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Analysis of Twitter Messages for Sentiment

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Analysis of Twitter Messages for Sentiment and Insight for use in Stock Market Decision Making

By

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DISSERTATION APPROVAL FORM

This dissertation is approved as a credible and independent investigation by a candidate for the Doctor of Science in Information Systems degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department or university.

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DECLARATION

I hereby certify that this project constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

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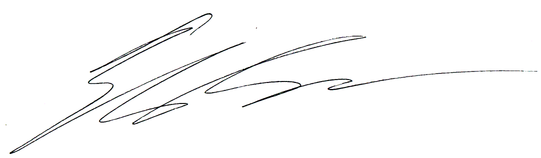

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CHAPTER 1: INTRODUCTION

For as long as there has been a market available for trading assets and financial instruments, there has been an interest in finding methods to gain an edge in that market. This search for an edge has led investors and researchers down many paths with many different approaches to analysis of the markets (Shostak, 1997).

Many theories have been put forth to explain the movements within the stock market with some theories focusing on the underlying business behind a stock's price, other theories focusing on historical price movements and others focusing on the human behavioral aspects of the market. Throughout most of the last century, market participants and academics have created analysis techniques and prediction methods that have been used to determine how and when money is invested into the stock market (Bessembinder & Chan, 1998; Lo, 2004). This type of research has developed over the years and can be loosely categorized into four main areas: 1) Efficient Markets; 2) Behavioral Finance; 3) Fundamental Analysis; and 4) Technical Analysis. While a detailed look into any of these areas is outside the scope of this study, each area is discussed briefly.

The most well-known and widely accepted theories within the academic community during the late-twentieth century have their foundations in the Random Walk Theory, which claims that price movement in the stock markets is random and previous price cannot accurately predict future prices (Fama, 1965a; Jensen & Benington, 1969). One of the most famous of the theories grounded in the Random Walk Theory is the Efficient Market Hypothesis (EMH) which claims that current stock prices reflect all known information and because of this it is impossible to predict future prices (Fama, 1965b). While popular in the late-twentieth century, the EMH began to lose support among both academic and stock market practitioners when various mathematical models built upon ideas from the EMH began to fail in the 1990's (Lo, 2004). Although these failures do not provide clear evidence that the EMH is incorrect, they do point to evidence that the EMH axiom that states that the prices within the stock market reflects all information is incorrect, or at least incomplete (Lo, 2004).

Another area of research that has become prominent over the last thirty years is behavioral finance (Thaler, 1999). This area of research starts with the clear distinction that markets are not made of rational actors as described by the EMH and, therefore, the assumption of rational actions is a false assumption (Shleifer, 2000). The study of behavioral finance has grown steadily and is now considered to be one of the most promising areas of research for understanding the markets and the market participants (Thaler, 1999).

Recently, researchers have attempted to build revisions to the EMH that add behavioral finance foundations to the EMH. One such theory is the Adaptive Market Hypothesis (AMH) which adds aspects of evolutionary theory to the EMH by describing the market, the competition seen in the markets, the size of profit opportunities and the ability of market participants to adapt to changes in the marketplace (Lo, 2004; Neely, Weller, & Ulrich, 2009). While the EMH specifically states that predicting price movements is not possible due to their randomness, the AMH allows for short-term predictions and in fact allows for the ability to predict the market provides for profit opportunities (Lo & MacKinlay, 2001). By providing for the predictability of markets, the ability for market participants to learn and adapt to market changes, competition between market participants, and the existence of profit opportunities within the market, the AMH is an excellent theoretical foundation to use as a framework to study predictive approaches to the marketplace (Neely et al., 2009).

In addition to the AMH, another area found within behavioral finance revolves around the idea of the 'sentiment' of the market or the market participants. The use of sentiment applied to the markets can be traced back many hundreds of years and had become popularized by the beauty contest analogy put forth by Keynes (1936) whereby investors are involved in a beauty contest when selecting a stock to invest their money in because these investors care about what other investors think about the stock. This contest describes the 'sentiment' of individuals and the market towards a particular stock or instrument and can be used to describe why some markets grow (and decline) rapidly (Keynes, 1936). In addition, the idea of the beauty contest can explain aspects of the underlying psychology of the market, including how assets can be valued at a price that is so far away from the underlying fundamentals of the asset or instrument (Gao, 2007).

The concept of sentiment has become a major element found in much of modern economics and market theory. In fact, the idea of sentiment has evolved from one of market sentiment to that of investor sentiment, whereby researchers and market participants attempt to measure the aggregate of sentiment of individual investors as found in surveys released by the National Association of Active Investment Managers (NAAIM) and American Association of Individual Investors (AAII). The AAII and NAAIM surveys are used by many investors to understand the overall sentiment of the market in order to make the necessary adjustments to their portfolios to take advantage of, or to protect themselves from, changes in market sentiment (AAII, 2012; NAAIM, 2012).

While Efficient Markets and Behavioral Finance research attempts to build over-arching theoretical foundations of the markets and market participants, the next two areas of analysis and research have a much more narrow focus. Market participants have used fundamental analysis and technical analysis for many years to better understand and predict stock movements. Fundamental analysis is an approach that focuses on the underlying business of the asset or instrument price (e.g., the fundamentals of the business) while technical analysis approaches market analysis by focusing purely on previous asset price, volume and other technical indicators along with advanced mathematical equations to highlight and predict activities within the market (McQuown, 1973).

Fundamental analysis is widely used and accepted as a method to analyze a company's underlying business operations and assets to determine whether an investment should be bought, sold or held for a period of time. For companies listed as public companies within the United States, meaning they are listed in one of the public stock markets, a number of requirements are imposed to ensure proper reporting of financial activities, financial assets and liabilities and any activities which occur that might have meaningful effect on the company's stock price (Thomsett, 1998). With these reports and other publicly available information, investors are able to determine a value for each company and, with that value, determine whether the current stock price is too low, too high or in line with the underlying business value (Greig, 1992). Using this information, an investor can then determine if they believe the company's stock price should continue to increase or decrease and thereby help determine whether they wish to invest their money in the company.

Technical analysis takes a different approach to the stock market. Unlike fundamental analysis, technical analysis methods place no real importance to the underlying business behind a company's stock price. The only thing that matters to technical analysis practitioners is the historical price and volume which are charted onto a stock chart using a particular timeframe which can be hourly, daily, weekly, or any other timeframe that is available (Marty, 2008). These stock charts are then analyzed to determine where price has been in the past and where price is most likely to go in the future. In addition, technical analysis researchers have created numerous mathematical equations and indicators to help better understand where a stock price might go in the future (Loh, 2006; Vasiliou, Eriotis, & Papathanasiou, 2006).

Within academic research, there has been a debate for years about the validity of technical and fundamental analysis with many arguing that there is no credible evidence that fundamental or technical analysis provides any long term success in the markets (Fama, 1965a; Greig, 1992; Jensen & Benington, 1969; Lo & MacKinlay, 2001; McQuown, 1973). There are many other researchers and practitioners who argue that either fundamental or technical analysis (or a combination of the two) can in fact provide reliable, long term success in the marketplaces (Bessembinder & Chan, 1998; Fiess & MacDonald, 1999; Greig, 1992; Marty, 2008; Shostak, 1997; Summers, 1986).

The purpose of this study was to determine whether sentiment might be used to predict future price movements by studying if real-time messages shared over the Internet provide predictive cues for an investor to use to make investing decisions. With this purpose in mind, the use of the approach described by behavioral finance research arguable provides the best opportunity for prediction utilizing sentiment as behavioral finance research allows for the ability to predict price and incorporate market participants into the prediction approach. Efficient Markets is not appropriate for this study since the underlying theory does not allow for predictions of future prices using past prices. While the areas of fundamental and technical analysis can be used to develop predictive capabilities, both approaches lack the ability to directly incorporate the market participants into the predictions of price movements. Because of the previously mentioned limitations, neither fundamental nor technical analysis techniques will be used as a major cornerstone of this research although some technical analysis methods were incorporated to assist with determining average prices and possible investment entry and exit strategies.

Purpose of the Study

In this study, automated analysis techniques were used to determine the sentiment of a Tweet using Bayesian Analysis techniques. Using this Bayesian Analysis approach to sentiment analysis, a sentence can be broken into words and then a sentiment probability value can be assigned to each word which is then summed up to provide an overall sentence probability (Lin, He, & Everson, 2010). This probability can then be used to assign a sentiment category to the sentence. These categories were then used as a method of predicting movements within the stock market. For the purposes of this study, the sentiment categories that were used were based on market nomenclature for positive and negative sentiment and trends. The categories used in this study are:

- **Bullish** for those Tweets that denote a positive sentiment.
- **Bearish** for those Tweets that denote a negative sentiment.
- **Neutral** for those Tweets that do not convey any discernible sentiment.

While it is difficult to describe the origination of the terms 'bullish' and 'bearish' as there are numerous different descriptions of how these terms came into use, they appear to have entered the lexicon of every-day investors from their use in the popular Dow Theory used in the early to mid-twentieth century (S. J. Brown, Goetzmann, & Kumar, 1998).

In order to use the Bayesian Analysis approach, a training dataset must be created before the sentiment analysis can be undertaken (Pang, Lee, & Vaithyanathan, 2002). The creation of the training dataset is a time consuming manual process whereby a random sampling of data is selected and codified into sentiment categories (Pang et al., 2002). For the purposes of this study, a training dataset was created using a random sampling of 10,000 Tweets with each Tweet assigned a value of Bullish, Bearish or Neutral. These manually codified Tweets were then used during the automated sentiment analysis of all other Tweets.

This study captured Tweets found in publicly available Twitter streams to determine if each Tweet could be assigned a specific sentiment value using automatic computational methods. This sentiment value was then used to determine if any actionable insight was found within the sentiment of Tweets shared on Twitter and, if so, how that sentiment might provide insight into price and volume movements in the stock market

This research contributes to a body of previously published research that has examined the use of Twitter sentiment to predict movements in the stock market. Bollen, Mao and Zeng (2010) reported on the outcome of a research project that uses Tweets and sentiment analysis to determine the mood of a large Twitter population to predict the movement of the Dow Jones Industrial Average (DJIA) on the following day with a claimed 87.6% accuracy.

Sprenger and Welpe (2010) reported on a research project in which they captured and analyzed Tweets mentioning the top 100 stocks of the Standard & Poor’s Index (S&P 100). The researchers were able to document that consistent correlations existed between Twitter sentiment and stock market returns as well as between Tweet volume and stock market volume.

In addition, this study built upon related research by Das and Chen (2007) who reported that sentiment is not an effective method of predicting the movement of individual stocks but does provide a valuable prediction method when applied to a group of stocks or an index based on the same set of individual stocks using a combined sentiment measure. This combined sentiment was shown to have more predictive power than the individual stocks (Das & Chen, 2007).

In the previous literature, there has been relatively little reported research into the effect of the reputation of the user supplying the message on the overall sentiment gathered in a given time period. Two separate research projects reported by Gu, Konana, Liu and Ghosh (2006) and Zhang (2009) studied the reputation of stock market message posters to assess whether reputations had any impact on market movement. While the research provides good insight into methods that were used to calculate user reputation in stock market message boards, it provides little insight into how a user’s reputation yields some measure of trust that could then be applied to that user’s Tweets during sentiment analysis. Sprenger and Welpe (2010) discuss the user’s reputation and suggest the need for future research to incorporate some form of a user reputation weighting mechanism that assigns more weight to Tweets from users who have better reputations than others.

Rather than focus on the macro Twitter environment and public mood like Bollen et al. (2010) or the S&P 100 like Sprenger and Welpe (2010), this study focused on a specific sector of the stock market by tracking a set of stocks that make up various sectors of the market. Additionally, rather than create a group of stocks at random, Exchange Traded Fund's (ETF) were used to track the certain sectors of the market. These ETF's were specifically developed as a means to track a group of stocks or a specific market index like the Dow Jones Industrial Average and each ETF can be traded on the stock market just like any other instrument (Bhaktavatsalam, 2012).

For the purpose of this study, the Energy Sector XLE ETF and the Consumer Staples Sector XLP ETF were used. All Tweets mentioning these ETF's and the stocks that are tracked by these ETF's were captured and analyzed during a given time period. The two sectors chosen for this study were selected because both make up about ten percent of the S&P 500 index, both sectors have an Exchanged Traded Fund (ETF) that covers the entire sector and both have an equal number of stocks. The Energy Sector ETF has the symbol of XLE and the Consumer Staples Sector ETF has the symbol of XLP and both consist of 41 companies. The XLE and XLP ETF’s and the companies that make up these sectors ETF’s are provided in Table 1.1.

