THREE ESSAYS IN MARKET EFFICIENCY: AN EXAMINATION OF MARKET REACTION TO INFORMATION

by

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ABSTRACT

JASON PHILLIP BERKOWITZ. Three essays in market efficiency: An examination of market reaction to information. (Under the direction of DR. STEVEN CLARK & DR. CRAIG A. DEPKEN, II)

The efficient market hypothesis (EMH) examines how quickly and accurately information is reflected in a security price, and as a result, it has become one of the primary areas of focus in financial literature. I explore three problems regarding the release of information and the impact it has on price. First, I show that securities' prices are influenced by the introduction of other securities. The offering of betting lines does influence the accuracy of pricing; however, the unbiasedness seems unaffected. Additionally, I find evidence of the linear relationship between the money line and sides line, similar to the security market line, ends up breaking down as a result of the bookmaker offering a higher payout in the money line to the favorite team in order to entice bettors. Next, I examine if winning or losing influences sports clubs' financial performance. While there is literature, with mixed results, that examine the market reaction to winning and losing for publicly-traded clubs, the question; does winning influence the clubs' financial performance has been sidestepped. Results from English soccer clubs suggest that match performance does impact a club's operating income, but the impact differs for "elite" and "non-elite" clubs. Lastly, utilizing English soccer club data again, I reexamine market reaction to good and bad news by looking at matches where both clubs were publicly-traded – seeing the market's reaction to the win and the loss simultaneously. While my results contradict previous literature, that the market reacts to good news faster, this is because I find that losing is a stronger signal.

DEDICATION

This dissertation is dedicated to my parents, Steven and Susan, who have supported me through all obstacles and have instilled the importance of an education, for which I am eternally grateful.

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CHAPTER 1: INTRODUCTION

The efficient market hypothesis (EMH) is one of the major academic contributions to the understanding of basic finance and is one of the primary areas of focus in the financial literature. The EMH's initial form argues that all relevant information is fully reflected in a security's price. Eugene Fama has been generally credited as the father of EMH, which stemmed from his Ph.D. thesis work in the 1960's at the University of Chicago and highlighted in his now classic Journal of Finance paper in 1970 entitled "Efficient Capital Markets: A Review of Theory and Empirical Work." Fama distinguishes between three types of market efficiency: weak, semi-strong, and strong. Since the land mark work of Fama there have nevertheless been anomalies that bring into question the existence of market efficiency, such as the January effect or the existence of market crashes. As a result, over the ensuing years, and especially during the last two decades, many papers have appeared providing supporting evidence for and against market efficiency. This dissertation consists of three essays that examine the market's reaction to the release of information through different channels. These three essays use unique datasets related to sports to examine and extend the literature on market efficiency. All three papers extend the previous literature by examining market efficiency as it relates to the release of information, firm performance, and the release of additional securities.

My second chapter, “More Accurate Asset Pricing: Analysis from the Betting Market” examines whether the release of additional securities provides more accurately priced securities. That is, does each additional security provide additional information to the market about the firm’s financial performance and investor expectation of future cash flows? Testing this hypothesis is not straight-forward, as noted by Smith (1986). To avoid many of the measurement problems that are encountered in other contexts, I utilize a unique set of NCAA college basketball betting data. In betting on college basketball games there are three types of betting lines: the sides line, the money line, and the totals line – not to mention a wide variation across games on which lines are offered. This particular betting market is convenient because, relative to a traditional stock market, there is less signaling on the part of management, the true price of a betting line is more accurately measured, and additional betting lines are not always offered. The findings in this paper indicate that while additional betting lines offer more information, the sides line’s accuracy is only marginally (negatively) affected when the totals line is missing. Yet this accuracy does not affect the market’s unbiasedness. A missing money line does not impact the accuracy of the sides line. The relationship between the money line and the sides line should be linear and comparable to the security market line in the traditional stock market. One of the biggest findings in this paper is that this linear relationship breaks down once the favorite is expected to win by more than seven points. The key novel approach taken in this paper is the examination of the impact of additional betting lines and the assessment as to whether they have any impact on each other.

My third chapter, “Does Winning Really Matter? An Examination of EPL Club Performance and Earnings” re-examines the discussion of whether winning in sports affects a club's financial performance. The previous literature focusing on stock price reaction to a club's on-field performance has provided mixed results. Until now the issue of whether a club's financial performance is affected by on-field performance has been sidestepped. Yet this relates directly to Fama's (1970) definition of market efficiency: A market in which prices always 'fully reflect' available information is considered 'efficient'. Announcements by firms can be noisy and have low dissemination, as a result of the leaking of information to insiders. Therefore, it is difficult to directly test the impact of good or bad news on firm performance. The findings indicate that winning affects (positively) elite and non-elite club financial performance differently, which is only minimally observed by the stock market reaction to a loss.

The fourth chapter, "A Re-examination of Asymmetric Reaction to Good and Bad News: A Test from Match Outcome" looks at the asymmetric market reaction to good and bad news. This literature primarily starts with Chan (2003), who finds the market generally reacts faster to good news. Using match-level data describing games in which both are publicly-traded, facilitates a test of whether the market responds simultaneously to good news and bad news. By its very nature, the end of a soccer match provides widely disseminated and purely public information. In the case of a draw, the information might be considered somewhat neutral for both teams. Therefore, it might not be expected to have much of a market reaction – all else equal. However, if one team wins the other team necessarily losses; for one team the news is ostensibly good news for the other ostensibly bad. Thus, the framework allows for the simultaneous investigation of the market reaction to good and bad news. The results found in this analysis indicate that losing is a stronger signal. The insinuation behind the results is that losing implies more losing in the future; whereas winning does not predict future winning.

CHAPTER 2: MORE ACCURATE ASSET PRICING: ANALYSIS FROM THE BETTING MARKET

Examining how information affects security prices has been a topic of great interest in the financial literature. There have been a number of event studies looking at common stock price reactions to security offerings, firm announcements, and macroeconomic announcements. Smith (1986) provides a summary of stock price reactions to additional security offerings. Smith generalizes that the average abnormal returns are non-positive. Similar to the securities offered by the firm, options on common stock impact common stock price.[1] The reaction of stock prices to the introduction of an option was positive until 1980, after which it became negative. Sorescu (2000), using an optimal switching means model, finds the optimal-switching date was sometime between December 12, 1980 and June 29, 1981.

The studies on options seem to have been inconclusive about their impact on common stock. The most common and celebrated model for pricing options is that of Black-Scholes (1973). Their model argues that options are redundant securities that can be replicated by a self-financing strategy in the underlying stock and a risk-free security. Although the Black-Scholes model has attracted a great deal of attention and achieved significant success, other models have been developed to price options, notably Ross (1976), Detemple (1990), Detemple and Seldon (1991), and Easley et al. (1998). These

[1] See Branch and Finnerty (1981), Conrad (1989), Detemple and Jorion (1990), Sorescu (2000) and Danielsen and Sorescu (2001).

alternative theoretical models imply that options can impact stock prices. In fact, empirical evidence seems to support the argument that options do impact the underlying stock's price. This is illustrated by Back (1993), who develops a pricing model that incorporates the intuition that options can increase the amount of information available concerning the underlying asset.

This paper does not test the question of whether there is a reaction to the offering of additional securities. Rather, the empirical analysis focuses on whether the price of a common stock becomes more accurate when additional securities on a firm's future cash flows exist. Additional securities might reveal additional information about the firm and its future cash flows, resulting in a more accurate common stock price. Furthermore, if additional securities result in more accurate pricing of a common stock, does this yield a more efficient market? There are two major hurdles in attempting to directly answer these questions. First is the difficulty in determining the true or fundamental value of the stock.[2] Second, other securities may have other consequences that arise from the information asymmetry between managers and investors. Smith discusses five possible reasons for his non-negative findings, all of which can impact the test that additional securities result in more accurate common stock prices.[3]

To date, a gap in the literature is whether additional securities on a firm result in more accurate pricing of these securities. To assess this problem and to avoid the inherent problems with using traditional stock markets, this paper takes advantage of the

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[2] Kumar et al. (1998) conclude option listings result in more efficient pricing on the underlying asset by using Hasbrouck (1993) model that looks at pricing errors and uses a test that the market is weakly efficient, i.e. stock prices follow a random walk.

[3] Smith (1986) offers the following explanations for the non-negative stock returns after an additional security is offered: (1) optimal capital structure; (2) implied cash flow; (3) unanticipated announcement; (4) information asymmetry; and (5) ownership change.

unique characteristics of betting market data from the National Collegiate Athletic Association (NCAA) Division I (DI) basketball. The key benefit in using a betting market is that the end result of each game is observed, which allows one to actually assess the effective true price and accuracy of the betting lines. These outcomes allow one to look back and see how accurate the different betting lines were.[4] This is in contrast to a standard stock market, in which it is difficult to determine the true price of the stock because it is difficult, if not impossible, to accurately assess the value of the firm – whether at a given time or over time. Additionally, in the standard stock market, common stock never matures; one never gets the opportunity to reach an end point and accurately look back and see what the price should have been.

Additionally, it has been shown that bookmakers are not necessarily the most informed people in a betting market, similar to the idea that market makers are not necessarily the most informed individuals in traditional financial markets. Unlike in the case of a firm issuing additional debt or equity securities, in a betting market there is no concern of bankruptcy if an additional betting line is offered on a particular game. The offering of additional lines does not result in any of the five possible negative reactions that Smith discusses for the common stock non-negative reactions.

The betting market allows for a more direct examination into whether additional securities, in this case additional betting lines, reveal additional information about the underlying asset and whether any additional information has implications for asset pricing and unbiasedness. The NCAA DI basketball betting market has three types of betting lines. Section 1.1 provides a general overview of the betting market and

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[4] See section I for an overview of the betting market and an explanation of the three types of betting lines.

description of the three types of betting lines. Having additional betting lines allows informed traders more possible positions and strategies which might allow them to take advantage of any information they hold. Additionally, as discussed in Section 1.1, these additional lines reveal more information to the market about a game's outcome than would be available if the lines were not offered. This is similar to how additional securities can provide additional information about how the market views a firm's cash flows and future performance.

In the data employed in this paper, the sides line, which reflects the market's expectation of how the game will conclude (in terms of point differential between the favorite and the underdog), exists for all games for which betting is offered. The same is not true for the money line, which reflects the relationship between money won and money bet regardless of the points scored on which team wins. Nor is it true for totals line, which reflects the market's expectation of the total points scored in the game – regardless of which team wins. These two additional betting lines serve the same purpose as additional securities: Offering the money line and/or the totals line allows bettors (investors) to take positions they could not have taken given initial information. The money line and totals line both result in the release of more information about the game's predicted outcome, and, therefore, act in a similar way as to the offering of additional securities by providing more information on the underlying asset.

Results obtained using standard techniques, suggest that sides line accuracy increases when a totals line is offered, as reflected in a smaller forecast error, but does not change with the existence of a money line. Additional analysis reveals that the expected linear relationship between the money line and the sides line breaks down once the favorite becomes too heavily favored. Very large sides lines have a diminishing impact on the favorite team's subjective probability of winning, consistent with diminishing returns to additional information concerning the favorite's probability of winning – partly because of the natural upper bound to the favorite's subjective probability of winning. This concave relationship suggests that, for a large number of games in the sample, the money line does not offer sufficient additional information to impact the accuracy of the sides line. However, there is no evidence that this improved accuracy in the sides line reduces or impacts any bias that may exist in the sides line.

2.1 Overview on NCAA Basketball Betting Markets

Before providing an overview of the betting market for NCAA DI basketball, it is useful to consider the schedule structure of an NCAA basketball season. During November and December, the first two months of the NCAA basketball season, teams generally schedule non-conference games and participate in tournaments across the United States, Virgin Islands, Bahamas, and Puerto Rico, although a few teams do start playing conference games during the last few days of December. The tournament games are generally considered to be held at neutral sites, that is, at neither team's home court.[5] From January through the first week of March, teams engage primarily in conference play; the teams play other teams within their conference, although a non-conference game may be scheduled. The first two weeks of March focus on conference tournaments which determine conference champions. The winners of these tournaments generally receive automatic berths in the NCAA Tournament, commonly referred to as March Madness.[6] The last weeks of March and the first couple of weeks in April are associated with the four national post-season tournaments.[7]

Unlike betting in the National Football League (NFL), where the market is open for about a week, the NCAA basketball betting market is only open for a short period of

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[5] Some of the more notable tournaments are the Great Alaska Shootout, the Maui Invitational, the National Invitational Tournament (NIT) Season Tip-Off, and the Puerto Rico Tip-Off.

[6] The Ivy Conference is the only conference that does not use a tournament to declare the conference champion. The Ivy Conference Champion is the team with the best record at the end of regular season play and receives an automatic berth into the NCAA Tournament.

[7] The NCAA Tournament, NIT, College Basketball Invitational Tournament (CBI), and CollegeInsider.com Postseason Tournament (CIT) are the four tournaments that are held at the end of the season. The 2007 season was the inaugural season for the CBI and 2008 was the inaugural season for the CIT. All games in the NCAA tournament are played at neutral sites. The semifinals and finals of the NIT are played at Madison Square Garden while the earlier rounds are played on the home court of the higher seeded team, with a few exceptions. The CBI and CIT are played on the home court of the higher seeded team.

time, not exceeding 12 hours, similar to the National Basketball Association's (NBA) betting market. The NCAA betting market begins with the posting of the opening lines at 8:00 a.m. Pacific Standard Time (PST) at all the major sports booking sites in Las Vegas for all of the games scheduled that day. The market for each game closes at tip-off, resulting in betting lines for some games being open for only a couple hours while for other games betting lines may be open for up to 12 hours depending on the exact location and time zone of the game.[8]

Opening lines represent the bookmaker's expectation of the game outcome (expectation for the line or difference between the scores of the favorite and the underdog at the end of the game) and the bookmaker's perception of the betting market's evaluation of these outcomes (Gandar et al. 1998). The intent of the bookmaker is to pick the line such that equal dollar amounts are wagered on each side of the line.[9] The lines can fluctuate while the betting line is open, reflecting differences between the expectation of the bookmaker and the expectation of the market. Therefore, the closing line can be viewed as the market's expectation of the game's outcome.

In the NCAA betting market there are three types of betting lines; for example, Table 1 provides the betting information for the game between Maine and Richmond on November 5, 2007. This example will be used to help explain each of the three types of betting lines. The first betting line is the sides line (SL), which allows a bettor to make a wager on either team. The SL also includes what is called "points" to encourage betting

[8] On Saturday and Sunday tip-offs on the east coast start at noon or one in the afternoon, which results in the market only being open for an hour, compared to games that are on the west coast or Hawaii that could stay open for as long as 12 hours if the game is played in the evening local time.

[9] Levitt (2004) shows that the books are not always balanced and that the bookmaker generates a profit from his ability to more accurately predict game outcomes than the average bettor, by limiting the amount that can be wagered by any bettor. Humphreys et al. (2009) find that changes in sides line bets on NCAA basketball games are not induced to balance betting on either side.

on the underdog. These points are commonly referred to as the point spread. As a result, a wager on the favored team only wins if the favored team wins by more than the stated point spread. Looking at Table 1, the SL is listed as 5.5 for Richmond, which means that for a wager placed on Richmond to win, Richmond must win the game by six points or more, otherwise the wager on Maine wins. In case the SL is a whole number, and the SL turns out to be the actual difference between the score of the favorite and the underdog, all wagers are returned with no winners. This outcome is commonly referred to as a "push". In the Maine-Richmond example, the line is 5.5, so there is always a winner; a push cannot occur.

TABLE 1: Betting Data for Maine and Richmond Game on November 5, 2007

Below are the closing betting lines for the first game in the dataset

Date	Team	SL	TL	ML
11/5/2007	Maine		127.5	200
	Richmond	5.5		-240

The second type of betting line is the totals line (TL). The TL allows a bettor to make a wager on the combined score of both teams. In the Maine-Richmond example, the TL is 127.5. In this situation, one can wager that the combined score will exceed 127.5, commonly referred to as the "over", or wager that the combined score is less than 127.5, commonly referred to as the "under". As with the SL, if the TL is an exact number and the actual combined scores equals the TL, the result is a "push". The TL also differs from the SL in that the wager is not tied to which team actually wins the game.

The third type of betting line is the money line (ML), which allows a wager to be placed on which team will win regardless of the difference in scores. Here the underdog is posted as a positive wager, and the favorite is posted as a negative wager. The negative wager on the favorite indicates the amount of money that must be wagered in order to win $100 plus the value of the original wager. In the case of a positive wager on the underdog, the value indicates how much will be won on $100 wager on the underdog. In Table 1, the ML on Maine is +200 and for Richmond is -240. The interpretation of the +200 for Maine is that a wager on Maine of a $100 will result in a payoff of $300 (which corresponds to the $200 plus the original wager of $100) if Maine wins and a payoff of zero if they lose. The interpretation of the -240 for Richmond is that a wager on Richmond (the favorite as indicated by the negative number) of $240 will result in a payoff of $340 (which corresponds to $100 plus the original wager of $240) and a payoff of zero if they lose.

It should be noted that by having the ML for both teams, one can calculate the subjective probability of each team winning the game. This is explained in the following example using the approach and notation employed by Sauer (2005). The first step in this calculation is to convert the ML into equivalent odds measured as the ratio between payoff and amount bet; for Table 1, these odds are 2.0 (2.0/1.0) for Maine and 0.416 (1.0/2.4) for Richmond (i.e. a $1 bet on Maine pays $3 and a $1 for Richmond pays $1.42). In an efficient market with no transaction costs, these odds can be converted to a probability: $\mathrm{p}^0 = 1/[1 + \mathrm{odds}]$. In the example above the probability of Maine winning is 0.333 and probability of Richmond winning is 0.706. When bookmakers do not offer fair odds, the probabilities total to more than 1.0; the approach is to normalize the probabilities to obtain the subjective fair probability, p^{fair}. This is done by dividing each team's probability of winning by the sum of both teams' probabilities, to give the subjective probability of winning. In this example, the normalized fair probability for Maine is 0.321 (0.333/[0.333+0.706]) and for Richmond is 0.679 (0.706/[0.333+0.706]). When the ML does not exist, these probabilities cannot be generated from only offering the SL and TL.

While the SL and TL cannot be utilized to calculate the probabilities of each team winning, they do offer other information. From the definitions for the SL and TL, each can be expressed as:

$$SL = E[Favorite\ Points - Underdog\ Points] \tag{1}$$

$$TL = E[Favorite\ Points + Underdog\ Points] \tag{2}$$

When both SL and TL are offered, one can calculate the expected points scored by each team, as shown by Borghesi and Dare (2009) and Dare and Dennis (2011) using equations 3 and 4:[10]

$$Favorite\ Points = \frac{TL+SL}{2} \tag{3}$$

$$Underdog\ Points = \frac{TL-SL}{2} \tag{4}$$

When either line (TL and SL) is not offered, it is not possible to calculate the expected points scored by both teams.

From the discussion above, the betting lines ML and TL clearly provide additional information to the market that is not necessarily available to all market participants when only the SL is available for a given game. In this paper, the SL is

[10] While the team scores are expressed as favorite and underdog, one could express them as home and away as demonstrated in Dare and Dennis (2011).

considered analogous to a common stock since it always exists whether the other betting lines are offered. The betting lines ML and TL are considered additional investment vehicles in the betting market. The empirical question is whether the availability of any additional betting lines provides information to market participants that is reflected in a more accurate SL or a more unbiased market.

While betting occurs in almost all sports, the NCAA basketball betting market is used here because it has a larger amount of variation in the betting lines offered among games compared to other popular sports.[11] This variation in the market facilitates testing the impacts of offering additional lines on the accuracy of the SL.[12]

[11] For example, during the 2007-2010 NFL regular seasons the betting market offered all three betting lines for all games played. When looking at NCAA DI football, almost all of the games offer all three betting lines, while only a handful of games were missing betting lines.

[12] While the authors assume that bookmakers randomly do not offer lines, it is possible there is a selection bias in the data where bookmakers may not offer certain lines as a result of game characteristics. This issue is left for future research.

2.2 Literature Review

A. Overview of Literature on Common Stock Price Reaction to Offerings

While the examination of the impact of additional securities on the accuracy of common stock prices has been unexamined, the impact of their offering on common stock reaction and returns has been examined in great detail. Smith (1986) offers a summary of previous findings on common stock price reactions to new offerings (common stock, preferred stock, convertible preferred stock, straight debt, and convertible debt), with preferred stock and straight debt having effects that are not significantly different from zero. It is important to note that for preferred stock and straight bond offerings, the common stock price reaction was not significantly different from zero, but were significantly negative for common stock, convertible preferred stock and convertible bond offerings. Smith provides the generalization that the average abnormal returns of common stock are non-positive, as well as five explanations for these findings.

Until the 1990s, most of these event studies looked only at the short-term affects. Looking at long-term (five-year) performance of common stock price after initial public offerings and seasoned equity offerings (SEO), Loughran and Ritter(1995) find both underperform, which is consistent with the results using short-term performance. In particular, their findings for SEO are similar to Spiess and Affleck-Graves (1995). Furthermore, Spiess and Affleck-Graves (1999) find long-run stock price underperformance following straight or convertible debt offerings, which is different than the results discussed in Smith (1986) for straight debt in the short-run.[13] Nevertheless, the results of Spiess and Affleck-Graves are weakly supported by Dichev and Piotroski (1997), who find underperformance for firms in the quintile for largest debt offering, but not for all debt offerings.

In more recent years, there has been a greater focus on common stock reaction to the offering of options. Branch and Finnerty (1981) were the first to look at this. While they conclude that the underlying stock price increases after call options are offered, their finding stems from what they recognize as a selection bias – in that call options are only offered on the better performing stocks. However, they find the reaction to the introduction of puts or dual listings, both puts and calls, is generally random. In examining their results as a whole, they conclude that their findings suggest that initial option listings on a stock tend to have a positive impact on the price and trading volume of the underlying stock. Conrad (1989), who looks at the introduction of options from 1974-1980, finds a permanent price increase around the introduction – not the announcement of an option. Additionally, the variance of the underlying stock's return declines after the option on a stock is introduced while the systemic risk is unaffected. Conrad concludes that "the evidence suggests that options are not completely redundant securities." Detemple and Jorion (1990), using data from 1973-1986, confirmed Conrad's findings that the underlying stock price increases when an option is introduced. They also find that the volatility of the underlying stock declines after the listing date of an option, indicating that the introduction of an option actually stabilizes the underlying

[13] Smith (1986) uses results from Dann and Mikkelson (1984), Eckbo (1986), and Mikkelson and Partch (1986) for his discussion on straight debt. They all find a negative, but insignificant, reaction to the offering of straight debt.

price of a stock. What is most interesting about their work is that their results are weaker in the latter part of their sample period, which is consistent with Sorescu (2000) findings that the introduction of an option results in a price increase in the underlying stocks during the time period from 1973 to 1980, but after 1980 the effect of options becomes negative. Sorescu uses an optimal switching means model and concludes the optimal switching date was determined to have occurred sometime between December 12, 1980 and June 29, 1981. While Sorescu acknowledges the argument of Detemple and Jorion (1990), that this change may be the result of the introduction of stock index options in April 1982, he proposes that a change in regulatory environment of standardized option trading during 1980 and 1981 might be the source of these results.

Chakravarty et al. (2004) are the first to examine and point out that the percentage of price discovery on a stock comes from the options market while also providing evidence of price discovery in the option market. They find that the option market's contribution to price discovery on the underlying asset is about 17%. These results provide support to the argument that additional securities on the same cash flows should provide more information leading to more accurate prices.

The question addressed in this paper is most similar to that addressed by Kumar et al. (1998), who look at the impact of option listings on the underlying asset and conclude that options benefit underlying stocks by having higher liquidity, lower information asymmetry, and greater price efficiency. Kumar et al. (1998) use Hasbrouck's (1993) model to look at pricing errors and conclude that the introduction of options decreases the pricing errors in the underlying asset, leading to the underlying stock being more efficiently priced after the listing of an option. Hasbrouck's model argues that an efficient price evolves as a random walk, which implies a stock price is efficient if it follows a random walk consistent with the weak-form of the EMH. This paper tries to examine a much broader scope of the problem concerning whether additional information in securities is able to be incorporated into more accurate pricing.

