U.S. Sports Championships and Market Returns

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CHAPTER 1: INTRODUCTION

1.1 ABSTRACT/INTRODUCTION

This study examines stock market returns the trading days before and after sports championships in the United States. The motivation for the study is to support the growing number of anomaly studies, particularly sports related studies. Previous studies have found relationships between domestic, post-event index returns and international game outcomes. This study analyzes returns on the Dow Jones Industrial Average surrounding major U.S. sporting events such as the Super Bowl, World Series, NBA Finals, Stanley Cup, MLS Cup, NCAA Basketball Championship game, and the BCS National Championship game. Several methodologies were tested including a customized event study with differing estimation periods, a t-test for difference in means, a z-test for difference in proportions, and an ordinary least squares regression. The results suggest limited evidence in support of a pre-event effect for the Big Four leagues (MLB, NFL, NBA, NHL) in which the DJIA declines in value on average the trading day before the event. Additionally, there may be a positive, pre-event effect for MLS events, though the observation count is low. Lastly, it appears that some effects are more prominent in different time periods. This is notable in the first half of the MLB, NBA, Big Four, and total samples where there is a significant, negative effect on the day after the event.

1.2 SPORTS IN THE UNITED STATES

Sports are considered an important part of culture in the United States. In fact, some of the most popular, modern sports were introduced and developed in the U.S.. Because sports are such a large part of the culture, they represent a large market in the U.S. economy. According to Plunkett Research, a reasonable estimate of the total U.S. sports market ranges annually from $400 to $435 billion. Additionally, WR Hambrecht predicts that the percentage share of spectator sports of total personal consumption (a measure of goods and services targeted toward individuals and consumed by individuals) will continue to grow. Just over the last five years, spectator sports' PCE grew at a 6.4% compounded annual growth rate compared to the overall PCE CAGR of 2.6%.

The "Big Four" in U.S. sports terms refers to the most popular sports leagues. These are the National Football League (NFL), Major League Baseball (MLB), National Basketball Association (NBA), and the National Hockey League (NHL). These four leagues combined bring in approximately $23 billion in revenue during an average year (Plunkett Research). Although these four leagues are considered the "Big Four", it is important not to allow these leagues to overshadow the popularity of collegiate sports. College basketball and football are in some standards, such as TV viewership, more popular than other sports such as soccer. Therefore, this study aims to include certain sports or leagues outside of the Big Four in order to fully evaluate whether the market reacts to different sports and leagues and also to enhance robustness by increasing the sample size.

1.2.1 Football

According to Gallup, football is America's favorite sport and has surpassed baseball in the late 1960's or early 1970's. Since then, football has kept its position with increasing interest while baseball has steadily slipped from public interest. The nation's professional league, the NFL, is the highest level of professional football in the world and hosts a 17 week season before a playoff schedule characterized by a wild-card round, a divisional round, a conference round, and, finally, the Super Bowl is played between the winners from each conference.

It is important to note that college football is also an immensely popular sport in the U.S.. Sports Media Watch reported an average viewership of the 2013 Super Bowl game of 108.4 million; the BCS National Championship game, which is the championship for NCAA division 1 football, reached 26.4 million. While comparing viewership to the Super Bowl seems unimpressive, consider that the 2012 World Series had viewership of only 15.5 million viewers on average. NCAA football, unlike the NFL, does not have a playoff system to determine the national champion. Rather, national champions are selected by computer selection models and polls in which sports writers and coaches vote for the national champion. Prior to 1998, there could be multiple national champions delegated if the polls differed on selection. Since 1998, the Coaches Poll is contractually obligated to name the winner of the BCS National Championship game as the national champion.

1.2.2 Baseball

Baseball, known as America's pastime, is the U.S.' oldest professional sport. The sport's professional league, MLB, was founded in 1869 with the organization of the first professional team, the Cincinnati Red Stockings. Baseball is a cultural icon in the United States; the history is full of scandals, myths, legends, and was also an important piece in breaking the color barrier. A MLB season consists of 162 games followed by a postseason which is similar to the NFL's in structure. First, there is a wildcard round, then divisional and conference (or league in this case) rounds follow with a 'best of five' and a 'best of seven' setting, respectively, and the season ends with the World Series, which is also a 'best of seven' setting.

1.2.3 Basketball

Basketball is considered the third most popular sport in the U.S. with 9% of respondents claiming it as their favorite sport to watch. The U.S. professional league is known as the NBA and was founded as the Basketball Association of America in 1946. The playoff format is 'best of seven'. College basketball is also rather popular compared to other sports; average viewership for the last game of the 2013 NBA Finals was 26.3 million while the 2013 NCAA Division 1 championship reached an average viewership of 23.4 million.

1.2.4 Hockey

The last of the Big Four is that of the National Hockey League, or NHL. Started in Canada in 1917, the NHL has grown to seven Canadian teams and 23 U.S. teams. Like the MLB and NBA, the NHL's Stanley Cup consists of a 'best of seven' format. Hockey ranks fourth on Gallup's poll with 4% of respondents saying the sport is their favorite to watch.

1.2.5 Soccer

While not as popular as its European counterpart, soccer in the U.S. is a growing sport. Despite only having an average viewership of 797 thousand for the 2012 MLS Cup, MLS surpassed the NHL and NBA in average attendance in 2011 with 17,872 spectators per game (NHL and NBA averaged 17,132 and 17,323, respectively, for their most recent seasons); however, MLS Cup venues typically hold more spectators than NBA arenas. MLS shares a similar championship format as the NFL with a single game event known as the MLS Cup.

1.3 OBJECTIVES

1.3.1 Primary Objective

- Determine if there are abnormal returns the day before and day after sports championships. In order to test for abnormal returns, a number of statistical methods are used to distinguish mean returns at t-1 and t+1 from mean returns of non-event trading days.

1.3.2 Secondary Objectives

- Various variables will be regressed in order to see if there are certain aspects of games that cause such abnormal returns, if they exist;
- Review similar studies and expand research on stock market anomalies.

1.4 MOTIVATION

Studies of market reactions to sports events are quite limited but continue to grow in number. Existing studies have found mixed results in different markets and different sports. Most of these studies share a common aspect in that they investigate international-level games instead of national games. This has led to the belief that there may be a present mood effect that influences stock market returns the day after the event. Furthermore, some studies have been criticized of data dredging, which is peering into large sets of data and inaccurately finding relationships within the data. In order to address this, a number of statistical methods will be applied to the data to test for abnormal performance. In addition to including several different methods, the methods will be applied to different time periods to determine if any market irregularities were more significant in another time period. Because there is a lack of sports studies regarding the U.S. stock market, this research aims to expand sports event induced anomalies on a geographical scope. Furthermore, because U.S. sports competition is largely based on a national level, potential abnormalities defy reasoning that is often applied to international-level sporting events. The idea of examining the relationship between national sports events and stock market returns was influenced by previous research that found a significant relationship between holidays and stock market returns. While holidays and sports events are entirely different, independent events, they share similarities on both economic and social aspects. Both events are known to be instances when family and friends gather and there is usually no shortage of food and drinks. While on a much smaller scale than holidays, significant sports events entice consumers to spend. The National Federation of Retail (NFR) predicted that consumers would spend on average $68.54 in anticipation of the 2013 Super Bowl. An annual survey by Visa showed that respondents planned to spend upwards of $300 for the 4th of July in 2013. Beer, which is a staple of both holidays and sports events, can be used as a decent proxy for the similarity of such events. The following table shows sales of beer cases (in millions) for the two weeks leading to each event (Nielsen):

Beer Sales	
Event	**Sales (mm)**
4th of July	63.5
Memorial Day	61.0
Labor Day	60.2
Thanksgiving	52.8
Christmas	52.8
Halloween	50.7
Super Bowl	49.2

The finding of statistically positive, abnormal returns the day before holidays (Lakonishok & Smidt 1988) has generated an interest to examine returns around sports events. This study is among the first to do so from a national competition perspective.