Table 1.1

Listing of Sectors and Companies

Energy - ETF Symbol: XLE		**Consumer Staples - ETF Symbol: XLP**	
$XLE	$NBL	$XLP	$AVP
$XOM	$MEE	$PG	$SLE
$CVX	$VLO	$PM	$MJN
$SLB	$CAM	$WMT	$CCE
$COP	$MUR	$KO	$TAP
$OXY	$FTI	$KFT	$CLX
$APA	$CNX	$MO	$CAG
$HAL	$SWN	$CVS	$HSY
$APC	$DNR	$PEP	$EL
$MRO	$NBR	$CL	$SWY
$DVN	$RDC	$WAG	$MKC
$BHI	$RRC	$COST	$BFB
$NOV	$COG	$KMB	$TSN
$EOG	$TSO	$GIS	$WFMI
$HES	$SUN	$ADM	$CPB
$CHK	$NE	$HNZ	$SJM
$WMB	$NFX	$SYY	$DPS
$PXD	$DO	$KR	$STZ
$BTU	$EQT	$K	$HRL
$SE	$QEP	$RAI	$SVU
$EP	$HP	$LO	$DF

In addition to the XLE and XLP ETF’s, all Tweets mentioning the Standard & Poor’s 500 SPY ETF were captured and analyzed. The S&P 500 is considered by many to be a good baseline for measuring market performance due to the breadth of market coverage contained within the five-hundred companies tracked within this index (S&P, 2012). Because of the importance and popularity of the S&P 500, the SPY ETF, which tracks all stocks within the S&P 500, was monitored during this study as a way to determine a baseline measurement for performance as well as another data point for analysis.

Objectives of this Study

This study investigated whether Tweets can be considered a leading or lagging indicator when compared with price movement in the stock market. Additionally, an analysis was conducted on the effect that volume of Tweets has on the price of a specific stock or on an entire sector. In addition, an analysis of a user's reputation was performed to understand if there are methods that can improve the accuracy of prediction for stock price movement. This study was designed to:

- Determine whether the sentiment for a sector as a whole matches the aggregated sentiment of the companies that make up the sector.
- Determine if there are times or days that provide more valuable sentiment data from Twitter.
- Determine whether a Tweet sender's reputation or number of Twitter followers affects the contribution of that user's sentiment towards a stock or sector.

The outcomes of this study were used to try to help shed light on the specific research topics. These topics are:

- To determine if the Twitter sentiment of a sector affects or responds to the Twitter sentiment of the stocks that make up that sector.
- To determine whether there are times of day or days of the week that provides more useful sentiment information for a stock or sector.
- To determine how Twitter is being used to share information about the stock market.
- To determine how users and groups of users impact the movement of specific stocks or financial instruments.
- To determine whether a stock or sector's sentiment has predictive capabilities for price or volume action.

Research Questions

Based on a detailed literature review and a preliminary analysis of the types of data gathered from publicly available Twitter streams, the following research questions were examined in this dissertation:

- **RQ-1**: Using a given sector of the stock market, does the sentiment for that sector match the aggregated sentiment for the stocks that make up that sector? How well does the sentiment predict price / volume movement?
- **RQ-2**: Are there specific stocks within a given sector that supply the majority of the sentiment for that sector? If so, do these stocks supply sentiment in correlation to the weighting give to them by ratings agencies (e.g., Standard & Poor's)?
- **RQ-3**: Are there times of the day or days of the week that provide a more accurate and informative sentiment for a stock or sector?
- **RQ-4**: Are there specific users that provide more 'weight' to a sentiment of a stock or sector based on the users' reputation?

Hypotheses

This study evaluated the following hypotheses in order to answer the above Research Questions:

- **H1a**: The sentiment of a sector will match the overall averaged sentiment of all stocks within the sector.
- **H1b**: The sentiment of a sector can be used to predict the movement of all stocks in that sector.
- **H1c**: The sentiment of an sector or stock on any given day will provide a prediction for the next day's movement in that stock
- **H2a**: The sentiment of a stock within a given sector will affect the sentiment of the overall sector based on the relative market cap weighting of that stock assigned to that stock within the sector.
- **H2b**: The stocks that provide the most weight toward the sentiment of a sector are also the stocks with the highest number of mentions on Twitter.

- **H3:** There is a difference in the effect that Tweets sent during non-market hours (i.e., evenings and weekends) and Tweets sent during market hours have on sentiment and price.
- **H4**: The number of followers of a Twitter user determines the effect that users' Tweets will have on sentiment for a stock or sector.

Mapping Hypothesis and Research Questions

In order to better visualize the relationship between each research question and the hypotheses that were tested within this study, a mapping between research questions and the hypotheses for those questions was created. This mapping table is provided in Table 1.2.

Description of the Remainder of the Study

The remainder of this study is organized into the following chapters:

- Chapter 2 – Literature Review: Provides an exploration of the literature necessary to understand what has come before this study and provide a review of the existing body of knowledge.
- Chapter 3 – Research Methodology: Provides an overview of the study's research questions, hypotheses, research methods, including the approach to data collection and analysis that are used throughout the study.
- Chapter 4 – Data Collection, Analysis and Findings: Describes the analysis and findings of this study.
- Chapter 5 – Conclusions, Discussions and Future Research: Provides a discussion of the findings of this study as well as provides a road map for future research projects.
- Appendices: A listing of all items pertinent to this study but not included in detail within the study itself.
- References: Provides a full listing of all publications used throughout this study.

Table 1.2

Mapping Hypothesis and Research Questions

Research Question	**Hypothesis**
RQ-1: Using a given sector of the stock market, does the sentiment for that sector match the aggregated sentiment for the stocks that make up that sector? How well does the sentiment predict price / volume movement?	H1a, H1b, H1c
RQ-2: Are there specific stocks within a given sector that supply the majority of the sentiment for that sector? If so, do these stocks supply sentiment in correlation to the weighting give to them by ratings agencies (e.g., Standard & Poor's)?	H2a, H2b
RQ-3: Are there times of the day or days of the week that provide a more accurate and informative sentiment for a stock or sector?	H3
RQ-4: Are there specific users that provide more 'weight' to a sentiment of a stock or sector based on the users' reputation?	H4

CHAPTER 2: LITERATURE REVIEW

In this literature review, a brief overview of the modern day stock market is provided for context. A review of theories and areas of study that have been developed to explain the movements found within modern markets is also provided. In addition to a review of modern day markets, a review of literature covering more technical fields that will be referenced throughout the remainder of this study is provided. Fields such as social network analysis, natural language processing, text mining and sentiment analysis are described. A review of previous research projects along with a theoretical foundation to be used throughout the remainder of this study will be provided. This literature review is organized into five main sections: 1) The Stock Market; 2) Social Networks and Social Network Analysis; 3) Text Mining; 4) Sentiment Analysis; and 5) Applications of Sentiment and Social Analysis to the Markets.

The Stock Market

The idea of a marketplace to trade shares has been a mainstay of the financial industry of most modern cultures since the early seventeenth century. The first modern securities market can be traced back to 1602 and the founding of the Dutch East India Company and the Amsterdam market (Petram, 2011). This first market for trading shares is described as the first modern securities market whereby participants invested, traded and speculated in the shares of a company's stock (Petram, 2011).

While modern day markets are much different than the Amsterdam Exchange from the seventeenth century, the basic concept of exchanging money for shares of a company’s stock remains the same (Lo & MacKinlay, 2001). Though the basic concepts remain the same, modern day markets, at least in the United States, are no longer made up of individuals trading shares with each other directly but are now fully electronic markets where the majority of trading is performed via computers, whether by individual traders issuing buy and sell orders or by automated trading algorithms (Amihud & Mendelson, 2012; Janzen, Smith, & Carter, 2012).

Although the modern markets have become computerized, the underlying concepts remain the same whereby an investor or trader is attempting to find an edge to use for making decisions on how best to invest in the market and whether to buy, sell or hold (Jegadeesh & Titman, 2012). This edge may be a theory in how markets operate; a new technical indicator that highlights the ideal spots to buy or sell or it could be the application of existing or new technologies to the markets (Azizan, Mohamed, Phooi, & Chan, 2011; Sykora, 2009).

The remainder of this section describes the literature used to build the underlying theoretical framework to allow for the use of sentiment as a valid input to the investment decision-making process. Additionally, modern methods used by investors and traders during their decision making process will be reviewed.

Theoretical Foundations

Efficient Markets

As long as the markets have existed, there have been theories developed that attempt to describe how markets work. These theories have been developed and applied to markets in attempts to not only understand the markets but to make money in the markets.

During the twentieth century, there were a number of theories produced that attempted to describe the markets with the most well-known theory being the Efficient Market Hypothesis developed by Eugene Fama (1965a) and expanded upon throughout the rest of the twentieth century. This theory, known in the literature as EMH, states that markets are efficient and that all known information about a particular stock or security is already included in the price of that stock or security and all price fluctuations within the stock or market are random (Fama, 1965a).

According to the EMH, as new information about a company arrives, the market instantaneously reacts to that information in an efficient manner to re-price a company’s stock (Lo, 2004). This re-pricing is performed randomly such that no investor would be able to predict what might happen when new information is made available (Balvers, Cosimano, & McDonald, 2012). Due to the combined factors of random price movements, instantaneous incorporation of news and the rational and efficient marketplace, the EMH states that it is impossible to predict price movements in the future given past data (Balvers et al., 2012; Timmermann & Granger, 2004).

Due to the efficiency of the market and the random nature of price movements, the EMH claims that there is little chance of any investor beating the returns generated by the market (Sheikh & Noreen, 2012). From this, the EMH claims that the optimum approach to investing is the buy-and-hold approach, which suggests that an investor purchase stock in a company with good fundamentals (e.g., good revenue and margins) and hold that stock forever, or at least until the fundamentals of that company change (Sheikh & Noreen, 2012). With the buy-and-hold approach, rational investors can expect to make, on average, a return equal to the overall market returns as long as the stocks they own are selected based on good fundamental data (Timmermann & Granger, 2004).

While the Efficient Market Hypothesis is a popular theory and has been one of the main theories used for managing investments by large organizations, there have been many arguments against the theory by practitioners, economists and academics (Gustafsson, 2012; Malkiel, 2005). There has been no direct proof that the EMH is invalid; however, there also is no direct proof that the EMH is valid for all markets and all market conditions (Lo & MacKinlay, 2001; Malkiel, 2005).

The longest lasting criticisms of the EMH are found in the arguments that the theory makes for rational market participants (Malkiel, 2005). There have been many experiments conducted by psychologists and behavioral economists showing that humans will not always respond to pressures in a rational manner (Egidi, 2012; Kahneman, 2012). In fact, there have been many experiments that show investors exhibiting irrational behavior in the face of economic decisions which often lead to financially ruinous outcomes (Kahneman, 2012).

Due to these criticisms, and the growth of interest in areas outside of finance and economics, notably the areas of psychology and behavioral sciences, a new field of study emerged in the late twentieth century that attempts to merge finance, economics, human behavior, psychology and elements of neuroscience and is designed to use these fields to create new theoretical frameworks for applications to the stock market (Kahneman, Slovic, & Tversky, 1982). This field is called often called Behavioral Finance or Behavioral Economics (Iyengar & Ma, 2010). For the purpose of this study, the term Behavioral Finance will be used.

Behavioral Finance

Within the framework of the Efficient Market Hypothesis, the act of predicting future prices or market direction is considered a fruitless endeavor since there is no way of predicting future prices from past prices (Timmermann & Granger, 2004).While this particular aspect of the EMH is controversial even among EMH proponents, the fact that theory does not easily allow for predictions makes it unsuitable as a framework to use for this study. With this in mind, the field of behavioral finance is reviewed to determine if there might be a suitable framework for use as a theoretical foundation to use for this study.

Behavioral finance can be defined as the study of the psychology and human behavior applied to stock market participants and the effect behavior has on the markets (Sewell, 2007). Although the modern interpretation of behavioral finance can be traced to the 1970's and 1980's, the ideas have been around since the early 1900's, having been introduced by Selden (1912) with additional research contributions to the theoretical foundations throughout the twentieth century (Sewell, 2007).

The roots of modern behavioral finance theory can be traced to work by Bondt and Thaler (1985) where they introduce the concept of non-rational behavior in the market in which they describe a discovery of investors overreacting to news in very non-rational ways, which went against the prevailing Efficient Market Hypothesis (EMH) theory (Bondt & Thaler, 1985; Sewell, 2007). This concept of non-rational investors is the key underlying argument of behavioral finance and it runs counter to arguments made in the EMH. As mentioned previously, the EMH claims the market is made up of rational investors making rational decisions while investing their money (Fama, 1991).

The argument at the heart of behavioral finance is the following: investors are not rational and they allow bias, fear, prejudice or beliefs to cloud their judgment while thinking through their investing activities (Thaler, 1999). Much work has been done in the area of behavioral finance to build a theoretical foundation that builds upon the non-rational investor mindset to explain how investors actually make decisions when deciding how and when to invest (Lo, 2004).

A review of the entirety of the literature covering behavioral finance is beyond the scope of this literature review. One theory that is possibly worth noting is a theory that combines the Efficient Market Hypothesis with behavioral finance foundations. This theory, called the Adaptive Market Hypothesis (AMH) and first described by Lo (2004) as a hypothesis to account for behavioral biases within the markets (Lo, 2004).

