorites win 35.8% of their races compared to average posted odds of 32.4% and long shots win 2.1% of their races compared to average posted odds 2.8%. Both differences are statistically significant at the 1% level.

The profitability of contrarian strategies are supported by stock market research from DeBondt and Thaler (1985) who find that stocks with low returns over the previous three years outperform stocks with high returns during the same period over the next three years by 25%. Likewise, Fama and French (1992) find that very high book to market (B/M) "value" portfolios have an average monthly return of 1.8% compared to the very low B/M "growth" portfolios that return 0.3%.[30] Bauman (1965) creates two

[29] As shown in the previous chapter, the breakeven probability is about 52.4%.
[30] Book value is the value of an asset at the time it is bought less depreciation afterwards.

hypothetical stock portfolios based on how many investment managers own them. Over a ten year span, the "Least Popular Group" of stocks enjoyed higher returns than the "Most Popular Group."

Some research focuses on sentiment as an explanation for these patterns of returns. Kahneman and Riepe (1998) note that, "The human mind is a pattern-seeking device, and it is strongly biased to adopt the hypothesis that a causal factor is at work." In other words, humans search for patterns in order to improve decision making even when no underlying patterns exist, as is often the case in predictive markets like the stock or sports betting markets. This is seconded by Lakonishok, Shleifer and Vishny (1994) who wrote, "Putting excessive weight on recent past history, as opposed to a rational prior, is a common judgment error…" Gilovich, Vallone and Tversky (1985) find that basketball observers place too much weight, compared to what is empirically observed, on baskets consecutively made or missed in predicting the result of the next basket attempt.

Another potential source of sentiment comes from stock analysts who recommend buy and sell decisions. Jegadeesh, Kim, Krische and Lee (2004) find that these analysts tend to look favorably towards characteristics usually associated with growth stocks. Upward recommendations engender even more public sentiment in growth stocks.

A puzzle is why value stocks have continued to have a tendency to outperform growth stocks considering that arbitrageurs would be sure to profit from the gap until it disappears. Shleifer and Vishny (1997) offer a reason through a conceptual model that explains the behavior of arbitrageurs. They conclude that when an investment strategy takes time to learn or when volatility is high, it becomes more costly to arbitrage. In the case of value stocks tending to outperform growth stocks, there still may not be enough reliable information to realize arbitrage profits, especially if the arbitrageurs are acting on behalf of sponsors with shorter investment horizons. Hence the value/growth spread persists.

Avery and Chevalier (1999) estimate the effect hypothesized sources of sentiment have on changes to NFL point spreads from when they are first set at the beginning of the week prior to the games to when the last bet is placed right before the games start. The potential sources they investigate include favorable opinions from publicly acknowledged football experts, similar to the stock analysts studied in Jegadeesh *et al.* (2004), teams that have tended to win in the recent past (the "hot hand") and prestigious teams who advanced to the playoffs the previous season. As a measure of anti-sentiment, they also note those teams who finished in last place in their divisions the previous season. Avery and Chevalier find that bettors tend to extrapolate these measures too far, to the point where the betting odds become overpriced against the sentimentally preferred team. Contrarian bets win at a rate of 54.7%.

3.3 The Model

Let S_i be the amount of sentiment on team i, i being one of the 32 teams in the NFL, and let $S_{f\text{-}u}$ be the amount of sentiment towards the favorite team less that of the underdog. Avery and Chevalier (1999) find that relative sentiment between teams can have an impact on point spreads. Thus, it is likely that the proportion of bettors who place wagers on the favorite, denoted P_f, to beat the point spread, depends on $S_{f\text{-}u}$:

$$P_f = \rho_0 + \rho_1 S_{f\text{-}u} + \varepsilon \tag{1}$$

Since the number of bets placed on the favorite should increase as sentiment for the favorite increases, $\rho_1 > 0$. ρ_0 is the average proportion of bets placed on the favorite when there is no additional sentiment on the favorite compared to the underdog.

To test if the betting market uses the information contained in sentiment efficiently, a simple regression like Equation (2) below could be used:

$$W_f = \gamma_0 + \gamma_1 S_{f\text{-}u} + \varepsilon \tag{2}$$

W_f is a dummy variable that equals one if a bet placed on the favorite to beat the spread wins. By Avery and Chevalier's (1999) definition of sentiment, there should be no profitable signal so the null is $\gamma_1 = 0$. However, as noted in the previous section, there have been a number of findings in the stock market that growth stocks that have gained sentiment by previously outperforming value stocks tend to reverse fortune. This, along with Avery and Chevalier's results and Camerer's (1989) rejection of the "hot hand" hypothesis, leads to an alternative hypothesis that $\gamma_1 < 0$.

Equation (2) may be omitting variables that may have some ability to explain variations in W_f hence resulting in a biased estimate of γ_1. Equation (3) below, identical to that cited in the previous chapter of this dissertation, is used as a baseline to account for these biases that may be coming from betting strategies based on who is the home/visiting team or who is the favorite/underdog team.

$$W_f = \alpha^{HF} HF + \alpha^{VF} VF + (\beta - 1) SPR_{f\text{-}u} + \varepsilon \tag{3}$$

HF equals one if the favorite team is also the home team, zero otherwise, and *VF* equals one if the favorite team is also the visiting team, zero otherwise. $SPR_{f\text{-}u}$ is the point spread. The null hypothesis of market efficiency is $\alpha^{HF} = \alpha^{VF} = \beta - 1 = 0$. The measure of sentiment is appended to Equation (3) to arrive at:

$$W_f = \alpha^{HF} HF + \alpha^{VF} VF + (\beta - 1) SPR_{f\text{-}u} + \delta S_{f\text{-}u} + \varepsilon \tag{4}$$

The joint null hypothesis becomes $\alpha^{HF} = \alpha^{VF} = \beta - 1 = 0$ and $\delta \geq 0$. The alternative one-sided hypothesis is $\delta < 0$.

3.4 Data and Sentiment Variable

Game data including point spreads are downloaded from covers.com. The sample period is from the seven NFL regular seasons from 2004 – 2010. Appended to this data is the proportion of bets placed on the visiting team which is obtained from sportsinsights.com. After excluding games with missing observations and games that are either pushes, pick 'ems or played at neutral sites there are 1,721 observations.[31]

The measure of sentiment is taken from survey results conducted by the Harris Poll. Each year towards the beginning of the NFL season respondents who identify

[31] Since the model is based on potential home/away and favorite/underdog biases, pushes, pick 'ems and neutral site games contribute nothing to the estimation and are therefore omitted.

themselves as NFL fans are asked, “What are your two favorite National Football League teams?” Survey results in rank order during year t, denoted R_{it}, are listed in Table 3.1. I assume that the respondents’ answers reflect the sentiment of bettors and do not change during the year, regardless of any of the teams’ on-field performances. This is a practical matter as the surveys are only conducted once a year. I also assume that the respondents’ answers depend not only on the teams’ on-field performances but also on other factors such as:

- how close the teams are geographically located to the respondents
- how many years the team has been in existence
- off-field events that may help or hurt a team’s reputation
- the hiring of a popular player

In this respect, using this survey data may be a more complete measure of sentiment than using on-field performance alone.