1.5 HYPOTHESIS

The primary objective of this research is to test for abnormal returns the day before and the day after a sports event (championship game) takes place. Specifically, the mean return of t-1 and t+1 days will be compared to the mean return of non-event trading days of the Dow Jones Industrial Average. Secondary objectives include determining a possible cause for potential abnormal returns and building upon existing sports anomaly research. The hypothesis is set as follows:

H_0: There is no relationship between championship sports events and returns on the Dow Jones Industrial Average (DJIA)

H_1: There exists a relationship between championship sports events and returns on the Dow Jones Industrial Average (DJIA)

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

There are few studies that investigate the effect of sports events on stock market price changes. Ashton *et al* (2003) is one of the first studies in which broad market stock returns were evaluated the day after a sports event in an effort to determine if abnormal returns are present after the national team (England) won, tied, or lost a soccer game. Since Ashton *et al*, a number of similar studies have examined effects in different geographical markets and different sports. This literature review aims to summarize and compare previous findings and to suggest potential reasoning for such results.

The idea of an efficient market would hold that sports events or sports results could have no effect on market price movements unless there is an expectation that the event would provide an economic stimulus. To date, there have not been any empirical studies that research the macroeconomic impact of professional sport events in the U.S.. Yet, it is often touted that such events are an economic stimulant, particularly for the host cities. Rockport Analytics claims there was $264 million in total attendee/visitor spending for the city of Indianapolis during the 2012 Super Bowl. In an article on www.nola.com, a local New Orleans news website, it is estimated that the 2013 Super Bowl would aid the local economy by $434 million. Even on a national level, the National Retail Federation (NFR) predicted that more than 179 million people would view the Super Bowl and average spending per consumer would hit record highs of $68.54 for a total of nearly $12.3 billion. However, these are merely pre-event predictions and empirical studies tell us differently. Matheseon and Baade (2007) find that evidence from host cities during the 1970-2001 Super Bowls indicate that the event contributes approximately a quarter of what "boosters" often promise. Their study also notes insignificant results for games that contribute more than $300 million to an economy. They spread their research to other leagues, such as MLB, and find similar results. Porter (1999) goes further to suggest that there is no economic impact, as historical sales figures show little difference when hosting or not hosting the event. Szymanski (2002) researches the impact on economic growth for hosts of the World Cup and the Summer Olympics. However, Szymanski only finds a statistically significant negative impact on the host economy during the year of hosting the World Cup; the years before and after prove to be insignificant. Additionally, he finds that there is no significant impact on economic growth for the host economy for the years before, during, and after the Olympics. Because of a lack of evidence of economic stimulus related to these events, it can be expected that markets do not react abnormally to the presence of a sports event. In the following section, we analyze literature that has found evidence of a relationship between sports events and stock returns and provide potential reasoning for such relationships. Thereafter, we examine literature that supports the Efficient Market

Hypothesis in that there is a failure to find a relationship. A conclusion will compare the goal of this study to these previous studies.

2.2 RELATED LITERATURE

2.2.1 Presence of a Relationship between Sports Events and Stock Returns

A number of studies have focused on public (actively traded on the stock market) club shares and their respective returns following a sports event. Scholtens and Peenstra (2009) analyze 1,274 matches of eight European soccer teams and find a significant stock market response in the trading day following a match with wins generating a positive abnormal return of 0.36% and losses generating a negative abnormal return of 1.41%. Renneboog and Vanbrabant (2000) found similar results while evaluating English soccer teams listed on the London Stock Exchange with abnormal returns of almost 1% after a win and abnormal returns of -1.4% after a loss. Benkraiem *et al* (2009) show that volatility is increased around UK soccer matches, particularly defeats at home, and they confirm similar results to Renneboog and Vanbrabant. Because these studies deal with stock market-listed clubs rather than broad indices, we will not divulge into these studies. Club shares may be affected in consideration of advancing to another game in a tournament, for example, as it is logical to believe that an extra game could theoretically increase the cash flows associated with the club through increased ticket sales, for instance. It is important to note that Scholtens and Peenstra (2009) and Benkraiem *et al* (2009) document a larger effect for losses; an often cited "loss effect" will be discussed shortly.

One of the first studies to examine broad index reactions to sports events was that of Ashton *et al* (2003). Ashton *et al* examine the reaction of the FTSE 100 index from 1984 to 2002 the day after an English national soccer team event. Mean returns on the index after wins, losses, and draws are recorded as well as binomial statistics that test whether returns are greater or less than the unconditional mean on non-event days. The results show transitive evidence of an effect with positive mean returns after a win, a small decline after a draw, and a larger decline after a loss. Furthermore, the loss effect becomes evident with a statistically significant number of returns that are less than the unconditional mean for losses. Lastly, their results from their GMM regression model show that the performance of the English national team is significantly associated with the next trading day's stock market return and the strength of the association increases with game importance. The authors note two potential reasons for such results: there may be a 'feel-good' factor, in which investors would have greater confidence about the future or there may be expectations of economic benefits derived from the national performance.

The majority of published studies since Ashton *et al*'s first study have documented significant market reactions to sports results. Furthermore, most of these studies note a strong "loss effect", in which the domestic index performs poorly in reaction to a national team loss, yet there is either no effect after a national team win or the effect is not as large as the effect of a loss. Edmans *et al* (2007) document this effect well and suggest that the effect is a result of investor mood. Their study uses international soccer, rugby, cricket, ice hockey, and basketball results as a mood variable to test for the stock market's reaction to changes in investor mood. Using a cross-section of 39 countries, data ranging from 1973 to 2004, and a variety of controlled OLS regressions with GARCH adjustments, they find highly significant, negative returns following losses on the losing country's index, but no effect for wins. The full sample of international soccer losses (524 losses) has a net effect on index returns of -21.2 basis points, while basketball, cricket and rugby losses have effects on indices of -20.8, -18.7, and -9.5 basis points, respectively. The only insignificant result was that of ice hockey (hockey was positively significant after wins using trimmed means). Edmans *et al* continue to document that the effect is more profound for small stocks. They reject that the loss effect is economically driven by controlling for pre-game expected outcomes. Edmans *et al* is considered the first study which emphatically considers the effect of a mood variable. As evidence of the possibility that abnormal returns following sporting events are caused by mood, they document several further studies tied to sports, sentiment, and psychology. Some of these studies are: Hirt (1992), in which it is found that Indiana University students estimate their own performance to be better after watching the University basketball team win; Schweitzer *et al* (1992), which found that students who rooted for the winning team of a televised football game found the probability of a war in Iraq and the potential casualties as being significantly lower than the probabilities expressed by fans of the losing team; lastly, White (1989) documents that a city experiences a rise of homicides when their respective team loses in the NFL playoffs. Edmans *et al* (2007) argue, therefore, that sports events may be a priori for investor sentiment and argue that a mood variable must satisfy three critiques: the event must drive mood in a substantial and unambiguous way, it must be shown to impact the mood of a large proportion of a population, and it must be correlated across the majority of a population.

Kaplanski and Levy (2010) build on Edmans *et al* (2007) by demonstrating that the loss effect, in some cases, extends internationally rather than only to national markets. They examine returns during the World Cup on the NYSE Composite Index from 1950 to 2007 using similar methodology as Edmans *et al* (2007) and find that the average return on the U.S. market over the World Cup's effect days is -2.58%, which compares to +1.21% for all days over the same period length. These results prove to be significant at the 1% level. They go on to state that foreign investors accounted for 33% of all U.S. equity market transactions in 2006 and that it is possible that the U.S. suffers a spillover effect. Approximately 31 teams will lose in the World Cup; domestic markets of these losing nations may experience the loss effect, which effectively alters their mood, and this sentiment then spills over to the U.S. markets through foreign investment, such as with dual-listed shares.

It is remarkable that the outcome of the event is irrelevant, as documented by Kaplanski and Levy, and that a market that is not even in contention is affected. This is a key argument in the work of Gerlach (2011). Gerlach reports a loss effect, such as that of Edmans *et al* (2007); however, Gerlach suggests that market prices are not affected by investor sentiment. Gerlach contradicts Kaplanski and Levy as well by using three arguments: there are similarly low returns in the U.S. the four weeks before the World Cup starts, there are no negative effects on U.S. markets during European soccer championships, and the World Cup effect weakens over time.

1) Gerlach argues that because the World Cup has not started and that all qualifying games are finished in the four weeks before the World Cup starts, it is not possible for World Cup soccer matches to cause negative returns.

2) The U.S. market does not have a negative effect during the European soccer championship. If the World Cup effect holds true, there should be a similar effect for the European soccer championship because the two events generate similar interest among Europeans and Europeans are the largest group of foreign U.S. equity investors.