B. Literature on Betting Markets

A large part of the economic and financial literature utilizing betting market data has done so with the purpose of examining if prices have a bias. Betting markets provide an optimal examination of market unbiasedness because of the short time horizon and the well-defined end point of its offerings. These aspects allow economists to look back and see what the true betting lines should be. This is not possible in the stock market, where there is no clear consensus of the true price of any given stock and a stock does not have a designated maturity date. While there is a large body of literature that has investigated the unbiasedness of different betting markets, here the focus is on only that associated with the area of basketball because the data used in this paper is an NCAA basketball dataset.[14]

Brown and Sauer (1993a) look at the changes in the SL for NBA games to examine the observed unexplained asset price volatility and find that the noise component of the error is not irrelevant but, in fact, a vital component in predicting the outcome of a game. Gandar et al. (1998) look at the change in the opening and closing SL data for NBA games and conclude from their findings that closing SL are more accurate predictors of the game outcome than the opening SL. Their main conclusion is that the changes in the prices are the result of informed traders influencing the market, and not

[14] For an overview of the betting market in general, specifically related to horse-racing, see Sauer (1998).

just noise. Hence, it can be argued that as a result of the prices reflecting the new information into the SL that this market is at least weakly unbiased. Gandar et al (2000) extend their previous work to investigate unbiasedness of the TL betting line in the NBA betting market. They show that the closing TL is a more accurate forecast of the total points scored in a game than the opening TL, similar to their work on the SL. Gandar et al. (2000) conclude that bettors have information that is not initially priced into the bookmakers' opening SL and TL. Paul et al. (2004) confirm that the NBA TL is unbiased as a whole, but they also find some groupings of TL, that under some conditions, seem to win at a statistically higher percentage than 50%. Nevertheless, these occurrences do not result in a profitable strategy using the log-likelihood test. Paul et al. provide a psychological argument indicating that this is likely the result of the tendency to have a consumption value of cheering for more points rather than fewer points. This leads to a situation of over-betting the over in the total market. Paul and Weinbach (2005a) investigate the NCAA basketball SL market from the 1996-2003 seasons to examine its unbiasness. They conclude that, in general, the NCAA basketball betting market is an unbiased market.

While, as a whole, basketball betting markets seem to be unbiased, much like financial markets, there have been some observed biases. The most notable bias in betting markets is referred to as the "favorite-longshot bias". The favorite-longshot bias is a phenomenon where on average bettors tend to over bet the longshot (i.e. underdog) winning and under bet the favorite winning. In some betting markets, the opposite has been observed, which is referred to as the "reverse favorite-longshot bias". Paul and Weinbach (2005a) look at the NCAA basketball betting market and find that favorites of

20 points or more are not fair bets at the 10% level, since underdogs win 52.9% of the time. These results would be consistent with favorite-longshot bias, but are not large enough to be profitable. They also find that road favorites expected to win by ten or more points end up winning 54.57 percent of the time. While these teams win a significantly higher amount of games than the value for market efficiency, of 50%, this strategy is not profitable. In looking at the NBA betting market Paul and Weinbach (2005b) find multiple cases where betting on underdogs resulted in statistically higher than 50% winning wagers, but only betting on home underdogs, who are expected to lose by more than ten points, was the only strategy that was profitable.

Another anomaly discussed in the betting literature, is the argument of the hot-hand, which was first looked at by Gilovich et al. (1985). The thought here is that bettors overweight the situation that winners will continue winning and losers will continue losing, the latter is generally referred to as the cold hand. Gilovich et al. (1985) create an experiment allowing players and observers to bet on a player's performance while he shoots free throws. They observe that both players and observers make larger bets after the player has made a successful basket, which is consistent with the hot-hand theory, but the bet size and actual outcome are uncorrelated. Extending Gilovich et al.'s work, Camerer (1989) investigates the hot-hand theory on professional betting markets and finds that the market is influenced by the hot-hand phenomenon; however, the error is not profitable. Brown and Sauer (1993b) reexamine Camerer's findings, using more strenuous testing, and find convincing evidence that the hot hand affects the SL betting market, resulting in their inability to reject Camerer's hypothesis that the SL is "affected by mythical hot hand beliefs." Nevertheless, their results could not be shown to be consistent with "real hot hand effects in the score differences." Paul and Weinbach (2005b) look at the strategy of betting against teams on a winning streak and find this strategy does not only result in the rejection of a fair bet, it is also statistically profitable, supporting the notion that bettors overweight the hot hand. However, Paul et al. (2004) find that the market acts efficiently when incorporating winning and losing streaks into NBA TL.

At present, it appears that the idea of investigating multiple betting lines to assess the potential impact that they may have on each other has, in fact, not been researched. With that said, Borghesi and Dare (2009) and Dare and Dennis (2011) use the SL and TL to compare actual team performance relative to the market's expectations of team performance. Borghesi and Dare (2009) investigate whether point shaving occurs in NCAA basketball.[15] They test whether favorites tend to slack on defense, which would be preferred to slacking on offense when shaving points. They conclude that favorites are the least likely to slack at defense and conclude anomalies in the betting market are not the result of point shaving, but are more likely the result of coaching strategies, such as resting star players in games where the team is up by a large amount. By examining each team's performance in comparison to the expected scores, Dare and Dennis (2011) are able to show that the home underdog bias is strictly a downward bias on home underdogs and not a bias against away favorites.

This paper is similar to Colquitt et al. (2001), in that they use the NCAA basketball betting market to look at efficiency differences across conferences and compare it to efficiency differences seen across stock exchanges. Previous research has

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[15] For more research related to college basketball and point shaving see Wolfers (2006) and Paul and Weinbach (2011).

shown greater availability of fundamental information for stocks traded on the New York Stock Exchange than stocks traded on other markets. As a result, Colquitt et al. (2001) look at unbiasedness across the different conferences in the NCAA betting market and argue that more information is available for games between teams in an elite conference than those in a non-elite conference. The authors utilize the traditional unbiasedness test, originally used by Gander et al. (1988) and Sauer et al. (1988), and an examination of the absolute forecast errors. While the results developed by Colquitt et al. using traditional unbiasedness tests show no bias across conferences, the absolute forecast errors are statistically smaller for the elite conferences. The authors conclude by saying the following: "Evidence supports conclusions reached in studies of stock markets suggesting that differences in fundamental information result in different relative pricing efficiencies across those markets."

2.3 Data

The data employed in this paper were provided by Sports Book Reviews and includes opening and closing sides line (SL), opening and closing totals line (TL), closing money line (ML), the game date, whether the game was played at a neutral site, and the actual final score for 14,510 NCAA DI games played during the 2007-2010 seasons. The 60 games which do not have an opening or closing SL (nor TL or ML) are, therefore, not included in the analysis. There are 1,903 games played at neutral sites. When examining accuracy of the SL, the sample can be divided into 14 subgroups depending on the various betting lines available on each game. For example, there are 19 games where the ML and TL were not offered and 21 games where the SL and TL were not available when the market opened but were eventually offered before tip-off yet the ML was never offered.

In the sample, there are seven subgroups with more than five games comprising a total of 14,432 games. The seven subgroups, as well as their data population, are:

1. ALLDATA: All betting lines are offered (12,235 games)
2. NOOTL: Opening TL is not available[16] (1,537 games)
3. NOML: ML is not offered (100 games)
4. NOTL: TL is not offered (480 games)
5. NOOL: Opening TL and opening SL are not available (40 games)
6. NOMLTL: ML and TL are not offered (19 games)
7. NOOLML: Opening TL, opening SL, and ML are not available (21 games)

[16] While the opening TL is not offered a closing TL is, indicating that at some point the TL was introduced, but it is unclear how shortly after the market opens the line becomes available.

Only four subgroups have at least 100 games; the remaining ten subgroups have 40 games or less and are, thus, removed from the dataset when examining market efficiency due to small sample size. Thus, a total of 14,352 of the original 14,510 games are included in the final sample to examine whether the market is efficient

Table 2 provides a breakdown of the games by subgroups and by year while Table 3 provides summary statistics on the closing SL and actual point spread from the favorite-underdog prospective. From Table 3, it can be seen that in all cases the standard deviation of the actual score is always larger than the standard deviation of the SL, consistent with the previous literature.

It is important to note that of the 480 games where the TL is not offered, 471 of these games are in the beginning of the season before conference play. When looking at games where only the opening TL is not offered, over 90% (1,391) of the games are in the 2010 season; the remaining games are in the 2009 season, except for one game in the 2007 season. These cases are most likely to occur at the beginning of the season and never occur for post-season tournaments in NCAA basketball in March and April when the betting market has its largest volume.[17] The large increase in the delay of providing an opening TL may be an indication of the bookmaker realizing that there are bettors who are more informed than the bookmaker, causing the bookmaker to be unwilling to offer lines when uncertainty or information asymmetry is largest.

A unique aspect of college basketball is the large number of neutral site games played throughout the season: neutral site games make up a little over 13 percent of the

[17] March Madness is considered to be one of the largest events in the betting markets around the world. It has been compared to generate the same amount of money as the Super Bowl, the event with the highest wagers every year.

games in the dataset. All neutral site games occur in the beginning or end of the season, when many of the tournaments are played. Also there are no neutral site games in January and February since all conference games are played at the home team's court.

TABLE 2: Summary Statistics on Number of Observations

This table breaks down the games played by subgroups and when games are played by year and month. Each year represents the full season that includes November and December of that year and January, February, March and April of the following year. TG represents the total number of games played and Neutral indicates that the games are played on a neutral court.

	TG	Neutral	ALLDATA	NOOTL	NOML	NOTL	NOOL	NOMLTL	NOOLML
2007	3523	470	3445	1	43	29	0	1	0
November	560	183	503	1	23	28	0	1	0
December	581	59	571	0	9	1	0	0	0
January	909	0	898	0	11	0	0	0	0
February	893	0	893	0	0	0	0	0	0
March	572	222	572	0	0	0	0	0	0
April	8	6	8	0	0	0	0	0	0
2008	3478	435	3375	0	21	63	0	1	0
November	487	162	431	0	7	30	0	1	0
December	591	31	549	0	9	33	0	0	0
January	988	0	987	0	1	0	0	0	0
February	906	0	902	0	4	0	0	0	0
March	500	238	500	0	0	0	0	0	0
April	6	4	6	0	0	0	0	0	0
2009	3719	491	3152	145	21	298	38	9	20
November	561	166	159	90	5	287	0	7	0
December	640	38	568	55	3	11	0	2	0
January	1035	0	979	0	12	0	5	0	17
February	951	0	915	0	0	0	33	0	3
March	528	284	527	0	1	0	0	0	0
April	4	3	4	0	0	0	0	0	0
2010	3790	507	2263	1391	15	90	2	8	1
November	577	174	180	312	9	60	0	6	0
December	676	40	159	491	0	21	0	1	1
January	1012	1	482	509	5	8	1	1	0
February	974	0	915	55	1	1	1	0	0
March	547	289	523	24	0	0	0	0	0
April	4	3	4	0	0	0	0	0	0
TOTAL	14510	1903	12235	1537	100	480	40	19	21

TABLE 3: Summary Statistics on Closing Sides Lines and Actual Point Spread

Summary statistics are from a favorite-underdog prospective.

	TG		Neutral		ALLDATA		NOOTL		NOML		NOTL		NOOL		NOMLTL		NOOLML	
Games	14195		1844		12008		1521		98		475		40		19		21	
	CSL	AS	CSL	AS	CSL	AS	CSL	AS	CSL	AS	CSL	AS	CSL	AS	CSL	AS	CSL	AS
Std. Dev	5.9	12.1	4.9	12.1	5.6	11.9	6.0	12.3	8.5	14.5	7.6	14.3	5.5	10.0	3.8	11.5	7.0	13.6
Mean	8.1	7.8	6.8	6.4	7.8	7.5	8.6	8.1	19.3	18.8	10.5	11.1	8.7	9.2	21.6	18.3	8.12	9.33
Median	6.5	8	5.5	7	6.5	8	7.5	8	20	16	8	11	8	9	21.5	16	6	6
Min	1	-52	1	-30	1	-52	1	-33	1	-11	1	-21	1	-13	15	-1	1	-13
Max	43.5	69	34	57	39	61	37.5	57	36	69	43.5	64	22	38	27.5	39	30.5	38

2.4 Methodology

A. Testing Accuracy in the Sides Line (SL)

Here, three tests examine the accuracy of the SL under the different possible line offerings. While there have been many papers that examine unbiasedness in the betting market, accuracy has not been a focal point of the literature. The first test is a slightly modified version of a basic test for market unbiasedness:

$$PS_i = b_0 CSL_i + b_1 SLNOOTL_i + b_2 SLNOOCTL_i + b_3 SLNOML_i + b_4 SLNOOSL_i + \varepsilon_i. \quad (5)$$

In Equation (5) PS represents the actual point difference between the two teams at the end of the game and CSL represents the closing SL for each game. The remaining four variables (SLNOOTL, SLNOOCTL, SLNOML, and SLNOOSL) all represent CSL multiplied by the respective dummy variable for missing betting information (opening TL, closing TL, ML, and opening SL) and ε is a zero-mean random error term. The intercept is suppressed to allow for the model to directly examine the accuracy of the SL when other lines are missing, by using joint tests of whether the parameter on SL in different subgroups is statistically different from one.[18]

The expectation is that b_0 is not significantly different from one, indicating for subgroup one the market is accurate. The expectation for subgroup three, four, and six (NOML, NOTL and NOMLTL), is that the joint coefficients are significantly different from one for each subgroup, which would indicate that the market is not as accurate when the other lines are missing. As for subgroups two, five, and seven (NOOTL, NOOL and NOOLML) no expectations are made, since it is unclear how the market will react to the

[18] The results from the model are qualitatively the same when the intercept is included.

introduction of lines, and it is unknown when the lines were introduced between the opening line and the closing of the betting window at the beginning of the game.

The second test looks at the accuracy of the SL by examining the absolute forecast error. The absolute forecast errors are calculated as follows:

$$AFE = |PS - CSL|, \tag{6}$$

where PS and CSL are defined above. The expectation is that the absolute forecast error is smaller when all the betting lines are offered, compared to when information is missing. In order to test a difference in means, the Wilcoxon-Mann-Whitney test is used because the absolute forecast error does not seem to be normally distributed.

The third test is nearly identical to the second test, but the forecast errors generated from Equation (5) are used instead of just the difference between the actual and the expected score, that is, the closing SL. Here the Wilcoxon-Mann-Whitney test is used because even though the forecast errors from the model are assumed to be normally distributed, the absolute forecast errors are likely not normally distributed.

For test three, the expectations are the same as in test two, that is, that the absolute forecast error is significantly larger for the subgroups missing betting lines when compared to subgroup one, where all lines exist.

B. Testing Unbiasedness in Betting Market

The second question examined is whether any increased accuracy in the SL that occurs when additional betting lines are present results in a reduction in any possible bias in the market? While this paper is not the first to test unbiasedness markets in the betting market, it is the first to look at unbiasedness while considering the interaction between betting lines. Zuber et al. (1985), Gandar et al. (1988), and Sauer et al. (1988) utilize the following basic test of unbiasedness in the betting market:[19]

$$PS = b_0 + b_1 CSL + \varepsilon, \tag{7}$$

where PS and CSL are the same as described above, and ε is a zero-mean random error. Unbiasedness implies that the following joint hypothesis test cannot be rejected: $b_0 = 0$ and $b_1 = 1$.[20] When using this simple test, the order of which team comes first in the calculation of PS is important because, as pointed out by Gandar et al. (1988), the model is sensitive to which approach is used. In developing this test there are three approaches: (1) home minus away, (2) favorite minus underdog, and (3) a random method.[21] When using the home-away approach, games played at neutral sites are dropped from the analysis while in the favorite-underdog approach "pick-em games", that is, games where no team is a favorite, are dropped from the analysis. Here, the tests are run using both the home-away method and the favorite-underdog method.

Dare and MacDonald (1996) address the issues with using Eq. 7 and develop a model that incorporates all five possible types of games:

1. Favored-home team plays underdog-away team
2. Favored away team plays underdog-home team
3. Pick-em home team plays pick-em away team
4. Favored team plays underdog team on neutral site

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[19] This test has been criticized in the literature for not being a valid test of market efficiency. The claim of being unbiased is not a sufficient condition for market efficiency. See Russo et al. (1989), Even and Noble (1992), and Gandar et al. (1993)

[20] Zuber et al. (1985) point out that an alternative test would be that $b_0 = b_1 = 0$, indicating the SL has no impact on actual point difference.

[21] Golec and Tamarkin (1991) try to control for the bias of using home-away or favorite-underdog by randomly using the home or favorite differencing method on each observation. The problem with this approach is each run of the test yields different results.

5. Pick-em teams play on neutral site

By using the favorite-underdog difference when possible and using dummy variables for favored, underdog, home, away, pick-em, and neutral site games, five equations can be generated, one for each type of game. These models can be reduced into the following single equation:

$$\begin{bmatrix} PS^{FH} \\ PS^{FA} \\ PS^{FN} \\ PS^{HP} \\ PS^{PN} \end{bmatrix} = \beta_0^F \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \beta_0^P \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} + \beta_0^H \begin{bmatrix} 1 \\ -1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \beta_0^N \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} + \beta_1^F \begin{bmatrix} CSL^{FH} \\ CSL^{FA} \\ CSL^{FN} \\ 0 \\ 0 \end{bmatrix} + \beta_1^H \begin{bmatrix} CSL^{FH} \\ -CSL^{FA} \\ 0 \\ 0 \\ 0 \end{bmatrix} +$$

$$\beta_1^N \begin{bmatrix} 0 \\ 0 \\ CSL^{FN} \\ 0 \\ 0 \end{bmatrix} + \varepsilon, \qquad (8)$$

where PS and CSL are as described above. The superscripts indicate the perspective of the line, e.g., FH represents favored teams that play on their home court (FA = favored away team and FN = favored team at neutral site). PN represents pick-em games played on neutral court, a case where there is neither a favorite nor a home team; as a result, the differencing approach is arbitrary. As a result, Dare and MacDonald subtract the score of the visiting team, listed by the betting line, from the home team, listed by the betting line. The test of market unbiasedness is: $\beta_0^F = \beta_0^P = \beta_0^H = \beta_0^N = \beta_1^H = \beta_1^N = 0$ and, jointly, $\beta_1^F = 1$. The authors test their model using NFL and NCAA football betting data but acknowledge that the model can be used to investigate any betting market with favorite and home team characteristics.

Dare and MacDonald is not the only paper to derive an alternative model to address the problems inherent in the basic unbiasedness test. Even and Noble (1996) used a likelihood ratio statistic to look at the probability of PS exceeding the closing SL. If the market is unbiased, the probability should be 0.5. The authors use a likelihood ratio test because it does not impose equal median and mean on the forecast errors. The likelihood ratio statistic for the null hypothesis that the probability of PS > SL is 0.5 is:

$$2(L^{u} - L^{r}) = 2\{n[\ln(\hat{q})] + (N - n)[\ln(1 - \hat{q})] - \mathrm{N}[\ln(0.5)]\}, \tag{9}$$

where L^u is the unrestricted log-likelihood function, L^r is the restricted log-likelihood, N is the total number of observations, n is the number of observations where PS > SL, and $\hat{q}$ is the observed proportion of observations where PS > SL (i.e. $\hat{q} = n/N$). The likelihood ratio statistic has a χ^2 distribution with one degree of freedom.

Gandar et al. (1993) show that the likelihood ratio statistic in Even and Noble (1996) is nearly similar to a Z^2-test statistic. Gandar et al., however, go one step further to show that a modest improvement occurs when changing the denominator in the standard Z-statistic from the null hypothesis variance $[q_0(1 - q_0)/N]$ to the sample variance $[\hat{q}(1 - \hat{q})/N]$, resulting in a $(Z')^2$-test statistic that takes the following from:

$$(Z')^2 = (\hat{q} - q_0)^2/[\hat{q}(1 - \hat{q})N^{-1}], \tag{10}$$

where $q_0 = 0.5$ when testing that the null hypothesis of an unbiased market. Gandar et al. (1993) show that their $(Z')^2$-test does result in a slightly more power test to reject a false null hypothesis than the Even and Noble log-likelihood test. In both Even and Noble's likelihood ratio statistic, and in Gandar et al.'s $(Z')^2$-test statistic, the test is performed using the favorite-underdog method and the home-away method.

To test the impact of the additional lines, TL and ML, the four tests above are run using the four subgroups discussed in section 2.3. This allows one to see the impact that these additional lines have on the SL and whether these additional betting lines actually result in more accurate and unbiased results.

By using the ALLDATA subgroup in the above basic model, and the Dare and MacDonald model, the TL and ML can be included in the model directly to see if the information in these lines is already included in the SL. In taking this approach, the ML is incorporated as a probability. As a result, Eq. 7 becomes:

$$PS = b_0 + b_1 CSL + b_2 MLP + b_3 CTL + \varepsilon, \tag{11}$$

where MLP indicates the probability, calculated from the ML, of the home (favored) team winning, and CTL is the closing TL. Unbiasedness would imply that $\mathrm{b}_0 = \mathrm{b}_2 = \mathrm{b}_3 = 0$ and, jointly, $\mathrm{b}_1 = 1$. Looking at the Dare and MacDonald model, Eq. 8 now becomes the following:

$$\begin{bmatrix} PS^{FH} \\ PS^{FA} \\ PS^{FN} \\ PS^{HP} \\ PS^{PN} \end{bmatrix} = \beta_0^F \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \beta_0^P \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} + \beta_0^H \begin{bmatrix} 1 \\ -1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \beta_0^N \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} + \beta_1^F \begin{bmatrix} CSL^{FH} \\ CSL^{FA} \\ CSL^{FN} \\ 0 \\ 0 \end{bmatrix} + \beta_1^H \begin{bmatrix} CSL^{FH} \\ -CSL^{FA} \\ 0 \\ 0 \\ 0 \end{bmatrix} +$$

$$\beta_1^N \begin{bmatrix} 0 \\ 0 \\ CSL^{FN} \\ 0 \\ 0 \end{bmatrix} + \beta_2^F \begin{bmatrix} MLP^{FH} \\ MLP^{FA} \\ MLP^{FN} \\ 0 \\ 0 \end{bmatrix} + \beta_2^H \begin{bmatrix} MLP^{FH} \\ 1 - MLP^{FA} \\ 0 \\ MLP^{HP} \\ 0 \end{bmatrix} + \beta_2^N \begin{bmatrix} 0 \\ 0 \\ MLP^{FN} \\ 0 \\ MLP^{PN} \end{bmatrix} + \beta_2^P \begin{bmatrix} 0 \\ 0 \\ 0 \\ MLP^{HP} \\ MLP^{PN} \end{bmatrix} +$$

$$\beta_3^T \begin{bmatrix} CTL \\ CTL \\ CTL \\ CTL \\ CTL \end{bmatrix} + \varepsilon, \tag{12}$$

where MLP^{jk} indicates the probability, calculated from the ML, of team k winning with j being the differencing method and CTL is the closing TL. The test of market unbiasedness is: $\beta_0^F = \beta_0^P = \beta_0^H = \beta_0^N = \beta_1^H = \beta_1^N = \beta_2^F = \beta_2^H = \beta_2^N = \beta_2^P = \beta_3^T = 0$ and, jointly, $\beta_1^F = 1$.

The results of the above tests are presented and discussed in the following section.

2.5 Results for Accuracy in Sides Line

The results from using the altered basic model for market unbiasedness, Equation (5), are provided in Table 4. The results provide weak evidence that for subgroup NOTL, that is, when the totals line (TL) is not offered, the sides line (SL) is less accurate: The slope coefficient is statistically greater than one at the 10% level. No other subgroup has a coefficient that is statistically different from one. The expectation was that a missing TL would result in a less accurate SL. Additionally, it is not surprising to see that the subgroups that were missing opening lines, NOOTL and NOOL, do not result in a less accurate SL. This is likely the result of the market reacting to the release of the information and reflecting accurate SL by the closing of the market. Since it is unknown when the exact release of the lines is, it is not possible with the current data to estimate how quickly the market does react to this information.

The more intriguing finding is that there is no difference in the accuracy of the SL in either subgroup NOML or NOMLTL, both of which were expected to yield less accurate SL. It was expected that a missing ML would result in a less accurate SL because of the reduced amount of information available to market participants. Moreover, subgroup NOOLML does not have a coefficient different from one as expected. Finally, among the games missing both the ML and the TL, there seems to be no reduction in unbiasedness. One possible explanation for this is the small size of this subgroup (19 games). In section 2.7, a closer examination of the relationship between the ML and the SL is provided to offer additional insight into why the accuracy of the SL is unaffected by the ML.

TABLE 4: Basic Model Result for Accuracy

The results from Eq. 5 in the paper are presented below using robust standard errors and from a favorite-underdog prospective. The F Tests are testing that the intercept forth subgroup is not different from one.

Variable	Coefficient		p-value
CSL	0.988	***	0.000
SLNOOTL	-0.032		0.274
SLNOCTL	0.115	**	0.014
SLNOML	-0.051		0.337
SLNOOSL	0.104		0.352
F-Statistic	2377.00	***	0.000
R^2	0.468		

F Tests	Subgroup	Coefficient		p-value
CSL=1	ALLDATA	1.41		0.236
CSL+SLNOOTL=1	NOOTL	2.57		0.109
CSL+NOOTL+NOOSL=1	NOTL	0.30		0.584
CSL+NOML=1	NOML	1.44		0.230
CSL+NOOTL+NOCTL=1	NOOL	3.41	*	0.065
CSL+NOOTL+NOCTL+NOML=1	NOMLTL	0.11		0.735
CSL+NOML+NOOTL+NOOSL=1	NOOLML	0.01		0.935

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

The results when using absolute forecast errors are provided in Table 5. The results from both measures of absolute forecast errors are nearly identical and are similar to the other accuracy test. Here, the only absolute forecast errors that are statistically different are found in subgroup NOTL, that is, when no TL is offered. These absolute forecast errors are significantly different from the absolute forecast error when all betting lines are offered at the 10% level. Overall, there is evidence that the SL is not as accurate when the TL is not offered, but that the SL is unaffected when the ML is not offered.