Table 3.2 shows how much a team’s on-field performance relates to sentiment for that team. Spearman rank correlations are computed between the ordinal rank from the Harris Poll surveys in one year and the ordinal rank of the number of wins from the previous year. In general, the results show that a team gains more sentiment if they win more often during the previous season. Although the two appear to be correlated with the expected sign, the relationship is in general not exceptionally strong. This could mean that there are off-field factors, such as those listed above, which also influence sentiment.

Regressions that use ordinal rankings can be difficult to interpret. For instance, how is a one unit increase in rank to be interpreted? Is the impact different depending on the level of the rank? It would be more informative to have the data in raw form where the number or percent of respondents for each team is known, however that information is not available.

To address this shortcoming, each team is assigned to one of three portfolios based on sentiment, a high sentiment portfolio S^*_H made up of the eight most sentimentally preferred teams, a low sentiment portfolio S^*_L made up of the eight least sentimentally preferred teams and a medium sentiment portfolio S^*_M made up of the remaining 16 teams. S^*_H is also given an ordinal value of two, S^*_M a value of one and S^*_L a value of zero. For instance, in games where the favorite is in the low sentiment portfolio and the underdog is in the high sentiment portfolio the difference in the ordinal values is -2. I am most interested in determining the impact on the point spread when teams from different portfolios play against each other, something I call *relative portfolio sentiment*. Dummy variables are used to record the occurrence of relative portfolio sentiment between the opposing teams and equal one under the following conditions (zero otherwise):

Relative portfolio sentiment dummy	If favorite in…	…and underdog in
$dS^{*}_{-2,f\text{-}u}$	S^{*}_{L}	S^{*}_{H}
$dS^{*}_{-1,f\text{-}u}$	S^{*}_{L}(or S^{*}_{M})	S^{*}_{M} (or S^{*}_{H})
$dS^{*}_{1,f\text{-}u}$	S^{*}_{M} (or S^{*}_{H})	S^{*}_{L} (or S^{*}_{M})
$dS^{*}_{2,f\text{-}u}$	S^{*}_{H}	S^{*}_{L}

For example, in 2010 the Dallas Cowboys are assigned to portfolio S^{*}_{H} since it is the most sentimentally preferred team and the Jacksonville Jaguars are assigned to portfolio S^{*}_{L} since it is the least sentimentally preferred team. If Jacksonville is favored to beat Dallas, then the dummy variable $dS^{*}_{-2,f\text{-}u} = 1$ and all of the other relative portfolio sentiment dummies are equal to zero.

Measuring relative portfolio sentiment between two teams leads to the following model for the proportion of wagers placed on the favorite team from Equation (1):

$$P_f = \beta_0 + \alpha^{HF} HF + \alpha^{VF} VF + (\beta - 1)\, SPR_{f\text{-}u} + \rho_1\, dS^{*}_{-2,f\text{-}u} + \rho_2\, dS^{*}_{-1,f\text{-}u} + \rho_3\, dS^{*}_{1,f\text{-}u} + \rho_4\, dS^{*}_{2,f\text{-}u} + \varepsilon \qquad (5)$$

where potential biases from the right hand side of Equation (3) are also included. Given previous results that contrarian investments against an asset with high investor sentiment tend to profit, the hypothesized values for the coefficients are:

- $\rho_1 < 0$ and $\rho_2 < 0$: bettors have less sentiment for the favorite than the underdog,
- $\rho_3 > 0$ and $\rho_4 > 0$: bettors have more sentiment for the favorite than the underdog,
- $\rho_2 < \rho_1$ and $\rho_3 < \rho_4$ given the magnitudes of the relative differences in sentiment.

To test for efficient markets, the relative portfolio sentiment dummies are appended onto Equation (3):

$$W_f = \alpha^{HF} HF + \alpha^{VF} VF + (\beta - 1)\, SPR_{f\text{-}u} +$$
$$\delta_1\, dS^*_{-2,f\text{-}u} + \delta_2\, dS^*_{-1,f\text{-}u} + \delta_3\, dS^*_{1,f\text{-}u} + \delta_4\, dS^*_{2,f\text{-}u} + \varepsilon \tag{6}$$

The null hypothesis is that all coefficients equal zero. Given a profitable contrarian strategy, the alternative is $\delta_1 > 0$, $\delta_2 > 0$, $\delta_3 < 0$ and $\delta_4 < 0$.

3.5 Results

The estimated coefficients for Equation (5), with p-values from the appropriate one-sided hypothesis tests described above, are:

$$P_f = \underset{[0.000]}{64.9882} - \underset{[0.000]}{15.6019}\, HF - \underset{[0.000]}{1.2529}\, SPR_{f\text{-}u} +$$
$$\underset{[0.012]}{-3.7965}\, dS^*_{-2,f\text{-}u} - \underset{[0.076]}{1.0584}\, dS^*_{-1,f\text{-}u} + \underset{[0.200]}{0.5220}\, dS^*_{1,f\text{-}u} + \underset{[0.250]}{0.6347}\, dS^*_{2,f\text{-}u} \tag{7}$$

In all other games not accounted for by the explanatory variables, about 65% of the bettors place a wager on the favorite, a result that is consistent with Levitt (2004). While all of the relative portfolio sentiment dummies are of the hypothesized signs, only the dummies when the favorite team has lower measure of sentiment on it than the underdog are statistically significant. When the favorite team is in the high sentiment portfolio and the underdog is in the low sentiment portfolio then 3.8% fewer bets are placed on the favorite. These results suggest that sentiment, as measured in this chapter, has an impact on the relative flow of bets placed on teams.