3) The World Cup effect weakens over time with an estimated effect of -30 basis points on event effect days during the time period of 1950-1978 to just -10 basis points in the time period of 1979-2007 (Gerlach 2011). As foreign portfolio holdings of U.S. securities increased, the effect should have intensified.

In his study, Gerlach replaces the global index as a benchmark with the index of a neighbor country of a World Cup competitor and finds similar results to those of Kaplanski and Levy; these 'matching' countries also experience statistically significant losses the day after their matched 'participant' country experiences a World Cup loss despite not having their national team in the competition. Interestingly, there is a loss effect of 63 basis points for matching countries in group stage matches, while the country in competition experiences a loss effect of 56 basis points. Gerlach finds similar matched-country effects for the Edmans *et al* (2007) study and the Ashton *et al* (2003) study. He finds that the entire sample of rugby, basketball, cricket, and ice hockey matches result in -11 basis points for matched countries while there is a -20 basis point result for directly involved countries. Additionally, matched countries have a similar transitive feature as shown in the Ashton *et al* (2003) study. It would seem that matching countries are susceptible to losses as a result of spillover effects on the national indices; however, Gerlach makes a point by stating that only a small percentage of the total market capitalization in one country is held by the matching countries. Typically, matched countries are also considered rivals of the participants (for example, England and France or Brazil and Argentina), so it is difficult to believe matched country investors would have a negative psychological view after a World Cup participant loss; sentiment should be offsetting at the least. Gerlach hypothesizes that news unrelated to investor sentiment causes stock market declines for both World Cup participants and matching countries rather than a change in investor sentiment. Nevertheless, there is an effect on market index prices following sports events.

2.2.2 Absence of a Relationship between Sports Events and Stock Returns

Klein *et al* (2008) repeat Ashton *et al* (2003) and reverse its claims as evidence of data mining. Klein *et al* were able to replicate the study, but were unable to find significant results after correcting the errors. Among the errors found were: Ashton *et al* extracted returns from Datastream, which erroneously reports a zero return on holidays, they also incorrectly copied and pasted data from the national soccer team's website, and, lastly, Klein *et al* argue a timing issue, in which an efficient market would immediately reflect an effect of the event rather than on the next trading day. In their repeated study, they do find binomial statistics that are highly significant at the 1% level for losses from 1984 to 1993, but the effect has disappeared in the latter 1994-2002. Klein *et al* (2009) would repeat the study once more with an expanded time from 1990 to 2006 and further included as many European soccer teams as possible. They find few statistically significant results, such as the proportion of positive excess returns after a win for games including qualifications. However, they argue that the data does not make sense as 9 of 14 negative excess returns occurred after a win for an important game, albeit that the results are insignificant. Instead, Klein *et al* argue that, in large datasets, it is likely that some data can be significant by pure coincidence. Ashton *et al* (2011) would once again repeat their study with an increased timeframe of 1984 to 2009 and included a GARCH regression in accordance with Edmans *et al* (2007). They argue that, although Klein *et al* (2008) are correct in that the effect has been shown to decrease in significance over time, which is in accordance with anomaly literature, they are still able to show statistical significance in abnormal returns the day after the event for the original and total sample periods. For their full sample, the loss effect is still present with the proportions of returns less than the unconditional mean significant at the 5% level.

Aside from Klein *et al*., Boyle and Walter (2003) fail to find a relation between sports event outcomes and stock market returns. Their study focuses on the New Zealand national rugby team (known as the All Blacks) and analyzes games from 1950-1999. Though the results are insignificant statistically, they found a higher proportion of positive returns (68%) during months in which the All Blacks lost more games than won; this defies the idea that a loss would affect returns the following day negatively. They argue that investors may be more aware of their mood following a sports event (as in elated after a win or depressed after a loss) compared to unnoticed reactions to changes in weather, for instance, and that this heightened awareness may prevent irrational decision making. The initial methodology for the Boyle and Walter study is unique from related studies; like Ashton *et al* and Klein *et al*, Boyle and Walter compare sample proportions and means, but instead use monthly data and classify a month as a positive month or negative month depending if the All Blacks had more wins or losses in a given month. Adjusting to daily returns using the NZ All Ordinaries Gross Index still found no significant difference between mean returns of event days and non-event days. Boyle and Walter provide additional insight that investors' moods may be relatively unaffected if their team wins when a win is expected or when their team loses if a loss is expected. Scholtens and Peenstra (2009) answer this concern to an extent, though only on a publicly-listed club level, and find that abnormal returns for a win when the club is expected to win are higher and significant than when the club wins a game when the club is expected to lose. Similarly, a loss when the club is expected to lose results in a larger decrease than when the club is expected to win. Interestingly, there may be a 'nail-biter' effect, as Scholtens and Peenstra find statistically significant abnormal returns of -1.4% after draws of games in which the club was expected to win.

Botha and de Beer (2011) analyze soccer, cricket, and rugby matches' effects on the Johannesburg Stock Exchange from 1990 to 2010 using similar methodology as Ashton *et al* (2003) and Boyle and Walter (2003). They find significant abnormal returns following trading days in each sport using the constant mean methodology; however, the OLS regression provides insignificant results. Only rugby results show a possible asymmetrical relationship between wins and losses, though it is not statistically significant. The authors cite that the data frequency employed may be a cause for insignificant results as the dataset of daily returns is large with few sporting results.

2.3 CONCLUSION

As noted in the below table, there are more studies that find a relationship between sporting events and market prices than those that find no relationship. In light of Gerlach (2011), it is difficult to determine a cause for such a relationship; yet, there is surmountable evidence of such an effect. It is important to note that previous studies examine reactions on an international level. This study proposes to examine returns around national sporting events. Because of this, it is difficult, if not impossible, to cite results as a mood effect under the criteria of Edmans *et al* (2007). While major U.S. sports events could impact the mood of the majority of the population, these moods are likely offsetting, as Boyle and Walter state, "one fan's elation is another fan's misery if they support opposing teams." Therefore, this study aims to evaluate returns before and after major U.S. sports events. This is among the first studies in which pre-event returns will be evaluated around sports events.

Researcher(s)	Year	Index	Years	Sport	Findings
Ashton *et al*	2003	FTSE 100	1984-2002	Soccer	Returns are highly associated with game outcomes; significant loss effect
Klein *et al*	2009	FTSE 100	1984-2002	Soccer	Dismissed Ashton *et al* as data mining; find a relationship for 1984 -1993, but little other results
Klein *et al*	2009	Various	1990-2006	Soccer	Find almost no significant relationships and data does not make logical sense
Ashton *et al*	2011	Various	1984-2009	Soccer	Confirm previous findings from 2003 study; effect is diminishing
Edmans *et al*	2007	Various	1973-2004	Soccer, etc.	Find a significant loss effect for international soccer, cricket, rugby, and basketball games
Kaplansi, Levy	2010	NYSE Comp.	1950-2007	Soccer	Find a significant loss effect on the NYSE Composite Index during the World Cup
Gerlach	2011	Various	1974-2002	Soccer	Investor sentiment cannot be a cause for decilnes; matching countries suffer losses as well
Boyle, Walter	2003	NZ All Ord.	1950-1999	Rugby	Fail to find any relationship between sports and returns
Myshra, Smyth	2010	Nat. Stock Ex.	1995-2005	Cricket	Finds a significant loss effect; the effect is more profound when Sachin Tendulkar plays in the match
Worthington	2007	ASX All Ord.	1961-2005	Horse Racing	Finds that the Tuesday of the Melbourne Cup exhibits significantly positive returns
Berument *et al*	2009	Istanbul St. Ex.	1987-2006	Soccer	Istanbul stock market improves significantly after a Beşiktaş win
Batha, de Beer	2011	JSE Daily All-Share	1990-2010	Soccer, etc.	Mean returns for soccer, cricket and rugby show limited evidence; regressions prove no relation

CHAPTER 3: RESEARCH METHOD

3.1 INTRODUCTION

This chapter describes the research method employed in this study. A number of event study methods were used and different data sources were compared in order to avoid data snooping (Lakonishok & Smidt 1988). MacKinlay (1997) states that while there is no specific, unique structure to an event study, there is a general flow of analysis. First, it is important to identify an event of interest and then identify the event window. It is then necessary to determine the selection criteria for the inclusion of a given firm (or index in this study's case). In order to evaluate an event's impact on prices, normal and abnormal returns must be defined. For this study, returns will be defined in the methodology section. An estimation window must be defined in which normal returns can be observed from. Lastly, the empirical results can then be presented. Because event studies can be set up in numerous different fashions, this study employs methods similar to Ashton *et al* (2003), Boyle & Walter (2007), Edmans *et al* (2007), as well as using a customized method. Using several different methods allows for unbiased results and may prevent finding false, nonexistent relationships.