The Adaptive Market Hypothesis embraces irrational behavior in a way that helps to describe a more realistic stock market by describing the fact that different investors are approaching the market for changing purposes (Lo, 2004). The AMH describes investors as rationally, but realistically, profit focused and loss averse individuals (Neely et al., 2009). These normally rational investors allow fear and greed to affect their judgment and turn their rational investing mindset into a short-term non-rational approach to the markets (Kahneman et al., 1982; Lo, 2004).

More importantly, as a foundational framework for this study, the AMH describes four main practical implications for investors that are adverse to the EMH: 1) profit opportunities do generally exist throughout the markets; 2) learning, competition and more participants will eventually erode any new profit opportunities; 3) simple investment strategies will erode more quickly than those strategies based on more complex strategies; and 4) innovation is the key to surviving in the markets long term (Lo, 2004; Neely et al., 2009). Lastly, the AMH describes 'survival of the fittest' as the key objective for all market participants and drives all decisions made by participants (Lo, 2004).

The Adaptive Market Hypothesis will be used as a foundational framework for this study. The AMH provides a framework based upon the psychological aspects of investors via the field of behavioral finance. Using the AMH and the practical implications described in the previous paragraph, investing strategies can be built that take advantage of the profit opportunities that arise. While the AMH doesn't specifically provide for a means to predict future prices based on current or past data, it does provide for the possibility of forecasting future movements in the markets (Lo, 2004). Combining the AMH with other methods that will be discussed in later sections of this study, entry and exit points will be reviewed to determine if there are profitable strategies that might be found.

Fundamental Analysis

The use of a company's financial information to analyze the company for investing decisions is known as fundamental analysis (Contreras, Hidalgo, & Núñez-Letamendia, 2012; Mahmoud & Sakr, 2012). Fundamental analysis is a standard method used by many investors to determine if a company's stock price is valued fairly when compared to the underlying financial information of that company (Mahmoud & Sakr, 2012). Included in this information are the fundamental details of the company's financial history and performance including revenue, profit margin, future looking revenue guidelines and other aspects of a company's financial reports (Contreras et al., 2012).

Applying fundamental analysis methods, an investor can use current and past financial data of a company to forecast a company's future earnings, which would also lead to a forecast of a company's future stock price (Seng & Hancock, 2012). By forecasting future prices using fundamental financial information, an investor can then determine whether money invested at the current price would provide a reasonable return if the company's share price met the future forecasted price (Mahmoud & Sakr, 2012).

In addition to applying the fundamental analysis method to company stock prices, it can be applied to the overall economy as well as to an industry. Many investors use fundamental analysis by combining the overall economic fundamentals, the fundamentals of an industry and a company's fundamental information to make investing decisions (Yuen, 2012).

In analyzing fundamental information about a company, investors are looking for companies with stock prices that are lower than fundamental financial values found within the company (Malkiel, 2003). When investors find a company considered to be undervalued, further analysis is performed to forecast what prices should be in the future, given that company, industry and economic fundamentals remain the same or improve (Seng & Hancock, 2012).

Fundamental analysis methods are quite useful for understanding the fundamental value of a company and are widely used throughout the world of investing (Seng & Hancock, 2012). One key contribution of fundamental analysis that will be used within this study is the idea of a 'contrarian' approach to investing. Contrarian investing has been popular for many years having been introduced by many early fundamental analysis proponents (Dreman, 1998; Graham & Dodd, 2004). In the contrarian style, an investor may take the opposite approach from the general investing community by buying shares in a company when it is not a popular idea or selling shares when a company has become extremely popular. Using this approach, an investor might determine that a company's stock price is undervalued by looking at fundamental financial data and forecasting that the stock price should be higher, which would provide a signal for the investor to buy (Dreman, 1998). This approach allows investors to ignore the overall market and focus strictly on fundamentals regardless of whether the market is seen as going up or going down, that is currently in a 'Bull' or 'Bear' market respectively (Graham & Dodd, 2004).

Although fundamental analysis is well regarded by many investors, it does have its critics. Many critics claim that fundamental analysis - and generally any type of analysis that attempts to predict future prices – is a waste of time and resources due to the random nature of price movement in the markets (Fama, 1965b; Shleifer, 2000). While critics exist, there are studies showing positive expectations from investing utilizing fundamental analysis methods with proper risk management strategies in place (Greig, 1992; Oberlechner, 2001; Seng & Hancock, 2012).

Technical Analysis

While fundamental analysis is focused on studying the financial information of a company to determine if the current stock price is undervalued, technical analysis is focused solely on price action of a stock (Yuen, 2012). Rather than study revenues, earnings and other fundamental data, the investor using technical analysis methods is mainly concerned with patterns and price levels (Azizan et al., 2011).

Investors using technical analysis methods focus on price charts of financial instruments and the patterns that arise over time as well as other mathematically derived measures of price action (Azizan et al., 2011). Price charts can be historical data covering any timeframe from seconds to minutes to larger timeframes like daily, weekly and monthly (Yuen, 2012). With these price charts, investors can overlay many different measures of price action to help more easily visualize price movements (Bessembinder & Chan, 1998). For example, a set of moving averages might be overlaid onto a chart to smooth out price action in order to more easily understand whether the underlying stock is moving up, down or sideways (Edwards, Magee, & Bassetti, 2007). These various measures of price action, also called indicators, have been around for many years with new indicators being developed and released on a regular basis by both practitioners and researchers alike (Edwards et al., 2007).

Many investors using technical analysis methods tend to put a great deal of emphasis on the abilities of indicators to forecast future price action (Azizan et al., 2011). While these indicators are useful for helping to determine a thesis on future price action, the over-reliance on them as a predictor has led many investors to ruin (Azizan et al., 2011). Like fundamental analysis, technical analysis faces criticism for the same reasons from many who believe in the random movements in the stock market (Fama, 1965b; Seng & Hancock, 2012; Shleifer, 2000). Technical analysis methods and technical indicators are dangerous if used incorrectly, but they can provide definite value to investors if approached properly and with proper risk management (Azizan et al., 2011; Marty, 2008; Yuen, 2012). Additionally, research shows that with proper planning and technical indicator selection, technical analysis methods can provide an accurate forecast for changes in the Dow Jones Industrial Average over a long period of time (Bessembinder & Chan, 1998).

For the purposes of this study, a small number of technical analysis methods will be utilized. Specifically, the basic moving average indicator, the concept of technical support and resistance and the idea of extreme levels were used. A moving average is defined as a simple averaging of price over a finite number of periods to smooth out the price data (Edwards et al., 2007). Technical support and resistance levels are nothing more than those price levels at which stocks tend to be bought or sold by many investors and can be defined as areas where price changes direction (Edwards et al., 2007). Lastly, technical analysis practitioners use the idea of an extreme reading as a way to gauge potential price or trend reversals to understand when changes may be about to occur in the market(Edwards et al., 2007).

Automating Analysis and Investing Methods

In the late twentieth century and early twenty first century, computers have been transformed from an aid used by investors to make decisions to being the central tool used by investors (Hong, Kubik, & Stein, 2005). Computers are used for analyzing numbers for fundamental analysis as well as visualizing price data and calculating technical indicators for use by technical analysis methods (Wattenberg, 1999).

In addition to their use as aids by investors, computers have become an important part of the decision support process by both fundamental and technical investors to filter the large market of financial instruments into only those that meet criteria set by an investor (Yuen, 2012). There are many investors and organizations that have spent an enormous amount of time and money developing trading strategies to be executed by computers in an automated fashion (Kearns & Ortiz, 2003).

Automated trading will not be fully utilized in this study, but aspects of this approach are used to test trading strategies. To test trading strategies using historical data, called backtesting, the well-known trading platform Tradestation will be used. Tradestation is a software platform that allows investors to view price charts, review fundamental data, write automated trading strategies, build custom technical and fundamental scans, build custom indicators and much more (Tradestation, 2012).

Social Networks and Social Network Analysis

A social network has been defined broadly as a set of nodes (e.g., people, organizations) and the connections or ties between these nodes, which represent the relationships between people or organizations (Katz, Lazer, Arrow, & Contractor, 2004; Marin & Wellman, 2011; Wasserman & Galaskiewicz, 1994). The study of social networks has its origins in sociology to study the social connections between different aspects of societies and how connections can strengthen or weaken based on inclusion or removal of new connections (Marin & Wellman, 2011; J. Scott, 1988; Serrat, 2009). Over time, the study of social networks began to expand beyond sociology and psychology to include mathematics, statistics, graph theory, network theory, linguistics and many other scientific fields (Marin & Wellman, 2011; Scholand, Tausczik, & Pennebaker, 2010; Ter Wal & Boschma, 2009; Wasserman & Galaskiewicz, 1994).

With this expansion of new methods and tools for analyzing social networks, the field of social network analysis was developed (Marin & Wellman, 2011; J. Scott, 1988). Social network analysis consists of measuring and graphing the relationships and information flow between nodes of a social network (Jamali & Abolhassani, 2006). This field was formalized with mathematical constructs and methods, including network theory and analysis tools, and became a popular sociological tool for studying various aspects of society throughout the late twentieth century (Freeman, 2004; W. R. Scott & Davis, 2003). The field of social network analysis has grown in popularity and is widely used today in many areas including organizational development, social sciences, mathematics, biological sciences, economics, information systems and many other fields (Katz et al., 2004; Marin & Wellman, 2011; Scholand et al., 2010; W. R. Scott & Davis, 2003; Ter Wal & Boschma, 2009; Wasserman & Galaskiewicz, 1994).

The invention and subsequent popularity of the Internet has led to the creation of Internet-based social networks, which has fostered growth in the popularity of social network research and social network analysis (Akrouf, Meriem, Yahia, & Eddine, 2013; Gloor, Krauss, Nann, Fischbach, & Schoder, 2009; Marin & Wellman, 2011). The growth of sites like MySpace, Flickr, YouTube, Facebook and Twitter resulted in many opportunities to improve social network analysis methods, tools and processes (Akrouf et al., 2013; Mazur, Doran, & Doran, 2010).

Social network analysis uses graphs, network theory and matrices to visualize and analyze the network (Jamali & Abolhassani, 2006). Using matrices is one of the simplest methods of social network analysis, allowing a researcher to list each node and the relationship each node has to other nodes (Jamali & Abolhassani, 2006). Although simple, this approach is not ideal for large networks and can be quite complex once the social network reaches a size greater than just a few nodes (Jamali & Abolhassani, 2006). With the introduction of computer based analysis tools, the use of network theory to analyze social networks has increased the usefulness of social network analysis techniques on Internet-based social networks (Mislove, Marcon, Gummadi, Druschel, & Bhattacharjee, 2007).

To perform social network analysis on internet based social networks, access to the social networks' data is necessary in order to gather useful information to analyze (Ediger et al., 2010). If this data is accessible, it can be used to visualize network topology, central nodes and study information propagation to determine influence throughout the network (Catanese, De Meo, Ferrara, & Fiumara, 2010; Gloor et al., 2009; Mislove et al., 2007).

Text Mining

Text mining, also known as knowledge discovery in text or text data mining, is defined as the use of computers to analyze text to discover, extract and make further use of knowledge within text (Feldman & Dagan, 1995; Hotho, Nürnberger, & Paab, 2005; Tan, 1999). The use of text as a storage device is quite natural and some research reports that more than three-fourths of all information is stored in some form of unstructured text documents (Tan, 1999). With such a large amount of information stored textually, it has been necessary to develop techniques to identify and extract knowledge from this unstructured data (Berry, 2003; Feldman & Dagan, 1995; Larsen & Aone, 1999).

While the definition of text mining is widely accepted and used throughout much of the literature, the application of text mining techniques varies among research areas (Ananiadou & McNaught, 2006; Srivastava & Sahami, 2009; Weiss, Indurkhya, Zhang, & Damerau, 2004). In some applications, a simple extraction of information from text is sufficient while in others the extracted text is then used as an input into other processing and classification techniques (Srivastava & Sahami, 2009).

As mentioned, text mining is the identification, extraction and use of information found within text. While a review of every technique used for text mining is beyond the scope of this literature review, a brief description of a generalized framework for text mining is appropriate. The following paragraphs provide a description of a generalized text mining process.

The first step in any text mining technique is the data-gathering phase which consists of collecting the various texts to be analyzed (Weiss et al., 2004). Gathering text can be as simple as placing a group of documents in a folder for future analysis or as complex as gathering text in real-time as it is published (Atkinson & Van der Goot, 2009).

Once the text acquisition process is in place and the relevant text is available, some form of analysis must be performed to dissect the captured text and identify relevant information within that text (Dörre, Gerstl, & Seiffert, 1999). In most cases, this identification and extraction is performed using automated techniques to identify important pieces of text (Srivastava & Sahami, 2009). The automated techniques used to identify importance within text normally fall into the area of research called Natural Language Processing (NLP), which can be defined generally as the use of computational techniques to analyze and represent text using linguistic analysis techniques (Liddy, 2001; Obermeier, 1987). In order to use NLP techniques, a set of rules must be created that define words to be ignored (e.g., ‘a’, ‘and’, ‘or’, etc.), word reduction approaches (e.g., stemming a word to its root), correction of spelling mistakes, setting basic grammar rules and creating rules to deal with ambiguity within text (Grishman, 1984; Joshi, 1991; Kao & Poteet, 2006).