Probit estimates for Equation (6), with *p*-values in brackets, yield the following results:

$$\underset{}{W_f} = \underset{[0.500]}{0.0198\,HF} + \underset{[0.178]}{0.0408\,VF} - \underset{[0.016]}{0.0084\,SPR_{f-u}} +$$

$$\underset{[0.110]}{0.1223\,dS^*_{-2,f-u}} + \underset{[0.815]}{0.0081\,dS^*_{-1,f-u}} + \underset{[0.234]}{0.0345\,dS^*_{1,f-u}} + \underset{[0.213]}{0.0546\,dS^*_{2,f-u}} \qquad (8)$$

None of the relative portfolio sentiment dummy variables are statistically significant at any of the conventional levels. The most significant coefficient is on $dS^*_{-2,f-u}$ which is also not quite significant at the 10% level. The estimated coefficient on $dS^*_{-2,f-u}$ implies there is a 12% increase in the probability of winning a bet placed on the favorite if the favorite has low sentiment and the underdog has high sentiment. Given the marginal statistical insignificance, this weakly supports the hypothesis that contrarian strategies tend to be profitable.

The regressions are run under the unrealistic assumption that equal amounts of money are bet on each game. However, amounts wagered are not included in the database, hence weighting the observations is not possible. If more money is wagered in games involving teams with high sentiment then, with the given data, games involving teams with high sentiment are underweighted. Therefore, the results are less significant than would be the case if proper weights are applied.

Over the sample period there are 43 games played between favorites in the low sentiment portfolio and underdogs in the high sentiment portfolio with the favorite beating the spread 26 times for an above breakeven success rate of 0.605. However, given these conditions a binomial process with a success rate that equals the breakeven probability of 0.524 has a probability of 0.2519 of exceeding 0.605. Therefore, the results are not significantly different from breakeven.

Equation (7) shows that there are more bettors who wager on a team with high sentiment compared to an opponent who has low sentiment. Whether or not this has an impact on the point spread and betting profits is debatable since the results from Equation (8) and the in-sample betting record are only weakly supportive. This suggests the possibility that the contrarian bettors, although a minority in number, tend to bet in larger amounts thus closing off any profitable opportunities. To test if these conditions exist, I examine the distribution of money bet on the favorite compiled from sportsinsights.com, as opposed to the number of bets placed. There are 710 games, or about 41%, of the games in the sample for which this kind of data is available.

I compare the proportion of money bet on the favorite between the 22 games in the sample where the favorite is in S^{*}_{L} and the underdog is in S^{*}_{H} (treatment sample T), and the other 688 games (control sample C). If the point spread is set so that there are no biases in terms of money bet associated with a contrarian strategy then the proportions of money bet on the favorite in both the treatment and control samples should be the same. In the treatment sample the mean value is $\mu_T = 0.4837$ with a standard deviation of 0.1862 and in the control sample the mean value is $\mu_C = 0.5331$ with a standard deviation of 0.1972. A t-test of the null hypothesis that $\mu_T = \mu_C$ yields an insignificant p-value of 0.2469. Thus, the statistical evidence supports the hypothesis that the money wagered by sentimental bettors is balanced by money wagered by contrarian bettors.

3.6 Conclusions

Bettors who place wagers based on sentiment appear to be similar to stock market investors who invest in growth stocks. Lakonishok *et al.* (1994), among other finance researchers, often refer to growth stocks as glamour stocks in an acknowledgement that growth stock investors sometimes make decisions based on sentimental reasons. There is evidence that a contrarian investment strategy in favor of value stocks tends to profit. Avery and Chevalier (1999) find evidence of a marginally profitable contrarian strategy in the NFL betting market.

The evidence in this chapter finds that the market, as a whole, is not using sentiment in a biased fashion. However, results from Equation (7) show that, everything else the same, sentimental betting leads to overpricing the sentimentally preferred team. Contrarian bettors take the opposite bet in betting amounts that offset the sentimental bettors. Sentimental bettors tend to lose their wagers, and their losses are given to the contrarian bettors who tend to win their wagers. However, taken as a whole the betting market appears to be making efficient use of sentiment.

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Table 1.1(a): Coefficients Significantly > 0 by Referee, 2004 - 2011

	Regression (8)					Regression (9)						
Referee	χ^2 joint	α_1	α_2	α_3	α_4	α_1	α_2	α_3	α_4	β_1	β_2	β_3
Donaghy												X
1												
5												
9				X								
10	X	X						X				
11	X	X				X						
13												
14	X			X				X				
16			X									X
18				X								
19					X				X			
22		X										
23										X		X
27												
32	X			X				X				
33		X										
35												
41			X	X				X				
42	X			X		X		X				
44	X	X		X		X			X			
46				X							X	
50	X			X				X				
51												
52						X						
53												
59												
63			X									
64												
69	X			X				X				
71												
73												X
77	X	X				X						
78												
79	X	X				X					X	
81												
85												
86										X		

Table 1.1(b): Coefficients Significantly > 0 by Referee, 2008 - 2011

	Regression (8)			Regression (9)				
Referee	α_2	α_3	α_4	α_2	α_3	α_4	β_2	β_3
1				X				
5								
9		X			X			
10		X			X		X	
11					X			
13								
14		X			X			
16								
18		X			X			
19								X
22								
23					X			
27								
32		X						
33								
35				X	X			
41								
42		X						
44			X		X	X		
46								
50								
51								
52								
53								
59								
63								
64				X				
69		X			X			
71		X						X
73		X			X			
77					X			
78								
79								
81								
85					X			
86								X

Table 2.1: Circadian Advantage Betting Strategies

Strategy	Team bet on	Favorite team	Game start time (ET)	Number of observations
1F	Favorite	WC	7:00 – 9:00 p.m.	42
1U	Underdog	EC	7:00 – 9:00 p.m.	21
2F	Favorite	EC	4:00 – 5:15 p.m.	98
2U	Underdog	WC	4:00 – 5:15 p.m.	181
3F	Favorite	EC	12:30 – 2:00 p.m.	50
3U	Underdog	WC	12:30 – 2:00 p.m.	69

Table 2.2: Circadian Advantage Evening Strategy Bets Won and Lost by Year

Year	W	L	Year	W	L
1988	1	0	1999	2	0
1989	3	1	2000	1	1
1990	4	1	2001	4	0
1991	0	1	2002	2	3
1992	3	1	2003	1	0
1993	1	3	2004	1	0
1994	0	0	2005	2	3
1995	2	3	2006	1	0
1996	3	2	2007	2	1
1997	2	0	2008	3	1
1998	3	0	2009	0	1

1988-1998	22	12	(0.647)
1999-2009	19	10	(0.655)
1988-2009	41	22	(0.651)

Table 3.1: Rank Order of Respondents' Favorite NFL Teams

Rank ordering to question, "What are your two favorite National Football League teams?" where a rank of "1" signifies most favorite and a rank of "32" signifies least favorite.