TABLE 5: Absolute Forecast Error Results for Accuracy

Panel A provides the results from the mean difference test on the absolute forecast errors, where the forecast error is just the difference is actual points scored minus the expected points scored (closing sides line). The Wilcoxon-Mann-Whitney test is used as a result of the distribution not being normal. Panel B provides the results from the mean difference test on the absolute forecast error, where the forecast errors are the errors from Eq. 5. Here too the Wilcoxon-Mann-Whitney test is used.

Panel A			
Subgroup 1	Subgroup 2	Z	p-value
ALLDATA	NOOTL	-0.649	0.516
ALLDATA	NOML	-1.066	0.287
ALLDATA	NOTL	-1.822 *	0.069
ALLDATA	NOOL	0.824	0.410
ALLDATA	NOMLTL	-1.332	0.183
ALLDATA	NOOLML	0.421	0.674
Panel B			
Subgroup 1	Subgroup 2	Z	p-value
ALLDATA	NOOTL	-0.684	0.494
ALLDATA	NOML	-0.879	0.380
ALLDATA	NOTL	-1.832 *	0.067
ALLDATA	NOOL	0.673	0.501
ALLDATA	NOMLTL	-1.369	0.171
ALLDATA	NOOLML	0.404	0.687

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

2.6 Results from Market Unbiasedness

In general, the results across all models seem to conclude that any unbiasedness in the SL is unaffected by the existence of additional betting lines. This means that the more accurate pricing of the SL when the TL is available does not result in an effect in the unbiasedness tests – any affect it may have on unbiasedness is too small to be measured using these tests.

A. Basic Model

Results from the basic model are found in Table 6, with Panel A displaying results from the home-away differencing approach (HADA) and Panel B containing the results from the favorite-underdog differencing approach (FUDA).[22] One of the first things to notice is that the results are similar for both differencing approaches, which is not the case in other studies.[23] One surprising result is that for the subgroup ALLDATA, where all three betting lines exist, the coefficient on the intercept is different from zero at the 1% level using the HADA and at the 5% level using the FUDA. One might expect that this subgroup would be the least likely to have a bias because it is the subgroup with the most information freely available to market participants, but under both approaches it is not strictly unbiased. In addition, under both approaches the subgroup where the TL is not offered when the market opens (NOOTL) and the subgroup where the ML is not offered (NOML) are the two cases in both differencing approaches where one cannot reject the null of an unbiased market. In the subgroup, where the TL is not offered

[22] The Dare and MacDonald tests are reported with robust standard errors as a result of finding heteroscedasticity, using the Cameron-Trivedi decomposition. However, heteroscedasticity was not found in the basic model. As a result robust standard errors are not needed.

[23] Gandar et al. (1988) note that their results are dependent on the differencing method used.

TABLE 6: Basic Model Results for Market Unbiasedness

Panel A and B provide the results of the basic model (Eq. 7). Panel A provides the results using the HADA. Panel B provides the results using the FUDA. ALLDATA indicates all betting lines are offered, NOTL indicates the TL was not offered when market opened but is offered by tip-off (market closes), NML indicates no ML was offered, and NTL indicates no TL was offered. The null hypothesis is $\beta_0 = 0$ and $\beta_1 = 1$. Panel C looks at subgroup ALLDATA and includes MLP, the closing ML of the home/favorite listed as a probability, and TL, the closing TL, into the model (Eq. 11). The null from Panel A and B are still the same, but the null on both additional variables are as follows $\beta_3 = 0$ and $\beta_4 = 0$. The joint test for each model is the null for each panel jointly tested.

Panel A													
		ALLDATA			NOOTL		NOML		NOTL			
	Test	Coefficient		p-value	Coefficient	p-value	Coefficient	p-value	Coefficient		p-value
Constant	β=0	-0.334	***	0.005	-0.024	0.945	-0.338	0.862	-1.079		0.138
Close SL	β=1	1.005		0.702	0.949	0.113	0.977	0.797	1.136	**	0.011
F-Statistic		6755.81		0.000	874.34	0.000	117.32	0.000	459.18		0.000
Joint Test		4.78	***	0.008	1.89	0.151	0.19	0.827	3.31	**	0.038
R^2		0.389			0.383		0.569		0.555		
Observations		10,609			1,409		91		370		

Panel B											
		ALLDATA			NOOTL		NOML		NOTL		
	Test	Coefficient		p-value	Coefficient	p-value	Coefficient	p-value	Coefficient		p-value
Constant	β=0	-0.395	**	0.016	-0.495	0.304	-0.403	0.892	-0.979		0.275
Close SL	β=1	1.020		0.243	0.999	0.979	0.995	0.972	1.149	**	0.031
F-Statistic		3569.68		0.000	476.69	0.000	50.48	0.000	277.47		0.000
Joint Test		3.86	**	0.021	1.68	0.186	0.09	0.915	0.03		0.872
R^2		0.229			0.239		0.345		0.370		
Observations		12,008			1,521		98		475		

TABLE 6: (Continued)

Panel C					
		Home-Away		Favorite-Underdog	
	Test	Coefficient	p-value	Coefficient	p-value
Intercept	$\beta=0$	1.288	0.457	-0.551	0.757
Close SL	$\beta=1$	1.026	0.612	1.005	0.929
MLP	$\beta=0$	-0.808	0.676	0.693	0.749
TL	$\beta=0$	-0.009	0.376	-0.002	0.859
F-Statistic		2252.01	0.000	1139.28	0.000
Joint Test		0.96	0.413	0.01	0.998
R^2		0.389		0.229	
Observations		10,609		12,005	

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

(NOTL), the coefficient of the closing line is significantly different than one at the 5% level using both differencing approaches. These results indicate that the offering of the other lines using the basic unbiasedness test does not impact the SL.

When MLP and CTL are included into the basic model, the R^2 for both differencing approaches remains unchanged and, as expected, these variables are not individually or jointly significant. This indicates that both the ML and the TL are incorporated into the SL. The result using the simple unbiasedness test shows that information provided by the other lines (ML and TL) is in fact incorporated into the SL.

B. Dare and MacDonald Model

The results using the Dare and MacDonald model are provided in Table 7. Panel A runs the model on the four subgroups of data. Looking at subgroup ALLDATA, where the expectation is that the market should result in the most accurate SL, one can reject the null of the coefficients being jointly different from zero at the 5% level, indicating the market is biased. In the subgroup NOML, one can reject the null that the coefficients are jointly different from zero at the 1% level. The interesting result in this model comes from the subgroups NOOTL and NOTL. Here, one fails to reject the null that the coefficients are jointly different from zero. Since in all subgroups one fails to reject $\beta_1^F = 1$, these results imply that when the TL is not offered, or is introduced after the market opens there is no unbiasedness in the market. However, there is biased when all lines are offered, and when the ML is not offered. As a result, it is unclear whether the additional betting lines result in a reduction in the SL bias. While it cannot be said that these other betting lines have no impact, the results from the Dare and MacDonald model

TABLE 7: Dare and MacDonald Model Result for Market Unbiasedness

The results presented in this table use the Dare and MacDonald model. Panel A provides the results using Eq. 6 across the subgroups. The joint test tests if f0 = p0 = h0 = n0 = h1 = n1 = 0 and f1 = 1. Panel B incorporates the ML and the TL into the Dare and MacDonald model. Joint test A in Panel B tests if f0 = p0 = h0 = n0 = h1 = n1 = 0 and f1 = 1, Joint test B tests h2 = f2 = n2 = p2 = CTL = 0 and f1 = 1, and Joint test C tests f0 = p0 = h0 = n0 = h1 = n1 = h2 = f2 = n2 = p2 = CTL = 0 and f1 = 1.

Panel A									
		ALLDATA		NOOTL		NOML		NOTL	
	Test	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
f0	β=0	-0.298	0.135	0.058	0.926	-0.406	0.859	0.168	0.886
p0	β=0	-0.804	0.315	6.118 *	0.099	13.032 ***	0.000	1.999	0.588
h0	β=0	-0.208	0.295	-0.720	0.245	-0.532	0.815	-2.708 **	0.021
n0	β=0	-0.770	0.122	-3.089	0.165	-2.772	0.488	-1.162	0.572
f1	β=1	1.034	0.198	0.902	0.227	1.032	0.820	1.037	0.714
h1	β=0	-0.015	0.569	0.101	0.212	-0.035	0.799	0.205 **	0.042
n1	β=0	0.055	0.376	0.543 *	0.063	0.424 *	0.068	0.114	0.527
Joint Test		2.78 **	0.011	1.35	0.230	23.06 ***	0.000	1.20	0.305
F-Statistic		12364.6 ***	0.000	825.6 ***	0.000	78.3 ***	0.000	106.6 ***	0.000
R^2		0.445		0.468		0.764		0.610	
Observations		12,235		1,537		100		480	

TABLE 7: (Continued)

	Panel B		
	Test	Coefficient	p-value
f0	β=0	0.670	0.726
p0	β=0	3.813	0.792
h0	β=0	-0.107	0.624
n0	β=0	-2.243	0.587
f1	β=1	0.874	0.211
h1	β=0	0.169 *	0.092
n1	β=0	0.176	0.432
h2	β=0	-6.639 *	0.064
f2	β=0	5.543	0.124
n2	β=0	-3.812	0.641
p2	β=0	-1.783	0.95
CTL	β=0	-0.003	0.720
Joint Test A		0.97	0.44
Joint Test B		0.75	0.58
Joint Test C		1.90 **	0.03
F-Statistic		800.0 ***	0.000
R^2		0.445	
Observations		12,232	

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

do not indicate that the SL betting market is less biased as a result of the TL and ML being offered.

Panel B of Table 5 includes the closing TL value as well as the addition of the ML, using h2, f2, n2 and p2, in the model. Here, one rejects the joint test that $\beta_0^F = \beta_0^P = \beta_0^H = \beta_0^N = \beta_1^H = \beta_1^N = \beta_2^F = \beta_2^H = \beta_2^N = \beta_2^P = \beta_3^T = 0$ and $\beta_1^F = 1$. This indicates that the market is biased and the information revealed in the ML and the TL is not incorporated into the SL. However, the Adjusted R^2 is unaffected implying that the information from the ML and the TL is already incorporated into the SL. As a result, the information revealed in the ML and the TL is not incorporated into the SL.

C. $(Z')^2$-Test and the Likelihood Ratio Test

Both of these tests follow a χ^2 distribution and yield nearly identical results. However, Gandar et al. (1993) show that their $(Z')^2$-test does result in a power test to reject a false null hypothesis. The results from both models are in Table 8.

In Panel B where pushes, games where the actual spread is equal to the closing SL, are removed, results for home and away/favorite and underdog teams have the same $(Z')^2$-test and likelihood ratio.[24] When pushes are included, the home team seems to win at a statistically higher rate than 50% in all but the NOML subgroup. In the subgroup ALLDATA, the favorite and, hence, the underdog, both win at a rate significantly different from 50%. It seems that these results are significantly influenced by the pushes, since in the ALLDATA sample both favorite and underdog win 5,869 games respectfully, which includes 239 games where pushes occur. As a result, Panel B seems to be a more efficient examination of these two models.

[24] This is not the case when pushes are included because the sum of the probability of either team winning does not add to one.

TABLE 8: $(Z')^2$-Test and the Likelihood Ratio Test for Market Unbiasedness

This table presents the results of the Even and Noble (1992) Likelihood Ratio and the Gandar et al. (1993) modified square of the standard Z-test. Panel A includes pushes, when the SL equals the actual spread, while Panel B removes pushes, which results in home and away/favorite and underdog having the same likelihood ratio and $(Z')^2$ test. Both follow a χ^2 distribution with one degree of freedom: critical values are 2.7055 (10% level), 3.8415 (5% level), and 6.6349 (1% level)

	Panel A							
	ALLDATA		NOTL		NOML		NOTL	
	Home	Favorite	Home	Favorite	Home	Favorite	Home	Favorite
LR	28.839 ***	6.071 **	4.892 **	2.610	1.333	0.654	4.333 **	0.356
$(Z')^2$	28.904 ***	6.074 **	4.906 **	2.614	1.349	0.657	4.375 **	0.356
	Away	Underdog	Away	Underdog	Away	Underdog	Away	Underdog
LR	0.530	6.071 **	0.205	0.016	0.892	0.368	1.829	2.025
$(Z')^2$	0.530	6.074 **	0.205	0.016	0.899	0.369	1.836	2.032
	Panel B							
	ALLDATA		NOTL		NOML		NOTL	
	Home	Favorite	Home	Favorite	Home	Favorite	Home	Favorite
LR	9.509 ***	0.000	1.817	0.566	1.113	0.506	3.004 *	1.039
$(Z')^2$	9.517 ***	0.000	1.819	0.566	1.125	0.508	3.025 *	1.041

*, **, and *** indicates statistically significant from null at, 10%, 5%, and 1% levels.

In Panel B, favorites do not win at a rate higher than 50% in any of the subgroups – while home teams win at a significantly greater than 50% rate in the ALLDATA and NOTL subgroups, at the 1% and 10% level respectively. One interpretation of these results is that there is a possible home team bias in both subgroups. The rejection of market unbiasedness in the ALLDATA subgroup is rather surprising since the ALLDATA subgroup contains games in which the market should have no bias because of the greater amount of freely available information provided to market participants.

2.7 Relationship between the Money Line and the Sides Line

Up to now, the relationship between TL and SL has been the focus with no discussion about the relationship between the ML and the SL. The ML can be used to calculate the subjective probability of each team winning and the SL provides the market expectation of how much the favorite team will win by, referred to as the point spread.[25] Each additional half point in the point spread should result in a stepwise increase in the subjective probability of the favorite team winning. This is because there is no magic point spread where each additional increase in the spread results in a larger or smaller probability of the favorite winning. As a result, there should be a linear relationship between the ML and the SL. This linear relationship is similar to the security market line (SML) in financial markets where one can view the point spread as the measure of risk one is taking when betting in the money line. From the SML prospective, the return, which is the payoff for the wager in the ML, should linearly adjust with the amount of risk of the outcome occurring. The measure of risk can be measured in the betting market by looking at the SL, where a higher SL implies smaller risk when betting on the favorite and larger risk when betting on the underdog.

Using the ALLDATA subgroup, subjective and objective probabilities of the favorite winning are calculated for each SL. While the subjective probability is derived from the ML, the objective probability is just the observable probability. Here one can calculate the objective probability of the favorite (underdog) winning is by dividing the number of games where the favorite (underdog) wins for a given SL (ML) by the total

[25] A subjective probability is a probability that is derived from one's judgment of the likelihood of an outcome to occur. In this case it is the market's judgment and in section I the calculation on how to derive these subjective probabilities from the money line is discussed

number of games played with the same SL (ML). Figure 1 plots the subjective and objective probability for each SL. It is quite obvious that the relationship is not linear; each additional half point increase in the SL does not result in a constant increase in the probability of winning and vice versa. As a result, different ML may provide more information than other ML. In fact, the relationship is best fit by a linear regression model until the SL reaches seven, after which each half point increase in the SL has a diminishing, but positive, impact on the probability of the favorite winning, resulting in the quadratic model being a better fit.[26] Results from the linear and quadratic models are presented in Table 9. This breakdown in the linear relationship is a likely reason that the existence of the ML has no impact on the accuracy of the SL. From this finding, it becomes an interesting question to see if all the information in the SL is fully reflected in the ML. However this question is left for future research.

Additionally, in Figure 1, the objective probability for each SL is plotted. In all but two cases the objective probability is larger than the subjective probability. This may possibly be explained in that bettors are more likely to wager on the underdog, especially when the underdog is a heavy underdog, expected to lose by a large margin. Also when the SL is in the neighborhood of seven points, this difference seems to become larger, implying that the bookmaker may be offering a discount on the ML for the favorite – perhaps to entice bettors to make a wager on the favorite. A ML wager on a ten point favorite is likely to pay $100 on a $500 to $600 wager. It may be at this point that the cost of making a wager on the favorite becomes less appealing, does not offer a high

[26] The Adjusted R^2 is utilized to examine the best fit between the linear and quadratic models. All observations at or below the specified SL are used.

enough return, and, as a result, the bookmaker provides a discount on the amount needed to wager in order to win $100.

Table 9: Linear and Quadratic Output of the Sides Line and Money Line Relationship

The results provided below are for the linear and quadratic OLS models that look at the relationship between the SL and the ML.

Panel A: SL ≤ 6				
	Linear Model		Quadratic Model	
Constant	0.4781	***	0.4790	***
FSL	0.0372	***	0.0365	***
FSL^2			0.0001	***
Adj. R^2	0.9744		0.9744	
Obs.	5832		5832	
Panel B: SL ≤ 6.5				
	Linear Model		Quadratic Model	
Constant	0.4789	***	0.4772	***
FSL	0.0369	***	0.0380	***
FSL^2			-0.0001	***
Adj. R^2	0.9781		0.9781	
Obs.	6270		6270	
Panel C: SL ≤ 7				
	Linear Model		Quadratic Model	
Constant	0.4800	***	0.4754	***
FSL	0.0365	***	0.0394	***
FSL^2			-0.0004	***
Adj. R^2	0.9800		0.9803	
Obs.	6693		6693	
Panel C: SL ≤ 7.5				
	Linear Model		Quadratic Model	
Constant	0.4810	***	0.4743	***
FSL	0.0361	***	0.0403	***
FSL^2			-0.0005	***
Adj. R^2	0.9818		0.9824	
Obs.	7064		7064	

*, **, and *** indicates statistically significant from null at, 10%, 5%, and 1% levels.

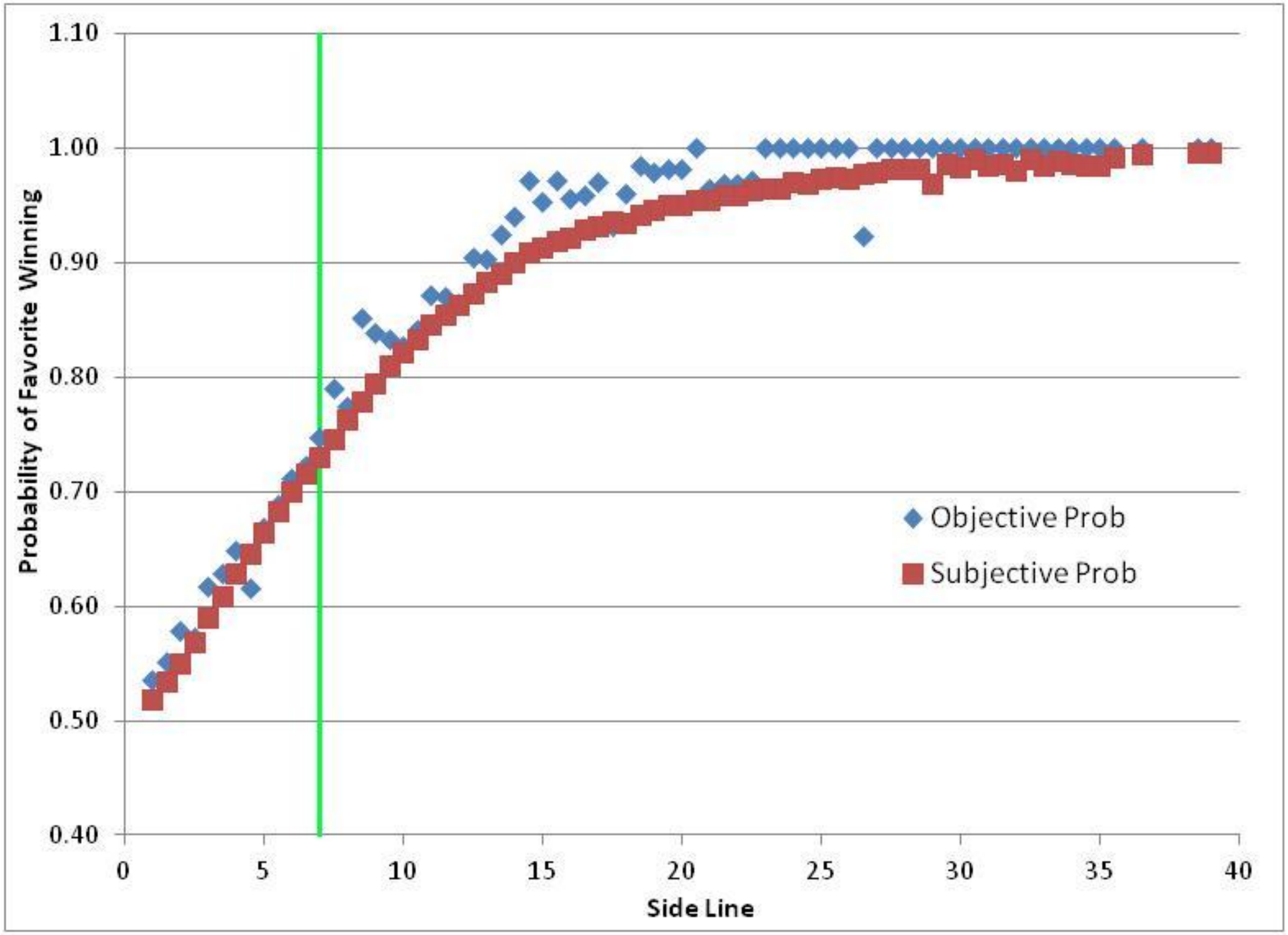

FIGURE 1: Plot of Sides Line and Probability of Favorite Winning

The green line represents a SL of seven, after which the linear relationship between the SL and the ML breaks down.

2.8 Conclusion

This paper examines the implications of missing betting lines on the accuracy of the SL. Additional betting lines provide freely available and unique information to market participants that otherwise is not offered. When the information is freely available to market participants it might impact the accuracy of the SL. In this paper, evidence is provided indicating that the omission of the TL results in less accurate SL. While similar results are not found when there is the omission of the ML or the ML and TL jointly missing, possible explanations have been provided to explain these occurrences. However, when examined by previous unbiasedness tests, they seem to be uninfluenced, indicating any increase in accuracy does not yield a more unbiased SL.

One question is why the additional information does not impact the market as intuition would predict? A possible explanation is that the information embodied in the additional lines is provided by the bookmakers free of charge to actual and potential market participants. For games in which the information embodied in the TL is not of high value, that is, when the accuracy of the SL will not be dramatically altered, the bookmaker might be more prone to revealing this information to all participants. On the other hand, if the information is of high value to the bookmaker, and they are confident that their information is superior to that of market participants, then it might be profitable for the bookmaker to not provide the information embodied in the TL. The bookmaker can take advantage of this information asymmetry by not revealing the TL. This is clearly an avenue for future investigation.

While previous literature has examined betting line unbiasedness, this is the first paper to examine unbiasedness while considering the potential impact other betting lines could have on each other.

This paper provides the groundwork for future investigations for examining the role and relationship between betting lines. While this paper looks at the impact of the TL and the ML on the SL, further investigation into their impact on each other in other betting markets other than NCAA DI basketball is warranted. Betting market research provides a good environment to look at specific finance questions, especially because of the natural maturity date that occurs in the betting market. Finally, this paper adds significant value into the betting market literature in finding that the linear relationship expected between the ML and the SL seems to breakdown once there is a heavy favorite, a team favored to win by at least seven points.

CHAPTER 3: DOES WINNING REALLY MATTER? AN EXAMINATION OF EPL CLUB PERFORMANCE AND EARNINGS

Most publicly-traded companies release information concerning their financial performance four times a year. These quarterly financial reports typically represent the only detailed performance information available to the public concerning these publicly-traded companies. However, in the case of publicly-traded sports teams, performance, in terms of success or failure on the field of play, is reported on a daily or weekly basis and is, therefore, easily measured. With the advantage of readily available performance information, investors of a publicly-traded sports club might react immediately to the wins and losses of the club. As a result, publicly-traded sports club data has been utilized in recent years to examine investor sentiment and market efficiency. While the general argument is that stock prices of publicly-traded sport clubs will react positively to a win and negatively to a loss, this will only be true if winning influences a club's profitability. Results from such studies provide unique insight into the more general issue of investor sentiment and market efficiency.

While the stock price of a sports club might be of interest, the underlying question of whether a sports club's performance influences its financial statement seems to have been sidestepped.[27] Financial theory suggests a correlation between investment value and firm performance. The difficulty, however, arises in interpreting a firm's performance.

[27] Szymanski and Smith (1997) find a positive relationship between log of profit margin (revenue/cost) and performance on the field but do not directly test the significance of this relationship.