3.2 DATA COLLECTION

In order to evaluate sports events' effects on the stock market, the Dow Jones Industrial Average (DJIA) was used due to its lengthy history dating back to 1896. The DJIA represents a value-weighted average of 30 component stocks that are considered major factors in their respective industries. The data was collected from the St. Louis FED's website, *Federal Reserve Economic Data* (FRED), and verified with index data from Bloomberg. Because Major League Baseball's first official World Series was played in 1903, the data begins with this year and is expanded to June 2013. Major League Baseball World Series data was collected from mlb.mlb.com and dates from 1903-2012. NFL Super Bowl data was collected from www.nfl.com and dates from 1967-2013. NBA Finals data was collected from www.nba.com and dates from 1947-2013. NHL Stanley Cup data was gathered from www.nhl.com and ranges from 1927-2013. NCAA division 1 football and basketball data were retrieved from www.ncaa.com and have dates of 1999-2013 and 1939-2013, respectively. Some exceptions to the data should be mentioned. The 1914 MLB World Series was excluded due to the stock market closing in late 1914 in response to the First World War. Also, despite the rich history of NCAA division 1 football, the data begins in 1999 due to previous years having champions elected by a polling process that allowed for multiple championship games.

3.3 DATA PREPARATION

To study the impact of a sports event, the daily returns on the DJIA the days before and after the event were recorded. In many cases, such as with the Super Bowl, games occur on weekends. In these cases, the last trading day before the event and the first trading day after the event are used. Despite that an event may have taken place during trading hours, the trading day after the event is evaluated in order to reflect a full trading day and to ensure that an event's outcome is known.

Daily DJIA returns are calculated using the following formula:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{3.1}$$

where R_t represents the continuously compounded return on day t. P_t represents the closing value of the index on day t while P_{t-1} represents the closing value of the index on the previous trading day. With returns defined, it is possible to generate descriptive statistics (see Table 4.1 in the results section).

3.4 METHODOLOGY

3.4.1 Customized Event Study

A customized event study was completed in order to compare to methods employed by previous sports event related research. This method treats the trading day before and trading day after a sports event as two independent events and tests for abnormal returns using a standard 180 day estimation window. However, 120 and 240 day estimation windows are also used in order to examine differences. Normal returns are generated using the constant mean return model:

$$R_t = \mu + \varepsilon_t \tag{3.2}$$

Where R_t is the index return on day t and μ is a constant. The error term, ε_t, is assumed to be identically and independently distributed. Despite being a simple model, Brown and Warner (1980) argue that the mean return model often has similar results to more complex models and that the variance of abnormal returns is not reduced much by choosing these more complex models. The abnormal return is then described by MacKinlay (1997) as:

$$AR_t = R_t - E(R_t|X_t) \tag{3.3}$$

Where AR_t is the abnormal return, R_t is the actual return, and $E(R_t|X_t)$ is the expected normal return. X_t denotes the conditioning information for the normal return model. The estimator of the average abnormal return is defined as:

$$AAR_i = \frac{1}{N}\sum_{i=1}^{N} AR_t \quad (3.4)$$

Where AAR_i is the average abnormal return on index i, AR_t is, as mentioned before, the abnormal return, and N denotes the number of abnormal returns observed.

Because many sports events are rather close in proximity, some events are removed to avoid event clustering. This is often the case with NBA and NHL finals, which are normally played within two weeks of each other.

3.4.2 Z-test for Difference in Proportions

Ashton *et al* (2003) use a z-test for difference in proportions to evaluate whether the returns following the English national team's win or loss is significantly different from the unconditional mean of non-event trading days. Boyle and Walter (2007) also use this method, but unlike Ashton *et al*, Boyle and Walter test for differences between positive and negative returns, as well as positive and negative/neutral returns.

3.4.3 T-test for Difference in Means

Boyle and Walter (2007) additionally test for the difference in means on trading days following New Zealand's rugby games. While this metric is similar to the customized event study approach mentioned before, this method removes all events from the sample and compares their means to non-event trading days. Therefore, the estimation window for this method is the entire sample period exclusive of the events.

3.4.4 Ordinary Least Squares Regression

Edmans *et al* (2007) and Myshra and Smyth (2008) use simple dummy-variable OLS regressions to examine returns for wins and losses of respective teams. This study employs a similar model, with the exception that instead of win and loss dummies, the dummies indicate pre and post events. The regression model is noted as:

$$R_t = \beta_0 + \beta_t PRE_t + B_t POST_t + \varepsilon_t \quad (3.5)$$

Where R_t is the log return on day t, and PRE_t and $POST_t$ are dummy variables that take the value of 1 to represent the trading day before or after the event, otherwise the value is 0.

Additionally, a cross sectional regression is used on the post-event abnormal returns from the customized event study in order to determine if certain game aspects are related to abnormal returns. The regression model is taken partly from Bartha and de Beer (2011) and is specified as:

$$AR_{it} = B_0 + \sum_k \beta_{ik} D_i + \varepsilon_t \qquad (3.6)$$

Where AR_{it} is the abnormal return on the index on day t, D_i is a vector of dummy variables, and ε_t is the error term. Dummy variables and other independent variables are described in the following table.

Variable	**Description**
Shutout	The winner wins without allowing any points scored against them
Streak	The number of years since the winner last won a championship
Sweep	The winner won every game of the final playoff series
Canadian	The winner is a team located in Canada
HFWin	The winner won at their home field/rink/court
Wildcard	The winner was a participant in a wildcard match
AL/East/NFC	The winner was from a certain conference in the league
Blowout	The winner won by a blowout (defined below)
	-Football = 21pts, basketball = 20pts, baseball = 7 runs, hockey = 5 goals
Distance	The winner is further away from Wall Street than the loser
Population	The winner's state population is less than the loser's state population
Nielsen	The game's television rating, as measured by Nielsen Ratings
Attendance	The game's attendance

CHAPTER 4: RESULTS

4.1 INTRODUCTION

This section presents the results of the statistical methods performed. First, descriptive statistics are shown in order get an idea of the properties of the data. Then, the customized event study results are examined. The t-tests for differences in means are then examined and explained, followed by the z-tests for differences in proportions. Lastly, the regression results are examined.

4.2 DESCRIPTIVE STATISTICS

Below, the descriptive statistics can be found for the complete dataset. The sample size begins in March 1903 and extends to June 2013; the mean daily log return for all trading days is 0.0181%. At first glance, one should notice the negative mean daily returns for several separate sports as well as the combination of events. Given that the sample size for Major League Soccer and NCAA football events are rather small, some statistical techniques for these leagues may be inappropriate. The negative skewness and high kurtosis noted in all trading days signifies that market returns do not follow a normal distribution. This is in accordance with previous literature. Fama (1965) has noted in his PhD thesis that the distributions of stock returns generally have fatter tails than would be expected in a normal distribution.