	2004	2005	2006	2007	2008	2009	2010
Arizona Cardinals	32	31	29	29	24	16	11
Atlanta Falcons	21	18	23	28	27	13	10
Baltimore Ravens	29	28	30	26	28	26	19
Buffalo Bills	27	23	27	30	20	27	29
Carolina Panthers	18	16	13	14	19	25	23
Chicago Bears	6	8	6	5	6	3	9
Cincinnati Bengals	24	30	23	18	32	29	27
Cleveland Browns	24	15	19	13	22	22	26
Dallas Cowboys	2	2	2	1	1	1	1
Denver Broncos	9	10	11	16	15	12	14
Detroit Lions	26	18	17	25	29	31	30
Green Bay Packers	1	1	4	4	5	6	3
Houston Texans	19	25	28	31	26	23	17
Indianapolis Colts	11	9	3	2	3	4	2
Jacksonville Jaguars	28	32	32	32	30	32	32
Kansas City Chiefs	21	21	20	23	22	27	25
Miami Dolphins	13	18	13	14	16	17	21
Minnesota Vikings	15	16	21	19	12	10	8
New England Patriots	3	3	5	6	2	5	6
New Orleans Saints	30	29	31	21	17	24	5
New York Giants	4	13	9	7	7	8	7
New York Jets	6	11	22	17	9	20	16
Oakland Raiders	12	7	10	11	13	21	17
Philadelphia Eagles	5	5	7	8	8	7	13
Pittsburgh Steelers	15	3	1	3	4	2	4
San Diego Chargers	31	27	23	10	18	14	20
San Francisco 49ers	8	6	8	9	11	11	12
Seattle Seahawks	14	24	12	19	14	14	31
St. Louis Rams	20	21	26	23	30	30	24
Tampa Bay Buccaneers	17	11	17	21	21	19	27
Tennessee Titans	23	25	15	26	25	9	21
Washington Redskins	10	14	16	12	9	17	15

Source: Harris Poll

Table 3.2: Spearman Rank Coefficients on Sentiment and Lagged Performance

Year	Correlation
2004	0.2947
2005	0.0686
2006	0.3048
2007	0.3185
2008	0.4089
2009	0.5750
2010	0.6700