After the text has been refined and dissected to identify the relevant pieces of information it contains, a final step of knowledge distillation is performed (Tan, 1999). In the final stage of the text mining process the output can then be used in various operations that allow the user to categorize, visualize, model or further refine the text (Berry, 2003; Tan, 1999).

There are an almost infinite number of ways to use the output of this final stage of text mining. The output can be used for visualization techniques that show patterns in text, connections between different texts, grammatical usage and comparison's within and between texts and other forms of visualization (Don et al., 2007; Fan, Wallace, Rich, & Zhang, 2006). Another use of the output of text mining techniques is modeling grammatical and language usage within organizations (Berry, 2003; Tan, 1999). Another area that has become fairly popular in recent years is the use of text mining as an input to classification techniques used to classify text by sentiment, information types and other types of knowledge (Berry, 2003; Feldman & Dagan, 1995; Srivastava & Sahami, 2009).

The use of the output of text mining is important to this study. Using text mining techniques combined with other analysis methods, user generated content will be gathered and analyzed to determine if sentiment exists. This approach, called sentiment analysis, will be described in the following section.

Sentiment in Investing

The idea of sentiment and the markets dates back many years. Sentiment's use in the markets was popularized in the early twentieth century when Keynes (1936) introduced the beauty contest analogy. In this analogy, Keynes argued that investors are involved in selecting the most beautiful (i.e., the most popular) stock to invest in because they care more about what other investors think about the stock than the underlying value of the stock price (Keynes, 1936). This idea of the beauty contest can help to explain why some stocks are valued at a much higher level than fundamental data suggests they should be (Gao, 2007).

The concept of market and investor sentiment is widely used today by many investors (Baker & Wurgler, 2007; Mian & Sankaraguruswamy, 2010). Investors have access to many surveys like the National Association of Active Investment Managers (NAAIM) and American Association of Individual Investors (AAII) reports that provide regular reports on investor and market sentiment (AAII, 2012; NAAIM, 2012). Sentiment surveys like these are used by investors to understand the other market participant's sentiment toward the market and economy as well as toward industries and sectors (Mian & Sankaraguruswamy, 2010).

Each investor uses the concept of sentiment differently. That said, there is a group of investors that use sentiment as a contrarian measure (G. W. Brown & Cliff, 2004; Dreman, 1998). For example, when a contrarian investor notices that sentiment is extremely negative, the investor may actually buy many more stocks than they normally would because they believe levels of extreme sentiment are predictors of changes to come in the market (G. W. Brown & Cliff, 2004).

Sentiment Analysis

Sentiment analysis, also called opinion mining in computer science literature, has become a popular research area for both academic researchers and industry practitioners (Pang & Lee, 2008). Sentiment analysis has its beginnings in research performed in subjectivity analysis and computational linguistics in the late twentieth century with research attempting to understand the use of language that shares opinions (Lui, 2010; Pang & Lee, 2008; Wiebe, 1994). This subjectivity analysis research formed a foundation for more automated forms of sentiment analysis by building a base of knowledge for automating the identification of opinion-laden words using natural language processing techniques (Dave, Lawrence, & Pennock, 2003).

The use of natural language processing for automated sentiment analysis has seen a growth in popularity in recent years with researchers studying sentiment analysis techniques (Abbasi, Chen, & Salem, 2008; Boiy & Moens, 2009; Choi, Kim, & Myaeng, 2009; Narayanan, Liu, & Choudhary, 2009) and the application of those techniques to various domains including movie reviews (Pang et al., 2002), general opinion mining (Hui & Gregory, 2010; Hursman, 2010; Romero, Meeder, & Klienberg, 2010) and even attempts to predict the movement of the stock market (Antweiler & Frank, 2004; Bollen et al., 2010; Chua, Milosavljevic, & Curran, 2009; Sprenger & Welpe, 2010).

The growth of sentiment analysis has been assisted by the general availability of large datasets for analysis as well as the ability to apply inexpensive computing technology for analyzing these datasets (Choi et al., 2009; Pang & Lee, 2008). This growth has led to a wide variety of natural language processing techniques for automated sentiment analysis (Pang & Lee, 2008).

While computational power and the availability of datasets have led to more interest in the field, there are some basic factors, namely proper keyword selection and training dataset development, found in sentiment analysis that have not been solved by utilization of computational power (Choi et al., 2009; Consoli, 2009; Lui, 2010). The selection of keywords for use in training datasets for automated sentiment analysis is one of the most difficult and time consuming aspects of building a sentiment analysis tool and can lead to incorrect results if not approached in a scientific manner (Lui, 2010; Narayanan et al., 2009; Wei, Chen, & Yang, 2010). While difficult and time-consuming, if care is taken, keyword selection for training dataset can be performed in a manner that creates very accurate analysis outcomes (Boiy & Moens, 2009; Pang & Lee, 2008).

For the purposes of this study, the Naïve Bayesian Classification technique was selected for its simplicity, high accuracy ratings when used with good training datasets, wide adoption, ease of implementation and visibility into the classification process (Durant & Smith, 2006; Frank & Bouckaert, 2006; Lin et al., 2010). Additionally, previous research using sentiment analysis techniques applied to the financial markets have used the Naïve Bayesian Classification method (Antweiler & Frank, 2004; Sprenger & Welpe, 2010). This study uses a similar approach to allow for ease of comparison between the studies.

Naïve Bayesian Classification performs text and sentiment classification by assigning probabilities to text based on the conditional probability of the words in that text occurring in a document that is classified as a member of a particular class (Lewis, 1998; Lin et al., 2010). The conditional probabilities found in this approach are calculated with the use of a training dataset created that contains manually classified documents, texts or keywords (Lin et al., 2010). This training dataset is then used to compare unclassified texts and documents and a probability is determined for these unclassified texts which is then assigned to one of the classifications held within the training dataset (Frank & Bouckaert, 2006; Lin et al., 2010). While Naïve Bayesian Classification is widely used and straightforward to setup, it is highly reliant on a well-developed and codified training dataset (Frank & Bouckaert, 2006; Lin et al., 2010).

There are a number of software implementations of the Naïve Bayesian Classification method (Frank & Bouckaert, 2006; Go, Bhayani, & Huang, 2009). The implementation used within this research is the Natural Language Toolkit (NLTK) for the Python programming language (Loper & Bird, 2002). This toolkit is a faithful representation of the Naïve Bayesian Classifier and is widely used within academic and industry research and was chosen for its straightforward implementation using the Python programming language (Bird, Klein, & Loper, 2009; Robinson, Aumann, & Bird, 2007).

Sentiment and Social Network Analysis to the Financial Markets

The use of sentiment analysis for determination of sentiment and opinion as it is applied to the financial markets is a key component of this research project. As mentioned previously, Keynes (1936) popularized the idea of sentiment with the beauty contest analogy. Both academic and market practitioners have developed models based on investor and market sentiment (Baker & Wurgler, 2007; Barberis, Shleifer, & Vishny, 1998; Otoo, 1999). In the past, many sentiment measures have been gathered and calculated on a longer time frame using surveys of investors, brokers and other market participants (AAII, 2012; NAAIM, 2012). In recent years, there have been attempts at collecting investor sentiment in shorter time frames and taking near term action based on these sentiment measures (G. W. Brown & Cliff, 2004; Das & Chen, 2007; Zhang, 2009).

Wysoki (1998) conducted a research project that studied stock message boards for over 3,000 stocks to determine if there were significant correlations between discussion board message volume and volume and price changes for each stock. A key contribution of this research shows a strong positive correlation between the volume of Tweets posted on the discussion boards during the hours that the stock market is closed (between 4:01 PM and 8:29 AM weekdays) and the next trading day's volume and stock returns. The researchers report that a tenfold increase in message postings in the overnight hours led to an average increase in the next day's stock grade volume of approximately 15.6% and a 0.7% increase in next day stock returns (Wysocki, 1998).

Tumarkin and Whitelaw (2001) conducted a study that researched how Internet stock forum postings could be used to predict stock returns or stock trading volume. For this project, the researchers used a popular website called Raging Bull (RagingBull.com) and studied Internet Service companies to analyze the messages posted for specific companies to determine if any predictive features could be found from the volume of messages on the discussion boards as well as from a rudimentary sentiment analysis of messages posted. They arrived at the conclusion that there are no predictive capabilities found within message board activity (Tumarkin & Whitelaw, 2001).

In a similar research project, Antweiler and Frank (2004) studied how messages posted on stock-related Internet message boards are related to movements in the stock market. The researchers examined approximately 1.5 million messages posted on two message boards for 45 companies that make up the Dow Jones Industrial Average Index and the Dow Jones Internet Index. They performed text classification and sentiment analysis to understand the sentiment of each message. The researchers were able to show a strongly positive correlation between message board posts, trading volume, trading volatility and a minor correlation between message board posts and price activity on the following day (Antweiler & Frank, 2004).

Das and Chen (2007) added to the previous research in the field by investigating a more formal approach to the use of sentiment analysis techniques when applied to internet stock message boards. Previous research used either manual classification techniques or simple text classification algorithms to assign a ‘buy’, ‘sell’ or ‘hold/neutral’ signal to messages. While these approaches delivered acceptable results, the researchers set out to find a more automated and more robust classification techniques to classify message as ‘bullish’, ‘bearish’ or ‘neutral’. While the classification technique is worth further study, a key contribution from this study is that there appears to be no significant correlation between sentiment and individual stock price movements but there is a reported positive correlation of the aggregate sentiment of a set of aggregate stocks (Das & Chen, 2007).

Research by Gu, et al. (2006) and Zhang (2009) took a slightly different approach to the study of stock message boards by focusing on the reputation of the message poster rather than purely on the message sentiment or message volume. Both studies show that measuring the reputation of the message poster and then using that reputation to determine whether the poster’s comments should be followed or included in any formulas or algorithms utilizing sentiment to make stock trading decisions resulted in more accurate models (Gu et al., 2006; Zhang, 2009).

While previous research used stock message discussion boards on Yahoo or Raging Bull, there have been recent attempts to use other forms of media like blogs, Twitter and other social media outlets to determine sentiment of a stock, sector and/or the market as a whole. For example, O'Hare et al. (2009) used sentiment analysis techniques to classify text within financial blogs. Bollen, Mao and Zeng (2010) have conducted a study using sentiment analysis of Tweets to determine public mood and Sprenger and Welpe (2010) use sentiment analysis of Tweets to determine sentiment towards individual stocks. The methodology used by Bollen et al. (2010) and Sprenger and Welpe (2010) will be applied to the proposed research.

The approach taken in this study focuses on the shorter time frames and uses real-time collection techniques to collect, analyze and determine sentiment for the market, sectors and individual stocks using publicly available Tweets sent by users across the social networking website Twitter. Twitter, one of the most popular Social Network websites today has grown from its founding in 2006 to over 140 million users and handles over 340 million Tweets sent per day (Twitter, 2012b). This rapid growth and quick adoption by users has allowed Twitter to move into the general lexicon of modern society.

The basic premise behind Twitter is to provide a service that allows users to share information across a wide network using short messages of 140 characters or less (Twitter, 2012a). The origination of Twitter began as a short messaging service (SMS) system for the Internet, which explains why there is a 140-character limit on each message. The system soon quickly grew from an SMS replacement to one of the most important and active social networking platforms in use today (Sagolla, 2009).

While the use of the Twitter service is quite simple and straightforward, many users have built complex relationships, communities and businesses on top of the Twitter service. One community that has taken advantage of the Twitter platform is a community of investors and traders that use Twitter to share investing ideas, trade outcomes and other pertinent information. In 2008, a few entrepreneurs, sensing the value of Twitter for investors, started a company called StockTwits with the goal of creating a socially driven reporting and communication platform for the financial and stock market community and has grown to over 150,000 users (Stocktwits, 2011). The StockTwits platform is built to run on top of the Twitter platform, which allows any user on StockTwits.com to see content shared on Twitter and vice versa. This integration with Twitter, the relatively large user base and the development of the StockTwits platform has created a widespread community built around the stock market.

In addition to sending a message via Twitter, referred to as sending a Tweet, users can resend another user's Tweet, which is called a ReTweet and denoted by the acronym 'RT' on Twitter (Twitter, 2012a). Additional features available are the ability to search for other users and subscribe to their Tweets in order to be notified whenever these users send out Tweets. In addition, a Twitter user may search for previously sent Tweets and subscribe to their search results so that any future Tweets that are sent which include the search term are displayed to the user. This act of subscribing to a user's Tweets or to search terms is called 'following' on the Twitter platform (Twitter, 2012a).