While the release of a new product or service may be interpreted as good news, the information is never black and white. Sports clubs have the unique nuance of providing clear market signals about performance, where winning is good and losing is bad. Also, in sports the information is available to everyone at the exact same time; there is no concern of the information being leaked early to certain investors. Yet, if a win or loss does not affect a club's income then it should not have a fundamental impact on the club's stock price. This relates directly to Fama's (1970) definition of market efficiency: A market in which prices always 'fully reflect' available information is called 'efficient'. As a result, if a given win or loss does not affect the team's financial fundamentals, then, under market efficiency, one would not expect the stock price to react to the game outcome either. Intuition suggests that as a club wins more games, its potential for advancing into the playoffs is increased, which, in turn, further increases its ability to generate a larger profit, conditional on players' salaries being fixed in the short run.[28] To the extent that success (winning games) increases a club's revenue through increased attendance, memorabilia sales, and perhaps sponsorship contracts, a club's success should be positively correlated with its stock price. Using this intuition, this paper investigates the relationship between a sport club's performance and its operating

[28] Since Scully (1974) discusses the labor market in Major League Baseball (MLB) and finds a positive relationship between players' pay and performance, there have been many discussions on a team's performance and the pay it provides to its players. Forrest and Simmons (2002b) test this relationship using the four major North American sports leagues and three European soccer leagues and, in general, find statistically significant support that club wages and club performance are related. These results seem to indicate that it could be possible, especially for some clubs, that the cost of winning may exceed the revenues from winning.

income.[29] The empirical evidence suggests that winning does, in fact, influence financial success of English soccer clubs but in different ways for elite and non-elite clubs.

While operating income is affected differently across clubs, the market seems to consistently react positively to all wins and negatively to an elite club's international loss. While this falls in line with winning is good news and losing is bad news, it is interesting that all wins are treated the same regardless of the type of match, or if the club is elite or non-elite.

[29] Deadspin's recent release of the financial statements of six Major League Baseball (MLB) clubs has sparked the debate of the relationship between a club's field performance and financial performance. The statements were provided by an anonymous source, which later was revealed to be an insurance company. The reports were released on August 23, 2010 and August 24, 2010 and contain the financial statements of the Florida Marlins, the Los Angeles Angels of Anaheim, the Pittsburgh Pirates, the Seattle Mariners, the Tampa Bay Rays, and the Texas Rangers. Table 10 provides the operating income and net income of the six teams from the report. The most intriguing information in the Deadspin report is that the Pittsburgh Pirates had been very profitable in the late 2000's although the team won relatively few games; in fact, the Pirates have not had a winning season since 1992. While these reports do not provide direct evidence that revenues and profitability in MLB are directly related to a club's field performance, they do increase the debate about the relationship between winning and team profitability.

TABLE 10: Financial Performance of MLB Clubs

This table provides the operating income and net income for six MLB teams, as reported from Craggs (2010). Note that Florida, Los Angeles, Seattle, and Texas provided financials to the nearest thousand.

Panel A: Operating Income						
	Pittsburgh Pirates	Tampa Bay Rays	Seattle Mariners	Florida Marlins	Los Angels Angels of Anaheim	Texas Rangers
2009				$ 11,107,000		$ (7,450,000)
2008	$ 21,790,402	$ 14,202,206	$ (7,672,000)	$ 37,841,000		$ (356,000)
2007	$ 16,197,554	$ 21,687,569	$ 13,765,000			

Panel B: Net Income						
	Pittsburgh Pirates	Tampa Bay Rays	Seattle Mariners	Florida Marlins	Los Angels Angels of Anaheim	Texas Rangers
2009				$ 3,900,000	$ 10,732,000	$ (11,982,000)
2008	$ 14,408,249	$ 4,016,163	$ (4,533,000)	$ 29,462,000	$ 7,088,000	$ (10,435,000)
2007	$ 15,008,032	$ 11,066,191	$ 17,864,000			

3.1 Literature Review

While stock markets have been around for a long time, it is only recently that sports teams have made the decision to go public. The Amsterdam Stock Market is the oldest stock market in the world, dating back to 1602, but the oldest publicly-traded team, Tottenham Hotspur (English soccer club), went public only in 1983. This is likely the result of leagues and clubs not wanting to disclose their financial information to the general public, and that, until recently, the sports industry was not viewed as a big business.

The seminal paper that looks at publicly-traded sports teams is Brown and Hartzell (2001). They look at how the stock price of the National Basketball Association's Boston Celtics reacted to the club's performance over a 12-year period of time. They find that, while only regular season losses had a significant impact on stock price, both wins and losses in the postseason impact both stock price and volume.

Since Brown and Hartzell (2001) there have been a number of papers that have investigated the relationship between a publicly-traded sports club's performance and the club's financial data. In most cases, these studies focus on publicly-traded soccer clubs. Renneboog and Vanbrabant (2000) investigate 20 publicly-traded English and Scottish soccer clubs and find wins generate abnormal returns while draws and losses both generated negative abnormal returns. They also note that most publicly-traded clubs underperform the market index and that many investors are fans who hold shares as a way of supporting their team. Benkraiem et al. (2002) look at 18 publicly-traded European soccer clubs over the course of one year and find similar results to Renneboog and Vanbrabant – except they find no significant reaction to wins. Benkraiem et al.

(2002) are the only authors to examine the effect of where the game is played (i.e. Home versus Away), and find home losses have a larger negative impact on stock returns than away losses. Zuber et al. (2005) look at club performance and stock market data for ten English Premier League (EPL) clubs traded on the London Stock Exchange (LSE) over a period of three years. They find that investors do not react to a soccer club's performance on the field, and argue that stockholders of EPL clubs are not typical investors, but are rather 'investor-fans' who solely value the stock on the idea of ownership in the club. Lastly, Stadtmann (2006) investigate the stock of Borussia Dortmund, a publicly-traded German soccer club, and its reaction to match outcomes. Results from this work are unable to reject the two hypotheses that winning a match positively influences the club's stock return and losing a match negatively influences the club's stock return.

Palomino et al. (2009) and Bernile and Lyandres (2011) also examine the relationship between club performance on the field and club stock performance, but their focus is on investor sentiment. Palomino et al. (2009) note that the market reacts faster to winning, interpreted as good news, than to losing, interpreted as bad news. This finding is consistent with the previous literature that finds the market reacts to good news faster (see Chan 2003). Remarkably, Palomino et al. (2009) observe that there is not a market reaction to the release of betting odds, even though they demonstrate betting odds are excellent predictors of game results. Palomino et al. (2009) conclude that investor sentiment influences news absorption by stock market investors. It is important to note that while Palomino et al. (2009) do not find a relationship between stock market prices and betting odds, betting odds are used in almost all papers investigating the impact of game outcomes as proxy for ex ante market expectations.

Bernile and Lyandres (2011) look at 20 European premier soccer clubs that are publicly-traded in an attempt to assess investor sentiment. Their unique measure of investor sentiment allows them to show that pre-event stock prices do not reflect expected postgame prices. They find investor sentiment is an ex-ante occurrence. Bernile and Lyandres (2011): “Findings are consistent with the hypothesis that pre-event stock prices are inefficient [and they] cannot reject the hypothesis that post-event prices are efficient.” Lastly, Bernile and Lyandres find that market reaction to game outcomes is asymmetric; losses are associated with significantly negative postgame returns, while wins are followed by near-zero returns, which is consistent with the findings of Brown and Hartzell (2001) and Edmans et al. (2007). Overall, it seems that investors overestimate the probability of winning ex ante.

Similar to Palomino et al. (2009) and Bernile and Lyandres (2011), Edmans et al. (2007) investigate investor mood, by focusing on the relationship between national team matches and stock market reactions to these matches. They argue that the mood of investors is affected by their national team performance. They document a strong negative stock market reaction to losses by the national soccer teams, which are both economically and statistically significant, but the same is not found for wins.

In the previous literature, all clubs have been treated as equals, that is, it is assumed that every club’s intention is to win each game they play. However, this may not always be the case, and this raises the question whether soccer clubs try to maximize profits or wins; the debate of businesses intentions is a central economic question.

Garcia-del-Barrio and Szymanski (2009) find Spanish and English clubs closely approximate win maximization subject to a zero-profit budget constraint. When looking at competitive restraints (i.e. salary caps and revenue sharing), Fort and Quirk (1995) and Vrooman (1995) find competitive constraints raise clubs' profitability when clubs are profit maximizers, but Kesenne (1996 & 2000) treat clubs as win maximizers and gets different results. Thus, the objective of the clubs can have a significant impact on competitive restraints implications.[30]

[30] Going back to the data in the Deadspin reports, the Pittsburgh Pirates have generated large profits without winning most of their games. This brings into question whether all teams are trying to win every game. In fact, it maybe that, for some clubs it is their intention to put together a weak team at low costs in order to generate large revenues from the diehard fans. Better yet, is it possible that some clubs are win maximizers and some are profit maximizers?

3.2 Data

A. Season Data

The data used in this paper was obtained from the annual reports generated between 1992 and 2008 for 16 of the 17 publicly-traded EPL clubs on the London Stock Exchange (LSE), PLUS Market Group (PZ), or Alternative Investment Market (AIM).[31] Operating income data for each club was gathered from Bloomberg, as well as, the annual UK Consumer Price Index (CPI). Operating income is used instead of revenue, since revenues will be affected by the club's financial leverage. For game results, competition, and location of match the following two sources were used: ESPN.com and statto.com. [32] All 16 clubs included in the analysis have fiscal years that end between May and July, which allows each soccer season to be reported annually; see Table 11 for a list of all 16 clubs.[33]

In terms of competition, games were distinguished between regular season games (EPL, Football League Championship, or Football League Two) and games associated with the Football League Cup (FL Cup), Football Association Cup (FA Cup), Community Shield, Anglo-Italian Cup, Winners' Cup, Union of European Football Association (UEFA) Cup, Super Cup or Champions League. The EPL is the premier soccer league in England while the Football League Championship is the second-best

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[31] The PZ is a London-based security exchange formerly known as OFEX, which is a less liquid market than LSE. The AIM is a part of the LSE, but is designed for small and growing companies, which results in the AIM having less restrictive listing requirements.

[32] Data was collected from ESPN going back to the 2004-05 season. This data was used to confirm the validity of statto.com to verify their results. Statto.com is then used to get game results from 1992-93 to 2003-04.

[33] It should be noted that Birmingham City Football Club (FC) was left out of the analysis because their annual report ends on August 31st which causes the first month of one season and nine months of another season to be combined in each annual report, which in term could cause misleading results.

TABLE 11: EPL Publicly-Traded Clubs

This table provides information on the 16 EPL clubs included in the data. Below is each club's ticker symbol, years of available financials, years of international play between the 1992-93 season and the 2007-08 season, and club type.

Club	Ticker	Yrs of Available Financial Reports	Yrs of Int'l Play	Club Type
Arsenal	AFC PZ	1998-2008	14	Elite
Aston Villa	ASV LN	1996-2006	6	Elite
Chelsea	387382Q LN	1997-2004	2	Non-Elite
Charlton	CLO LN	1996-2002	12	Elite
Leeds United	LUFC LN	1993-1995 & 1997-2003	7	Elite
Leicester City	LCC LN	1998-2001	4	Non-Elite
Manchester United	MNU LN	1993-2004	16	Elite
Manchester City	MANV PZ	1998-2006	1	Non-Elite
Newcastle United	NCU LN	1996-2005	10	Elite
Nottingham Forrest	NGF LN	1998-2000	2	Non-Elite
Sheffield United	SUT LN	1993-2008	1	Non-Elite
Southampton	SOO LN	1996-20005 & 2007-2008	1	Non-Elite
Sunderland	SUA LN	1996-2005	1	Non-Elite

soccer league in England, followed by the Football League Two. The FA Cup and the FL Cup are knockout tournaments played in England between EPL teams and non-EPL English teams. The FA Cup in recent years has seen a rapid increase in participating teams with 731 clubs competing in the 2007-08 FA Cup, while the FL Cup has consistently had only the top 92 England clubs. The Community Shield is played annually between the champion of the EPL and the FA Cup winner. The Anglo-Italian Cup was played periodically between 1970 and 1996. In 1992, it became an international competition between second-tier English and Italian clubs, but was stopped due to match conflicts. As a result, Anglo-Italian Cup games are included as international play, but are not included as international play when considering if a club is an elite club. The Winners' Cup, UEFA Cup, and Champions League are played between the top European teams – the Champions League being the pinnacle of European Soccer. In the ranking of the international cups, the Champions League is considered the highest level of international play, followed by the Winners' Cup, and then UEFA Cup. The Winners' Cup was abolished to allow the Champions League to expand after the 1998-99 season. The elite European clubs that do not qualify for the Champions League play in the UEFA Cup. Every year at least two of the top EPL teams qualify for the Champions League the following season. Similar to the Community Shield, the Super Cup is played between the reigning champions of the Champions League and the UEFA Cup.

For each season, the total number of games played, games won, lost and drawn for each type of game were collected. In addition, each of the 16 club's longest losing streak during the regular season, where a draw or a win broke the losing streak, were recorded. A team's losing streak is collected because fans might become less interested in a team if the team continues to lose consecutive games. This is closely related to the uncertainty of outcome hypothesis (UOH) that argues that fans receive higher utility from matches where the clubs are closely balanced. In other words, the more uncertain the outcome, the higher the expected attendance will be. Jennett (1984), Peel and Thomas (1988), and Forrest and Simmons (2002a) all looked at the UOH as it relates to soccer and conclude that soccer supporters appear to prefer well-balanced matches.

Also gathered were the total number of international games played and the total number of home games played during the entire season, excluding "friendly" matches in which data was not easily accessible.[34]

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[34] A "friendly" match is where the outcome does not count towards the standings of the two clubs involved, commonly referred to as an exhibition game.

Table 12 provides descriptive details of the variables. The sample period is from 1992-2008; all variables have 156 observations. The mean operating income, adjusted for inflation, is -£0.146 million, with a minimum and maximum of -£29.326 and £51.549 million, respectively. Operating income is adjusted by the UK CPI to control for inflation, so all figures are in terms of 2010 British pounds. The mean for the dummy variable EPL is .718, indicating 71.8% of the season observations were of clubs competing in the EPL. The mean winning percentage for the first half of the season (first half) for all clubs is .547, with a minimum of .263 and a maximum of .848. The mean winning percentage for the first half multiplied by non-elite dummy variable[35] (NEHALF1) is .308, with the minimum of zero and a maximum of .760. The mean winning percentage for the second half of the season (second half) for all clubs is .549, with the minimum of .029 and a maximum of .917. The mean winning percentage for the second half multiplied by non-elite dummy (NEHALF2) is .301, with a minimum of zero and a maximum of .850. The mean number of international matches played per season is 2.86, with a minimum of zero and a maximum of 18. The mean club's longest losing streak per season is 3.01, with a minimum of zero and a maximum of 15. The mean number of home team matches that a team plays a season is 25.0, with a minimum of 19 and a maximum of 34. The means for the dummy variables concerning relegation and promotion are .071 and .083, respectively, indicating that there are 11 observations where the club was relegated down a league and 13 observations where the club was promoted up a league.

[35] The non-elite dummy variable takes a value of one if the club is elite and zero otherwise

TABLE 12: Seasonal Variables Summary Statistics

This table reports variables definitions, mean, standard deviation, minimum, and maximum observation.

Variable	Definition	Mean	Std Dev	Min	Max
OIADJ	Operating income adjusted for inflation	-0.146	12.518	-29.326	51.549
HALF1	Winning percentage for league games played between August and December	0.547	0.130	0.263	0.848
NEHALF1	HALF1 multiplied by dummy variable that takes a value of 1 if club is not an elite club and zero otherwise	0.308	0.264	0	0.759
HALF2	Winning percentage for league games played between January and May	0.549	0.155	0.029	0.917
NEHALF2	HALF2 multiplied by dummy variable that takes a value of 1 if club is not an elite club and zero otherwise	0.308	0.264	0	0.759
IG	Number of international games played	2.859	4.817	0	18
NEIG	IG multiplied by dummy variable that takes a value of 1 if club is not an elite club and zero otherwise	0.301	1.425	0	10
DG	Number of games played in the FL Cup and FA Cup	24.32	2.7776	19	33
NEDG	DG multiplied by dummy variable that takes a value of 1 if club is not an elite club and zero otherwise	14.929	12.192	0	34
PROMOTION	Dummy variable that takes the value of 1 if club is promoted to the lower level the following year	0.083	0.277	0	1
RELEGATION	Dummy variable that takes the value of 1 if club is relegated to the lower level the following year	0.071	0.257	0	1
EPL	Dummy variable that takes the value of 1 if club played in EPL during the season and zero otherwise	0.718	0.451	0	1
LSTREAK	Number of consecutive league games lost	3.006	1.776	0	15

It is important to note that HALF1 and HALF2 have nearly identical averages, maximums and minimums. The same can be noted for NEHALF1 and NEHALF2. This implies that clubs tend to perform consistently over the entire season.

B. Match Data

Individual game data was collected for all 8,740 market reactions to a publicly-traded club's match outcome from August 1992, the beginning of the 1992-1993 season, until May 2008, the end of the 2007-2008 season. These matches represent all the matches played with at least one publicly-traded club that competed in at least one year in the EPL during this time horizon. Of the 8,740 observations, betting market data is available for 5,879 observations, going back to the 1998-1999 season. Of these 5,879 match outcomes, 2,453 resulted in a publicly-traded club win, 1,885 resulted in a publicly-traded club loss, and the remaining 1,541 resulted in a draw. Each match is classified into one of six categories: EPL (3,533), Division I (D1) (1,700), Division II (D2) (42), D1 Playoff (9), English knockout tournament (232), and international knockout tournament (363). Additional match data includes the betting odds (from Betexplorer.com), date of match, goal differential, and where the match was played. Table 13 provides summary statistics on match outcomes. Each day of week variable is a dummy variable that takes a value of one if the match was played on that day and a zero otherwise; SOCCERMONTH is the month of the year converted to correspond to the soccer season schedule, i.e. the first month of the soccer season is August so for all matches in August SOCCERMONTH takes a value of 1, for September a value of 2, and so forth until May for which SOCCERMONTH takes the value of 10 and is the last month of the season; HOME is a dummy variable that takes a value of one if the

TABLE 13: Match Variable Summary Statistics

This table reports variables definitions, mean, standard deviation, minimum, and maximum observation.

Variable	Definition	Mean	Std. Dev.	Min	Max
ACAR1	Abnormal cumulative abnormal return from close before match to first close after match	0.000	0.036	-0.429	0.665
ACAR2	Abnormal cumulative abnormal return from close before match to second close after match	0.000	0.047	-0.407	0.842
ACAR3	Abnormal cumulative abnormal return from close before match to third close after match	0.000	0.056	-0.428	0.934
WIN	Dummy variable for if the publicly-traded club won the match	0.417	0.493	0.000	1.000
LOSE	Dummy variable for if the publicly-traded club lost the match	0.321	0.467	0.000	1.000
DRAW	Dummy variable for if the match ended as a draw (tie)	0.262	0.440	0.000	1.000
EWIN	WIN variable multiplied by a dummy variable, ELITE, that takes a value of one if the club is an elite club and a zero otherwise	0.178	0.382	0.000	1.000
ELOSE	LOSE variable multiplied by a dummy variable, ELITE, that takes a value of one if the club is an elite club and a zero otherwise	0.089	0.285	0.000	1.000
EDRAW	DRAW variable multiplied by a dummy variable, ELITE, that takes a value of one if the club is an elite club and a zero otherwise	0.094	0.291	0.000	1.000
IWIN	WIN variable multiplied by a dummy variable, INTERNATIONAL, that takes a value of one if the match was played against a non-English club and a zero otherwise	0.033	0.179	0.000	1.000
ILOSE	LOSE variable multiplied by a dummy variable, INTERNATIONAL, that takes a value of one if the match was played against a non-English club and a zero otherwise	0.014	0.118	0.000	1.000

TABLE 13 (continued)

Variable	Definition	Mean	Std. Dev.	Min	Max
IDRAW	DRAW variable multiplied by a dummy variable, INTERNATIONAL, that takes a value of one if the match was played against a non-English club and a zero otherwise	0.014	0.119	0.000	1.000
EIWIN	WIN variable multiplied by ELITE and INTERNATIONAL variables	0.031	0.172	0.000	1.000
EILOSE	LOSE variable multiplied by ELITE and INTERNATIONAL variables	0.013	0.114	0.000	1.000
EIDRAW	DRAW variable multiplied by ELITE and INTERNATIONAL variables	0.013	0.115	0.000	1.000
MONDAY	Dummy variable that takes a value of one if the match is played on a Monday and a zero otherwise	0.057	0.232	0.000	1.000
TUESDAY	Dummy variable that takes a value of one if the match is played on a Tuesday and a zero otherwise	0.114	0.317	0.000	1.000
WEDNESDAY	Dummy variable that takes a value of one if the match is played on a Wednesday and a zero otherwise	0.096	0.294	0.000	1.000
THURSDAY	Dummy variable that takes a value of one if the match is played on a Thursday and a zero otherwise	0.022	0.146	0.000	1.000
FRIDAY	Dummy variable that takes a value of one if the match is played on a Friday and a zero otherwise	0.015	0.121	0.000	1.000
SATURDAY	Dummy variable that takes a value of one if the match is played on a Saturday and a zero otherwise	0.551	0.497	0.000	1.000
SUNDAY	Dummy variable that takes a value of one if the match is played on a Sunday and a zero otherwise	0.146	0.353	0.000	1.000
HOME	Dummy variable that takes a value of one if the match is played in the club's home stadium	0.499	0.500	0.000	1.000
GOALDIFF	Goals scored by the observed club minus the goals scored for the unobserved club	0.202	1.722	-7.000	8.000
SOCCERMONTH	Month of the season that the match was played in, with August equal to one and May equal to ten	5.176	2.872	1.000	10.000
UNEXPLOSE	Implies the club considered a heavy favorite (expected to win) according to the betting markets and loses	0.021	0.143	0.000	1.000

TABLE 13 (continued)

Variable	Definition	Mean	Std. Dev.	Min	Max
UNEXPWIN	Implies the club considered a heavy underdog (expected to lose) according to the betting markets and wins	0.026	0.159	0.000	1.000

publicly-traded club is playing in their home stadium and a zero otherwise; EXPWIN (EXPLOSE) is a dummy variable that takes a value of one when the club is a heavy favorite (underdog) that loses (wins) and a zero otherwise. A heavy favorite (underdog) is calculated from the betting odds where the club is one standard deviation above the mean for the probability of a win (loss). In order to calculate the probability of each outcome occurring, the betting market data is converted into probabilities for each outcome. Following Sauer (2005), the probability of each outcome can be calculated as the ratio of one to one plus the stated payout for the given outcome for all three possible outcomes, $p^{odd} = \frac{1}{1+payout}$. However, the three probabilities add up to greater than one, which is the result of the bookmakers not offering fair odds – they are in business to make a profit. To account for this, the probabilities are normalized to obtain the subjective fair probability, p^{fair}, obtained by dividing each nominal probability by the sum of the three probabilities. The fair probabilities now add up to one.

3.3 Empirical Models

A. Firm's Financial Impact from Game Outcome

Since the data covers the sample period 1993-2008, all operating incomes are adjusted for inflation by using the UK CPI, with 2010 as the base year, yielding the variable, OIADJ, which is used as the dependent variable in the following empirical model:

$$OIADJ_{it} = \beta_1 + \beta_2 HALF1_{it} + \beta_3 NEHALF1_{it} + \beta_4 HALF2_{it} + \beta_5 NEHALF2_{it} + \beta_6 IG_{it} + \beta_7 NEIG_{it} + \beta_8 DG_{it} + \beta_9 NEDG_{it} + \beta_{10} PROMOTION_{it} + \beta_{11} RELEGATION_{it} + \beta_{12} EPL_{it} + \beta_{13} LSTREAK_{it} + \varepsilon_{it}, \tag{13}$$

where the β's are parameters to be estimated, the index i denotes the club, the index t denotes the year, and ε_{it} is a composite error term with a club specific effect, c_i, and an independently and identically distributed two-sided error term, u_{it}.

The explanatory variables are designed to test how winning affects financial performance of the club, specifically if all clubs are identical in this aspect and whether matches earlier or later in the season influence clubs' financial performance differently. A club's regular season matches are divided into the club's first half winning percentage (HALF1) and the club's second half winning percentage (HALF2).[36] Additionally, the clubs used in this paper are divided into two groups: elite clubs, which participated in international play at least four out of the 16 years, and non-elite clubs.[37] The expectation

[36] HALF1 includes league games played from August to December while HALF2 includes league games played from January to May.

[37] While 25% international participation rate seems rather arbitrary there seems to be a clear break in the number of seasons of international play, with elite clubs participating in at least 6 years of international play, while Tottenham, the non-elite club with the highest amount of international play, only had three seasons where they qualified for international play. Additionally, no elite club was relegated from the EPL while publicly-traded; the only other club not relegated while publicly-traded is Tottenham, who has never been relegated from the EPL.

is that elite clubs are more likely to see on-field performance impact in their financials. For non-elite clubs, winning may not impact the financials of the club in the same manner as it does for elite clubs because of their lower status. NEHALF1 (NEHALF2) is HALF1 (HALF2) multiplied by a dummy variable that takes a value of one if the team is a non-elite club and zero otherwise. For international play and domestic cups, FA Cup and FL Cup, winning percentage is not used. Instead, the number of matches played is employed. This approach is used because clubs play a different number of matches, which could influence their winning percentage and put lower weight on each game the further they advance. The only way to advance in international play and domestic cups is to win the previous round. IG is the number of games played internationally and DG is the number of matches played in domestic cups. Additionally, NEIG (NEDG) is IG (DG) multiplied by a dummy variable that takes a value of one if the team is a non-elite club and zero otherwise.