Table 4.1					
Descriptive Statistics	**Number**	**Mean**	**St. Dev.**	**Skewness**	**Kurtosis**
All trading Days	29912	0.0181%	1.0987%	-1.0140	32.8560
Non-event Days	29133	0.0193%	1.0981%	-1.0512	33.3435
All Event Days	784	-0.0218%	1.1138%	0.3055	16.2994
All Pre-event Days	393	-0.0416%	0.9820%	0.0953	6.9476
All Post-event Days	391	-0.0020%	1.2318%	0.3874	18.9508
MLB Pre-event Days	107	-0.0632%	0.9705%	-0.6993	3.1290
MLB Post-event Days	107	-0.1171%	1.8827%	-0.0318	13.2437
NFL Pre-event Days	47	-0.0891%	0.8123%	-0.3629	0.4584
NFL Post-event Days	47	-0.0834%	0.8772%	0.5076	1.7699
NBA Pre-event Days	67	-0.0891%	0.8123%	-0.3629	0.4584
NBA Post-event Days	67	-0.1245%	0.8225%	-0.2794	1.7909
NHL Pre-event Days	86	-0.1186%	1.0971%	-1.0911	5.0844
NHL Post-event Days	86	-0.0902%	1.0225%	-0.9206	2.8126
MLS Pre-event Days	17	0.5051%	1.6086%	2.8692	10.6484
MLS Post-event Days	17	0.0675%	2.4301%	-1.3957	5.1249
NCAA Football Pre-event Days	15	-0.3544%	1.3338%	0.8553	2.2062
NCAA Football Post-event Days	15	0.1990%	1.0290%	-0.4190	0.0576
NCAA Basketball Pre-event Days	75	-0.0620%	0.6443%	-0.4171	0.4374
NCAA Basketball Post-event Days	75	-0.0162%	0.8671%	-0.3692	2.2678

4.3 CUSTOMIZED EVENT STUDY

Table 4.2 displays the results of the customized event study with a 180 day estimation window. For all tests except for the Big Four, the abnormal returns are not significantly different from zero. The pre-event for the Big Four leagues generates an average abnormal return of -0.1061% and is significant at the 10% level (p-value is 0.0653). Abnormal returns are negative on average for each of the Big Four sports with the exception of pre-event abnormal returns for the NFL, yet all post abnormal returns are negative on average. One may also notice the exceptionally high pre-event average abnormal return for MLS; however, as noted before, there are few observations and the standard deviation of these returns is quite high.

Table 4.2										
Customized Study - 180-day estimation window										
Event	**Sport**	MLB	NFL	NBA	NHL	MLS	NCAA Foot.	NCAA Bask.	"Big Four"	Full Sample
Pre-Event	Ave. Abnormal Return (%)	-0.0465	0.0041	-0.1284	-0.1049	0.4964	-0.3668	-0.0883	-0.1061*	-0.0621
	Standard Deviation (%)	0.9380	1.0241	0.8141	1.0467	1.7351	1.3783	0.6500	0.9762	0.9769
	# of Observations	107	47	67	86	17	15	75	288	393
	Test Statistic	-0.5132	0.0274	-1.2905	-0.9296	1.1796	-1.0307	-1.1767	-1.8438	-1.2593
	P-Value	0.6089	0.9783	0.2014	0.3552	0.2554	0.3201	0.2431	0.0662	0.2087
Post-Event	Ave. Abnormal Return (%)	-0.1296	-0.0945	-0.1637	-0.1156	0.0588	0.1866	-0.0426	-0.0864	-0.0237
	Standard Deviation (%)	1.8796	0.8626	0.8323	1.0193	2.5506	1.0521	0.8784	1.3528	0.7033
	# of Observations	107	47	67	86	17	15	75	286	391
	Test Statistic	-0.7130	-0.7512	-1.6102	-1.0521	0.0950	0.6868	-0.4200	-1.0801	-0.6650
	P-Value	0.4774	0.4563	0.1121	0.2957	0.9255	0.5035	0.6757	0.2810	0.5065
* Significant at the 10% level										

Different estimation windows of 120 and 240 days were also calculated in order to determine if significant results remain present with different normal returns. Tables 4.3 and 4.4 present the results.

Table 4.3										
Customized Study - 120-day estimation window										
Event	**Sport**	MLB	NFL	NBA	NHL	MLS	NCAA Foot.	NCAA Bask.	"Big Four"	Full Sample
Pre-Event	Ave. Abnormal Return (%)	-0.0735	0.0006	-0.1368	-0.1201	0.5111	-0.2836	-0.1010	-0.1081*	-0.0723
	Standard Deviation (%)	0.9593	1.0361	0.8002	1.0531	1.7629	1.3994	0.6548	0.9788	0.9804
	# of Observations	107	47	67	86	17	15	75	288	393
	Test Statistic	-0.7928	0.0039	-1.3996	-1.0572	1.1955	-0.7848	-1.3362	-1.8737	-1.4619
	P-Value	0.4296	0.9969	0.1663	0.2934	0.2493	0.4456	0.1856	0.0620	0.1446
Post-Event	Ave. Abnormal Return (%)	-0.1273	-0.0980	-0.1722*	-0.1308	0.0735	0.1361	-0.0553	-0.0907	-0.0309
	Standard Deviation (%)	1.8879	0.8556	0.8268	1.0153	2.5645	1.0109	0.8878	1.3544	1.2376
	# of Observations	107	47	67	86	17	15	75	286	391
	Test Statistic	-0.6977	-0.7854	-1.7048	-1.1944	0.1182	0.5215	-0.5395	-1.1326	-0.4943
	P-Value	0.4869	0.4363	0.0929	0.2356	0.9074	0.6101	0.5912	0.2583	0.6213
* Significant at the 10% level										

Table 4.4										
Customized Study - 240-day estimation window										
Event	**Sport**	MLB	NFL	NBA	NHL	MLS	NCAA Foot.	NCAA Bask.	"Big Four"	Full Sample
Pre-Event	Ave. Abnormal Return (%)	-0.0861	-0.0064	-0.1174	-0.1018	0.4907	-0.2804	-0.0860	-0.1087*	-0.0715
	Standard Deviation (%)	0.9607	1.0296	0.8151	1.0887	1.7314	1.4233	0.6535	0.9779	0.9788
	# of Observations	107	47	67	86	17	15	75	288	393
	Test Statistic	-0.9268	-0.0426	-1.1793	-0.8673	1.1686	-0.7630	-1.1401	-1.8863	-1.4486
	P-Value	0.3561	0.9662	0.2425	0.3882	0.2597	0.4581	0.2579	0.0603	0.1482
Post-Even	Ave. Abnormal Return (%)	-0.1399	-0.1050	-0.1528	-0.1125	0.0531	0.1393	-0.0403	-0.0896	-0.0388
	Standard Deviation (%)	1.8892	0.8655	0.8251	1.0231	2.5561	1.0166	0.8732	1.3588	1.2071
	# of Observations	107	47	67	86	17	15	75	286	391
	Test Statistic	-0.7660	-0.8319	-1.5160	-1.0199	0.0856	0.5306	-0.3998	-1.1150	-0.6360
	P-Value	0.4454	0.4098	0.1343	0.3107	0.9328	0.6040	0.6905	0.2658	0.5252
* Significant at the 10% level										

With 120 and 240-day estimation windows, the negative and significant abnormal returns remain for the Big Four. Note that with a 120 day estimation window, the NBA has an average abnormal return of -0.1722% the day after the final game of the NBA Finals and the result is significant at a 10% level. It is important to compare such results because data mining is rather easy with a method such as this. Considering that the NBA post-event effect is not significant in the 180 or 240 day methods, the effect can be dismissed as random chance. However, because the Big Four pre-event effect is significant in each case, it could be said that there is a significant effect, yet this effect should be examined using other methodology to determine if the effect persists.

Edmans *et al* (2007) suggest evaluating trimmed means in order to eliminate or reduce the influence of outliers in the data[1]. Table 4.5 reports the trimmed results for all leagues. The only significant data is that of the Big Four, yet only with a 120-day estimation window. This suggests that results are still significant after removing 2.5% of values from the top and bottom tails of the data. Because trimming the abnormal returns by 5% is not a substantial trim and that the Big Four results are only significant with a 120-day estimation window, it should be concluded that significant results may be influenced by outliers.