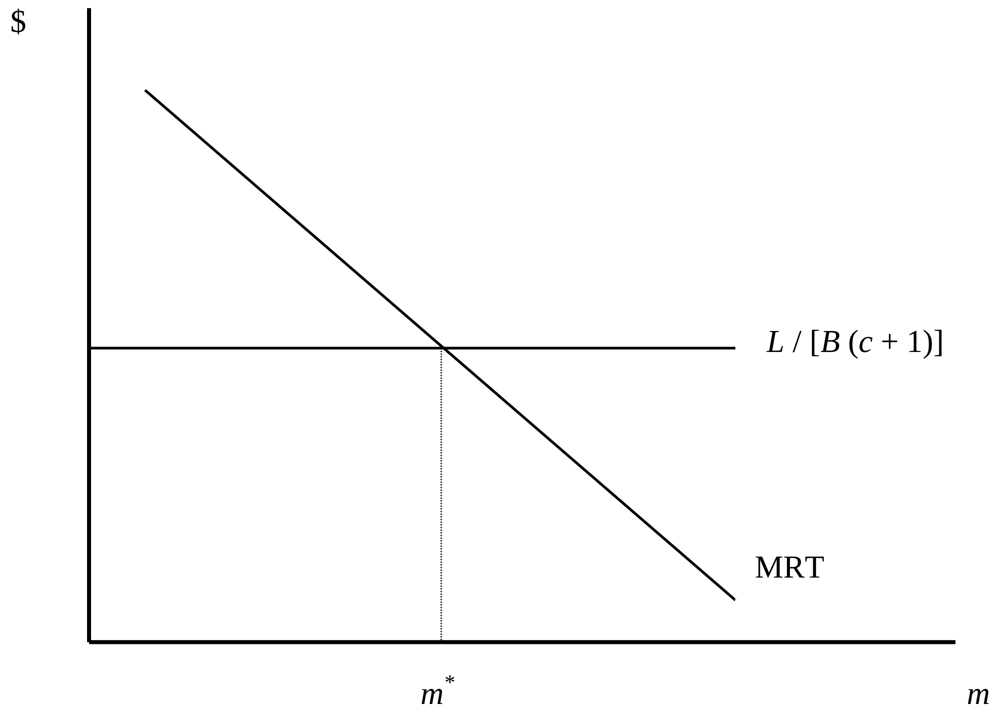

Figure 1.1: Optimal Amount of Manipulation

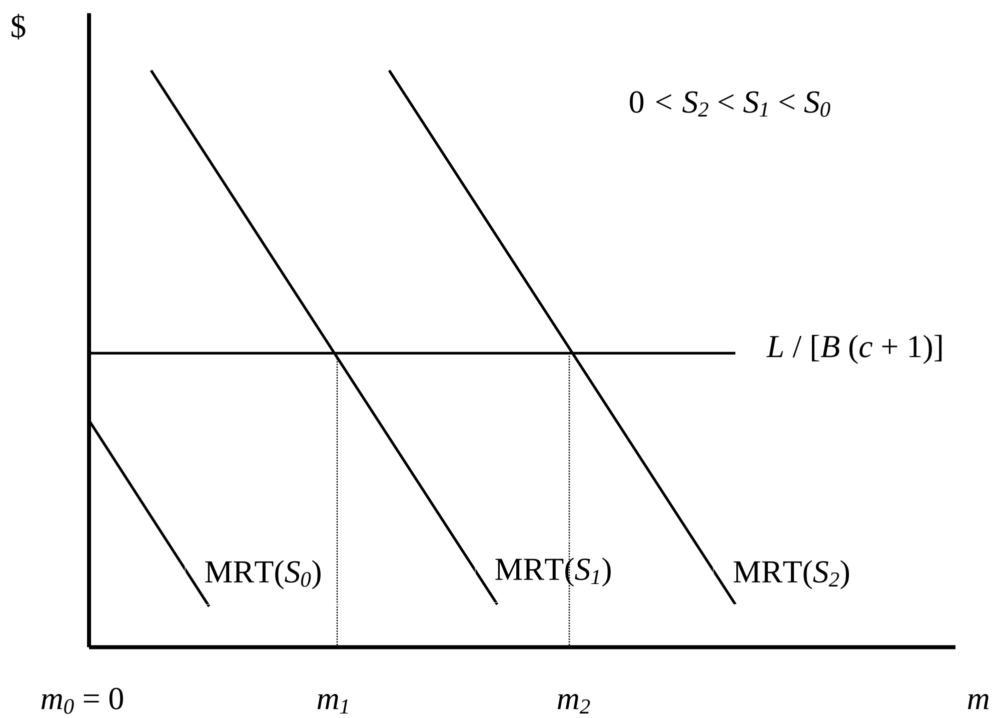

Figure 1.2: Manipulation Increases as Score Gets Closer to the Spread

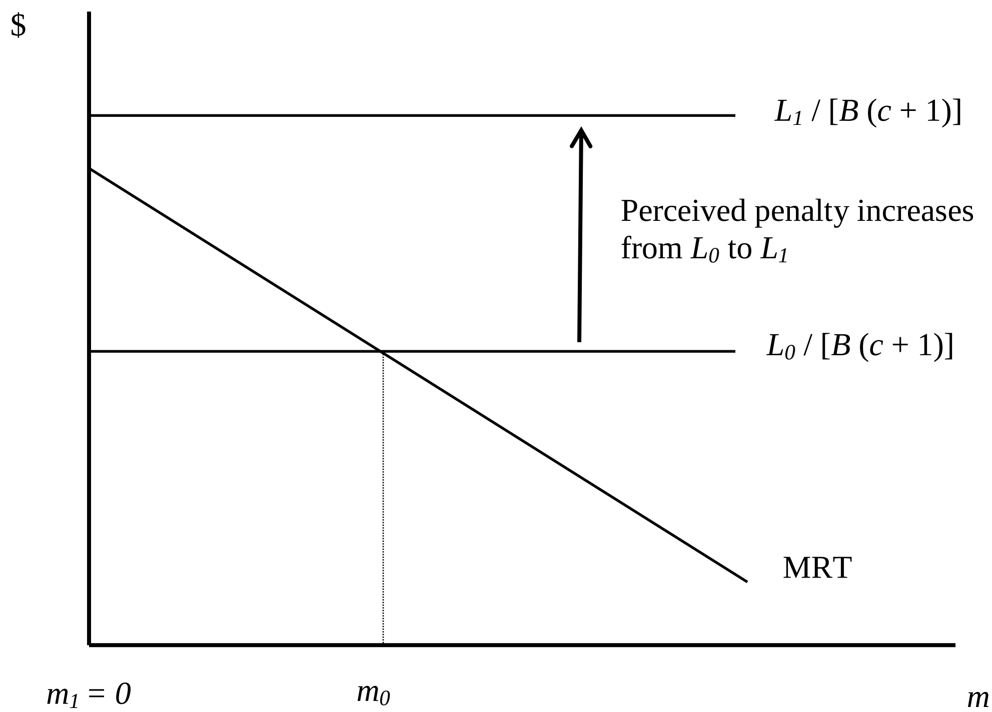

Figure 1.3: Manipulation Decreases as Penalty from Manipulation Increases

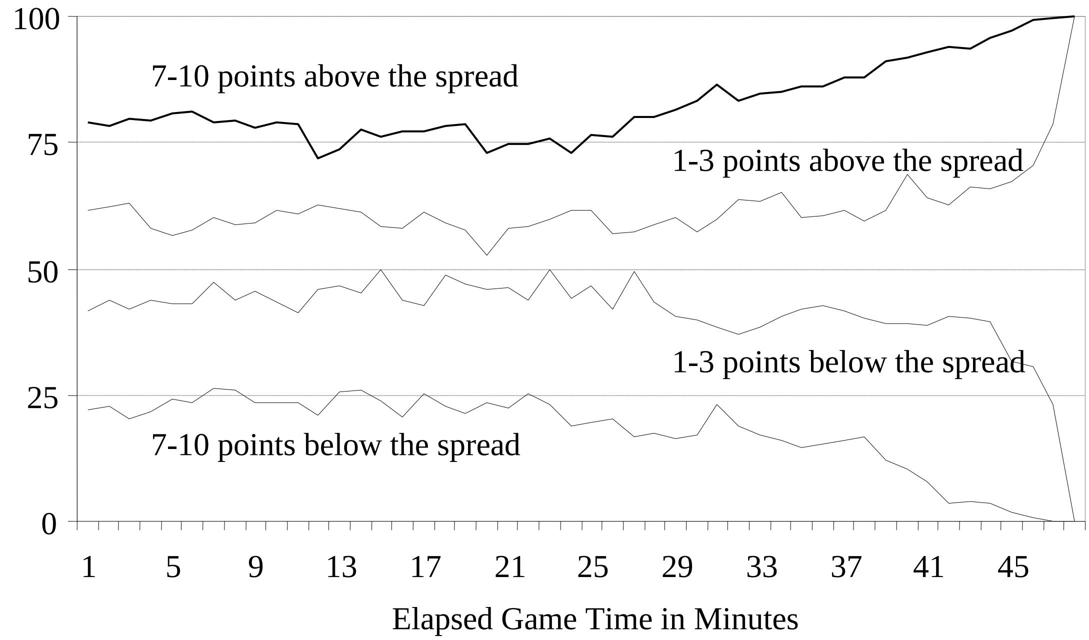

Figure 1.4: Probability (in %) of Team Bet on to Beat the Spread

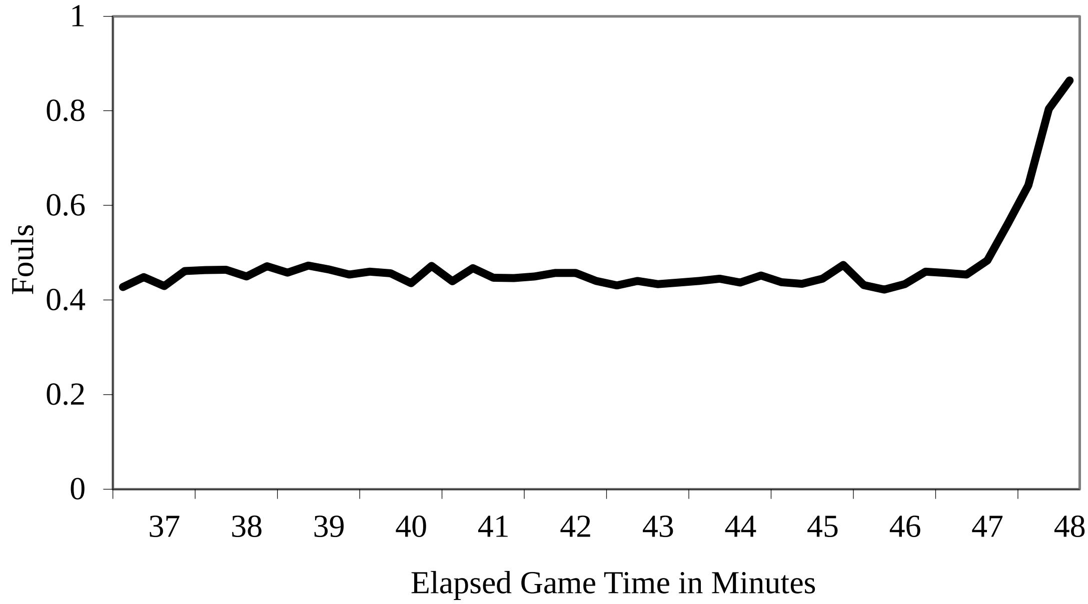

Figure 1.5: Standard Deviation of Fouls Called

When manipulation more likely to occur → Half of game ↓	When difference in scores are within three points of the spread	When difference in scores are within nine points of the spread
First		
Second	**Larger values of the *CFCI* should occur only in this cell.**	