The following variables are included as control variables. PROMOTION (RELEGATION) is a dummy variable that takes the value of one if the club is promoted (relegated) the following year and a zero otherwise. EPL is a dummy variable that takes the value of one if the club competes in the EPL that year and a zero otherwise. LSTREAK is the club's longest losing streak excluding non-regular season games for the season.

With the four measures of performance for elite and non-elite clubs, there are several possible hypotheses for each variable; Table 14 provides a list of all hypotheses. Hypotheses one through six deal with performance in regular season matches, while hypotheses seven through 11 deal with domestic cups and international matches. The

TABLE 14: Hypotheses

This table provides a list of the hypotheses being tested and the implication on the betas for each hypothesis.

Hypothesis	Summary	Implications
H1	League play impacts elite clubs' operating income	$\beta_2 > 0$ & $\beta_4 > 0$
H1A	The second half play has a larger impact on elite clubs' operating income	$\beta_4 > \beta_2 > 0$
H2	League play does not impact elite clubs' operating income	$\beta_2 = 0$ & $\beta_4 = 0$
H3	League play does not impact non-elite clubs' operating income	$\beta_2 + \beta_3 = 0$ & $\beta_4 + \beta_5 = 0$
H4	League play impacts non-elite clubs' operating income	$\beta_4 + \beta_5 > 0$ & $\beta_2 + \beta_3 > 0$
H4A	The second half play has a larger impact on non-elite clubs' operating income	$\beta_2 + \beta_3 > \beta_4 + \beta_5 > 0$
H5	Elite clubs incur a larger impact from winning league matches than non-elite clubs	$\beta_2 > \beta_2 + \beta_3$ & $\beta_4 > \beta_4 + \beta_5$
H6	Non-elite clubs incur a larger impact from winning league matches than elite clubs	$\beta_2 + \beta_3 > \beta_2$ & $\beta_4 + \beta_5 > \beta_4$
H7	Winning international matches matters for both elite and non-elite clubs	$\beta_6 > 0$ & $\beta_6 + \beta_7 > 0$
H7A	Elite clubs incur a larger impact from winning international matches than non-elite clubs	$\beta_6 > \beta_6 + \beta_7$
H7B	Non-elite clubs incur a larger impact from winning international matches than elite clubs	$\beta_6 + \beta_7 > \beta_6$
H8	Winning in domestic cups impact elite clubs' operating income	$\beta_8 > 0$
H9	Winning in domestic cups does not impact elite clubs' operating income	$\beta_8 = 0$
H10	Winning in domestic cups impact non-elite clubs' operating income	$\beta_8 + \beta_9 > 0$
H11	Winning in domestic cups does not impact non-elite clubs' operating income	$\beta_8 + \beta_9 = 0$

first hypothesis, H1, posits that for elite clubs winning percentage for both halves of the season has a positive impact on operating income. This is because elite clubs are the dominant clubs that intend to play internationally, which requires one of the best records in league play. Taking this hypothesis one step further, H1A posits that the second half winning percentage has a greater impact on operating income than the first half winning percentage. Although all games are equally weighted in the league standings, as the season unfolds, each game may be viewed as more significant, especially when teams are jockeying for final position to qualify for international play – or to avoid relegation to a lower division the following year.[38] Hypothesis H2 argues the opposite of H1, i.e. that neither the first half or second half winning percentage has an impact on operating income. This could be the result of elite clubs in larger cities having larger fan bases and, thus, do not need as much success in order to have a high attendance. It could also be the result of elite fans caring more about international play than regular season play and thus winning in the regular season does not matter for elite clubs. Additionally, H2 would be more in line with the findings of the UOH applied to soccer. In this situation, fans would prefer to see more balanced games in comparison to seeing their club that wins every game.

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[38] May 13, 2012 was the last day of the 2011-12 EPL season. It also could be argued to be the most exciting final day of the EPL ever. Going into the last day the championship was still up in the air with either Manchester City or Manchester United winning, but that was just the tip of the iceberg into the impact of positioning. The third position in the standings is the last guaranteed spot to play in the Champions League next year and going into the last day of the season three clubs, Arsenal, Tottenham and Newcastle, were still battling for the prized position. Arsenal did end up sneaking into third place over Tottenham by just one point. Although not decided until ex post, the fourth place position can also advance to the Champions League. This year Chelsea won the Champions League and the fourth place does not qualify for the Champions League. As for the bottom of the EPL, while Blackburn Rovers and Wolverhampton Wonders surely being relegated the third club to be relegated was still dependent on the outcome of the matches on the last day. Depending on how things worked out Aston Villa, Bolton Wanderers, or Queens Park Rangers (QPR) would be relegated. As it worked out Bolton ended up being relegated by one point over QPR. This is just an example of the possible importance of the final matches of the season.

The next hypotheses deal with non-elite clubs' regular season performance. While winning is perceived to be more important to elite clubs, non-elite clubs might not expect to win the league and, as a result, design a club that maximizes profits through other means than winning as many matches as possible, this is the intuition behind H3. Hypothesis H3 says that neither half of the regular season impacts the non-elite club's financial performance. Hypothesis H4 posits that non-elite clubs' winning percentages for both halves of the season have a positive effect on operating income. Since non-elite clubs generally do not play internationally, the focus of their fans may be league play and winning as many league games as possible. Hypothesis H4A argues that non-elite clubs' winning percentages for the second half have a larger impact on operating income than the first half. During the second half, the competition to place in the top of the division to play internationally and not to finish in the bottom three, which results in relegation, becomes the focus of discussion. As a result, fans may attend matches more regularly due to the perceived importance of the match. Also, being relegated is expected to be financially detrimental to a club, as is discussed later. Combining H1 and H3 yields hypothesis H5 which posits that the winning percentage in both halves for elite clubs is larger than for non-elite clubs. Combining H2 and H4 yields H6 which posits that the winning percentage in both halves for non-elite clubs is larger than for elite clubs.

With international matches, it is expected that winning should be significant for both types of clubs, which is posited in hypothesis H7. International play gives clubs more exposure domestically as well as internationally. This exposure can result in more fans, higher merchandise sales, as well as more home games, which should all generate higher operating income. While the expectation is that winning at the international level is significant to all clubs, is it more significant to one type of club? Hypothesis H7A posits that winning is more significant to elite clubs than non-elite clubs because the elite clubs are more dependent on making international play to be able to pay their higher payroll associated with winning.[39] The higher payrolls may leave elite clubs vulnerable to a cash shortfall since they have high salaries and are expected to compete in more international matches to recoup this expense. On the other hand, since non-elite clubs do not regularly compete internationally, winning could result in international play and exposure where winning impacts non-elite clubs more, which is stated in hypothesis H7B.

The remaining variables investigate winning and a club's financial performance through domestic cup play. The first two hypotheses look at elite clubs and the impact that winning domestic games has on a club's financial performance: H8 posits that domestic cup play increases an elite club's operating income; advancing further in domestic cups provides the club with more home games as well as more exposure to soccer fans. On the other hand, hypothesis H9 posits that domestic play does not impact an elite club's operating income, which would be the result if domestic cups cause players to tire or become injured and are unable to compete in more important matches, such as international play. Hypothesis H10 (H11) is similar to H8 (H9) but focuses on non-elite clubs. Hypothesis H10 (H11) follows the same justification as H8 (H9).

In addition to the above mentioned hypotheses, the following expectations hold for the coefficients of the control variables. A club that is relegated may have higher revenues for two reasons ($\beta_{11}>0$). First, a club may lower its payroll in order to generate

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[39] Forrest and Simmons (2002b) find a direct relationship between team payroll and team performance.

higher operating income, causing the club to perform poorly and be relegated to a lower league. Second, after relegation has been determined, fan attendance may actually increase for the remaining matches if the lower level of play the following year does not appeal to some fans. As for a club that is promoted, the expectation is not as straightforward. First, the operating income of a promoted club will rise as a result of any increase in attendance stemming from fans becoming more interested in attending matches when their club is winning. However, this increase may be offset by higher payroll, which would reduce operating income ($\beta_{10}\neq0$). Participating in the EPL should have a positive effect on operating income, since playing in the EPL generates higher revenue from sponsorship and media deals ($\beta_{12}>0$). The club's longest losing streak is expected to have a negative coefficient if losing streaks reduce revenues, as marginal fans become disinterested and choose not to attend the team's matches ($\beta_{13}<0$). However, it is also possible that when a losing streak becomes long, fans attend matches more as a likelihood of being relegated the following season increases ($\beta_{13}>0$).

B. Market Reaction to Game Outcome

With 5,879 observations from 1998-2008, this is the largest dataset used for market reaction to winning and losing to date. Similar to previous literature, betting data is utilized to help control for market expectations, and the day of the week to control is utilized to help control for day of week impacts.

In the model for market reaction to match outcome, the dependent variable is the abnormal cumulative average return (ACAR) which is calculated by taking the cumulative average return (CAR) of the club's stock minus the CAR of the market. Here the FTSE is used as the market index. The CAR is calculated as follows:

$$CAR_{i0} = \frac{P_i + D - P_0}{P_0}. \tag{14}$$

Here P_0 is defined as the closing price before the match is played and P_i is defined as the closing price i days after the match, where i= 1, 2, or 3. Lastly D represents all dividends paid out during this period.

The empirical model that is utilized to test market reaction to a club's on field performance is:

$$ACAR = \beta_0 + \beta_1 WIN + \beta_2 LOSE + \beta_3 EWIN + \beta_4 ELOSE + \beta_5 EDRAW + \beta_6 IWIN + \beta_7 ILOSE + \beta_8 IDRAW + \beta_9 EIWIN + \beta_{10} EILOSE + \beta_{11} EIDRAW + \beta_{12} TUESDAY + \beta_{13} WEDNESDAY + \beta_{14} THURSDAY + \beta_{15} FRIDAY + \beta_{16} SATURDAY + \beta_{17} SUNDAY + \beta_{18} HOME + \beta_{19} GOALDIFF + \beta_{20} SOCCERMONTH + \beta_{21} EXPWIN + \beta_{22} EXPLOSE + \varepsilon, \tag{15}$$

where the βs are parameters to be estimated and ε is the error term that is independently and identically distributed. WIN (LOSE) is a dummy variable that takes a value of one if the observed club wins (losses) the match and a zero otherwise. There is no dummy for a draw due to collinearity with both the WIN and the LOSE variables. The following nine variables: EWIN, ELOSE, EDRAW, IWIN, ILOSE, IDRAW, EIWIN, EILOSE, and EIDRAW are also dummy variables. All nine variables have one of the three possible outcomes for a given match – win, lose or draw at the end of the variable. These variables take a value of one if the observed match ended in that outcome (win, lose, or draw) and a zero otherwise. If there is an "E" in front of the three possible outcomes, this indicates that the variable is multiplied by a dummy variable that takes a value of one if the club was an elite club and a zero otherwise. If there is an "I" in front of the three possible outcomes, then the variable is multiplied by a dummy variable that takes a value of one if the match is an international match and a zero otherwise. As a result, "EI" represents elite international matches, so the variable is multiplied by both the elite and international dummy variables. All matches were originally broken out to have similar coefficients as international matches, but the results for all these types of matches were not significant. The following variables: TUESDAY, WEDNESDAY, THURSDAY, FRIDAY, SATURDAY, and SUNDAY all are dummy variables that take a value of one if the game was played on the designated day of the week and a zero otherwise. There is no variable for Monday as a result of collinearity with the other six variables for the day of the week. HOME is another dummy variable that takes a value of one if the observed club was playing at their home stadium and a zero otherwise. GOALDIFF is the difference between the goals scored by the publicly-traded club and the goals scored by the unobserved club; the GOALDIFF will be positive when the observed club wins, negative when the observed club losses, and zero when the match is a draw. SOCCERMONTH takes a value of one if the match is played in August, a two if the match is played in September, and so on up until the last month of the season, which is May – the tenth month. The last two variables, EXPWIN and EXPLOSE, are utilized to control for market expectations. EXPWIN (EXPLOSE) is a dummy variable that takes a value of one when the club is a heavy favorite (underdog) that loses (wins) and a zero otherwise. A heavy favorite (underdog) is calculated from the betting odds where the club is one standard deviation above the mean for the probability of a win (loss).

The expectations are that as long as the club's financial performance are affected by winning and losing, then the expectation is the market will react to the outcome as it would affect the profitability of the club. No clear expectations are defined for the days of the week, since there should not be a significant impact on the day of the week that the match is played. As for HOME, the expectation is that home matches do generate higher revenue for clubs through ticket, concession, and retail sales. With that said, it is unclear if a home match is more valuable than an away match. GOALDIFF provides by how much the club won or lost by, a draw results in a GOALDIFF of zero, which can imply how decisive the outcome was. GOALDIFF is expected to be positively correlated with the club's ACAR, as the more decisive the win or lose the stronger the signal. SOCCERMONTH could be expected to have a positive impact on market reaction if the matches later in the season are more important, or a negative impact if the earlier games are more important. As for UNEXPLOSE and UNEXPWIN, both imply unexpected outcomes – which means that they both should have a significant impact on the market's reaction, indicating unexpected news to the market. UNEXPLOSE (UNEXPWIN) should have a negative (positive) impact on the market, since the loss (win) was unexpected.

3.4 Results

A. Firm's Financial Impact from Game Outcome

Given that the sample is a panel, it is important to determine which estimator best fits the data: Pooled ordinary least squares (POLS), random effects, or fixed effects. Since each club likely has idiosyncratic levels of operating income, POLS does not seem to be suitable for the model. The random effects model provides a better estimator for the following reasons. First, not all of the EPL teams are included in the model, thus, the panels are unbalanced with as few as three observations to a maximum of 16 observations. Second, using the Hausman test to test fixed effects versus random effects and the Breusch-Pagan test to test the POLS model against the random effects, the random effects model is found to be superior. The Hausman and the Breusch-Pagan test results are included in panel B in Table 15.

Panel A in Table 15 reports the results from the random effects regression. All of the control variables except for losing streak are significant and have coefficients with the expected signs. EPL is significant at the 10% level and indicates that playing in the premier league increases operating income by more than £2.5 million per year.[40] This is likely the result of increased media coverage and more lucrative sponsorship deals. Clubs that are relegated experience an increase in operating income of £4.85 million, which is significant at the 1% level. This can be explained by one of two possibilities, the first being that when it appears a club will to be relegated the following year, fans may attend the remaining matches in greater numbers because expected competition the

[40] There was no statistically significant difference between the impact of EPL winning percentage and the Football League Championship winning percentage on a team's operating income.

TABLE 15: Season Level Model Results

Panel A reports the results from a random effects regression with adjusted operating income as the dependent variable and robust standard errors. The dependent variable is adjusted operating income. Panel B: The first two rows are the results of the Hausman test and the Breusch and Pagan test. The next two tests are the winning percentages' coefficients as they are statistically different from one another. The remaining tests look at the significance of non-elite clubs' field performances on adjusted operating income, which requires joint tests.

Panel A: Model Results				
Variable	Coefficient		Std. Error	z
HALF1	21.287	***	7.384	2.88
NEH1	-14.736	**	7.409	-1.99
HALF2	-4.624		8.922	-0.52
NEH2	18.139		10.872	1.67
IG	0.752	**	0.310	2.43
NEIG	0.944		0.705	1.34
DG	0.415		0.340	1.22
NEDG	0.086		0.398	0.22
EPL	2.502	*	1.437	1.74
RELEGATION	4.852	***	1.766	2.75
PROMOTION	-4.179	**	1.682	-2.48
LSTREAK	-0.513		0.463	-1.11
Intercept	-16.319	***	5.163	-3.16

Panel B: Tests for Statistical Significance				
Test	Coefficient		χ^2	p-value
Hausman (H_0: Random Effects)			11.19	0.513
Breusch and Pagan (H_0: Pooled OLS)			15.03	0.000
$\beta_{HALF1} - \beta_{HALF2} = 0$			2.99	0.084
$\beta_{HALF1} - \beta_{NEHALF1} - \beta_{HALF2} - \beta_{NEHALF2} = 0$			0.78	0.378
$\beta_{IG} = \beta_{IG} + \beta_{NEIG}$			1.79	0.181
$\beta_{HALF1} = \beta_{HALF1} + \beta_{NEHALF1}$			3.96	0.047
$\beta_{HALF2} = \beta_{HALF2} + \beta_{NEHALF2}$			2.78	0.095
$\beta_{HALF1} + \beta_{NEHALF1}=0$	6.550			0.140
$\beta_{HALF2} + \beta_{NEHALF2} = 0$	13.514	**		0.041
$\beta_{IG} + \beta_{NEIG} = 0$	1.696	***		0.007
$\beta_{DG} + \beta_{NEDG} = 0$	0.502	**		0.016

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

next season will be weaker. The second argument is that the club intentionally designs a lower quality club having lower player salaries, a component of operating expenses, to generate higher operating income. On the opposite side, being promoted the following year is significant at the 5% level and generates a loss of £4.18 million in operating income on average. This negative relationship supports the argument that a club's higher payroll more than offsets any increase in revenue generated by dominating play in the current level. Additionally, fans may decide not to attend matches at the end of the season and wait to attend matches the following season when the club is promoted to a better league with stronger competition. This could indirectly support the UOH argument that fans do not want to see clubs dominate their competition. The last control variable, losing streak, has a negative sign but is insignificant. It may be that some fans want to see the better clubs visit before the home club gets relegated, while others, likely marginal fans, become disinterested after the team's poor performance.

The variables of interest that are associated with a club's field performance and financial performance suggest that not all teams maximize profits in similar ways. For elite teams, first half performance is statistically significant while the second half is not significant. Each additional win results in an increase in operating income of £0.93 million to £1.18 million per game, depending on how many games are played in the first half. This finding goes against the hypothesis that the second half winning percentage is more important than the first half winning percentage, H1A. While possibly surprising, it is possibly explained by fans interests shifting in the second half to international play. In addition, each international game is significant at the 5% level and increases an elite club's operating income by £0.75 million, which indirectly means winning does matter in international play as well, since the only way to play more international games is to advance further in the competition by winning the previous round. The number of domestic cup games does not statistically impact operating income of elite club, which may result from the fact that fans are more focused on international play and possibly on league play.

To examine the impact of field performance by non-elite clubs on financial performance requires joint significant tests, which are found in panel B in Table 15. For non-elite clubs, their first half winning percentage is insignificant while their second half winning percentage is significant at the 5% level, resulting in each win increasing operating income by £0.56 million to £0.79 million depending on the number of games played in the second half. This result supports the hypothesis that the second half winning percentage has a bigger impact on the club's financial performance than the first half, H4A. This may be the result of fans becoming more interested in end-of-season games when their club may get relegated or promoted to another league. Each international game played, on average, increases non-elite clubs' operating income by £1.70 million, and is significant at the 1% level. This implies that winning international games impacts a club's financial performance, since, as mentioned above, the only way to play more international games is to advance further in the cup by winning. In addition, non-elite clubs, on average, benefit more from playing internationally than elite clubs, although the difference is not statistically significant, resulting in neither H7A or H7B being supported. This is likely the result of the uncommon occurrence of non-elite clubs participating in international play and the possible international exposure that these typical underdog clubs receive. Lastly, each additional domestic cup game, on average, increases operating income by £0.50 million and is significant at the 5% level. As mentioned previously, domestic cup games tests a club's performance in the FA Cup and FL Cup. As a result, non-elite clubs' performance in these cups does impact the club's operating income.

While club performance on the field is a driver of the club's financial performance for all clubs, there are differences between the elite and non-elite clubs. For elite clubs, performance at the beginning of the season is an important driver of operating income, while for non-elite clubs the second half of the season is important. These findings are statistically significant and provide support of H5 for the first half and H6 in the second half. One explanation is that elite fans focus on international play in the second half, while non-elite fans focus on not being relegated at the end of the season. While winning international games impacts both types of clubs' operating income, non-elite clubs experience a bigger impact. Non-elite clubs do not regularly compete in international play and so when they do it likely results in a bigger draw to their matches. In addition, such a situation might allow the non-elite club to generate relatively higher marketing contracts, when normalized to their typical base income in comparison to elite clubs, leading as a result to significantly greater impact to the non-elite clubs than a corresponding elite club. The last comparison looks at the performance in the FA Cup and FL Cup. Elite clubs' financial performance is not significantly affected by performance in domestic cups, which may provide support to Manchester United's controversial withdraw from the FA Cup in 1999-2000. The same is not true for non-elite clubs, where any additional exposure to fans is always good for these clubs.

To summarize the findings of this paper and the hypotheses tested, the following hypotheses were supported: H4A, H7, H9 and H10, while hypotheses H1A, H7A, H7B, H8 and H11 were all rejected. In the case of hypotheses H1, H2, H3, H4, H5 and H6, the results reported in this paper only partially supported their validity.

B. Market Reaction to Match Outcome

After using the Hausman test and the Breusch-Pagan test, the results imply that the POLS model best fits the panel data examining market reaction to match outcome. Additionally, the White test yielded heterostedasticity and, as a result, robust standard errors are used in all models presented in this section. Results gathered in this paper for this part of the study are as follows: The POLS output are presented in Table 16 Panel A, the tests for market reaction to winning and losing are presented in Panel B, testing for different price reactions to elite and non-elite clubs are presented in Panel C, and model tests are presented in Panel D.

Looking at Panel A, there are three variables that are consistently significant: WIN, GOALDIFF, and SOCCERMONTH. While WIN is significant, by itself it does not provide information, since it is jointly tested with other variables to test for market reaction to winning and losing. GOALDIFF is positive as expected and significant in all models at the 10% level or higher. It is more significant in the day preceding the match. The positive and significant coefficient implies that while winning and losing maybe significant, it is also important by how much the club wins or loses by. A win by one goal is not as decisive a win as winning by three or even four goals. This is important because previous literature has not controlled for goal differential. Hence, previous literature have treated all wins, losses, and draws as equal, and have not controlled for the

TABLE 16: Market Reaction to Match Outcome

Panel A presents the output of a Pooled OLS model with robust standard errors. The ACAR of the club's stock is the dependent variable. Panel B provides the coefficient for the two types of clubs for domestic and international matches. Panel C provides F-test outputs for testing if investors react differently to elite and non-elite clubs. Panel D provides results of different tests.

PANEL A: REGRESSION OUTPUT						
Variable	ACAR (0,1)		ACAR (0,2)		ACAR (0,3)	
Constant	-0.0009		0.0007		0.0006	
WIN	0.0052	***	0.0101	***	0.0126	***
LOSE	-0.0022		-0.0038	*	-0.0047	*
EWIN	0.0005		-0.0013		-0.0037	
ELOSE	0.0013		0.0054		0.0041	
EDRAW	0.0025		0.0029		0.0010	
IWIN	0.0024		0.0061		0.0008	
ILOSE	-0.0020		0.0091		0.0115	
IDRAW	0.0008		0.0045		-0.0042	
EIWIN	-0.0049		-0.0084		-0.0047	
EILOSE	-0.0051		-0.0239	**	-0.0238	
EIDRAW	-0.0050		-0.0114		-0.0055	
TUESDAY	0.0021		0.0003		0.0004	
WEDNESDAY	0.0016		0.0036		0.0053	
THURSDAY	0.0037		0.0007		0.0025	
FRIDAY	-0.0073		-0.0118	*	-0.0120	
SATURDAY	0.0007		-0.0006		-0.0012	
SUNDAY	0.0012		-0.0014		-0.0011	
HOME	-0.0012		-0.0014		-0.0004	
GOALDIFF	0.0014	**	0.0010		0.0011	
SOCCERMONTH	-0.0004	**	-0.0007	***	-0.0007	**
UNEXPLOSE	-0.0031		-0.0055		-0.0120	***
UNEXPWIN	0.0053		0.0021		0.0017	
PANEL B: TEST MARKET REACTION						
Non-Elite Win	0.0043	*	0.0108	***	0.0123	***
Non-Elite Lose	-0.0031		-0.0031		-0.0040	
Non-Elite Draw	-0.0009		0.0007		0.0006	
Elite Win	0.0048	*	0.0096	***	0.0095	**
Elite Lose	-0.0018		0.0023		0.0001	
Elite Draw	0.0016		0.0036		0.0016	
Non-Elite International Win	0.0067		0.0170		0.0141	
Non-Elite International Lose	-0.0051		0.0060		0.0075	
Non-Elite International Draw	-0.0002		0.0052		-0.0036	
Elite International Win	0.0023		0.0073		0.0057	
Elite International Lose	-0.0090	**	-0.0125	**	-0.0121	
Elite International Draw	-0.0026		-0.0033		-0.0081	

TABLE 16 (Continued)

PANEL C: ELITE VERSUS NON-ELITE						
Elite Win=Non-Elite Win	0.07		0.28		1.50	
Elite Lose=None-Elite Lose	0.54		3.98	**	1.53	
Elite Draw=Non-Elite Draw	1.74		1.36		0.12	
Elite Int. Win=Non-Elite Int. Win	0.41		0.67		0.47	
Elite Int. Lose=Non-Elite Int. Lose	0.24		3.12	*	1.70	
Elite Int. Draw=Non-Elite Int. Draw	0.15		0.43		0.16	
PANEL D: MODEL TESTS						
Hausman	5.11		13.07		19.97	
Breusch and Pagan	0.00		0.00		0.00	
White	180.53	***	177.97	***	220.58	***

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

magnitude of the outcome, i.e. the importance of the signal. As for SOCCERMONTH, the coefficient is negative and significant for all models at the 10% level or higher. The surprising result here is the coefficient is negative, which implies there is smaller positive reaction to winning and a stronger negative reaction to losing later in the season. This may be the result of losing in later months being interpreted as a stronger signal of possible relegation. Additionally, it may also imply that investors react more to the earlier matches since they are a measure of the club's performance throughout the remainder of the season than matches played later in the season, which are played when knowledge of the club's performance is more clear. The day of week control variables are all statistically insignificant at the 10% level in all models except for FRIDAY, which is negative and significant at the 10% level for the two day ACAR. UNEXPLOSE and UNEXPWIN are important control variables which represent when a club is upset or upsets another club. UNEXPLOSE is only statistically significant when looking at the three day ACAR, however, in all cases the coefficient is negative – as expected. UNEXPWIN, while positive in all models is statistically insignificant in all models.