Table 4.5

5% Trimmed Abnormal Returns, 180 Day Estimation Window

Pre-Event	**MLB**	**NFL**	**NBA**	**NHL**	**MLS**	**NCAA Foot.**	**NCAA Bask.**	**"Big Four"**	**Total**
Ave. Abnormal Return	-0.0709%	0.0159%	-0.1186%	-0.0831%	0.4964%	-0.3668%	-0.0826%	-0.0930%[1]	-0.0241%
P-Value	0.4486	0.9154	0.2374	0.4637	0.2554	0.3201	0.2748	0.1069	0.6952
Post-Event	**MLB**	**NFL**	**NBA**	**NHL**	**MLS**	**NCAA Foot.**	**NCAA Bask.**	**"Big Four"**	**Total**
Ave. Abnormal Return	-0.1090%	-0.1106%	-0.1608%	-0.0937%	0.0588%	0.1866%	-0.0337%	-0.0538%	-0.0204%
P-Value	0.5499	0.3840	0.1185	0.3963	0.9255	0.5035	0.7405	0.5021	0.7374

[1]Big Four pre-event, trimmed abnormal returns are significant at the 10% level for the 120-day estimation window

In addition, all samples other than MLS and NCAA football are split in half to determine if any effects are persistent over time. MLS and NCAA football are excluded due to rather small sample sizes of 17 and 15, respectively. Table 4.6 displays the results. Post-event MLB and NBA returns for the first half of their respective sample sizes are negative and statistically significant. These results are likely to heavily influence the post-event results for the 1903-1957 periods of the Big Four and total samples as MLB and NBA comprise a majority of the events in that time period. The NBA's pre-event abnormal return of -0.3544% for the latter 1980-2013 is likely a driving factor for the pre-event loss effect.

[1] Trimmed means are a measure of central tendency; a percentage of the largest and smallest values are removed before calculating the average. In the customized event studies, average abnormal returns are trimmed.

Table 4.6								
Split Samples	**MLB**		**NBA**		**NFL**		**NHL**	
Pre-Event	**1903-1957**	**1958-2012**	**1947-1979**	**1980-2013**	**1967-1989**	**1990-2013**	**1927-1969**	**1970-2013**
Ave. Abnormal Return	-0.1043%	-0.0477%	0.1045%	-0.3544%**	0.1539%	-0.1395%	-0.1083%	-0.1016%
P-Value	0.3845	0.7426	0.3967	0.0360	0.4662	0.5286	0.5505	0.4667
Post-Event	**1903-1957**	**1958-2012**	**1947-1979**	**1980-2013**	**1967-1989**	**1990-2013**	**1927-1969**	**1970-2013**
Ave. Abnormal Return	-0.3744%*	0.1107%	-0.2316%**	-0.0978%	-0.0024%	-0.1828%	-0.0937%	-0.0455%
P-Value	0.0584	0.7209	0.0244	0.5963	0.9898	0.3073	0.3963	0.7661

Split Samples	**NCAA Basketball**		**Big Four**		**Total**	
Pre-Event	**1939-1975**	**1976-2013**	**1903-1957**	**1958-2013**	**1903-1957**	**1958-2013**
Ave. Abnormal Return	-0.0048%	-0.1697%	-0.1156%	-0.0749%	-0.0998%	-0.0693%
P-Value	0.9561	0.1839	0.3054	0.2585	0.2978	0.2312
Post-Event	**1939-1975**	**1976-2013**	**1903-1957**	**1958-2013**	**1903-1957**	**1958-2013**
Ave. Abnormal Return	-0.1107%	0.0237%	-0.3308%**	0.0205%	-0.3028%**	-0.0361%
P-Value	0.2820	0.8934	0.0212	0.8340	0.0119	0.6212

* Significant at the 10% level, ** Signifiant at the 5% level

Lastly, it is important to test for the day-of-the-week effect because it may have an effect on this study's results. Lakonishok and Smidt (1988) document significant, negative returns on Mondays and significant, positive returns on the last trading day of the week. Additionally, similar studies, such as Boyle and Walter (2003), address this issue and test for differences between returns on Mondays following events and all other Mondays. Because the results from the customized event study suggest that there are negative abnormal returns the day before and after an event, it is necessary to examine the differences in means for Mondays of non-event days and event day Mondays. While the end of the week is usually associated with higher returns, because returns are negative on average, end-of-the-week effects may be disregarded. These results are displayed in Table 4.7.

Table 4.7	
Monday Effect	
Mean of All Other Non-Event Trading Days	0.044%
Mean of All Non-Event Mondays	-0.096%
T-test for Difference in Means (p-value)	0.000***
Mean of All Pre-event Mondays	-0.331%*
T-test for Difference in Means (p-value)	0.069
Mean of All Post-event Mondays	-0.329%
T-test for Difference in Means (p-value)	0.180
Mean of All Event Mondays	-0.330%**
T-test for Difference in Means (p-value)	0.046

* 10% Significance, ** 5% Significance, *** 1% Significance

Results are significant for 1-sided tests

Non-event Mondays in the dataset are significantly different from all other non-event trading days at the 1% level. The mean return of all pre-event Mondays is over three times the mean of all non-event Mondays and is statistically significant at the 10% level. While post-event Monday returns are not significantly different than all other non-event Mondays, the sample of all event Monday returns are statistically different at a 5% level. This suggests that the day-of-the-week effect can be disregarded as having a significant influence on pre-event returns and total sample returns; however, post-event Monday returns may be influenced by the effect.

4.4 T-TEST FOR DIFFERENCE IN MEANS

Table 4.8 displays the results for the t-test for difference in means. One-sided tests and two-sided tests were performed. One-sided tests test whether the mean is significantly greater or less than the unconditional mean, but not both simultaneously. A two-sided test considers the possibility that the mean could be significantly greater or less than the unconditional mean. One-sided and two-sided tests have different critical values; statistical significance is determined differently. Therefore, had this method examined the means from the perspective that pre and post-event returns could be greater or less than the unconditional mean, results would be insignificant. Having knowledge from the customized event study that there is a negative abnormal return effect before Big Four events, a one-sided test could be used to test whether mean returns are less than the unconditional mean. In this case, mean returns before Big Four events are negative and significantly different than the unconditional mean returns at a 10% level. It should be noted that the significant results of the NBA post-event and the pre-event for the Big Four are only significant for a one-sided test. The NBA has a significant, negative mean for the post-event; this may influence the significant, negative abnormal returns for the time period of 1903-1957.

Table 4.8				
T-Test for Difference in Means		**Mean Return**	**P-Value (1-sided)**	**P-Value (2-sided)**
MLB	Pre-Event	-0.0632%	0.1942	0.3885
	Post-Event	-0.1171%	0.2300	0.4600
NFL	Pre-Event	0.0152%	0.4804	0.9608
	Post-Event	-0.0834%	0.2085	0.4171
NBA	Pre-Event	-0.0891%	0.1281	0.2562
	Post-Event	-0.1245%*	0.0717	0.1433
NHL	Pre-Event	-0.0795%	0.1970	0.3940
	Post-Event	-0.0902%	0.1623	0.3245
MLS	Pre-Event	0.5051%	0.1265	0.2530
	Post-Event	0.0675%	0.4755	0.9509
NCAA Basketball	Pre-Event	-0.0620%	0.1255	0.2510
	Post-Event	-0.0162%	0.3426	0.6852
NCAA Football	Pre-Event	-0.3544%	0.1571	0.3143
	Post-Event	0.1990%	0.2589	0.5177
Big Four	Pre-Event	-0.0638%*	0.0779	0.1558
	Post-Event	-0.0676%	0.1505	0.3009
Total	Pre-Event	-0.0416%	0.1134	0.2267
	Post-Event	-0.0020%	0.3727	0.7454

*Significant at the 10% level

4.5 Z-TEST FOR DIFFERENCE IN PROPORTIONS

Boyle and Walter (2003) and Ashton *et al* (2003) both use proportions to evaluate any relationship between sports and market returns. As mentioned before, Ashton *et al* examines the proportions greater or equal/less than the unconditional mean while Boyle and Walter examine whether returns are positive and negative or positive and zero/negative. For this reason, all three tests are performed. Table 4.9 displays the results.