One key outcome of the StockTwits community development effort is the creation of the $TICKER nomenclature to allow users to communicate information regarding a company or stock by using the dollar sign ($) prepended to the stock symbol for a stock (Stocktwits, 2011). By using this nomenclature, it is quite easy to find other users that are discussing a particular stock. As an example, in order to mention Apple in a Tweet, a user would simply type '$AAPL' along with the rest of their content and their Tweet will be indexed by the StockTwits platform as well as be seen by any Twitter or StockTwits user 'following' Apple. If a user is interested in finding other users who are discussing Apple, they can do so by searching the Twitter or StockTwits platforms by typing '$AAPL' into the search engine. The search will return all Tweets with the term '$AAPL' in the Tweet.

Using the $TICKER nomenclature along with the Twitter Application Programming Interface (API), Tweets can be captured and stored in real-time and used in other applications or for other uses (Twitter, 2011b). The combination of the $TICKER nomenclature and the Twitter API provides methods for not only investors to use these Tweets, but also allows researchers to capture, store and analyze Tweets for research. For the purposes of this study, Tweets will be collected and stored for future analysis using an analysis technique called sentiment analysis.

It has been shown that Tweets can be analyzed for sentiment using various analysis techniques (Bifet & Frank, 2010; Go et al., 2009; Pak & Paroubek, 2010; Thelwall, Buckley, & Paltoglou, 2011). In addition, further research has reported that sentiment analysis of

Tweets does provide value for stock market decisions (Bollen et al., 2010; Sprenger & Welpe, 2010; Zhang, 2009).

Bollen et al. (2010) reported on the use of sentiment analysis of a large corpus of Tweets to determine the 'mood' of the Twitter population on a given day. This 'mood' is then used as an input into a neural network prediction engine to predict the movement of the stock market on the following day with a reported 87.6% accuracy of prediction of the Dow Jones Industrial Average (Bollen et al., 2010). While this research project shows a correlation between sentiment gathered via Twitter and market movements, the researchers used massive amounts of data from the Twitter population as a whole in an attempt to understand the overall sentiment of the Twitter population, rather than the sentiment of the population specifically directed toward the stock market.

Sprenger and Welpe (2010) have taken a more focused approach than previous researchers by concentrating on the Standard & Poor's top 100 stocks, known as the S&P 100, and gathered Tweets corresponding to these companies to study whether the sentiment of a company expressed on Twitter had any correlation to the movement in price, volume or a combination of both. The researchers took an approach to attempt to reduce the large amount of non-relevant Tweets on Twitter by using a dollar symbol ('$') to precede the stock market symbol, which has been popularized by the Stocktwits.com website. This nomenclature allowed the researchers to focus on Tweets that had been created and shared by only those people with an interest in the stock market. The outcome of the research shows that the sentiment of a company on Twitter closely follows market movements and that Tweet volume is positively correlated to the trading volume for that stock (Sprenger & Welpe, 2010).

Vu, Chang, Ha and Collier (2012b) report results that highlight the use of Twitter sentiment to predict daily movements of Google, Apple, Microsoft and Amazon stocks. In this study, Tweets are captured that mention a keywords that are connected with each company and then use these Tweets to determine sentiment which is then used to predict next day movements in each stock using sentiment classification methods (Vu et al., 2012b). The outcome of the study shows an accurate prediction capability with ranging from 69.23% to 84.62% accuracy in predicting daily up and down movements (Vu et al., 2012b). A downside to this research is that the study collected Tweets over a 41-day period which could present issues as these particular days might have fallen in the middle of an up-trending or down-trending market, which might skew the prediction results (Vu et al., 2012b).

Recent research by Saavedra, Hagerty and Uzzi (2011) take a slightly different approach than previous researchers. Rather than focus on forums, blogs and social media activities, the researchers have reviewed the activity and outcomes of traders that use instant messaging software to communicate in near real-time. The researchers found that many traders were communicating throughout the day with other traders and would, at times, find a level of synchronicity and begin trading similar stocks and similar patterns (Saavedra et al., 2011). While instant messaging between professional traders is slightly different than Tweets amongst both professionals and amateurs, there might be similarities. The use of Twitter may provide a method for traders to become 'synchronized' in their trading, possibly having an effect on price or volume of financial instruments being discussed (Saavedra et al., 2011).

Chapter Summary

Combining sentiment analysis and social network analysis with a broad theoretical foundation based in behavioral finance and the Adaptive Market Hypothesis, this study attempted to find investing strategies, using sentiment analysis, that were profitable and repeatable across multiple symbols and sectors. This study used theoretical foundations from economics, finance, the stock market, computer science, natural language processing and social networking to understand if user generated content on Twitter can be analyzed to determine if sentiment exists and, if so, use that sentiment as a means for providing signals for investing decisions.

Utilizing research in the aforementioned areas, Tweets were captured and analyzed using Naive Bayesian classification methods to determine sentiment contained within the Tweets. This sentiment could then be used as input into various investing strategies as signals for entry or exit criteria. Additionally, an analysis of the users who sent the Tweets captured during this study, an analysis as performed to understand if there are Twitter users who exert more influence when compared with others.

CHAPTER 3: RESEARCH METHODOLOGY

The purpose of this study was to investigate the use of automated analysis methods to determine sentiment from Tweets and determine if any inherent predictive capabilities exist. Additionally, this study analyzed Tweet volume to determine if any correlation exists between Tweet volumes, stock market volume and stock market price movements. Lastly, an analysis of a Twitter user's reputation was conducted to understand if there are any methods that might improve the accuracy of predictions for stock price movement. The outcomes of this study were used to try to help shed light on the following:

- To determine if the Twitter sentiment of a sector affects or responds to the Twitter sentiment of the stocks that make up that sector.
- To determine whether there are times of day or days of the week that provides more useful sentiment information for a stock or sector.
- To determine how users and groups of users impact the movement of specific stocks or financial instruments.
- To determine whether a stock or sector's sentiment has predictive capabilities for price or volume action.

Research Design

To conduct this research, it was necessary to have access to the Twitter 'stream' in order to access, download and store Tweets pertaining to the sectors and companies that were studied. Twitter provides an application programming interface (API) that can be used to access many aspects of the Twitter system, including user information and individual Tweets along with timestamps for those Tweets (Twitter, 2011a). The "track" method of the Twitter Streaming API was implemented to track stock symbols for the sectors and companies that were studied (Twitter, 2011a).

For this research project, a select number of companies within a given sector were tracked and studied to gauge sentiment. Rather than determine sentiment of the larger Twitter universe, this research is more interested in the sentiment of active investors and how these investors share this sentiment on Twitter. Therefore, taking an approach similar to Sprenger and Welpe (2010), only Tweets that use the "$" nomenclature made popular by the Stocktwits.com website and widely used within the Twitter investing and trading community were tracked. For example, in order to track Apple's stock symbol on Twitter, a "$" would be added to Apple's stock symbol, AAPL, to get $AAPL, which would be used to track Apple on Twitter.

Once Tweets were collected and stored, sentiment classification was performed using the Naïve Bayesian text classification algorithm found within the Natural Language Toolkit (Bird et al., 2009). The Naïve Bayesian text classification algorithm is a fairly simplistic but powerful approach to learning what particular words mean within the context of a dataset (Bird et al., 2009; Sprenger & Welpe, 2010). In order to use this algorithm, a training dataset of Tweets was developed consisting of randomly selected Tweets that have been captured. These Tweets were then manually classified into categories and used to train the Naïve Bayesian filter. After developing the training dataset, each Tweet was then analyzed for sentiment, which was then stored for use in future analysis.

In addition to the Tweet itself, the Twitter API also allowed for the capture of the time/date stamp for a Tweet, the sender of the Tweet and whether that Tweet was an 'original' Tweet or a 'ReTweet' from another user (Twitter, 2011a). By studying the timeline of Tweets an analysis was performed to determine whether the time of day a Tweet is sent has any effect on sentiment and whether there are any days of the week or month that provide more positive or negative correlation with the movement in the stock market. Lastly, an analysis of the person who sent each Tweet was conducted to determine whether the number of followers of a user has any correlation to how that user's Tweet(s) influence the sentiment of a sector or stock mentioned in the Tweet.

Another aspect of this study is the review of a Twitter user's reputation and an analysis of whether reputation might indicate more accurate predictions. This reputation analysis was accomplished using another aspect of the Twitter API that provides user information that can be downloaded and stored for analysis using various social network analysis tools (Smith et al., 2009).

Throughout this study, data collection and analysis were conducted using the Python programming language and a number of open-source modules for Python including SciPy, Pandas and the Natural Language Toolkit (Bird et al., 2009; Jones, Oliphant, Peterson, & others, 2001; McKinney, 2012; Rossum & Drake, 1991). Each of these modules are well regarded and often cited within academic literature and provide functionality for natural language processing, statistical analysis, data analysis and data manipulation (Bird et al., 2009; Jones, Oliphant, Peterson, & others, 2001; McKinney, 2012; Rossum & Drake, 1991)..

A central feature of this study concerned how sentiment might be used for predictions of movement in the stock market. Rather than build a market analysis platform from scratch to analyze market returns, Tradestation, an investing, analysis and strategy development platform, was used to analyze strategies and market performance (Tradestation, 2012). Using a platform like Tradestation allows the focus of this study to be on finding ways to use sentiment for prediction rather than on testing and building investment strategies from scratch.

Research Model

The method described in this chapter was designed to study publicly available Tweets and data regarding Twitter users to determine if useful aspects of these data points exist that can be used as inputs or filters for input into investing decisions. The research questions and hypotheses being considered and tested in this study are:

- **RQ-1**: Using a given sector of the stock market, does the sentiment for that sector match the aggregated sentiment for the stocks that make up that sector? How well does the sentiment predict price / volume movement?
  - **H1a**: The sentiment of a sector will match the overall averaged sentiment of all stocks within the sector. The null hypothesis (**H1a$_0$**) states that there will be no noticeable relationship between the sentiment of a sector and the overall averaged sentiment of stocks within the sector.
  - **H1b**: The sentiment of a sector can be used to predict the movement of all stocks in that sector. The null hypothesis (**H1b$_0$**) states that the sentiment of a sector will provide no predictive capability.
  - **H1c**: The sentiment of a sector or stock on any given day will provide a prediction for the next day's movement in that stock. The null hypothesis (**H1c$_0$**) states that there will be no predictive capability on price and sentiment from day to day.

- **RQ-2**: Are there specific stocks within a given sector that supply the majority of the sentiment for that sector? If so, do these stocks supply sentiment in correlation to the weighting give to them by ratings agencies such as the Standard & Poor's rating agency?
    - **H2a**: The sentiment of a stock within a given sector will affect the sentiment of the overall sector based on the relative market cap weighting of that stock assigned to that stock within the sector. The null hypothesis (**$H2a_0$**) states that the sentiment of a stock is not correlated with the market cap weighting of the stock in that sector.
    - **H2b**: The stocks that provide the most weight toward the sentiment of a sector are also the stocks with the highest number of mentions on Twitter. The null hypothesis (**$H2b_0$**) states that there is no relationship between the number of mentions on Twitter and the affect that the stocks have on the sector sentiment.
- **RQ-3**: Are there times of the day or days of the week that provide a more accurate and informative sentiment for a stock or sector?
    - **H3**: There is a difference in the effect that Tweets sent during non-market hours (i.e., evenings and weekends) and Tweets sent during market hours have on sentiment and price. The null hypothesis (**$H3_0$**) states that there is no difference in the effect of Tweets sent during market hours and non-market hours.
- **RQ-4**: Are there specific users that provide more ‘weight’ to a sentiment of a stock or sector based on the users’ reputation?
    - **H4**: The number of followers of a Twitter user determines the effect that users’ Tweets will have on sentiment for a stock or sector. The null hypothesis (**$H4_0$**) states that there is no relationship between the number of followers and sentiment on a stock or sector.

To address these questions, this study collected data from Twitter using the Twitter Application Programming Interface (API) and used automated sentiment analysis to determine whether these Tweets contain sentiment and, if so, how that sentiment might be used for investing decisions (Twitter, 2011a). Additionally, for each Tweet collected, information regarding the Twitter user was stored and analyzed on a per-user basis to determine if there are user reputation measures that might help to filter Tweets to improve investing decisions. A high level overview of this methodology used in this study is provided in Figure 3.1.

Twitter claims over 200 million users and over 400 million Tweets per day (Wickre, 2013). Rather than attempt to use the entire universe of Twitter users and the Tweets they generate, this study used a much smaller subset of Twitter users who have identified themselves as investors via the use of the StockTwits.com nomenclature of prepending the "$" with the stock symbol of a company (StockTwits.com, 2013). Of the 200 million Twitter users, roughly 0.1%, or 200,000, are members of StockTwits.com (StockTwits.com, 2013). This much smaller subset of users is the population used for this study as they are specifically discussing investing and trading ideas. This allowed the data collection and analysis aspects to be focused on Tweets that specifically mentioned markets and stocks.