Looking at Panel B of Table 16 provides the results of market reaction to match outcomes. The interesting finding is wins have a statistically significant impact on both elite and non-elite clubs' stock price while losses and draws have no statistically significant impact on stock prices. These results contradict other findings that both winning and losing have an impact on stock performance (Renneboog and Vanbrabant (2000)), in addition to finding that losing has a negative impact on stock price and winning has no impact on stock price (Brown and Hartzell, (2001) and Bernile and Lyandres (2011)). While losing is related to potential relegation, winning is associated with promotion to higher leagues and international play. In addition, while the previous section found that non-elite and elite clubs' financial performance are affected differently by winning and losing, the market reaction to winning and losing for elite and non-elite clubs are not statistically different, except for two-day ACAR for losses and international losses. Panel C provides F-tests to test if investors react differently to elite and non-elite club performance. This finding seems to imply that investors, for the most part, react to match outcome the same – regardless of club type. Lastly, international losses for elite clubs are the only international matches that result in a statistically significant outcome. The elite international loss yields negative ACAR for the one-day and two-day time horizon, but not the three-day. While international wins and draws are not significant, Edmans et al. (2007) provide the explanation that, in international play, a loss usually results in elimination and a win only signals possible advancement. This argument implies that losing may be a stronger signal than losing and explains why only losing yields statistically significant ACAR. It is possible that a non-elite clubs' performance in international play does not yield a reaction because these clubs are not expected to play internationally and have already exceeded expectations.

For robustness, the model is run without Arsenal and Manchester City, since their stocks are traded on the PLUS Market Group, a London-based security exchange formerly known as OFEX, which is a less liquid market than the exchanges where other clubs' stocks are traded. These results are presented in Table 17 and are nearly identical to the previous results. The three major differences are now as follows: The GOALDIFF is positive and statistically significant across all models, elite international losses are

TABLE 17: Robustness Market Reaction to Match Outcome

Panel A presents the output of a Pooled OLS model with robust standard errors. The ACAR of the club's stock is the dependent variable. Panel B provides the coefficient for the two types of clubs for domestic and international matches. Panel C provides F-test outputs for testing if investors react differently to elite and non-elite clubs. Panel D provides results of different tests.

PANEL A: REGRESSION OUTPUT						
Variable	ACAR (0,1)		ACAR (0,2)		ACAR (0,3)	
Constant	-0.0011		0.0008		-0.0017	
WIN	0.0050	**	0.0100	***	0.0129	***
LOSE	-0.0022		-0.0032		-0.0037	
EWIN	0.0020		-0.0003		-0.0022	
ELOSE	0.0010		0.0042		0.0024	
EDRAW	0.0025		0.0021		0.0006	
IWIN	0.0002		0.0030		-0.0033	
ILOSE	-0.0037		0.0062		0.0078	
IDRAW	-0.0014		0.0017		-0.0079	
EIWIN	-0.0045		-0.0079		-0.0070	
EILOSE	-0.0063		-0.0255	**	-0.0242	
EIDRAW	-0.0069		-0.0131		-0.0069	
TUESDAY	0.0030		0.0008		0.0033	
WEDNESDAY	0.0019		0.0031		0.0069	
THURSDAY	0.0066		0.0034		0.0083	
FRIDAY	-0.0060		-0.0143	*	-0.0125	
SATURDAY	0.0016		-0.0007		0.0004	
SUNDAY	0.0019		-0.0021		-0.0006	
HOME	-0.0018	*	-0.0018		-0.0006	
GOALDIFF	0.0018	***	0.0015	**	0.0015	*
SOCCERMONTH	-0.0004	**	-0.0006	**	-0.0006	*
UNEXPLOSE	-0.0030		-0.0052		-0.0128	**
UNEXPWIN	0.0051		0.0022		0.0019	
PANEL B: TEST MARKET REACTION						
Non-Elite Win	0.0039		0.0108	***	0.0112	***
Non-Elite Lose	-0.0033		-0.0024		-0.0054	
Non-Elite Draw	-0.0011		0.0008		-0.0017	
Elite Win	0.0058	*	0.0105	**	0.0090	*
Elite Lose	-0.0023		0.0018		-0.0030	
Elite Draw	0.0014		0.0029		-0.0011	
Non-Elite International Win	0.0040		0.0138		0.0079	
Non-Elite International Lose	-0.0071		0.0038		0.0024	
Non-Elite International Draw	-0.0025		0.0025		-0.0096	
Elite International Win	0.0015		0.0056		-0.0013	
Elite International Lose	-0.0123	**	-0.0175	**	-0.0193	*
Elite International Draw	-0.0070		-0.0085		-0.0158	**

TABLE 17 (Continued)

PANEL C: ELITE VERSUS NON-ELITE						
Elite Win=Non-Elite Win	0.70		0.01		0.36	
Elite Lose=None-Elite Lose	0.30		2.01		0.44	
Elite Draw=Non-Elite Draw	1.33		0.61		0.04	
Elite Int. Win=Non-Elite Int. Win	0.13		0.48		0.55	
Elite Int. Lose=Non-Elite Int. Lose	0.38		3.41	*	1.70	
Elite Int. Draw=Non-Elite Int. Draw	0.38		0.65		0.25	
PANEL D: MODEL TESTS						
White	173.79	**	178.72	***	234.76	***

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

negative and statistically significant across all models, and the elite international draws are statistically negative for the three-day ACAR.

3.5 Conclusion

The analysis provided herein shows that over the period from 1993-2008, game performance did impact the operating income of publicly-traded clubs. Nevertheless, it is important to note that this conclusion is not as straightforward as expected. Previous studies of stock market reactions to wins and losses have had mixed results. Yet, the previous literature did not separate clubs into elite and non-elite clubs. From the results generated in this work, it would appear that the two types of clubs are impacted by winning in different ways. It seems that elite teams benefit more from winning than lower tier clubs, since elite clubs experience a larger financial impact from league performance and tend to play internationally more regularly. While financials seem to be affected differently by the type of club, the market reaction to winning and losing does not seem to be influenced by the type of club. This is likely the result of investors being unaware of the difference between the strategies of these types of clubs.

The findings in this paper also are significantly different that other papers that have looked at market reaction to the on-field performance. Here it is found that winning in non-international play has a positive and statistically significant impact on stock price, while draws and losses have no statistically significant impact on stock price. This contradicts the two previous findings that losses and draws have a statistically negative impact on stock price, while wins have no statistical impact or the finding that all outcomes have a statistical impact. Although, when looking at international play, international losses for elite clubs do generate statistically negative reactions and, in some cases, so do international draws – which is consistent with Edmans et al. (2007).

While, in the United States, no sports team is currently publicly-traded[41], it is, nevertheless, likely the case that sports teams in the United States can also be broken into two types of teams as well, especially since leagues in the United States do not use promotion or relegation. When not facing promotion or relegation, teams may be able to reduce their payroll with little or no consequences. The findings in this paper suggest an explanation to the Pittsburgh Pirates financial success while not performing successfully on the field. If the Pirates are a lower tier MLB team, their financial success may not be influenced by on-field success compared to elite teams.

This paper fills a gap in the literature focusing on soccer clubs' field performances and its impact on the club's financial performance. Additionally, this paper shows that not all clubs are the same: Elite clubs are designed for winning; non-elite clubs are designed to simply compete. Nevertheless, when non-elite clubs play at the highest level, they benefit more than elite clubs.

The findings in this paper show that sports clubs are not the same: When looking at a club's stock reaction to match outcomes, all clubs should not be treated equally. With that said, a club's ability to win a match influences its financial performance in a positive relationship, indicating that a win can be interpreted as a signal of positive firm performance and a loss is a signal of bad firm performance. With these interpretations, the opportunity to use publicly-traded sports clubs' data to test financial implications should become more commonplace.[42] While the sports industry is a great empirical

[41] Note that some clubs are subsidiaries of publicly-traded corporations, but there are no independently traded clubs with their own stock. The Green Bay Packers are a publicly owned non-profit organization whose shareholders do not receive dividends and shares cannot be resold, except back to the team for a fraction of the original price (Kuriloff, 2010).

[42] Sports betting markets have been used extensively to test market rationality, efficient markets, and to find anomalies. Sauer (1998) provides a general overview on the betting market. Some key papers

laboratory for studies in economics and finance, it is important to realize not all clubs are identical.

looking at rationality and efficiency in the betting market include: Figlewski (1979), Gandar et al. (1988), Woodland and Woodland (1994), and Gray and Gray (1997).

CHAPTER 4: A RE-EXAMINATION OF ASYMMETRIC REACTION TO GOOD AND BAD NEWS: A TEST FROM MATCH OUTCOME

Market reaction to firm announcements has been a main area of financial research. This research focuses directly on the issue of market efficiency and how quickly information is reflected in stock prices. Evidence of stock drifts, caused by the slow incorporation of information into stock prices, contradicts the argument that financial markets are efficient. It has been shown that many types of announcements, from the release of macroeconomic indicators to firm specific news, are quickly and efficiently reflected in a firm's stock price.

The focus of this paper is on how stock prices react to good and bad news. This work builds off of Chan (2003), who finds that bad news correlates with negative drifts that last longer than the drift for good news. He interprets the longer drift for bad news as the market taking longer to fully react to the bad news.

In this paper the outcome of matches between publicly-traded English soccer clubs are used as a measure of good news, for the winner, and bad news, for the loser. Effectively, this study examines the stock price reactions to a win and a loss to determine whether the reaction to good and bad news is symmetric. Using the outcome of a sporting event is not new to the financial literature. Specifically, Palomino et al. (2009) looks at 16 UK soccer clubs over three seasons and finds that the stock market reacts faster to wins than losses. These results are consistent with Chan's (2003) findings, indicating that the market reacts faster to good news than bad news. However, Palomino et al. randomly dropped one of the clubs from their analysis when the match was played between two publicly-traded clubs. While they do not clearly explain why they dropped a club, it maybe because they assumed the reaction to a win and a loss would be symmetric. The major difference between Palomino et al. (2009) and this paper is that in the latter only matches between publicly-traded clubs are used and the impact of news on the stock prices of both clubs is tested.

A unique feature of using the release of sports scores as a source of information, is that they are readily reported, significantly reducing the issue of media bias. One major bias found, in general, with media information, is that negative news tends to generate higher media coverage. Specifically in economic news, this phenomenon has been documented by Harrington (1989) and Gaa (2008). Harrington (1989) finds that bad economic news gets greater media coverage than good economic news, except in election years. Gaa (2008) finds evidence of asymmetric reporting in earnings information, noting that more negative earnings information is likely to result in media coverage.

Using the features of match outcome between publicly-traded English soccer clubs offers a unique financial framework that allows for an ideal natural simultaneous test of market reaction to good and bad news: The test focuses on how the market responds to a single event that will impact two stocks simultaneously but in potentially different ways. By looking at the reaction of both stock prices to the outcome of the same match, it is possible to directly examine if there exists an asymmetric reaction to good and bad news. Due to the regular and rapid postings of match results in newspapers, TV reports, and many (reputable) sports-related internet websites, the specific match outcomes are rapidly disseminated to all shareholders simultaneously. This rapid and simultaneous dissemination of the same information, considered good news by some shareholders and bad news by others, eliminates the existence of investors who might be privy to information before it becomes public knowledge. An additional feature of sports scores is the clarity of information. A win is a win, and a loss is a loss. There is no grey area for information interpretation. As a result, any differential response between good news and bad news can be better assessed.

An important component of information is the validity and importance of the information. This directly relates to the discussion of does winning really matter to a soccer club’s financial performance. In the literature, there is the debate as to whether sports clubs are profit-maximizers or win-maximers. Since all sports clubs are firms, financial theory would say they must maximize shareholders’ value. Berkowitz (2011) finds that the field performance of English soccer clubs affects the club’s financial performance, which implies that relevant news regarding the club’s future financial performance is released in the matches’ outcomes. This information should result in changes in the club’s stock price and implies that sports clubs maybe both profit-maximers as well as win-maximizers, since winning has a positive impact on financial performance.

The rest of this paper is arranged as follows: Section 4.1 discusses the previous literature. Section 4.2 describes the data. Section 4.3 formulates the methodology used to test the hypotheses. Section 4.4 provides a discussion of the results, and Section 4.6 provides further analysis of the signals of winning and losing. Lastly, Section 4.7 offers concluding remarks.

4.1 Literature Review

This paper extends the literature in two different areas. The first is the relation of stock prices to media coverage. The second area is the examination of sports club's field performance and its impact on the club's stock price. While the first area of literature is extensive, only a brief general overview of the literature focusing on stock reaction to firm specific news is presented.

A. Market Reaction to Good and Bad News

Pritamani and Singal (2001) discuss three important characteristics of information signals. The first characteristic is magnitude, a measure of the signal's importance. Blume et al. (1994) suggest that price change is a good proxy for a signal's magnitude.

The second characteristic is precision, a measure of the signal's quality or validity; in the previous literature trading volume has been used as a proxy to measure precision. A potential problem with this is that there are two contradicting arguments to measuring precision using this proxy. A more precise signal could lead to a high volume, if it provides investors with more confidence in their valuation of a stock which would result in them taking larger positions. On the other hand, a precise signal could lead to a low volume, if it contributes to a convergence in expectations across investors, as they are more likely to have similar beliefs with a more precise signal. Vega (2006) finds that the more information investors have about the value of an asset, the more they trade on this information, supporting the argument that higher volume is correlated with precise signals.

The last characteristic is dissemination, or the percentage of traders who receive the signal. "For signals of the same precision, the greater the level of dissemination, the smaller will be the volume because with greater dissemination there will be a smaller divergence of opinion" (Pritamani and Singal, 2001). One concern with dissemination is the leaking of information to investors before public announcements, which is one possible reason why reactions are sometimes found prior to a signal. This latter complexity, however, concerning the early release of information does not exist in the case of sporting events, since the matches are highly publicized events and the results are displayed in real time to all interested parties.

Pritamani and Singal (2001) define an event as a large abnormal daily stock returns. They find that positive (negative) events accompanied by a public announcement are followed by a statistically significant positive (negative) abnormal return, which is not the case for events not accompanied by a public announcement. Their evidence is moderately consistent with both strategic trading under information asymmetry and the investor sentiment hypothesis. Antweiler and Frank (2006) examine the impact of news on daily returns of stock prices. Their results indicate that, in American stock markets, it is common place for a prompt reaction to be followed by a gradual reversal, the result of overreaction. Such a reversal is found to occur more frequently during periods of expansion.

Chan (2003) examines monthly stock returns focusing on stock performance when there is public headline news and when there is no news reported about the firm. Chan (2003) finds that bad news results in negative drifts that last longer than the positive drifts for good news, noting that the under reaction is mostly confined to small stocks.

From this Chan concludes that the longer drifts for bad news are the result of the market taking longer to react to the bad news. This result is confirmed in Hong et al. (2000), Depken (2001), Vega (2006), Schmitz (2007), and Palomino et al. (2009). In confirming Chan's results, Depken (2001), Vega (2006), and Schmitz (2007) provide some additional insight into market reaction to news.

Depken (2001) shows the variance of mature firms' reactions is symmetric for good and bad news while the variance of younger firms' reactions is asymmetric. Depken shows this by utilizing the GARCH model, but only uses ten randomly selected split stocks.

In the case of Vega (2006), the additional and more interesting finding is that "public announcements that generate under reaction are associated with the arrival rate of noise traders, while public information that make markets more efficient are associated with the arrival rate of informed traders."

Finally, in the case of Schmitz (2007), the following additional findings should be noted: a) an overreaction to good news the day following the release is reversed in the following trading days, and b) that short-term post-earning announcement drifts (PEAD) are stronger for bad news. Schmitz, similar to Chan, finds his results are stronger for small firms. Additionally, Schmitz finds that trading volume is abnormally high for both good and bad news several days after the event, indicating that investors trade more frequently after an event occurs. Furthermore, Schmitz looks at different types of investing behavior of investors and observes that individual investors react slower to new information than the average investor.

There is a growing amount of literature showing that bias in media coverage brings into question whether news is credible regardless of whether it is considered good or bad news. Shiller (2000) argues that the media hyped Internet stocks during the period of the Internet bubble and that hype was a major factor contributing to the Internet bubble. Evidence presented by Bhattacharya et al. (2009) supports Shiller's argument that the media hyped Internet stocks during the Internet bubble. However, they show that the media hype can only explain about 2.9% of the rise of Internet stock prices. There are additional biases in the media that confirm Shiller's argument that the media influences which events get more attention.[43]

While there is an overwhelming amount of literature that shows that drifts exist after news coverage or firm announcements, there are only several well-developed papers that provide a theoretical model to explain the existence of these drifts. Daniel et al. (1998) develop a model in which stock prices overreact to private-information signals and underreact to public signals. Their theory is based on overconfidence and changes in confidence arising from biased self-attribution. Lastly, they argue that overconfidence can decrease volatility around public news events. Similar to Daniel et al. (1998), Barberis et al. (1998) build a model involving investor sentiment to explain the under- and overreaction to new information. Their parsimonious model results in investors underreacting to earning announcements and similar events, which provides information that is of low strength but high in significant statistical weight. Additionally, they assume

[43] A common bias that is documented is the media tends to focus on negative news (See Harrington (1989), Soroka (2006), and Gaa (2008)). Soroka (2006) provides a general overview of the literature on asymmetric responses to information from multiple disciplines.

consistent patterns of good or bad news represent information that is high in strength but low in weight, which results in overreaction.

While Barberis et al. (1998) and Daniel et al. (1998) use representative agent models, Hong and Stein (1999) develop a model explaining under- and overreaction to information using two groups of bounded rational traders, each of which is able to process only a subset of the available public information. Their model is able to provide explanations to under- and overreaction. When news watchers are the only active group, prices adjust slowly to new information resulting in underreaction. However, when a second group of traders tries to exploit this underreaction with a simple arbitrage strategy, the result is overreaction created by excessive momentum in prices. Hong and Stein's (1999) model has three testable implications: (1) Both short-run continuation and long-run reversal should be more pronounced in those (small, low-analyst-coverage) stocks where information diffuses more slowly; (2) there may be more long-run overreaction to information, which is initially private, than to public news announcements; and (3) there should be a relationship between momentum traders' horizons and the pattern of return autocorrelations. Hong et al. (2000) find evidence consistent with the gradual-information-flow model in Hong and Stein (1999), but admit their findings could be the result of short-sale constraints impeding the adjustment of price to negative information.

Frazzini (2006) uses the disposition effect, introduced into the finance literature by Shefrin and Statman (1985), to explain the underreaction to news. The disposition effect is the tendency that investors sell winners and hold losers. Frazzini (2006) uses a dataset of mutual funds holdings to test his hypothesis that bad (good) news moves slowly across stocks trading at large capital losses (gains), leading to a negative (positive) price drift. He confirms his hypothesis that the disposition effect explains underreaction to news.

B. Literature on Sports Clubs' Stock Performance

Brown and Hartzell (2001) is the seminal paper that looks at the impact of a sports club's game outcome, winning or losing, on its stock price. In their work they look at the stock price of the National Basketball Association's Boston Celtics reaction to the club's performance over a 12-year period. They find that wins and losses in postseason play impacted stock price and volume, however, during the regular season only losses had a significant effect on stock price.

In Europe, there have been many publicly-traded professional soccer clubs. As a result, there have been multiple papers that have followed the Brown and Hartzell (2001) path to examine the impact of performance on publicly-traded soccer clubs. Renneboog and Vanbrabant (2000) find that winning generates positive abnormal returns, while draws and losses generate negative abnormal returns. The authors observe that publicly-traded soccer clubs tend to underperform the market and argue many investors are just fans that get utility from being part owners of a soccer club. Zuber et al. (2005) also note that these investors are not typical investors – referring to them as "investor-fans," who receive utility of holding a share of their favorite soccer club. Benkraiem et al. (2002) are the first to consider the location of the game, home or away, and find home losses have a greater negative impact on the club's stock than away losses. However, they find no significant reaction to a win. They utilize data for only the 2006-07 season for 18 publicly-traded European soccer clubs. Stadtmann's (2006) findings, using data from the

German soccer club Borussia Dortmund, are also consistent with Renneboog and Vanbrabant (2000).

Polomino et al. (2009) further extends the literature on winning and losing by looking at the speed of the reactions and find that the market reacts faster to winning (good news) than to losing (bad news). Their work is consistent with the literature related to market reaction to firm news.

A unique application of the use of sports clubs' performances has been to examine investor sentiment. Edmans et al. (2007) used national soccer clubs' performances as a proxy for investor sentiment and found an asymmetric reaction to losses, which resulted in a strong negative stock market reaction, while wins caused no significant stock market reaction.[44] They conclude that stock prices are affected by the investor's mood.[45] Kaplanski and Levy (2010) derive a strategy to exploit this phenomenon by utilizing the U.S. market, since one-third of all U.S. market transactions involve non-U.S. investors.

Bernile and Lyandres (2011) also use a novel proxy from sports to examine investors' expectations. Utilizing a sample of 20 publicly-traded European soccer clubs and contracts traded on betting exchanges as a proxy of investors' expectations, they find that investors' sentiment partially explains the systemic bias in the investors' *ex ante* expectations. This bias results in disappointment *ex post*, resulting in the negative abnormal returns *ex post* for losing teams.

[44] Edmans et al. (2007) also looks at international play in cricket, rugby, ice hockey, and basketball with similar findings, except for ice hockey.

[45] It should be noted that Boyle and Walter (2003) found no relationship between the New Zealand stock market's return and the performance of New Zealand national rugby team. Ashton et al. (2003) found that the English stock market did well (poorly), in the broadest of terms, when England's national soccer club won (lost).

4.2 Data

This paper uses English soccer matches' outcomes to test whether the market's reaction to good news and bad news is asymmetric. From 1992-2008 there were a total of 17 English soccer clubs whose stocks were traded on the London Stock Exchange (LSE), the Alternative Investment Market (AIM) or the PLUS Market Group (PZ).[46] Although some data exists for some clubs that were publicly-traded before 1992,[47] the data set primarily only goes back to 1992 because the English Football League restructured the various leagues for the start of the 1992-1993 season.[48] The sample period ends with the 2007-2008 season, with only six clubs still publicly traded, and three of these clubs going private within the year. The initial sample is comprised of 1,327 matches. Matches where the two clubs' stocks were not traded on similar days around the match are discarded, leaving 1,267 matches.[49] Additionally, there are 316 matches that ended in a draw, since a draw does not result in a clear signal of good news or bad news, they are removed. This leaves 951 matches to be used in the empirical analysis.

The time and date of each match was observed from statto.com and confirmed by BetExplorer and ESPN. Since the time of the match, be it early in the season or late in the season, will likely impact the findings, the variable MONTH is created that takes a value of one if the match is played in August (first month of the season), two if match is

[46] The PZ is a London-based security exchange formerly known as OFEX, which is a less liquid market of the three exchanges. The AIM is a part of the LSE, but is designed for small and growing companies, which results in the AIM having less restrictive listing requirements than LSE.

[47] The first publicly-traded English soccer club was Tottenham Hotspur in 1983.

[48] The Football League was restructured to allow the English Premier League (EPL) to compete more competitively with the other elite clubs across Europe. As a result of the restructuring the EPL was free to negotiate its own broadcast and sponsorship agreements.

[49] This is primarily the result of the PZ not always operating on same days as the other markets, primarily the result of holidays.

played in September (second month of the season), and so on up until ten, which represents a match played in May, the last month of the season.

Each type of match is recorded as well; there are five different types of matches. The first two types are regular season games with the first being between two EPL clubs, and the other is between two clubs in the Football League Championship, formally Division One, (D1). The third type of match is a playoff game, hereafter referred to as PLAYOFF. Only D1 has playoff games, which are used to select the third club to be promoted to the EPL for the following season from the clubs that finished between third and sixth in the standings. The fourth type of game is a tournament game, hereafter referred to as FAL, which is played in one of the two national tournaments, League Cup (FL Cup) and Football Association Cup (FA Cup). The FL Cup and the FA Cup are knockout tournaments played in England between EPL teams and non-EPL English teams. The FA Cup in recent years has experienced a rapid increase in participating teams, with 731 clubs competing in the 2007-2008 FA Cup, while the FL Cup consistently has only the top 92 English clubs. The last type of game is the Community Shield (SHIELD) which is played annually between the champion of the EPL and the FA Cup winner and has no bearing on a club's standings. The club's rank in their division is observed after each game, as well as the number of goals scored by each club. A ranking of one means the club is in first place, i.e. a lower ranked club has earned more points through the season and is arguable a better club.