Figure 1.6: Subsamples of the Game Where the CFCI is Measured Over

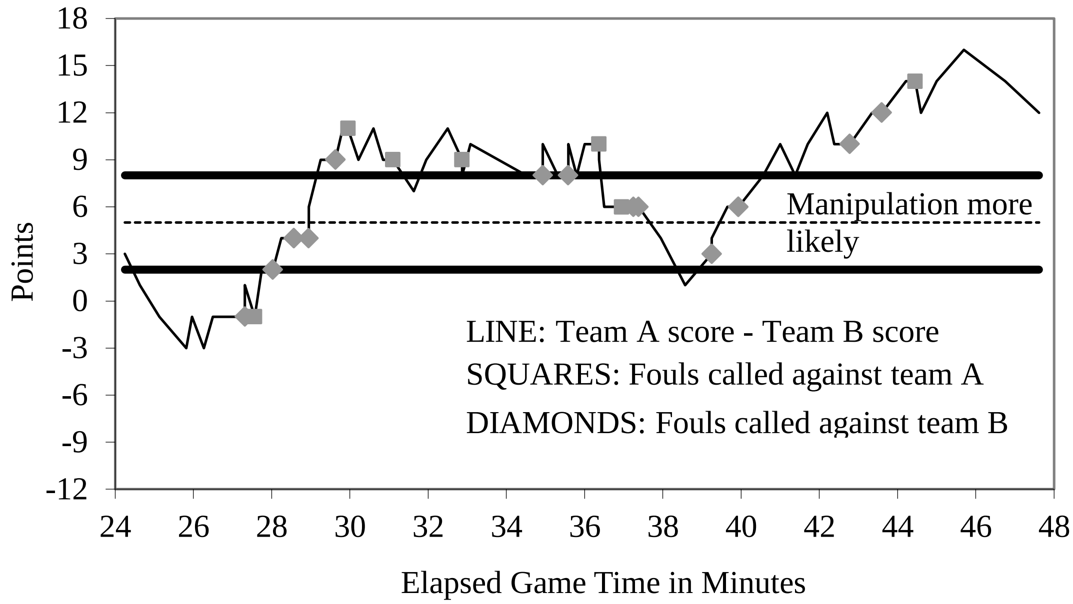

Figure 1.7: Illustration of CFCI

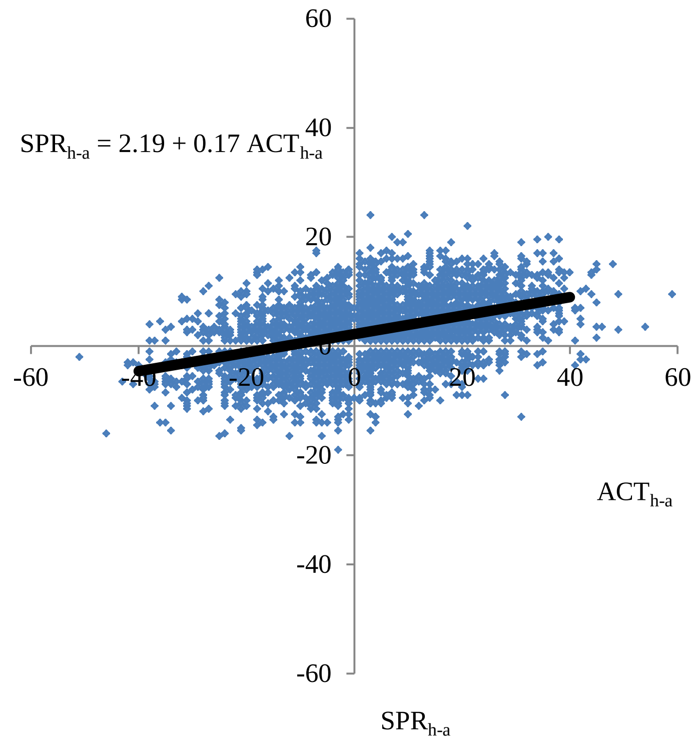

Figure 2.1(a): SPR$_{h-a}$ = f(ACT$_{h-a}$)

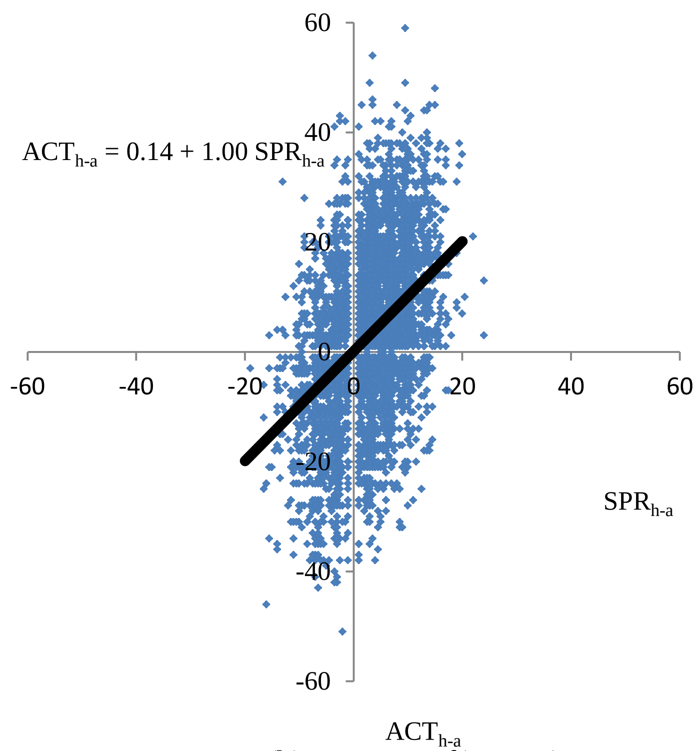

Figure 2.1(b): ACT$_{h-a}$ = f(SPR$_{h-a}$)