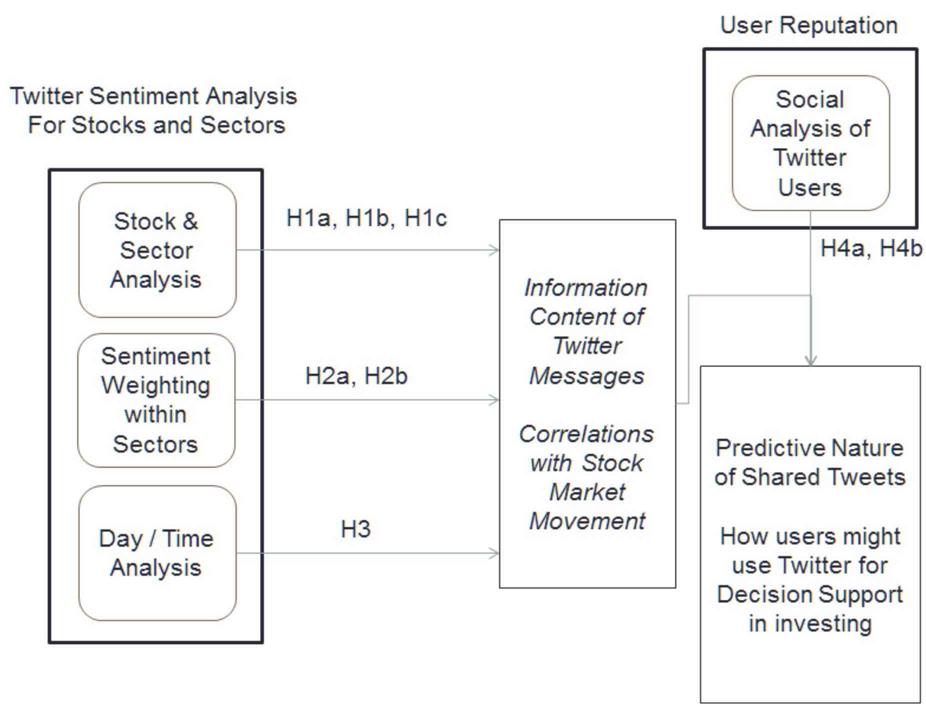

Figure 3.1: Research Model

Data Collection

For this study, the Twitter Application Programming Interface (API) was used to collect publicly available Tweets that use the StockTwits.com $TICKER nomenclature. The

Twitter API allows for capture of the Tweet, time and date of the Tweet and information about the user that sends the Tweet (Twitter, 2011a). Additionally, the Twitter API provides access to gather information about a Twitter user including number of followers, Twitter names of followers and other information that can be used to perform social network analysis on each Twitter user to determine reach, reputation and other social network measures (Twitter, 2011a).

For the purposes of this study, Tweets that contained references to three Exchange Traded Funds (ETF) and the stocks that make up these ETF's were captured. The Tweets containing references to the following ETF's were captured and analyzed in this study: S&P 500 ETF (SPY), the S&P Energy Sector ETF (XLE) and the S&P Consumer Staples ETF (XLP). Additionally, the stocks that make up the XLE and XLP sectors were captured and stored for analysis and comparison with the overall sector ETF. The list of stocks for each ETF is listed in Table 3.1.

Table 3.1

Listing of Sectors and Companies

Energy Sector ETF **Symbol: XLE**		**Consumer Staples Sector ETF** **Symbol: XLP**		**S&P 500 ETF** **Symbol: SPY**
$XLE	$NBL	$XLP	$AVP	Contains all stocks in the S&P 500 Index. A full list of all stocks in the S&P 500 ETF are shown in Appendix A.
$XOM	$MEE	$PG	$SLE	
$CVX	$VLO	$PM	$MJN	
$SLB	$CAM	$WMT	$CCE	
$COP	$MUR	$KO	$TAP	
$OXY	$FTI	$KFT	$CLX	
$APA	$CNX	$MO	$CAG	
$HAL	$SWN	$CVS	$HSY	
$APC	$DNR	$PEP	$EL	
$MRO	$NBR	$CL	$SWY	
$DVN	$RDC	$WAG	$MKC	
$BHI	$RRC	$COST	$BFB	
$NOV	$COG	$KMB	$TSN	
$EOG	$TSO	$GIS	$WFMI	
$HES	$SUN	$ADM	$CPB	
$CHK	$NE	$HNZ	$SJM	
$WMB	$NFX	$SYY	$DPS	
$PXD	$DO	$KR	$STZ	

Table 3.1

Listing of Sectors and Companies

$BTU	$EQT	$K	$HRL	
$SE	$QEP	$RAI	$SVU	
$EP	$HP	$LO	$DF	

When a Tweet that mentioned one of the above stocks or ETF's was found via the Twitter API, the Tweet, date and time the Tweet was sent and the user that sent the Tweet were all stored in a MySQL relational database. Starting on November 1, 2011, data collection was ongoing with few periods of downtime.

Previous studies addressing sentiment and the markets selected a small sampling of data to collect Tweets for comparison with market movements with some studies using data collected over short time-frames ranging from one month to a few months (Sprenger & Welpe, 2010; Vu, Chang, Ha, & Collier, 2012a). Unlike other studies, this study used a large Tweet dataset collected from January 1, 2012 to December 31, 2012. This twelve month period was selected to provide enough data to cover different market types which included a generally upward trending market with a considerable downward movement and choppy action throughout the year as show in Figure 3.2 (StockTwits.com, 2013). During the collection period, a total of 2,598,817 Tweets were collected from a total of 473,090 Twitter users.

In addition to collecting the Tweets, information about each Twitter user who's Tweets were captured were collected for further analysis. Using the Twitter API, data about the user including number of Tweets sent, number of followers, a listing of followers and other general information about the user were collected. This data was then stored in a MySQL relational database for further study.

The last piece of data that was collected for this study was the stock price data for the ETF's and the stocks that make up the ETF's. Rather than collect and store this data, data via a service that provides end-of-day stock market data. This service, called EODData, provided a benefit of using data that is widely accepted as valid and accurate (Hung, Lou, Wang, & Lee, 2013; Tapinos & Mendes, 2013). To access this data, an API call was made to the EODData service to download stock data for a particular stock symbol as needed during the analysis (EODData.com, 2012).

Figure 3.2: S&P 500 Price Chart from Jan 1 to Dec 31 2012

A visual representation of the research methodology used for this study was developed and may be seen in Figure 3.3. Descriptions of each portion of this research methodology are provided throughout this chapter of the study.

Data Analysis

In order to use the data collected to test the Hypotheses in this study, the data was analyzed to determine what useful information existed. To perform the necessary analysis, the Python programming language combined with data analysis modules like SciPy, pandas and the Natural Language Toolkit (NLTK) were used this study (Bird et al., 2009; Jones et al., 2001; Rossum & Drake, 1991). Using these widely utilized language and modules provided the ability to focus on testing the Hypotheses rather than developing new tools and methods for analysis.

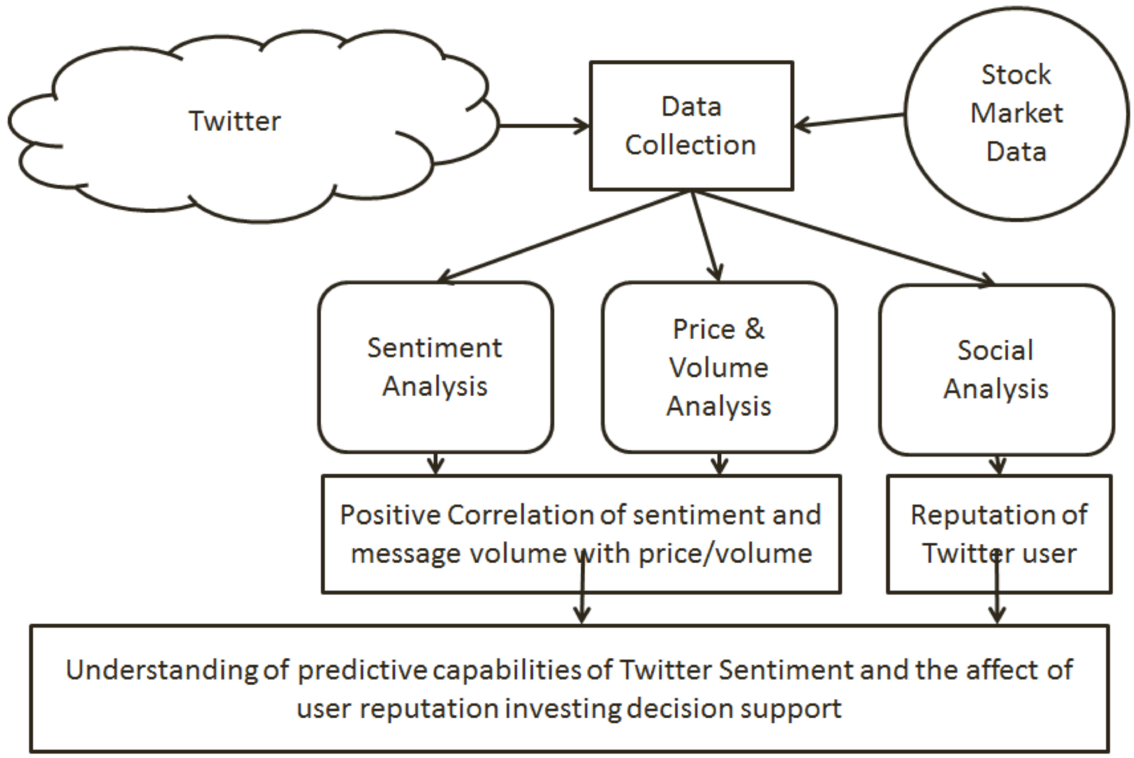

Figure 3.3: Research Methodology

Four main forms of analysis were performed within this study: Sentiment Analysis, Social Network Analysis, Hypothesis Testing and Analysis and, finally, Investment Strategy Performance Analysis. Each form of analysis is described in detail in the following sections.

Sentiment Analysis

In order to convert Tweets into useful information, these Tweets were analyzed to determine whether they contained any form of opinion or sentiment. This was accomplished using natural language processing methods to determine whether sentiment existed and, if so, whether the sentiment was positive, negative or neutral related to the market.

Sentiment Analysis was accomplished using Naive Bayesian Classification methods. This approach was used due to the fact that it is widely regarded as an accurate and fast classification method (Lewis, 1998; Lin et al., 2010). Additionally, implementations of the Naive Bayesian Classification methodology are widely available in both commercial and open source software.

Using the implementation of the Naive Bayesian Classification method found within the Python Natural Language Toolkit (2002), Tweets were analyzed for sentiment. Prior to performing sentiment analysis, a categorization scheme was developed. For the purposes of this study, the classification scheme consisted of two categories that denote positive and negative sentiment, a category for those Tweets that do not convey sentiment and a category for Tweets that were considered of no value. The four categories used in this study were based on market nomenclature that conveys positive, negative and neutral sentiment as well as a category for those 'no value' Tweets. The categories are:

- **Bullish** for those Tweets that denote a positive sentiment.
- **Bearish** for those Tweets that denote a negative sentiment.
- **Neutral** for those Tweets that do not convey any discernible sentiment.
- **Spam** for those Tweets that aren't delivering market information.

With the above classification scheme in place, a data set was developed in order to train the Bayesian Classifier. This data set, called the training data set, was created by randomly selecting a finite number of Tweets from the overall data-set and then manually codifying the selected Tweets using the above scheme.

To create the training data set, 10,000 Tweets were randomly selected from the collected Tweets and stored in a MySQL table. Each Tweet was then input into a script to remove Twitter user names, Twitter hash-tags and stock symbols to ensure only content that contains sentiment remained. Each Tweet was manually reviewed and assigned a category of Bullish, Bearish, Neutral or Spam and these classifications were then stored into another MySQL table to be used to create the final training data set. A sample of Tweets from the training data set is found in Table 3.2.

This manual codification process resulted in 1,013 Bullish Tweets, 1,001 Bearish Tweets, 6,941 Neutral Tweets and 1,045 Tweets categorized as Spam. The results of this classification work show that only a small number of Tweets collected actually provide some measure of sentiment with roughly 20% of all Tweets collected providing sentiment

Table 3.2

Training Dataset Samples

Bullish • consumer staples outperforming the broader market, expect this to continue • apple numbers are out! a monster blowout!
Bearish • if dexia doesnt get a bailout, markets will plunge%+ in a session, it is a lot bigger than lehman ever was. • if the charts werent broken before, they are now
Neutral • what to expect from the big google music announcement tomorrow • who needs those rating agencies anyways, we have jp morgan.
Spam • unlimited free tv shows on your pc, free channels • I always look like a new man after a haircut. SWAG

Once the training Tweets were manually codified, a sample of Tweets was taken and used as the Naive Bayesian Classification training data set. To ensure equal weighting for the classification algorithm, 1,000 Tweets from each classification was selected for the training data set. These Tweets were then converted into the format required by the Natural Language Toolkit. Prior to using the training data set for classification of the remaining Tweets, an analysis was performed to understand the accuracy of the Bayesian Classification method using the training data set. The NLTK provides an easy accuracy test by using the training dataset as both the training set and the classification set.