Betting odds from BetExplorer are collected for each match to control for expectations. Betting odds are only reported in 703 of the 951 matches in the sample. Until the start of the 1998-1999 season, no betting data was available on regular season games, and not until October 2004 is betting data available for all remaining types of games; although all SHIELD and PLAYOFF games in the dataset are before October 2004. The betting odds are transformed into the subjective probabilities using the identical approach as Sauer (2005), but adjusting the approach to include draws.

Summary statistics on the matches are provided in Table 18. While not going into great detail on the summary statistics, the results of the one-day returns from the entire dataset are discussed. It should be noted that similar analysis can be done on each subcategory. Looking at HOME, since this variable is a dummy variable, the mean of .603 indicates 60.3% of the matches, or 405 matches, in the dataset were won by the home club, indicating the remaining 39.7% of the matches, or 267 matches, where won by the away club. Similar analysis can be done to examine the percentage and number of matches within the dataset that fall into each game type (EPL, D1, and FAL), having an elite club as the winner (WELITE), and have an elite club as a loser (LELITE). Looking at the rank of the winning and losing clubs, on average, the winner's rank is lower than the loser's rank, which is not surprising especially when one examines the probability of outcomes from the betting odds. The betting odds imply the winning club was expected to win, as calculated from the subjective probability. Potentially the most interesting observation from Table 18 comes from the examination of daily returns in both panels where one can see that the average return tends to be non-negative. This is interesting in that previous papers in the literature tend to find the asymmetric reaction reduces, or is removed, several days after the event.

Daily closing stock prices are collected for all clubs for the entire period the club is traded from Bloomberg. Additionally, dividends, splits, issuance, or reverse-splits

TABLE 18: Summary Statistics of Returns

This table has summary statistics on matches used in analysis. Panel A includes all games while Panel B removes games that had a club whose stock was traded on the PZ.

PANEL A: All Data										
	1-DAY RETURN		2-DAY RETURN		3-DAY RETURN		4-DAY RETURN		5-DAY RETURN	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
HOME	0.603	0.490	0.606	0.489	0.611	0.488	0.627	0.484	0.635	0.482
GOALDIFF	1.799	1.020	1.802	1.009	1.823	1.026	1.831	1.039	1.849	1.052
MONTH	5.435	2.726	5.409	2.740	5.527	2.763	5.732	2.725	5.613	2.636
WRANK	6.290	4.830	6.292	4.843	6.235	4.864	6.460	4.965	6.450	5.004
LRANK	11.951	5.708	11.956	5.703	11.908	5.762	11.951	5.806	11.901	5.784
WELITE	0.551	0.498	0.548	0.498	0.555	0.497	0.538	0.499	0.541	0.499
LELITE	0.324	0.469	0.325	0.469	0.332	0.471	0.324	0.468	0.327	0.470
EPL	0.862	0.346	0.860	0.348	0.880	0.325	0.889	0.315	0.889	0.314
D1	0.121	0.326	0.122	0.328	0.102	0.304	0.099	0.299	0.096	0.295
FAL	0.018	0.133	0.018	0.134	0.018	0.132	0.012	0.111	0.014	0.119
WPROB	0.444	0.150	0.444	0.150	0.447	0.152	0.448	0.151	0.449	0.152
DPROB	0.274	0.035	0.282	0.129	0.273	0.036	0.273	0.036	0.273	0.037
LPROB	0.282	0.129	0.274	0.035	0.280	0.036	0.279	0.129	0.278	0.129
CUMULATIVE RETURN	0.011	0.047	0.014	0.063	0.021	0.081	0.024	0.093	0.023	0.099
DAILY RETURN[A]	0.011	0.047	0.004	0.034	0.004	0.031	0.001	0.039	0.001	0.036
Observations	672		662		566		485		416	

[A] Daily return tends to have one or two more/less observations than what is listed as a result of stock market information.

TABLE 18: (Continued)

PANEL B: Without PZ										
	1-DAY RETURN		2-DAY RETURN		3-DAY RETURN		4-DAY RETURN		5-DAY RETURN	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
HOME	0.600	0.490	0.604	0.489	0.605	0.489	0.618	0.487	0.616	0.487
GOALDIFF	1.748	0.964	1.749	0.948	1.776	0.980	1.777	0.985	1.793	0.992
MONTH	5.512	2.727	5.485	2.742	5.599	2.775	5.764	2.746	5.622	2.673
WRANK	6.694	4.804	6.715	4.813	6.651	4.840	6.844	4.919	6.847	4.985
LRANK	12.306	5.414	12.304	5.407	12.322	5.433	12.226	5.494	12.120	5.449
WELITE	0.526	0.500	0.522	0.500	0.519	0.500	0.508	0.501	0.514	0.501
LELITE	0.317	0.466	0.318	0.466	0.320	0.467	0.318	0.466	0.318	0.467
EPL	0.904	0.294	0.903	0.297	0.909	0.288	0.921	0.271	0.925	0.264
D1	0.082	0.275	0.084	0.277	0.075	0.263	0.067	0.025	0.060	0.238
FAL	0.013	0.115	0.014	0.116	0.016	0.125	0.013	0.113	0.015	0.122
WPROB	0.436	0.145	0.436	0.145	0.439	0.147	0.439	0.147	0.437	0.146
DPROB	0.277	0.033	0.277	0.033	0.276	0.033	0.276	0.034	0.276	0.034
LPROB	0.287	0.127	0.287	0.126	0.285	0.127	0.285	0.127	0.287	0.126
CUMULATIVE RETURN	0.012	0.052	0.014	0.067	0.022	0.085	0.023	0.099	0.022	0.105
DAILY RETURN[A]	0.012	0.052	0.003	0.036	0.006	0.033	0.000	0.042	0.000	0.038
Observations	523		513		441		390		333	

[A] Daily return tends to have one or two more/less observations than what is listed as a result of stock market information.

information is also collected. This data is used to calculate the club's stock reaction to each game outcome.

Lastly, it is important to note that all but two soccer clubs (Arsenal and Manchester United) are small stocks with market capitalizations below £400 million. Arsenal is slightly above the upper echelon of small cap stocks with a market cap as high as £724.8 million, this is only due to each share is in excess of one million British pounds; Arsenal only has about 600 shares outstanding. As a result, it is possible to make the case that Arsenal is also a small cap firm, with so few shares outstanding. Manchester United is likely the only club in this dataset to exceed the classification of a small cap firm with a market that peaked at £1,071.5 million. Since previous works have noted that the asymmetric market reaction to news is most common in small stocks, this dataset consists of firms that are likely to have an asymmetric reaction.

4.3 Methodology

This paper looks at average returns (AR) as well as average cumulative returns (ACR). The return on the stock over horizon T, where T is as short as one day or as long as five days, is:

$$r_{i,T} = \frac{P_{i,T} - P_{i,0} + D_{i,t}}{P_{i,0}}, \tag{16}$$

where $P_{i,T}$ is the closing price of stock i on day T, and $D_{i,t}$ is the dividend paid on stock i over the time period. To examine if the market reaction to winning and losing is symmetric, the return of the losing club is subtracted from the return on the winning club, DIFFRETURN.

To examine if the market reaction is symmetric a two-staged model is used. The first stage will control for club effects with the model taking the following form:

$$DIFFRETURN = \; b_0 + b_1 WINNER + b_2 LOSER + \varepsilon, \tag{17}$$

where WINNER is a vector of dummy variables that take the value of one if the designated club wins the match and a zero otherwise, LOSER is a vector of dummy variables that take the value of one if the designated club loses the match and a zero otherwise, and ε is a zero mean random error term.

The second stage will use the fitted returns from the first stage for each match and control for match characteristics. As a result, not only can the market reaction to winning and losing be observed, but which characteristics of the match result in stronger asymmetric reaction can also be examined. The second stage model takes the following form:

$$\widehat{DIFFRETURN} = b_0 + b_1 HOME + b_2 GOALDIFF + b_3 MONTH + b_4 WELITE + b_5 WRANK + b_6 WPROB + b_7 LELITE + b_8 LRANK + b_9 DPROB + b_{10} D1 + b_{11} FAL + \varepsilon, \quad (18)$$

where $\widehat{DIFFRETURN}$ is the fitted difference return from the first stage. HOME is a dummy variable that takes the value of one if the winning club is also the home club and a zero otherwise. GOALDIFF is the goals scored by the winning club minus the goals scored by the losing club. MONTH is the month of the season. WELITE (LELITE) represents if the winning (losing) club is an elite club and a zero otherwise. WRANK (LRANK) is the ranking of the winning (losing) club in their league as a result of the outcome of the match. WPROB is the probability of the winning club winning the match from the betting odds. DPROB is the probability of the match ending in a draw from the betting odds. Investor sentiment was proxied by using betting data to interpret expectations of outcome, which Baker and Wrugler (2006) show have implications on small stocks, which most soccer club stocks are classified as. The remaining variables (D1 and FAL) are dummy variables that take a value of one if the match is of that type and a zero otherwise. Note that EPL matches do not have a dummy, since they are used as the base matches.

4.4 Results

Discussed in this section are the results from the model using the entire dataset, the following section will offer robustness checks. Since the first stage of the model is just a model to control for club characteristics, all 951 matches still in the dataset are used where stock price data is reported in Bloomberg for both clubs. For the second stage, only 703 matches with betting data are utilized, since in the second stage betting odds are used as control variables to estimate investor's expectations of the match outcome.

Table 19 provides the output from the second stage and tests for the cumulative return (CR) to good news and bad news, winning and losing. When looking at the tests for symmetric reaction, Table 19 Panels B through D, the results indicate the market has no asymmetric reaction to winning and losing, the proxies for good and bad news. The market reaction is not significantly different from zero, which implies the market does not react faster to winning, for any of the types of matches or combinations of types of clubs. This evidence goes against Polomino et al. (2009) findings that the market reacts faster to the win. The advantage to our dataset is it looks at the market reaction to winning and losing simultaneously compared to Polomino et al. (2009), who look at the cumulative reaction of games over a season. As a result, it is likely that the simultaneous comparison is a better measure of market reaction to winning and losing. It is worth noting while the different types of clubs do not influence the results in panels B, C, and D, the coefficients in the model are of significance. When an elite club wins, the market reaction to the combined news is more positive after the first day, but by the combined cumulative reaction after the fifth day, the reaction is significantly negative. This is the

TABLE 19: Cumulative Returns

Below is the output from the second stage regression for cumulative returns while Panel B, C, and D provide the cumulative market return of the winner minus the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
CONSTANT	-0.0009	-0.0027	0.0069	0.0079	0.0091
HOME	0.0013	-0.0003	-0.0013	-0.0022	-0.0012
GOALDIFF	-0.0001	-0.0001	0.0001	0.0006	0.0006
MONTH	0.0000	-0.0001	-0.0003	-0.0004	-0.0005
WRANK	0.0001	0.0001	0.0002	0.0002	0.0002
LRANK	-0.0002 **	-0.0004 ***	-0.0006 ***	-0.0008 ***	-0.0009 ***
WELITE	0.0034 ***	0.0022	-0.0014	-0.0032	-0.0109 ***
LELITE	-0.0051 ***	-0.0040 ***	0.0102 ***	-0.0109 ***	-0.0147 ***
D1	-0.0051 ***	-0.0094 ***	-0.0110 ***	-0.0076	-0.0099 **
FAL	0.0010	0.0020	0.0103	0.0132	0.0152
WPROB	-0.0091	0.0019	0.0052	0.0124	0.0108
DPROB	0.0269 *	0.0295	0.0146	-0.0019	0.0193
F-stat	5.68 ***	5.11 ***	3.92 ***	3.20 ***	3.96 ***
Adjusted R^2	0.0713	0.0641	0.0538	0.0477	0.0728
# of Obs.	672	662	566	485	416

PANEL B: EPL MATCHES	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0009	-0.0027	0.0069	0.0079	0.0091
$b_0+b_4=0$	Elite	Non-Elite	0.0025	-0.0005	0.0055	0.0047	-0.0056
$b_0+b_7=0$	Non-Elite	Elite	-0.0060	-0.0067	-0.0034	-0.0030	-0.0008
$b_0+b_4+b_7=0$	Elite	Elite	-0.0026	-0.0045	-0.0048	-0.0062	0.0165

TABLE 19: (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0060	-0.0121	-0.0041	0.0003	-0.0008

PANEL D: FAL MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0001	-0.0008	0.0170	0.0211	0.0243
$b_0+b_4=0$	Elite	Non-Elite	0.0035	0.0014	0.0156	0.0179	0.0134
$b_0+b_7=0$	Non-Elite	Elite	-0.0050	-0.0047	0.0068	0.0102	0.0096
$b_0+b_4+b_7=0$	Elite	Elite	-0.0016	-0.0025	0.0054	0.0070	-0.0014

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

only case where one sees any evidence of overreaction. As for when elite clubs lose, the reaction is negative and significant at the 1% throughout the five-day period. This indicates the market seems to react stronger to the news that the elite club lost, likely the result of news against market expectations.

There is minimal variation in market reaction between EPL, FA Cup, and FL Cup matches resulting in the coefficient for FAL being insignificant. However, this is not the case for D1 matches, where the coefficient is significant and negative, which implies that the market reaction for the winner and the loser, combined, is more negative than for EPL matches, but when combined with the constant, it does not result in a reaction that is significantly different from zero. So while D1 matches seem to show a stronger asymmetric reaction with stronger reaction to losing, it is still not significant.

Looking at Panel A provides match characteristics that impact the asymmetric reaction. Many of the control variables seem to provide little explanatory power. While the WRANK is not significant in the model, the LRANK is significant and negative for all the cumulative returns. This implies the lower the quality of the losing club, the stronger the asymmetric reaction there is – which follows the argument that losing for lower ranked clubs may be more costly because they are closer to being relegated at the end of the season. Potentially the most surprising results are that the coefficients for WPROB and DPROB, which controls for market expectations, are insignificant. Only in the one-day return is DPROB significant at the 10% level, which indicates while the outcome may have been expected by some, it was not the entire market's expectation that this was the outcome. As a whole, it seems market expectations provide little explanation to the variation in the market reaction to winning and losing.

While there is no evidence in the cumulative return for a preference toward an asymmetric reaction of winning over losing, there seems to be some weak evidence of this occurring in the daily returns. The results from the daily returns can be seen in Table 20. Here, in both D1 and tournament matches, there is an asymmetric reaction in the third-day return. This is found in the D1 match and tournament matches between non-elite clubs, as well as in tournament matches where an elite club defeats a non-elite club. While these results are significant at the 10% and 5% levels, they do not clearly support the asymmetric reaction argument. It is possible this positive reaction is a delayed reaction to winning or a possible adjustment to overreaction to the losing club. Both of these explanations do not have implications supporting the markets asymmetric reaction to good and bad news. Additionally, for many types of matches, it is seen that there is a significant and negative reaction in the fifth-day returns. This reaction is found in six of the nine different matches. The most likely explanation for these daily returns may be that there is an overreaction to both good news and bad news. The market adjusts for the overreaction to losing on the third day, and adjusts to the overreaction to the win on the fifth day. The examination of reactions to winning and losing individually is found in the next section.

One of the most interesting findings in Table 20 is when examining the dummy variables WELITE and LELITE, the variables seem to switch signs over the time horizon. For WELITE the coefficient is positive and significant for the day-one and day-three daily returns. However, it actually flips and becomes negative and significant for the day-four and day-five daily returns. The coefficient for LELITE is negative for day-one, three, and five daily returns, but it is positive for the day-two daily return. It seems

TABLE 20: Daily Returns

Below is the output from the second stage regression for daily returns while Panel B, C, and D provide the cumulative market return of the winner minus the loser for an EPL match, D1 match and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
CONSTANT	-0.0009	-0.0017	0.0043	0.0013	-0.0075
HOME	0.0013	-0.0020 ***	0.0002	-0.0023	0.0019
GOALDIFF	-0.0001	0.0000	0.0000	0.0004	0.0000
MONTH	0.0000	-0.0001	-0.0001	0.0000	0.0000
WRANK	0.0002	0.0000	0.0001	-0.0001	-0.0001
LRANK	-0.0002 **	-0.0002 ***	0.0001	-0.0001	0.0000
WELITE	0.0034 ***	-0.0009	0.0014 *	-0.0024 *	-0.0058 ***
LELITE	-0.0051 ***	0.0033 ***	-0.0036 ***	-0.0001	-0.0025 **
D1	-0.0051 ***	-0.0024 ***	0.0027 ***	0.0014	-0.0057 ***
FAL	0.0010	0.0021	0.0041 **	-0.0013	0.0007
WPROB	-0.0091	0.0103 ***	-0.0049	0.0070	0.0052
DPROB	0.0269 *	-0.0006	-0.0118	-0.0095	0.0270 *
F-stat	5.68 ***	7.75 ***	6.23 ***	1.19	4.93 ***
Adjusted R^2	0.0713	0.1011	0.0925	0.0043	0.0942
# of Obs.	672	661	565	487	417

PANEL B: EPL MATCHES	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0009	-0.0017	0.0043	0.0012	-0.0075
$b_0+b_4=0$	Elite	Non-Elite	0.0025	-0.0026	0.0057	-0.0011	-0.0134 **
$b_0+b_7=0$	Non-Elite	Elite	-0.0060	0.0006	0.0007	0.0012	-0.0101 *
$b_0+b_4+b_7=0$	Elite	Elite	-0.0026	0.0007	0.0022	-0.0011	-0.0159 **

TABLE 20: (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0060	-0.0041	0.0070 *	0.0027	-0.0132 **

PANEL D: FAL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0001	0.0004	0.0084 *	0.0000	-0.0068
$b_0+b_4=0$	Elite	Non-Elite	0.0035	-0.0004	0.0098 **	-0.0024	-0.0127 *
$b_0+b_7=0$	Non-Elite	Elite	-0.0050	0.0037	0.0048	-0.0001	-0.0094
$b_0+b_4+b_7=0$	Elite	Elite	-0.0016	0.0028	0.0062	-0.0024	-0.0152 **

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% level.

that for elite clubs, winning results in a stronger reaction with an overreaction to winning that results in adjustments on the fourth and fifth day following the game. It is also possible that the negative reaction in the fifth-day's return is evidence of the lag in the market reaction to losing, and, therefore, supports the asymmetric reaction to good and bad news found in the literature.

When examining the control variables in the daily returns there are only minor changes. For example, HOME is now significant and positive for the daily returns on day two. Similarly, WPROB is now significant and positive at the 1% level for the daily return on day two. This seems to imply that there may be an underreaction on the first day following a match when a club is expected to win. LRANK in the CR was negative and significant for all CR. While in the daily returns, it is still negative and significant but for only the day-one and day-two returns.

While Polomino et al. (2009) find an asymmetric reaction to winning and losing, there is little evidence of this occurring in the findings presented here. The following section provides additional tests to confirm the findings above.

4.5 Robustness Check

In order to verify the findings presented in the previous section, a few robustness checks are performed. The first is to remove matches with clubs that are traded on the PZ, Arsenal and Manchester City, because this market tends to be less liquid than the LSE or AIM, which may be skewing the data. The second test is concerned with using only matches where all data is available, specifically examining only matches where neither club plays another game for at least five days. Lastly, the author looks at the market reaction of winning and losing separately to see if there is a clear discrepancy in the reaction to winning and losing individually.

A. Removal of PZ Clubs

As a result of removing the matches with clubs whose stocks are publicly-traded on the PZ, the results still remain similar with a few differences. Table 21 displays the CR and Table 22 displays the daily returns. Now controlling for month is negative and significant at the 10% level over the two-day and three-day CR, indicating the combined reaction is more negative in later months. This may be the result that losing results in worse news than winning results in good news, while this is possible, it would be hard to explain. Another change is that while LRANK is still negative, it is only significant in the two-day, four-day, and five-day CR. As for the reaction to each type of match and type of club, there is only one case where the reaction is significantly different from zero and that is the two-day CR for D1 matches. While D1 matches yield a negative and significant CR at the 10% level, it seems to be the result of the coefficient for D1 which

TABLE 21: Cumulative Returns without Clubs Traded on the PZ

Below is the output from the second stage regression for cumulative returns for matches without clubs whose stocks are publicly-traded on the PZ. Panel B, C, and D provide the cumulative market return of the winner minus the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
CONSTANT	-0.0048	-0.0096	-0.0014	-0.0023	-0.0064
HOME	0.0012	-0.0019	-0.0026	-0.0046	-0.0025
GOALDIFF	-0.0001	0.0001	0.0000	0.0001	0.0002
MONTH	-0.0002	-0.0004 *	-0.0006 *	-0.0007	-0.0006
WRANK	0.0000	-0.0001	0.0001	-0.0002	-0.0002
LRANK	-0.0001	-0.0004 ***	-0.0004	-0.0005 *	-0.0006 *
WELITE	0.0058 ***	0.0051 ***	0.0025	-0.0014	-0.0121 ***
LELITE	-0.0043 ***	-0.0028 *	-0.0088 ***	-0.0110 ***	-0.0179 ***
D1	-0.0048 **	-0.0087 ***	-0.0040	-0.0058	-0.0190 **
FAL	-0.0002	-0.0022	0.0103	0.0134	0.0172
WPROB	-0.0043	0.0150	0.1524	0.0203	0.0198
DPROB	0.0361 *	0.0437 *	0.0233	0.0262	0.0668
F-stat	4.80 ***	5.53 ***	2.58 ***	2.30 ***	3.37 ***
Adjusted R^2	0.0741	0.0888	0.0380	0.0356	0.0727
# of Obs.	523	513	441	390	333

PANEL B: EPL MATCHES

	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0048	-0.0096	-0.0014	-0.0023	-0.0064
$b_0+b_4=0$	Elite	Non-Elite	0.0010	-0.0045	0.0012	-0.0038	-0.0185
$b_0+b_7=0$	Non-Elite	Elite	-0.0009	-0.0124	-0.0101	-0.0134	-0.0243
$b_0+b_4+b_7=0$	Elite	Elite	-0.0033	-0.0073	-0.0076	-0.0148	-0.0364

TABLE 21 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0096	-0.0183 *	-0.0054	-0.0081	-0.0254

PANEL D: FAL MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0050	-0.0074	0.0090	0.0110	0.0108
$b_0+b_4=0$	Elite	Non-Elite	-0.0008	-0.0024	0.0115	0.0096	-0.0013
$b_0+b_7=0$	Non-Elite	Elite	-0.0092	-0.0102	0.0002	0.0000	-0.0072
$b_0+b_4+b_7=0$	Elite	Elite	-0.0035	-0.0051	0.0028	-0.0015	-0.0193

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

TABLE 22: Daily Returns without Clubs Traded on PZ

Below is the output from the second stage regression for daily returns for matches without clubs whose stocks are publicly-traded on the PZ. Panel B, C, and D provide the cumulative market return of the winner minus the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients

	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
CONSTANT	-0.0048	-0.0030	0.0034	-0.0009	-0.0045
HOME	0.0012	-0.0034 ***	0.0006	-0.0027	0.0036 **
GOALDIFF	-0.0001	0.0002	-0.0001	-0.0003	-0.0003
MONTH	-0.0002	-0.0003 ***	-0.0001	0.0001	0.0000
WRANK	0.0000	0.0000	0.0000	-0.0003 **	-0.0002
LRANK	-0.0001	-0.0003 ***	0.0003 ***	0.0001	0.0000
WELITE	0.0058	-0.0001	0.0021 ***	-0.0032 **	-0.0072 ***
LELITE	-0.0043	0.0042 ***	-0.0039 ***	-0.0007	-0.0032 **
D1	-0.0048	-0.0006	0.0048 ***	-0.0054 **	-0.0097 ***
FAL	-0.0002	0.0053 **	0.0061 ***	-0.0016	0.0036
WPROB	-0.0043	0.0186 ***	-0.0090 **	0.0057	-0.0002
DPROB	0.0361	0.0012	-0.0155	-0.0004	0.0280
F-stat	4.80 ***	8.64 ***	9.10 ***	1.84 **	6.47 ***
Adjusted R^2	0.0741	0.1410	0.1687	0.0231	0.1531
# of Obs.	523	513	440	392	334

PANEL B: EPL MATCHES

	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0048	-0.0030	0.0034	-0.0009	-0.0045
$b_0+b_4=0$	Elite	Non-Elite	0.0010	-0.0031	0.0055	-0.0041	-0.0116
$b_0+b_7=0$	Non-Elite	Elite	-0.0091	0.0012	-0.0005	-0.0016	-0.0077
$b_0+b_4+b_7=0$	Elite	Elite	-0.0033	0.0011	0.0016	-0.0048	-0.0148 *

TABLE 22 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0096	-0.0036	0.0082 *	-0.0063	-0.0142 *
PANEL D: FAL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0050	0.0023	0.0094 *	-0.0025	-0.0008
$b_0+b_4=0$	Elite	Non-Elite	0.0008	0.0022	0.0116 **	-0.0057	-0.0080
$b_0+b_7=0$	Non-Elite	Elite	-0.0092	0.0065	0.0056	-0.0032	-0.0040
$b_0+b_4+b_7=0$	Elite	Elite	-0.0035	0.6368	0.0077	-0.0064	-0.0112

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

is highly significant and negative, perhaps indicating losing in D1 is worse news than winning in D1. This outcome is likely the result for all clubs that are relegated to D1, since they are trying to get back into the EPL, which becomes more difficult after each D1 loss.