Table 4.9									
Positive/Negative Returns	**MLB**	**NFL**	**NBA**	**NHL**	**MLS**	**NCAA Foot.**	**NCAA Bask.**	**"Big Four"**	**Total**
Observations (N=)	**107**	**47**	**67/66**	**85/86**	**17**	**15**	**74**	**287/285**	**391/389**
Proportion of Positive Returns (pre)	0.4860	0.4894	0.4925	0.4471	0.7647*	0.3333	0.4595	0.4843	0.4860
P-value for difference in proportions	0.4068	0.7088	0.6025	0.1450	0.0524	0.1391	0.2538	0.1583	0.1431
Proportion of Positive Returns (post)	0.4953	0.4468	0.5303	0.5581	0.5882	0.6000	0.4865	0.5333	0.5294
P-value for difference in proportions	0.5245	0.3390	0.9234	0.5530	0.6275	0.5588	0.4988	0.8083	0.8057
Positive/Negative & Zero Returns	**MLB**	**NFL**	**NBA**	**NHL**	**MLS**	**NCAA Foot.**	**NCAA Bask.**	**"Big Four"**	**Total**
Observations	**107**	**47**	**67**	**86**	**17**	**15**	**75**	**288/286**	**393/391**
Proportion of Positive Returns (pre)	0.4860	0.4894	0.4925	0.4419	0.7647**	0.3333	0.4533	0.4826	0.4885
P-value for difference in proportions	0.4450	0.7439	0.6398	0.1323	0.0481	0.1461	0.2315	0.1730	0.1368
Proportion of Positive Returns (post)	0.4953	0.4468	0.5224	0.5581	0.5882	0.6000	0.4800	0.5315	0.5321
P-value for difference in proportions	0.5683	0.3633	0.9839	0.5158	0.6012	0.5421	0.4623	0.7740	0.8196
Above/Below Unconditional Mean	**MLB**	**NFL**	**NBA**	**NHL**	**MLS**	**NCAA Foot.**	**NCAA Bask.**	**"Big Four"**	**Total**
Observations	**107**	**47**	**67**	**86**	**17**	**15**	**75**	**288/286**	**393/391**
Proportion of Returns Above Mean(pre)	0.4766	0.4894	0.4776	0.4430	0.7647**	0.2667*	0.4533	0.4792	0.4809
P-value for difference in proportions	0.4320	0.8224	0.6109	0.2143	0.0382	0.0543	0.3331	0.2368	0.1840
Proportion of Returns Above Mean (post)	0.4860	0.4468	0.4776	0.5570	0.5882	0.6000	0.4800	0.5210	0.5192
P-value for difference in proportions	0.5533	0.4198	0.6109	0.4351	0.5353	0.5135	0.6123	0.8189	0.8584
* Significant at the 10% level; ** Significant at the 5% level									

In consideration of proportions, the pre-event loss effect is absent for the Big Four and total samples. The only significant results come from NCAA football and MLS, yet there are only 15 and 17 observations, respectively. All positive, pre-event proportions, except those of MLS, are below 0.50, which suggests that returns are more often negative before a sporting event.

4.6 ORDINARY LEAST SQUARES REGRESSION

A simple regression model, similar to that used by Mishra and Smyth (2010) and Edmans *et al* (2007), was used as a last method. The regression model is as follows:

$$R_t = \beta_0 + \beta_t PRE_t + B_t POST_t + \varepsilon_t \tag{4.1}$$

where the dummy variables PRE and POST take a value of one before and after an event, respectively, and are zero otherwise. While the methodology from the t-test for difference in means provides the mean returns of the pre and post-event returns and compares them to the mean of non-event returns, the dummy variables in Equation 4.1, given that they take a value of one in the presence of an event, show the average change from the average return on non-event days. Summary results are shown in Table 4.10.

Table 4.10						
League	**Pre-Event**	**P-Value**	**Post-Event**	**P-Value**	**Constant**	**P-Value**
MLB	-0.081870	0.442	-0.135690	0.203	0.0186***	0.004
NFL	-0.007630	0.960	-0.106240	0.490	0.0229**	0.019
NBA	-0.115390	0.323	-0.150780	0.197	0.0263***	0.000
NHL	-0.099810	0.408	-0.110520	0.360	0.2033***	0.007
MLS	0.47736*	0.095	0.039740	0.889	0.02774	0.109
NCAA Foot.	-0.371870	0.242	0.181490	0.568	0.01749	0.376
NCAA Bask.	-0.087170	0.429	-0.041450	0.707	0.0252***	0.000
Big Four	-0.083520	0.199	-0.084770	0.194	0.0198***	0.002
Total	-0.060790	0.276	-0.021190	0.705	0.0192***	0.003
* 10% Significance, ** 5% Signifiance, *** 1% Significance						

As can be seen from the p-values, there are no significant results other than pre-event MLS, which is significant and positive at the 10% level. One would interpret this as the presence of the MLS Cup positively affects returns on the day before by 0.4774% holding all other variables constant. Table 4.11 displays the results of a split sample regression. The results are consistent with those of Table 4.6; post-event returns are negatively affected and significant in the first half of the MLB, NBA, Big Four, and total samples, and the pre-event returns are negatively affected for the NBA in the latter half sample.

Table 4.11								
Split Samples	**MLB**		**NBA**		**NFL**		**NHL**	
Date	**1903-1957**	**1958-2012**	**1947-1979**	**1980-2013**	**1967-1989**	**1990-2013**	**1927-1969**	**1970-2013**
Pre-Event	-0.0010	-0.0006	0.0012	-.0034*	0.0014	-0.0015	-0.0011	-0.0009
P-Value	0.523	0.653	0.384	0.078	0.496	0.507	0.523	0.594
Date	**1903-1957**	**1958-2012**	**1947-1979**	**1980-2013**	**1967-1989**	**1990-2013**	**1927-1969**	**1970-2013**
Post-Event	-0.0037**	0.0010	-.0022*	-0.0008	-0.0002	-0.0019	-0.0019	-0.0003
P-Value	0.021	0.480	0.096	0.665	0.942	0.393	0.280	0.847

Split Samples	**NCAA Basketball**		**Big Four**		**Total**	
Date	**1939-1975**	**1976-2013**	**1903-1957**	**1958-2013**	**1903-1957**	**1958-2013**
Pre-Event	0.0000	-0.0017	-0.0011	-0.0008	-0.0010	-0.0005
P-Value	0.997	0.328	0.382	0.288	0.367	0.416
Date	**1939-1975**	**1976-2013**	**1903-1957**	**1958-2013**	**1903-1957**	**1958-2013**
Post-Event	-0.1055%	0.0002	-0.0034***	0.0002	-.0031***	0.0008
P-Value	0.425	0.908	0.008	0.759	0.008	0.175
* Significant at the 10% level, ** Signifiant at the 5% level, *** Significant at the 1% level						

Lastly, a cross-sectional regression was run in order to determine if certain game aspects influence post-event returns. Despite that some leagues were found not to have significant average abnormal returns, certain game aspects were found to influence abnormal returns. Results are displayed in Table 4.12. Variables that did not substantially reduce the observation count were used. Additionally, the non-Big Four leagues were excluded due to the use of variables that are inapplicable to these leagues; for example, these leagues do not have wildcard playoff formats.

Returns following events in which the team that won the event was a wildcard round participant tend to be negatively affected. This wildcard variable is negative and significant for MLB, NHL, and the Big Four samples. The NFL has a significant streak feature in which the greater the amount of years has passed since the winning team has last won a championship, there is a negative impact of 0.018% on post-event returns. The NBA has no game aspects that significantly affect post-event abnormal returns. The NHL has a blowout effect, in which post-event returns are positively affected following games where a team has won by at least a margin of five goals. This blowout variable persists in the Big Four regression. Additionally, returns are negatively affected following the final Stanley Cup game in which the champions played each game in the final playoff series without losing. In the Big Four regression, the blowout, wildcard, and home-field variables are significant. Abnormal returns following an event are negatively affected if the home team won the final game.

Table 4.12 Determinants of post-event abnormal returns

Sport	MLB		NFL		NBA		NHL		Big Four	
Variable	N = 103	p-value	N = 47	p-value	N = 66	p-value	N = 86	p-value	N = 234	p-value
(Constant)	0.0048	0.326	-0.0319*	0.100	0.0000	0.986	0.0013	0.599	0.0011	0.574
Canadian	0.0133	0.322	-	-	-	-	-0.0013	0.572	0.0000	0.995
Distance	-0.0062	0.123	0.0036	0.198	-	-	0.0018	0.396	-0.0010	0.600
Streak	0.0000	0.861	-0.0002*	0.087	0.0022	0.489	0.0034	0.304	0.0000	0.460
AL/NFC/East	-0.0051	0.193	0.0029	0.266	-0.0019	0.411	-	-	-	-
Shutout	0.0040	0.396	-	-	-	-	-0.0037	0.168	-0.0003	0.921
Sweep	0.0013	0.792	-	-	-0.0025	0.519	-0.0048**	0.043	-0.0008	0.724
Blowout	0.0096	0.136	-0.0040	0.212	-0.0029	0.592	0.0136**	0.014	0.0083**	0.025
HFWin	-0.0025	0.501	-	-	-0.0008	0.731	-0.0026	0.215	-0.0031*	0.096
Wildcard	-0.0219**	0.014	0.0016	0.646	-0.0027	0.454	-0.0132*	0.081	-0.0085*	0.041
Population	-	-	0.0039	0.108	0.0008	0.725	-	-	-	-
Nielsen	-	-	0.0004	0.375	-	-	-	-	-	-
Attendance	-	-	0.0000	0.300	-	-	-	-	-	-
Adjusted R^2	0.0548		0.1354		-0.0751		0.0984		0.0232	

* Significant at the 10% level, ** Significant at the 5% level

Lastly, Table 4.13 displays the split samples of the cross-sectional regression. The wildcard variable remains negative and statistically significant in the latter split sample for MLB, NHL, and the Big Four. There also is a positive and statistically significant effect for the same samples for the blowout variable.