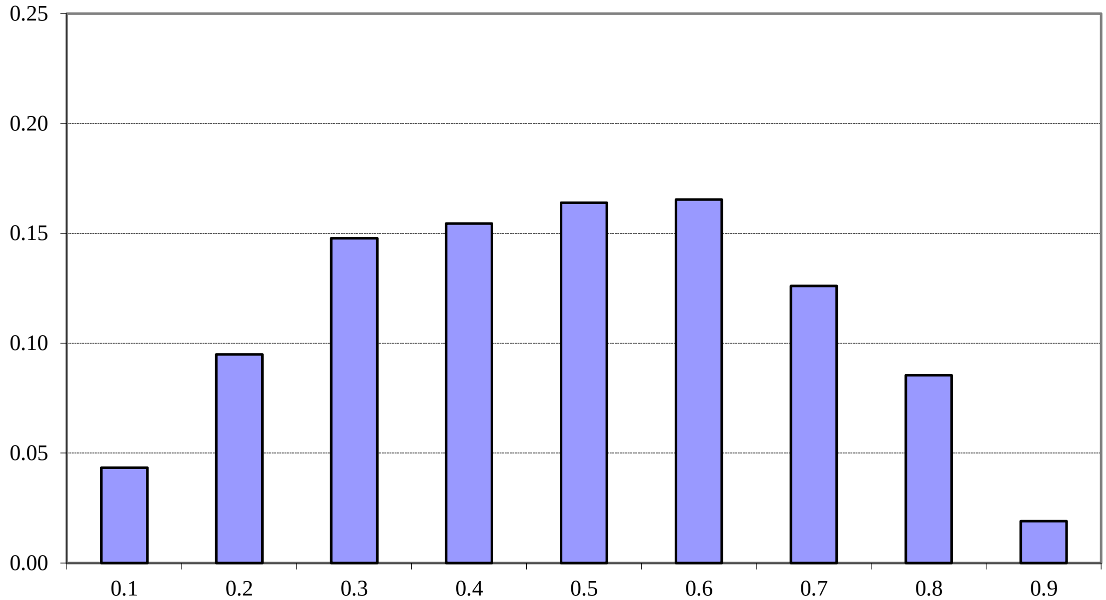

Figure 2.2: Proportion of Money Bet on Randomly Selected Team

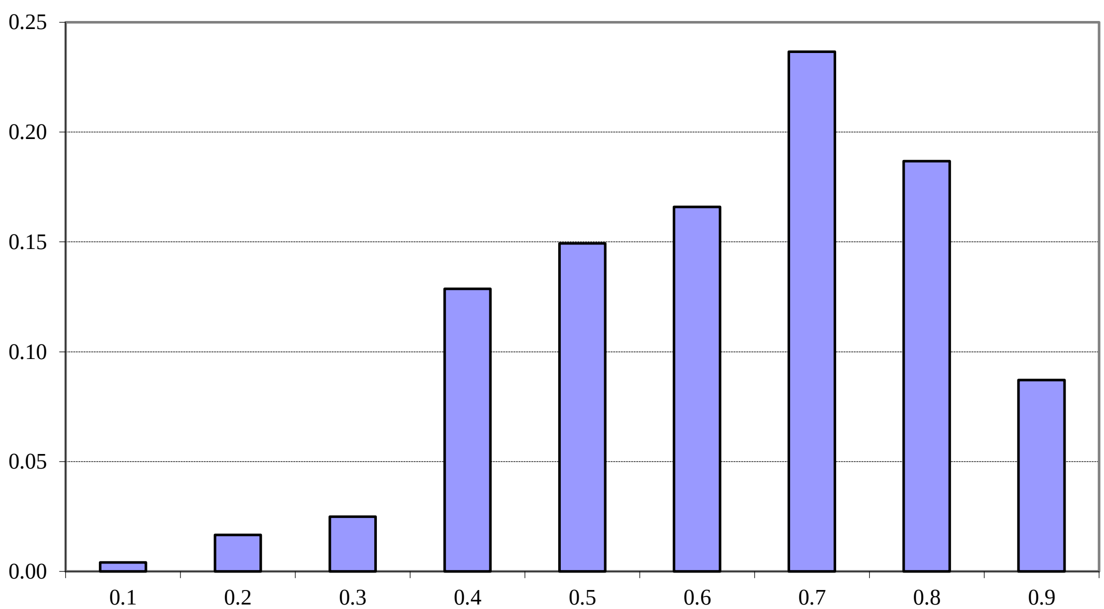

Figure 2.3: Proportion of Money Bet on Visiting Favorite

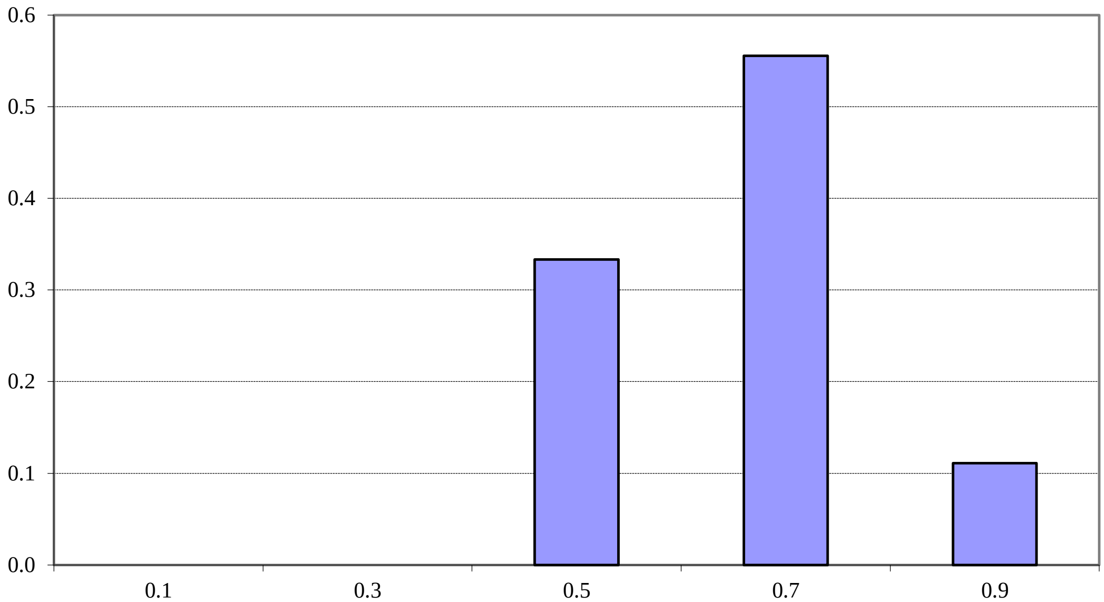

Figure 2.4: Proportion of Money Bet on EC Team vs. WC Team in the Evening

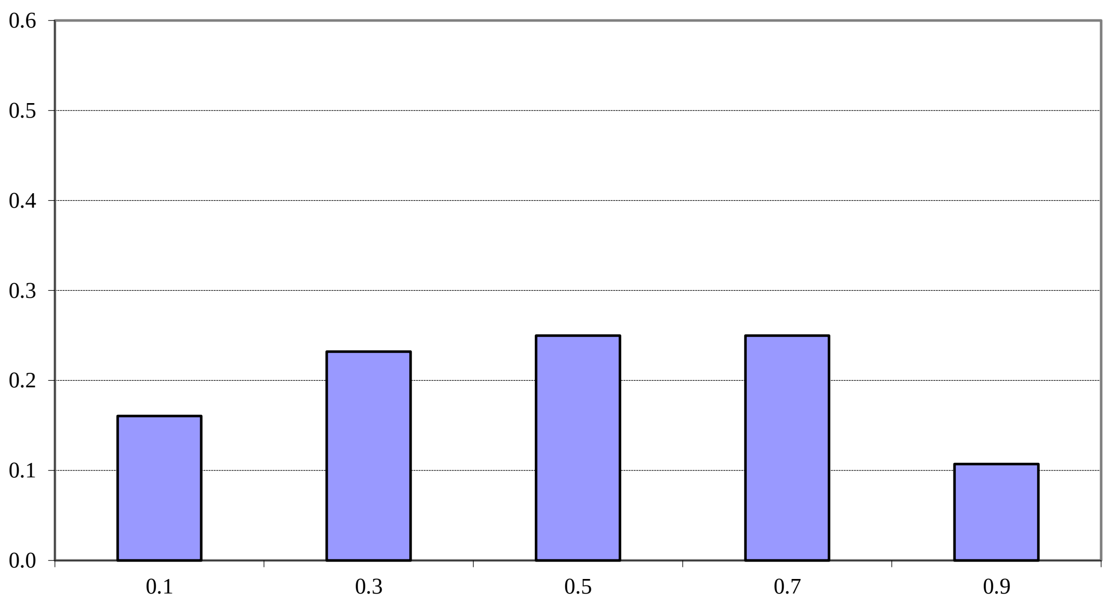

Figure 2.5: Proportion of Money Bet on EC Team vs. WC Team in the Afternoon

APPENDIX: COMPARISON AND COMBINATION OF CHAPTERS TWO AND THREE

The main result from Chapter Two is that the market inefficiently makes use of the circadian advantage, a finding that differs from Chapter Three where the market appears to be making efficient use of sentiment. The difference in conclusions could occur if there are many bettors who are aware of sentiment so that contrarian betting against sentiment arbitrages the market while there are few bettors who are aware of the circadian advantage. Therefore, while the sports book can use circadian advantage to manipulate the betting market to increase its profits it cannot do so for sentiment.

The regressions from Chapter Two and Chapter Three could both suffer from omitted variable bias since the variable of interest in one chapter is omitted in the other chapter. To address this issue, a regression that combines the regressions from the two chapters is estimated with results as follows:

$$W_f = \underset{[0.927]}{(-0.0030} - \underset{[0.019]}{0.0960}\,\delta)\,HF + (\underset{[0.499]}{0.0234} - \underset{[0.354]}{0.0531}\,\delta)\,VF - \underset{[0.164]}{0.0052}\,SPR_{f\text{-}u} +$$

$$\underset{[0.487]}{0.0906}\,S_1 + \underset{[0.309]}{0.0625}\,S_2 + \underset{[.496]}{0.0720}\,S_3 +$$

$$\underset{[0.033]}{0.1784}\,dS^*_{-2,f\text{-}u} + \underset{[0.493]}{0.0259}\,dS^*_{-1,f\text{-}u} + \underset{[0.022]}{0.0721}\,dS^*_{1,f\text{-}u} + \underset{[0.412]}{0.0384}\,dS^*_{2,f\text{-}u}$$

The first row of coefficients controls for other potential biases from Dare and Holland (2004), the second row are the circadian advantage strategies, and the third row are the measures of relative sentiment between the favorite and underdog.

As far as the coefficients' economic significance, all of the circadian advantage strategies appear to contribute in a meaningful way by adding approximately six to nine percentage points to the probability of winning a bet placed on the favorite. A contrarian bet against sentiment when the favorite team has low sentiment on it and the underdog has high sentiment is also economically significant by adding 18 percentage points to the chance of winning a bet on the favorite. However, while the contrarian sentiment bet is also statistically significant, the evening circadian advantage strategy S_1 no longer is.