Similar to the CR, the daily return models have similar results when the PZ clubs were included. The most striking changes are the R^2 increases for all models, as well as, the day-five daily returns are only negative for two of the nine types of matches. This indicates that the possible overreaction to winning or evidence of asymmetric reaction to winning and losing seems to be reduced, and may have been the result of the more illiquid securities impacting the results.

Overall the market reaction to winning and losing is still symmetric, and the previous evidence of the market reacting faster to winning than losing has disappeared.

B. Matches Without Another Match for Five Days

The CR and daily returns from the model using only data where another match is not played for at least six days after the match examined are in Table 23 and Table 24. Removing matches where a club played shortly after their last match, confirms that the next match does not have any impact on the returns for the matches observed. While the next match should not impact the results, since the match outcome is unobserved, this test just verifies this argument. As a whole, it is not surprising that the results are similar, since the data is similar.

While the constant is still not significant, it has become positive for all CR. This was not the case in the original dataset, where the CR was negative for the first two

TABLE 23: Cumulative Returns for Matches When Neither Club Plays a Game for at Least the Next Six Trading Days

Below is the output from the second stage regression for cumulative returns for matches where stock prices are available for all five days after the match and neither club had another match for at least six days following the match. Panel B, C, and D provide the cumulative market return of the winner minus the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients

	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
CONSTANT	0.0150	0.0051	0.0085	0.0132	0.0091
HOME	0.0021	-0.0021	-0.0014	-0.0028	-0.0012
GOALDIFF	0.0003	0.0002	0.0002	0.0006	0.0006
MONTH	-0.0001	-0.0003	-0.0005	-0.0005	-0.0005
WRANK	0.0002	0.0003	0.0005 *	0.0003	0.0002
LRANK	-0.0005 ***	-0.0008 ***	-0.0007 ***	-0.0008 ***	-0.0009 ***
WELITE	0.0025	-0.0007	-0.0018	-0.0036	-0.0109 ***
LELITE	-0.0129 ***	-0.0055 **	-0.0107 ***	-0.0107 ***	-0.0147 ***
D1	-0.0088 ***	-0.0127 ***	-0.0081 **	-0.0033	-0.0099 **
FAL	0.0031	0.0079	0.0130	0.0136	0.0152
WPROB	-0.0172	0.0075	0.0038	0.0061	0.0108
DPROB	0.0089	0.0228	0.0127	-0.0069	0.0019
F-stat	7.02 ***	3.51 ***	3.50 ***	2.34 ***	3.96 ***
Adjusted R^2	0.1376	0.0623	0.0620	0.0341	0.0728
# of Obs.	416	416	418	418	416

PANEL B: EPL MATCHES

	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0150	0.0051	0.0085	0.0132	0.0091
$b_0+b_4=0$	Elite	Non-Elite	0.0175	0.0044	0.0067	0.0097	-0.0018
$b_0+b_7=0$	Non-Elite	Elite	0.0021	-0.0004	-0.0022	0.0025	-0.0056
$b_0+b_4+b_7=0$	Elite	Elite	0.0046	-0.0011	-0.0040	-0.0011	-0.0165

TABLE 23 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0063	-0.0075	0.0004	0.0099	-0.0008
PANEL D: FAL MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0181	0.0130	0.0215	0.0269	0.0243
$b_0+b_4=0$	Elite	Non-Elite	0.0206 *	0.0124	0.0197	0.0233	0.0134
$b_0+b_7=0$	Non-Elite	Elite	0.0053	0.0075	0.0108	0.0161	0.0096
$b_0+b_4+b_7=0$	Elite	Elite	0.0078	0.0068	0.0090	0.0126	-0.0014

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

TABLE 24: Daily Returns for Matches When Neither Club Plays a Game for at Least the Next Six Trading Days

Below is the output from the second stage regression for daily returns for matches where stock prices are available for all five days after the match and neither club plays another match for at least six days following the match. Panel B, C, and D provide the cumulative market return of the winner minus the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients					
	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
CONSTANT	0.0150	-0.0097	0.0032	0.0020	-0.0075
HOME	0.0021	-0.0035 ***	-0.0006	-0.0026	0.0019
GOALDIFF	0.0003	-0.0001	0.0000	0.0004	0.0000
MONTH	-0.0001	-0.0002	-0.0002	0.0000	0.0000
WRANK	0.0002	0.0001	0.0002 *	-0.0002	-0.0001
LRANK	-0.0005 ***	-0.0002	0.0005	-0.0001	0.0000
WELITE	0.0025	-0.0018 *	-0.0014	-0.0032 **	-0.0058 ***
LELITE	-0.0129 ***	0.0074 ***	-0.0053 ***	0.0000	-0.0025 **
D1	-0.0088 ***	-0.0266 *	0.0040 ***	0.0027	-0.0057 ***
FAL	0.0031	0.0060 *	0.0045	-0.0015	0.0007
WPROB	-0.0172 *	0.0217 ***	-0.0006	0.0073	0.0052
DPROB	0.0089	0.0095	-0.0101	-0.0115	0.0270 *
F-stat	7.02 ***	8.22 ***	8.56 ***	1.46	4.93 ***
Adjusted R^2	0.1376	0.1609	0.1663	0.0119	0.0942
# of Obs.	416	415	418	420	417

PANEL B: EPL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0150	-0.0097	0.0032	0.0020	-0.0075
$b_0+b_4=0$	Elite	Non-Elite	0.0175	-0.0115 *	0.0018	-0.0012	-0.0134 **
$b_0+b_7=0$	Non-Elite	Elite	0.0021	-0.0023	-0.0021	0.0021	-0.0101 *
$b_0+b_4+b_7=0$	Elite	Elite	0.0046	-0.0041	-0.0035	-0.0012	-0.0159 **

TABLE 24 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0063	-0.0124 *	0.0072	0.0047	-0.0132 **

PANEL D: FAL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0181	-0.0037	0.0077	0.0006	-0.0068
$b_0+b_4=0$	Elite	Non-Elite	0.0206 *	-0.0056	0.0063	-0.0027	-0.0127 *
$b_0+b_7=0$	Non-Elite	Elite	0.0053	0.0037	0.0024	0.0006	-0.0094
$b_0+b_4+b_7=0$	Elite	Elite	0.0078	0.0018	0.0010	-0.0026	-0.0152 **

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

days. As for the control variables in the model, their results are nearly identical in significance and size as the output from using all matches.

Examining panels B through D, there is only one case where the CR is significantly different from zero, and that is found in the day-one returns for tournament matches – where an elite club defeated a non-elite club. Here the joint returns are statistically positive at the 10% level, indicating evidence of a potentially quicker or larger reaction to winning. While this is evidence of asymmetric reaction to good and bad news, it is important to note that the two types of clubs may have different impacts in the signal of winning and losing a tournament match, resulting in asymmetric signals, which would explain this result.

As for the daily reactions, there are more changes in the control variables than in the CR, resulting in the significances of some variables to change slightly. More importantly, the significant and positive daily return found on the third day after many matches is no longer significant, and the second-day returns are negative and significant for two of the nine types of matches. While this may be the adjustment of overreaction to the win, it could be evidence in the delay in the reaction to the loss. This will be discussed more when examining the returns of winning and losing separately.

It is interesting to note that looking at the proxy for investor sentiment, probability of the winning club winning; it has become significant for the first two days' daily returns. While it is negative for day one, it becomes positive and highly significant for day two. This seems to imply that when the outcome is expected the combined return seems to react to the loss more on the first day and is then followed by a stronger reaction to the win, which may imply the market reacts faster to the negative news, which is opposite to the findings of Chan (2003).

These results seem to be predominantly consistent with the previous results and show only weak evidence of asymmetric market reaction to good and bad news.

C. Winner and Loser

In previous tests, the returns of the winning and losing club have been combined to see if the market reaction to winning and losing is symmetric. In this section, the reaction to winning and losing will be separated to see how the market reacts to each component separately.

Table 25 and Table 26 report the CR and the daily returns for winners. When looking at the control variables for the CR, there is little consistency over time on significance. With that said, there are some clear consistencies that can be made. First, winning at home does result in a higher CR for the winner. Second, the market seems to have more positive reactions that are stronger when a non-elite club is not competing in the match. This is observed from the negative market reaction to the winner or loser being an elite club. Also, the reaction to winning D1 matches compared to EPL matches is smaller over the two-day horizon after the match, but it then reverses and results in a larger reaction to winning D1 matches than EPL matches. This significantly larger reaction to D1 over the longer horizon is the result of winning in D1 generates higher future revenues for the club than winning EPL matches. Clubs that win in D1 get promoted to the EPL – resulting in a large increase in revenues. Last, looking at the two control variables from the betting market to control for market expectations of the match, imply that winning when the club is not expected to win, or is a more competitive

TABLE 25: Cumulative Returns for Winners

Below is the output from the second stage regression for cumulative returns while Panel B, C, and D provide the cumulative market return of the winner for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients					
	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
CONSTANT	0.00261	0.00185	0.01062	0.00922	0.00964
HOME	0.00133	0.00144	0.00276 *	0.00298 **	0.00374 **
GOALDIFF	-0.00006	-0.00005	-0.00002	0.00023	0.00007
MONTH	0.00004	0.00004	0.00003	0.00004	0.00006
WRANK	0.00013 *	0.00007	0.00010	0.00020	0.00014
LRANK	0.00005	0.00001	0.00035	0.00002	0.00036
WELITE	0.00013	0.00048	-0.00187	-0.00314 **	-0.00445 ***
LELITE	-0.00073	-0.00068	-0.00196 *	0.00184	-0.00330 **
D1	-0.00046	-0.00323 **	0.00014	0.00452 **	0.00434 **
FAL	-0.00060	-0.00150	0.00668	0.00225	0.00099
WODD	-0.00716 *	-0.00470	-0.01222 *	-0.01121	-0.01652 *
TODD	0.02096 **	0.02647 **	0.01700	0.01378	0.02134
F-stat	4.12 ***	2.43 ***	3.56 ***	7.37 ***	7.97 ***
Adjusted R^2	0.0479	0.0228	0.0467	0.1251	0.1538
# of Obs.	683	674	575	491	423

PANEL B: EPL MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0026	0.0018	0.0106	0.0092	0.0096
$b_0+b_4=0$	Elite	Non-Elite	0.0027	0.0023	0.0087	0.0061	0.0005
$b_0+b_7=0$	Non-Elite	Elite	0.0019	0.0012	0.0087	0.0074	0.0063
$b_0+b_4+b_7=0$	Elite	Elite	0.0020	0.0017	0.0068	0.0042	0.0019

TABLE 25 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0021	-0.0014	0.0108	0.0137 *	0.0140

PANEL D: FAL MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0020	0.0004	0.0113	0.0115	0.0106
$b_0+b_4=0$	Elite	Non-Elite	0.0021	0.0008	0.0094	0.0083	0.0062
$b_0+b_7=0$	Non-Elite	Elite	0.0013	-0.0003	0.0093	0.0096	0.0073
$b_0+b_4+b_7=0$	Elite	Elite	0.0014	0.0002	0.0075	0.0065	0.0029

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

TABLE 26: Daily Returns for Winners

Below is the output from the second stage regression for daily returns while Panel B, C, and D provide the cumulative market return of the winner for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients					
	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
CONSTANT	0.00261	0.00088	0.00594 ***	0.00065	-0.00292
HOME	0.00133	-0.00028	0.00038	-0.00011	0.00008
GOALDIFF	-0.00006	0.00004	-0.00004	0.00017	-0.00007
MONTH	0.00004	-0.00002	-0.00003	-0.00001	0.00000
WRANK	0.00013 *	-0.00003 *	-0.00001	0.00001	-0.00003
LRANK	0.00005	-0.00003 *	0.00003	-0.00005	0.00003
WELITE	0.00013	0.00005	-0.00164 ***	-0.00013	0.00015
LELITE	-0.00073	0.00015	-0.00032	0.00020	0.00005
D1	-0.00046	-0.00170 ***	0.00366 ***	0.00241 ***	-0.00025
FAL	-0.00060	-0.00025	0.00049	-0.00134	-0.00118
WODD	-0.00716 *	0.00191	-0.00460 ***	0.00121	0.02325
TODD	0.02096 **	0.00263	-0.00709	-0.00731	0.00343
F-stat	4.12 ***	10.31 ***	39.51 ***	1.69 *	0.30
Adjusted R^2	0.0479	0.1323	0.4255	0.0152	-0.0184
# of Obs.	683	673	573	493	424

PANEL B: EPL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0026	0.0009	0.0059 ***	0.0006	-0.0029
$b_0+b_4=0$	Elite	Non-Elite	0.0027	0.0009	0.0043 ***	0.0005	-0.0028
$b_0+b_7=0$	Non-Elite	Elite	0.0019	0.0010	0.0056 ***	0.0009	-0.0029
$b_0+b_4+b_7=0$	Elite	Elite	0.0020	0.0011	0.0040 ***	0.0007	-0.0027

TABLE 26 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0021	-0.0008	0.0096 ***	0.0031	-0.0032

PANEL D: FAL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	0.0020	0.0006	0.0064 ***	-0.0007	-0.0041
$b_0+b_4=0$	Elite	Non-Elite	0.0021	0.0007	0.0048 ***	-0.0008	-0.0040
$b_0+b_7=0$	Non-Elite	Elite	0.0013	0.0008	0.0061 ***	-0.0005	-0.0041
$b_0+b_4+b_7=0$	Elite	Elite	0.0014	0.0008	0.0045 ***	-0.0006	-0.0039

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

match, results in a stronger reaction to the win. This can be seen by the negative coefficient for the probability of the club winning and the positive coefficient for the probability of the clubs drawing. The probability of the outcome being a draw can be the strongest measure of the uncertainty of the match, since close matches are the most likely to result in a draw. The control variables impact on the daily returns is relatively similar to their impact on the CR, except for HOME which has no significance when looking at the daily returns.

While many of the control variables are significant, the CRs are not significantly different from zero except for D1 matches looking at the four-day CR which is only significantly different from zero at the 10% level. When looking at the daily returns for all matches, there is a positive and highly significant reaction to winning on the third day of trading for all matches. This seems to imply there is a lag in the market to winning. While this lag does occur, there is no reversal. Overall, it seems the market does not have a strong reaction to winning.

Table 27 and Table 28 report the output of the CR and the daily returns of losing. For losing it seems the lower the clubs ranking in the standings, the stronger the reaction. This is likely the result of the club being relegated the next year. Similarly, the market reacts more negatively to a D1 loss than an EPL loss which implies losing in the EPL is not as bad a signal as losing in D1. – likely because an EPL club is already in the EPL, while a club in the D1 is trying to get back up to the EPL, which is less likely with every loss. Additionally, it is possible relegation from D1 or D2 is worse than being relegated from the EPL to D1, which is the result of continuously losing.

TABLE 27: Cumulative Returns for Losers

Below is the output from the second stage regression for cumulative returns while Panel B, C, and D provide the cumulative market return of the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
CONSTANT	-0.00817 ***	-0.01108 ***	-0.01166 **	-0.01627 **	-0.01900 **
HOME	-0.00030	-0.00020	-0.00039	-0.00067	-0.00092
GOALDIFF	0.00013	0.00000	0.00004	-0.00016	-0.00002
MONTH	-0.00003	-0.00006	-0.00017	-0.00022	-0.00023
WRANK	0.00003	0.00000	0.00001	0.00011	0.00017
LRANK	-0.00009 ***	-0.00015 ***	0.00022 ***	0.00014	-0.00011
WELITE	0.00010	0.00027	0.00061	0.00289	0.00075
LELITE	-0.00015	0.00047	-0.00266 ***	-0.00292 **	-0.00167
D1	-0.00257 ***	-0.00370 ***	-0.00583 ***	-0.00684	-0.00586
FAL	0.00212	0.00161	0.00359	0.00403	0.00515
WODD	0.00268	0.00352	0.00376	0.00511	0.00544
TODD	0.00750	0.01338 *	0.01257	0.01452	0.01801
F-stat	3.37 ***	6.22 ***	3.41 ***	2.70 ***	1.58
Adjusted R^2	0.0368	0.0786	0.0443	0.0367	0.0149
# of Obs.	684	674	573	491	420

PANEL B: EPL MATCHES	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0082 ***	-0.0111 ***	-0.0117 **	-0.0163 **	-0.0190 **
$b_0+b_4=0$	Elite	Non-Elite	-0.0081 ***	-0.0108 ***	-0.0110 *	-0.0160 **	-0.0183 **
$b_0+b_7=0$	Non-Elite	Elite	-0.0083 ***	-0.0106 ***	-0.0143 ***	-0.0192 ***	-0.0207 ***
$b_0+b_4+b_7=0$	Elite	Elite	-0.0082 ***	-0.0103 ***	-0.0137 **	-0.0189 ***	-0.0199 **

TABLE 27 (Continued)

PANEL C: D1 MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0107 ***	-0.0148 ***	-0.0175 ***	-0.0231 ***	-0.0249 ***
PANEL D: FAL MATCHES							
	WINNER	LOSER	1-DAY RETURN	2-DAY RETURN	3-DAY RETURN	4-DAY RETURN	5-DAY RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0080 ***	-0.0095 ***	-0.0081	-0.0122	-0.0138
$b_0+b_4=0$	Elite	Non-Elite	-0.0079 ***	-0.0092 ***	-0.0075	-0.0120	-0.0131
$b_0+b_7=0$	Non-Elite	Elite	-0.0081 ***	-0.0090 ***	-0.0107 *	-0.0152 *	-0.0155 *
$b_0+b_4+b_7=0$	Elite	Elite	-0.0080 ***	-0.0087 ***	-0.0101 *	-0.0149 *	-0.0148

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% level.

TABLE 28: Daily Returns for Losers

Below is the output from the second stage regression for daily returns while Panel B, C, and D provide the cumulative market return of the loser for an EPL match, D1 match, and a tournament match (FA Cup or FL Cup) after controlling for match characteristics.

PANEL A: 2nd Stage Coefficients					
	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
CONSTANT	-0.00817 ***	-0.00395 **	0.00076	0.00323	-0.00309
HOME	-0.00030	0.00022	-0.00043	-0.00028	0.00026
GOALDIFF	0.00013	-0.00008	-0.00003	-0.00011	0.00008
MONTH	-0.00003	-0.00003	-0.00013 *	0.00000	-0.00009
WRANK	0.00003	-0.00003	-0.00001	0.00001	-0.00002
LRANK	-0.00009 ***	-0.00006 **	-0.00003	0.00000	-0.00002
WELITE	0.00010	0.00016	0.00027	0.00026	-0.00030
LELITE	-0.00015	0.00078 **	-0.00209 ***	-0.00046	0.00063
D1	-0.00257 ***	-0.00091 *	-0.00153 **	-0.00004	-0.00172 **
FAL	0.00212	0.00165 *	0.00083	-0.00056	0.00134
WODD	0.00268	0.00162	-0.00124	-0.00433	0.00148
TODD	0.00750	0.00683	-0.00005	-0.00710	0.00757
F-stat	3.37 ***	3.45 ***	2.99 ***	1.05	1.28
Adjusted R^2	0.0368	0.0386	0.0367	0.0011	0.0074
# of Obs.	684	673	574	491	420

PANEL B: EPL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0082 ***	-0.0040 **	0.0008	0.0032	-0.0031
$b_0+b_4=0$	Elite	Non-Elite	-0.0081 ***	-0.0038 *	0.0010	0.0035	-0.0034
$b_0+b_7=0$	Non-Elite	Elite	-0.0083 ***	-0.0032 *	-0.0013	0.0028	-0.0025
$b_0+b_4+b_7=0$	Elite	Elite	-0.0082 ***	-0.0030	-0.0011	0.0031	-0.0028

TABLE 28 (Continued)

			DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
PANEL C: D1 MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0107 ***	-0.0049 **	-0.0008	0.0032	-0.0048
PANEL D: FAL MATCHES							
	WINNER	LOSER	DAY 1 RETURN	DAY 2 RETURN	DAY 3 RETURN	DAY 4 RETURN	DAY 5 RETURN
$b_0=0$	Non-Elite	Non-Elite	-0.0080 ***	-0.0023	0.0016	0.0027	-0.0017
$b_0+b_4=0$	Elite	Non-Elite	-0.0079 ***	-0.0021	0.0019	0.0029	-0.0020
$b_0+b_7=0$	Non-Elite	Elite	-0.0081 ***	-0.0015	-0.0005	0.0023	-0.0011
$b_0+b_4+b_7=0$	Elite	Elite	-0.0080 ***	-0.0014	-0.0002	0.0025	-0.0014

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

The market reaction is faster to losing than to winning. This can be seen by a negative market reaction to losing the next trading day, which is significant at the 1% level. For winning, the positive market reaction occurs on the third day. However, the market underreacts to losing, since there is still a negative market reaction on the second-day return for about half the matches. This lag in the reaction is consistent with previous literature looking at market reaction to negative news. Since there is no significant overreaction to losing the CRs are negative and significant for the entire five-day period for almost all matches. While these results are similar to previous findings they contradict the literature on good news and bad news. As a result, a further examination of winning and losing is necessary. Is it possible that the signal of winning is not equal to the signal of losing? Section 4.6 takes a closer look at whether these signals are of equal strength.

4.6 Winning and Losing Signal

In order to examine if winning and losing have the same signal, a total of 5,700 match outcomes are examined from 1992-2008. For each club, their matches are broken up by season, with the outcome of the match being one of three options, win, lose or draw. As a result, there are three dummy variables that are created that take a value of one if the match results in that outcome for the club. Additionally, there are six dummy lags as well: win, lose and draw for the previous match and for the match before the previous match, two matches ago. Two separate models are created with only the dependent variable being either a win or a loss in terms of the current game. The independent variables are concerned only with the outcome for the previous two matches.[50]

$$LOSE_{it} \ or \ WIN_{it} = LOSE_{it-1} + WIN_{it-1} + \ LOSE_{it-2} + WIN_{it-2} \tag{19}$$

A random effects model is utilized with for clustering by club to see if losing or winning a game has any explanatory power on future performance. The results are reported in Table 29. Panel A provides the output with the dummy for losing as the dependent variable. Here neither dummy for winning is significant, but both dummies for losing are significant. This implies while winning the previous matches has no bearing on whether the club will win the next match, losing the previous matches increases the chance of a club losing the next match. Examining the results from Panel B, where winning is the dependent variable, there is no effect of winning the previous matches, while losing the match two matches before is significant and negative, implying losing may reduce the

[50] The dummy for a draw is not included due to collinearity with win and lose dummies.

chances of winning future matches. As a result, from both models, it seems that losing is a stronger signal than winning. Since the market reacts faster to good news, this finding explains why the asymmetric reaction to good and bad news is not observed in the results presented above.

TABLE 29: Explanatory Power of Winning and Losing

Below is the output from random effects model seeing if past performance of the last two games has explanatory power on the outcome of the next game. Clustering is used to control for clubs. Panel A provides for losing while Panel B provides results for winning.

PANEL A: LOSING				
	Coefficient		Z	p-value
LAGWIN	0.0147		0.85	0.395
LAGLOSE	0.0364	**	2.49	0.013
LAG2WIN	-0.0033		-0.29	0.771
LAG2LOSE	0.0267	*	1.66	0.096
CONSTANT	0.2915	***	15.43	0.000
PANEL B: WINNING				
	Coefficient		Z	p-value
LAGWIN	0.0101		0.62	0.538
LAGLOSE	-0.0128		-0.73	0.465
LAG2WIN	0.0057		0.35	0.729
LAG2LOSE	-0.0342	*	-1.96	0.051
CONSTANT	0.4372	***	25.59	0.000

*, **, and *** indicates statistically significant from null at 10%, 5%, and 1% levels.

4.7 Conclusion

This paper uses a unique dataset of market reaction to matches between two British football clubs to test the reaction to good and bad news simultaneously. While other papers have found market reaction to be quicker to good news, the signal of good news in some cases can be arbitrary. In this paper, two clear simultaneous signals are provided, one good the other bad, from the one event, a football match. Using this situation it is actually observed that the market reacts faster to the bad news, losing. Upon further analysis, it is determined that the faster market reaction to bad news is actually a result of losing being a stronger signal than winning.

The fact that the signals of losing and winning are not of equal strength helps explain the results reported in this paper relative to the earlier findings of Brown and Hartzell (2001), Edmans et al. (2007), Benkraiem et al. (2009), and Bernile and Lyndres (2011) who all find a strong reaction to losing, but not to winning. Until now these finds were not able to be explained.

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