Table 4.13 Determinants of post-event abnormal returns

Sport	MLB		NFL		NBA		NHL		Big Four	
Years	1903-1957		1967-1989		1947-1979		1927-1969		1903-1957	
Variable	N = 49	p-value	N = 23	p-value	N = 32	p-value	N = 43	p-value	N = 82	p-value
(Constant)	-0.0040	0.5	-0.0572	0.122	-0.0019	0.499	0.0032	0.486	-0.0023	0.510
Canadian	-	-	-	-	-	-	0.0008	0.825	0.0020	0.624
Distance	0.0006	0.885	0.0011	0.85	-	-	0.0005	0.891	0.0005	0.861
Streak	0.0001	0.485	-0.0004	0.417	-0.0013	0.759	-0.0002	0.55	0.0001	0.464
AL/NFC/East	0.0007	0.871	0.0042	0.427	-0.0006	0.769	-	-	-	-
Shutout	0.0074	0.161	-	-	-	-	-0.0061	0.116	0.0000	0.997
Sweep	0.0065	0.266	-	-	-0.0042	0.238	-0.0067*	0.065	0.0008	0.82
Blowout	-0.0033	0.616	-0.0025	0.686	0.0015	0.696	0.0092	0.415	0.0003	0.95
HFWin	-0.0087**	0.042	-	-	-0.0013	0.525	-0.0019	0.59	-0.0042	0.18
Wildcard	-	-	-0.0031	0.802	-0.0072**	0.045	-	-	-	-
Population	-	-	0.0040	0.471	0.0031	0.141	-	-	-	-
Nielsen	-	-	0.0008	0.351	-	-	-	-	-	-
Attendance	-	-	0.0000	0.398	-	-	-	-	-	-
Adjusted R^2	0.0416		-0.1269		-0.0545		0.0067		-0.0506	

Sport	MLB		NFL		NBA		NHL		Big Four	
Years	1958-2012		1990-2013		1980-2013		1927-1969		1958-2013	
Variable	N = 54	p-value	N = 24	p-value	N = 34	p-value	N = 43	p-value	N = 152	p-value
(Constant)	0.0110	0.181	-0.0037	0.925	-0.0009	0.348	-0.0001	0.978	0.0028	0.262
Canadian	0.0124	0.443	-	-	-	-	-0.0068*	0.078	-0.0014	0.704
Distance	-0.0116*	0.09	0.0062	0.157	-	-	0.0057*	0.069	-0.0009	0.718
Streak	-0.0001	0.489	-0.0002	0.196	0.0049	0.381	0.0001	0.488	0.0000	0.875
AL/NFC/East	-0.0087	0.203	0.0018	0.651	-0.0010	0.852	-	-	-	-
Shutout	0.0089	0.281	-	-	-	-	-0.0013	0.764	0.0015	0.695
Sweep	0.0008	0.924	-	-	-0.0018	0.823	-0.0027	0.407	-0.0007	0.833
Blowout	0.0236**	0.044	-0.0066	0.228	-0.0135	0.319	0.0163**	0.012	0.0149***	0.004
HFWin	0.0015	0.809	-	-	0.0001	0.99	-0.0040	0.174	-0.0030	0.225
Wildcard	-0.0256**	0.019	0.0023	0.609	-0.0005	0.948	-0.0149*	0.052	-0.0100**	0.023
Population	-	-	0.0028	0.479	0.0003	0.958	-	-	-	-
Nielsen	-	-	-0.0002	0.874	-	-	-	-	-	-
Attendance	-	-	0.0000	0.731	-	-	-	-	-	-
Adjusted R^2	0.1025		0.0161		-0.1913		0.1867		0.0502	

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

4.7 CONCLUSION

While the regression and proportion methods show no significant sign of an effect except for MLS games, other methods suggest that there are, on average, negative returns before a championship sporting event for the major, pooled leagues. On the contrary, MLB and NBA games may have had a significant influence on returns the day following championship games in the first half of their history. As shown from the cross-sectional regression, certain game aspects may have influenced such returns. The customized event study and the t-test for difference of means displayed results consistent with a pre-event effect. However, these results may be influenced by outliers. Therefore, further evaluation is recommended in order to verify such results. This could be completed by using a different index, new methodology, or different sports in different geographical areas. Table 5.1 shows statistically significant results of the different methodologies.

Table 5.1

League	Event	Customized Event Study	T-Test for Difference in Means	Z-Test for Difference in Proportions	OLS Regression
MLB	Pre	-	-	-	-
	Post	-	-	-	-
NFL	Pre	-	-	-	-
	Post	-	-	-	-
NBA	Pre	-	-	-	-
	Post	-	10%	-	-
NHL	Pre	-	-	-	-
	Post	-	-	-	-
MLS	Pre	-	-	5%	10%
	Post	-	-	-	-
NCAA Foot.	Pre	-	-	10%	-
	Post	-	-	-	-
NCAA Bask.	Pre	-	-	-	-
	Post	-	-	-	-
Big Four	Pre	10%	10%	-	-
	Post	-	-	-	-
Total	Pre	-	-	-	-
	Post	-	-	-	-

CHAPTER 5: CONCLUSION

5.1 CONCLUSION

Stock returns surrounding championship games of major U.S. sports were examined in this study. Multiple methods were applied in order to determine if the presence of a significant sports event has any effect on market returns. The methods included a customized event study, a t-test for difference in means of event trading days and non-event trading days, a z-test for difference in proportions, and an ordinary least squares regression. Of these methods, only the customized event study and the t-test for difference in means suggest that the four most popular U.S. leagues (MLB, NFL, NBA, NHL) combined produce a negative abnormal return on the trading day before the event. The MLS Cup is shown to have a significant positive effect on returns the day before the event using both the z-test for difference in proportions and the OLS regression; however, the sample size is rather small to suggest a justified effect. Table 5.1 displays the collective results from each method for their full samples. Interestingly, the NBA and MLB were found to have significant, negative abnormal returns on the day after their respective events in the first half of each sample, which likely influenced the Big Four and total samples; for the period of 1903 to 1957, these samples were noted to have negative abnormal returns during in the custom event study of -0.331% and -0.303%, respectively, and were both significant at a 5% level. Likewise, the OLS regression suggested that post-event returns during the same period for both samples were negatively affected and significant at a 1% level. In summary, there is limited evidence for an effect on market returns caused by the presence of a major sports event.

5.2 SUGGESTIONS FOR FUTURE RESEARCH

There were several limitations to this study. First, Boyle and Walter (2003) argue that intra-day data may be more useful due to events that take place during trading hours; if effects are short-lived, effects may not persist the following trading day. This may have affected results in this study. For example, the first World Series game played at night wasn't until the 1971 World Series; therefore, many events may have taken place during trading hours. Intraday data or samples that only include night (prime-time) games would be more suitable to guarantee that the effect is captured.

The limited evidence of an effect should encourage further study on the effect of national sports events on market returns. Using different data and methodology is important to compare results and to determine if outliers continue to have a substantial effect on the results. For example, testing in different markets, such as European markets with soccer, may provide additional insight to a potential effect. Lastly, it would be of interest to examine causes for such returns in more detail. For example, it would be interesting to examine gambling data to determine if there is a relationship between the frequency or size of bets on Las Vegas sports books and option activity (or trade size/frequency) on the stock market before such sporting events and the payouts after the events. Such a relationship may suggest that returns are caused by increased risk-taking around such events.

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