For the training data set used in this study, the accuracy rating was 89.35%. This accuracy is considered quite good when compared to other studies using Naive Bayes methods and other classification methods which usually find accuracies in the range of 85% to 92% (Androutsopoulos, Koutsias, Chandrinos, Paliouras, & Spyropoulos, 2000; Dumais, Platt, Heckerman, & Sahami, 1998).

A process map for the sentiment analysis portion for this study is shown in Figure 3.4. This process map highlights the collection, storage and classification steps required for the sentiment analysis aspect of this study.

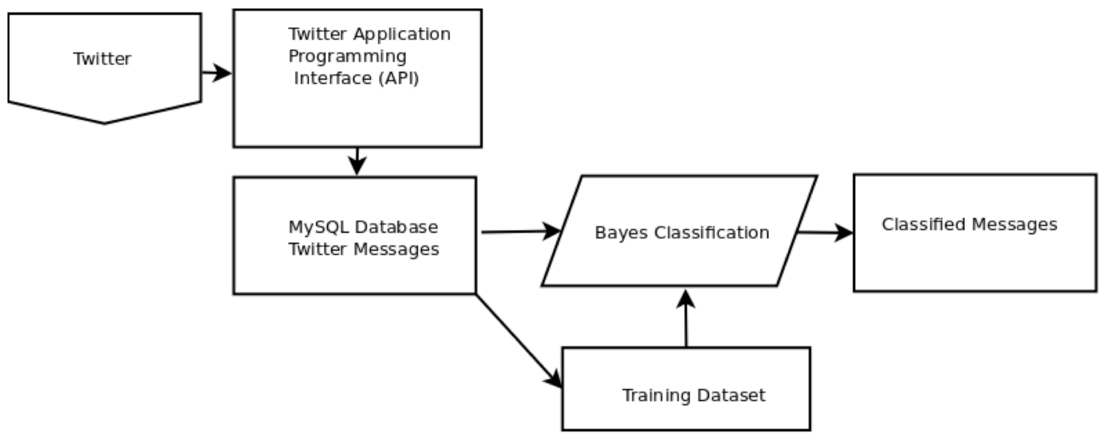

Figure 3.4: Sentiment Analysis Process

With the training data-set created and ready for use, each Tweet collected via the Twitter API was then run through the NLTK's Bayesian Classifier. Each Tweet was assigned a category of bullish, bearish, neutral or spam based on the probabilities of the features within the Tweets belonging to one of the categories. The classification for each Tweet was then stored in a MySQL table. For the purposes of this study, each Tweet had a numeric value assigned that corresponded to the category assigned to the Tweet. This mapping was performed to allow for summarization and statistical analysis. For reference, the mapping of numeric values and category can be seen in Table 3.3.

Table 3.3

Bayes Classification Mapping

Category	**Numeric Value**
Bullish	1
Bearish	-1

Table 3.3

Bayes Classification Mapping

Neutral	0
Spam	Discarded

Each Tweet was classified as bullish, bearish, neutral or spam and assigned a numeric value representing this classification, these Tweets were then summarized over a given time frame for analysis. For the purposes of this study, multiple time-frames including Daily, Weekly and Monthly time-frames were considered but the majority of research was conducted with the Daily time frame for the sake of completeness and to allow comparisons across the studies previously reported by other researchers (Bollen et al., 2010; Sprenger & Welpe, 2010).

In order to use the classified sentiment data as inputs into investment strategies, a measure of overall sentiment for a given time period needed to be created. For this study, a quantitative metric was developed that converts the large number of Tweets into a singular value that describes the overall sentiment for that time period. This metric, called the Bear/Bull Ratio can be calculated by looking at a particular time period and then taking a count of the number of Tweets with Bearish sentiment and a count of the number of Tweets with Bullish sentiment and then dividing the latter into the former. The general idea for the Bear/Bull Ratio was taken from the investing world's use of the Put/Call Ratio, which is considered a measurement of sentiment by measuring the buying and selling of Options. The Put/Call ratio is calculated by dividing the number of Puts traded by the number of Calls traded for a particular index or stock (Connors & Alvarez, 2012).

The Bear/Bull Ratio can be used to describe the overall sentiment for a symbol, sector or overall market using a single number. For the Bear/Bull Ratio, a value of 1.0 would equate to an equal number of Bearish and Bullish sentiment Tweets while a value greater than 1.0 would provide evidence that there are more Bearish Tweets during the measured time period. Conversely, a value less than 1.0 means that there are more Bullish Tweets than Bearish Tweets in a given time period.

Using the Bear/Bull Ratio provides a straightforward approach to converting Tweet sentiment into a numeric value that can then be used to compare with the stock market. In this numeric form, the Bear/Bull Ratio can then be used as an input into various investment strategies as a signal to buy or sell.

In addition to using the Bear/Bull Ratio as an input into investment strategies, various types of analysis can be performed on the ratio itself. For example, a moving average or exponential smoothing technique can be applied to the Bear/Bull Ratio to reduce the volatility of the signal, which might provide for cleaner measures of sentiment change. Additionally, other technical analysis methods might be applied to the Ratio to determine volatility or momentum values that might be used for decision-making purposes.

Twitter User Analysis & Social Network Analysis

The Twitter API provides access to user information such as number of followers, how many people the user is following, the identities of followers and much more data (Twitter, 2011a). Using the Twitter API and the identification of Twitter users who sent the previously captured Tweets, details about the users were captured and analyzed to better understand each user's Twitter network and social reach using standard social network analysis methods.

For the purposes of this study, social network analysis was used to gather data to be used to generate a measure of a user's reputation and social reach by building a user reputation model. This data was then to test H4 to understand whether Tweets from users with a higher reputation have a noticeable effect on sentiment. To build the user reputation model, the process seen in Figure 3.5 was used.

As part of the process of capturing Tweets, the user that sent each Tweet was captured and stored in the MySQL database along with each Tweet. A Python script was run against the database to provide a report, called the Tweet Number Report, to report on the number of times each user has sent a Tweet that has been captured and stored. The number of times each user's Tweets have been captured is used as an input into the user reputation model.

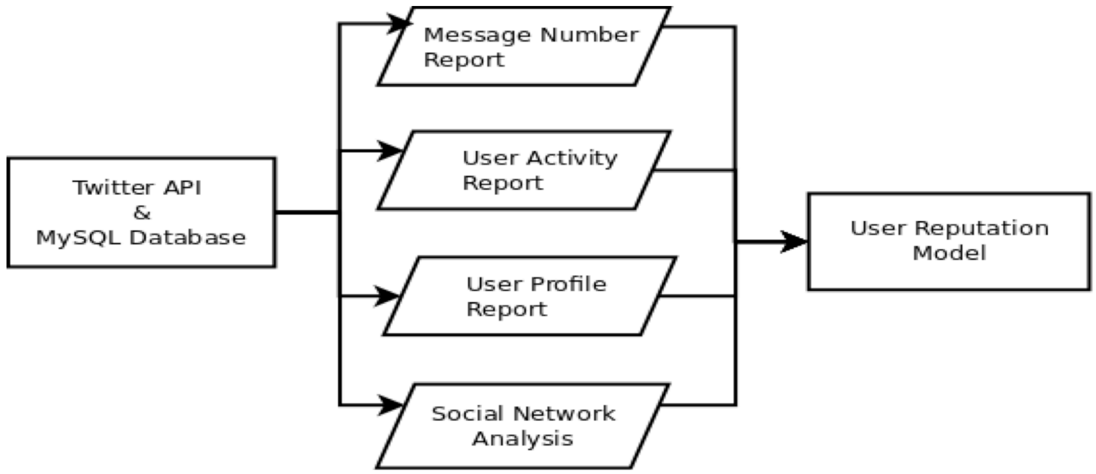

Figure 3.5 - User Reputation Modeling Process

Additionally, the Tweet Number Report was used as input into another Python script that searched through all captured Tweets to find any ReTweets or Tweets that mention the user. This second report, called the User Activity Report, is then used as input into the user reputation model. Lastly, using the Tweet Number Report, a call is made to the Twitter API for each user in the report to capture the number of followers and other user profile information and social network provided via the API. This user profile data is stored as a User Profile report and is the final input into the user reputation model.

Hypothesis Testing and Analysis

In order to test the hypotheses presented in this study, statistical analysis methods were used to understand any correlation between sentiment and the market. Descriptive statistics were used to understand the overall statistical arrangement of the data and these statistics are presented in summary tables in later chapters. Additionally, correlational analyses were performed to determine if correlation between sentiment and price and between Tweet volume and market volume exists. These correlation studies were repeated with and without user reputation filters in place to understand whether user reputation improves accuracy of sentiment for predictions.

Regression modeling was used to address the relationships between sectors and stocks and how the sentiment of a sector might be affected by the sentiment of a particular stock. Additionally, using Python and the StatsModels Python package, models were built using

Linear Regression modeling techniques to understand if Twitter sentiment can be used to forecast price values in the near term (McKinney, Perktold, & Seabold, 2011).

Investment Strategy Analysis

The final piece of analysis for this study is related to the performance of any investment strategies that might be developed with the output of the sentiment and social network analysis. While developing novel investment strategies was outside the scope of this study, there is a need to understand the performance of any strategies that might use signals generated from this study.

To analyze strategy performance, Tradestation, a well-established and popular investing software platform, was used. Tradestation provides access to stock market data such as price, volume and other data, that can be used to test investment strategies (Tradestation, 2012) . Additionally, Tradestation provides access to a programming language, called EasyLanguage, which allows developers to build automated investment strategies and run reports on the performance of those strategies (Tradestation, 2013). Using Tradestation as the platform for analyzing investment strategies along with data generated from Twitter sentiment, the performance of these strategies was analyzed and compared to other strategies. For the purpose of this study, investment strategies using sentiment were compared to investment strategies described in Table 3.4.

In order to analyze performance of investment strategies, a few standard metrics were utilized. Many investors believe the most important aspect to any investment strategy is whether the strategy is profitable. While profitability is key, there are metrics to consider including risk, volatility, number of trades, costs of trading along with other metrics that are specific to particular types of investing (Feibel, 2003).

Table 3.4

Investment strategies for comparison

Strategy	**Description**
Buy and Hold	With this strategy, an investment is made in a stock on a given date and that investment is held for a finite period of time. Decisions to invest could be based on fundamental, technical or

Table 3.4 *Investment strategies for comparison*	
	other reasons.
Random Entry	Using a random number generator, a random signal is generated and used as an entry signal using the same methods as used with the Twitter Sentiment strategies. This approach is used as a means to test whether Twitter Sentiment signals (or any signal) are really any better than a random entry into the market.

For the purposes of this study, the metrics described in Table 3.5 were used to determine performance of all investment strategies. The metrics used were selected as a means to understand how well investment strategies perform but also because they are well understood by most investors and traders. Additionally, these metrics are easily understood by non-investors as well, which gives the metrics additional value as they can be used to describe how well (or poorly) an investment strategy works in general terms.

Using the above performance metrics described above along with the comparative investment strategies, a few simple investment strategies using Twitter sentiment were built. These strategies are described in detail in the following section.

Investment Strategies – Initial Conditions

For both investment strategies used in this study, some underlying conditions were set to allow for ease of comparison across symbols, sectors and markets. For the purposes of this study, very straightforward investment strategies were used to ensure the initial conditions that will be used for all performance analysis metrics are provided in Table 3.6.

Investment Strategy – Sentiment Change

This strategy is based on the change in sentiment from one time period to the next. This change in sentiment was then used to make a prediction on price direction during the next time period. For example, if sentiment changes from an overall Bullish sentiment to an overall Bearish sentiment from Day 1 to Day 2, the prediction would be that market price action would move down the following day.

Table 3.5

Investment Strategy Performance Metrics

Strategy	**Description**
Total Net Profit	The Total Profit of the investment strategy expressed in Dollars.
Return on Initial Capital (ROIC)	A measure of the return provided by the investment strategy in percentage terms. ROIC = Total Net Profit / Initial Capital
Annual Rate of Return (ARR)	The return of all trades based expressed in annualized terms.
Profit Factor	A ratio of the amount gained divided by the amount lost. A higher positive value normally equates to a better performing strategy. PF = Total Gain / Total Loss
Number of Trades	A count of the total number of trades taken by the strategy.
Percent Profitable	The percentage of trades that were profitable
Buy and Hold Return	Measures the return of an investment made at the beginning of the analysis period and held throughout the period. Express in percentage terms.
Versus Buy and Hold Return	A measure of how much better or worse a strategy does than a simple buy and hold strategy.
Trading Period	The length of time used in the analysis

To test this strategy, a statistical analysis was performed to understand if any correlation exists between sentiment and price. If a correlation was found, analysis was then performed using regression techniques to determine if a model can be built for creating signals for market entry and exit.