One reason for the changes in statistical significance may be because of the data sample. The sample size from Chapter Two is from 22 seasons with 5,096 observations compared to the sample size from Chapter Three of six seasons with 1,479 observations so that the combined results could be due to statistical chance and do not describe the actual relation well. A second reason is that the evening circadian advantage strategy may coincidentally be a proxy for the contrarian sentiment bet. From Chapter Two, a bet on the WC team tends to win if it also enjoys the evening circadian advantage. From Chapter Three, a bet on the favorite team when it is significantly less popular than the underdog team tends to win. To match these results, it must be the case that the WC team tends to be less popular than the EC team, and that sentimental betting takes place more often in the evening when the games tend to have national interest.

Some evidence to support this comes from the Harris Poll. Of the eight most popular teams, on average, over the sample period five are based on the EC (New England, Pittsburgh, Indianapolis, Philadelphia, and the New York Giants) and none are based on the WC. Therefore, what was viewed in Chapter Two as a bet against the EC teams based on circadian advantage is actually a contrarian bet against EC teams because more bettors have sentiment for the EC team. As mentioned in the previous paragraph, betting on sentiment may be magnified during the evening when the more compelling games to watch are played.

At the beginning of this section it was mentioned that sports books may persistently be taking an active position involving the circadian advantage because a small proportion of bettors are aware of it. If it is the case that the circadian advantage is a proxy for the contrarian sentiment bet then persistence would have to exist for a different reason. Shleifer and Vishny (1997) cite the amount of variance around the signal as a factor. In this case, some bettors may be aware that contrarian sentiment wagers tend to win but there may be difficulties in measuring sentiment or in determining how much weight the market places on sentiment. In addition, the weighting may change over time. If this is the case, then the loss in reliability over the strategy's effectiveness may deter informed bettors from arbitraging away the sentiment bias.