Investment Strategy – Contrarian

This strategy is based on taking a contrarian approach to the market using Twitter sentiment. Using a contrarian strategy is taking the opposite trade that the overall market is taking or expecting to take (Dreman, 1998). For example, if Twitter sentiment a stock is Bearish, then investors on Twitter are expecting a down move in the stock price. Using the contrarian approach, an investor would buy this stock.

Table 3.6

Investment Strategy Initial Conditions

Initial Condition	**Value**	**Description**
Investing Time Frame	365 Days	January 1 2012 to December 31 2012
Period	Daily	Strategies were only tested on Daily time-frames
Initial Capital	$500,000	A starting value of $500,000.
Risk	3% of overall account = $15,000	For any investments made, a stop-loss of 3% or $15,000 was used to ensure proper risk management is in place
Stop Loss	Trailing Stop	Each strategy used a trailing stop equal to the Risk amount. A trailing stop is one that moves up as price moves up to lock-in gains.
Number of Shares	Maximum	Each trade taken was considered an “all-in” trade, meaning the strategy will use the entire account to buy the maximum number of shares possible.
Commissions	Standard commissions included.	Using industry standard commissions for stocks, futures and ETF's. Commissions are described whenever a strategy

Table 3.6
Investment Strategy Initial Conditions

		performance report is provided.
Slippage	Included	Slippage is the amount of movement seen in price before an order is filled. Slippage is used to simulate a real-world order and will be described whenever a strategy performance report is provided.

For the purposes of this study, a contrarian strategy using sentiment was created that uses the idea of an extreme value in sentiment. When sentiment reaches or exceeds an extreme value, a trade was made opposite the sentiment. For example, when a Bearish Extreme is reached, which means the majority of Twitter users are Bearish, the strategy will 'go long' – i.e., buy stock.

Chapter Summary

The purpose of this study was to investigate whether the outputs of automated methods for analyzing Twitter sentiment can be used as an input for a decision making process. Using sentiment analysis methods combined with social network analysis, statistical analysis was performed to understand whether correlations exist between Twitter sentiment and market price movements. Additionally, analysis of correlations between Tweet volume and stock volume was performed. After correlation studies were performed, modeling was undertaken to determine whether any models can be built using Twitter sentiment to determine if the price movements can be predicted based on sentiment values. The next chapter, Chapter Four, provides the results of the hypothesis testing, analysis and performance results found within this study.

CHAPTER 4: DATA COLLECTION, ANALYSIS AND FINDINGS

Data Collection

The Twitter Data for this study was collected using an Application Programming Interface (API) provided by Twitter. This API provides real-time access to all Tweets and allows programmers to capture each Tweet and store it into a database for later use (Twitter, 2011b). Data was collected from Jan 1, 2012 to Dec 31, 2012 using an automated collection system via the Twitter API. The collected Tweets were stored in a MySQL database for analysis. The fields captured, a description of each field and an example for each are provided in Table 4.1.

Table 4.1:

Fields Collected from Twitter API

Field Name	Data Type	Description	Example
id	Integer	The unique identifier given by Twitter for each Tweet.	153401189835350016
from_user	String	The unique Twitter username of the user sending the Tweet.	ericdbrown
from_user_id	Integer	The unique Twitter numeric identifier of the user sending the Tweet.	305339481
to_user_id	Integer	The unique Twitter numeric identifier of the user that from_user is sending a Tweet to.	312486342
text	String	The text of the Tweet.	Delta to buy ConocoPhillips refinery for $180 million | http://t.co/Jo0eYKQT $DAL $COP
created_at	DateTime	The Date and Time the Tweet is sent.	2012-01-01 09:04:28

The data collection script ran continuously from Jan 1, 2012 to Dec 31, 2012 and captured each Tweet made available via the Twitter API. While an attempt was made to capture every Tweet mentioning these symbols via the Twitter API, it is not known whether complete coverage and capture was performed. Some Tweets could have been missed due to the Twitter API availability or Internet connectivity issues, but a spot-check of Tweets captured versus Tweets available on Twitter shows that more than 98% of Tweets were captured.

Only Tweets that mentioned symbols found in the Energy Sector ETF (XLE), the Consumer Staples Sector ETF (XLP) and the Standard & Poor's (S&P) 500 Index ETF (SPY) were captured and analyzed. Additionally, Tweets mentioning the XLE, XLP and SPY ETF's were captured and stored for use in this study. For reference, a listing of these symbols is found in Table 3.1.

Using the Python programming language along with the pandas data manipulation and statistics module, descriptive statistics were generated and are shown for XLE, XLP and SPY in Tables 4.2, 4.3 and 4.4 respectively. A quick review of the descriptive statistics for XLE, XLP and SPY shows that, on average, there were not a large number of Tweets per symbol per day. Additionally, there were a relatively large number of Tweets captured for certain symbols when compared to the expected percentage of Tweets. For example, within the XLE sector the symbol $CHK received the most Tweets with 13.68% of Tweets while $CHK only makes up 1.7% of the index weight for XLE (SPDR, 2012).

The Python programming language along with the Natural Language Toolkit (NLTK) implementation of the Bayesian Classification and the pandas data manipulation module were used for sentiment analysis (Loper & Bird, 2002; Rossum & Drake, 1991). The standard implementation of the NLTK Bayesian Classifier was selected as it well regarded and well understood in both industry and academia (Androutsopoulos et al., 2000; Lin et al., 2010; Loper & Bird, 2002).

The NLTK's Naive Bayesian Classification algorithm was used to assign each Tweet a sentiment value, which was then analyzed further for correlation with the stock market. Well-known market nomenclature for market sentiment was used for positive and negative sentiment measures and four classes of sentiment ere used. These categories are: Bullish, Bearish, Neutral and Spam.

Table 4.2:
Descriptive statistics of collected Tweets for symbols in XLE

Start Date	January 1, 2012
End Date	December 30, 2012
Number of Symbols in XLE	42
Number of Days Tweets Captured	360
Number of Tweets	130,611
Number of Twitter Users	13,067
Average Tweets Per Day	362.81
Average Tweets Per User	9.99
Average Tweets Per Symbol	3,109.79
Average Tweets Per Symbol Per Day	8.64
Date with Most Tweets	May 2, 2012
User with Most Tweets	gasoilstocks
Number of Tweets from User with Most Tweets	8,707
Percentage of Tweets from User with Most Tweets	6.67%
Symbol Most Tweeted	CHK
Number of Tweets of Symbol Most Tweeted	17,873
Percentage of Total Tweets of Symbol Most Tweeted	13.68%

In order to use the NLTK Bayesian Classification algorithm, a training dataset was created. The training dataset used in this study was built by randomly selecting captured Tweets and manually categorizing each Tweet into one of the four sentiment classes of Bullish, Bearish, Neutral or Spam. This categorization process was performed to ensure rating and categorization of each Tweet was handled similarly. For this study, 1,000 Tweets were used for each of the Bullish, Bearish, Neutral or Spam classes.

Table 4.3:

Descriptive statistics of collected Tweets for all symbols in XLP

Start Date	January 1, 2012
End Date	December 30, 2012
Number of Symbols in XLP	42
Number of Days Tweets Captured	360
Number of Tweets	144,214
Number of Twitter Users	37,760
Average Tweets Per Day	400.59
Average Tweets Per User	3.82
Average Tweets Per Symbol	3,433.67
Average Tweets Per Symbol Per Day	9.54
Date with Most Tweets	December 6, 2012
User with Most Tweets	SeekingAlpha
Number of Tweets from User with Most Tweets	4,985
Percentage of Tweets from User with Most Tweets	3.46%
Symbol Most Tweeted	WAG
Number of Tweets of Symbol Most Tweeted	27,173
Percentage of Total Tweets of Symbol Most Tweeted	18.84%

A benefit of using the Python NLTK Bayesian Classification method comes from the self-testing functionality it provides to report on the accuracy of the classification system when using the training dataset (Loper & Bird, 2002). To measure the accuracy of a classifier's training dataset, the training dataset was used to train the classifier and then that training dataset was run through the classifier again. Running the accuracy method with the training dataset used in this study, the accuracy rating of 89.35% was returned. While there is very little reported in literature on what an acceptable accuracy rating should be, most research found using the NLTK classifier claims any accuracy over 75% is good and accuracies over 90% are considered excellent (Loper & Bird, 2002; Rajper, Vighio, Hussain, & Wagan).

Table 4.4:

Descriptive statistics of collected Tweets for all symbols in SPY

Start Date	January 1, 2012
End Date	December 30, 2012
Number of Symbols in SPY	500
Number of Days Tweets Captured	361
Number of Tweets	1,655,962
Number of Twitter Users	224,499
Average Tweets Per Day	4,587.15
Average Tweets Per User	7.38
Average Tweets Per Symbol	3,311.92
Average Tweets Per Symbol Per Day	9.17
Date with Most Tweets	December 5, 2012
User with Most Tweets	SeekingAlpha
Number of Tweets from User with Most Tweets	26,408
Percentage of Tweets from User with Most Tweets	1.59%
Symbol Most Tweeted	$AAPL
Number of Tweets of Symbol Most Tweeted	620,965
Percentage of Total Tweets of Symbol Most Tweeted	37.50%

With the accuracy of the classification system known and the training dataset developed, each Tweet was sent through the NLTK Bayesian Classification algorithm. A breakdown of the analyzed Tweets is provided for the symbols within the XLE, XLP and SPY

ETF's in Tables 4.5, 4.6 and 4.7 respectively. For those Tweets that are devoid of any information at all, no classification can possibly be made resulting in a very small number of Tweets with no classification.

Table 4.5:

Count of collected Tweet sentiment for all symbols in XLE

Number of Total Tweets	130,631	*Percentage*
Number of Bullish Tweets	45,883	35.12%
Number of Bearish Tweets	30,680	23.49%
Number of Neutral Tweets	50,886	38.95%
Number of Spam Tweets	3,482	2.67%
Number of Tweets with no classification	0	0

After analyzing each Tweet for sentiment, these qualitative measures were transformed into a quantitative index in order to automate analysis and decision-making. This index was created by counting the number of classified Tweets found within each time period and creating a ratio similar to the Put/Call Ratio that is commonly used within financial markets (Connors & Alvarez, 2012). The Put/Call Ratio is calculated by taking the number of Put Options, which are options that are generally Bearish in nature since they are expecting the market to go down, and then dividing the number of Call Options, which are options that are generally Bullish in nature since they are expecting the market to go up (Blynski & Faseruk, 2006; Connors & Alvarez, 2012).

Table 4.6:

Count of collected Tweet sentiment for all symbols in XLP

Number of Total Tweets	144,214	*Percentage*
Number of Bullish Tweets	32,315	22.41%
Number of Bearish Tweets	22,568	15.65%
Number of Neutral Tweets	60,572	42.00%
Number of Spam Tweets	28,757	19.94%

Table 4.6: *Count of collected Tweet sentiment for all symbols in XLP*		
Number of Tweets with no classification	2	0.001%

Using the Put/Call Ratio as a model, a ratio was created that uses Twitter sentiment values in the numerator and denominator. This ratio is created by dividing the number of Bearish Tweets by the number of Bullish Tweets to create the Bear/Bull Ratio. This ratio can then be used to provide a useful quantitative sentiment reading for a stock or sector. This ratio can also be used to analyze correlation between movements in sentiment and movements in the stock market.

Table 4.7: *Count of collected Tweet sentiment for all symbols in SPY*		
Number of Total Tweets	1,655,962	*Percentage*
Number of Bullish Tweets	310,371	18.74%
Number of Bearish Tweets	279,215	16.86%
Number of Neutral Tweets	972,429	58.72%
Number of Spam Tweets	93,943	5.67%
Number of Tweets with no classification	4	0.0002%

The Bear/Bull ratio does not have a particular scale, but generally, a ratio under 1.0 tends to be more bullish as the denominator is larger since there is more sentiment that is bullish. A ratio over 1.0 would point to more bearish sentiment since the numerator is larger due to more sentiment that is bearish.

During this study, only the daily time period was analyzed for Bear/Bull ratios and stock prices. An example of the Daily Sentiment Bear/Bull Ratio and closing price for the XLE ETF Symbol is shown in Table 4.8. For the closing price data in Table 4.8, EODData.com daily data was used (EODData.com, 2012). Additionally, all stock market price and volume data used throughout this study is from the EODData.com, a website that provides historical stock market data (EODData.com, 2012).

Table 4.8:

Example of Daily Bear/Bull Ratio and Closing Price for SPY ETF

Date	Number of Bearish Tweets	Number of Bullish Tweets	Bear/Bull Ratio	SPY Close
5/1/2012	181	197	0.92	136.95
5/2/2012	164	188	0.87	136.55
5/3/2012	181	184	0.98	135.5
5/4/2012	199	189	1.05	133.31

Data Analysis and Outcomes

With the data described at a high level, the research questions and hypotheses testing output can now be discussed. The remainder of this chapter is broken into four sections to correspond with the study's research questions. Each section is self-contained and addresses the research question and hypotheses associated with that question.

Before getting into the research questions and hypotheses, a more thorough look at the data set is required. While the XLE, XLP and SPY ETF's and the symbols making up those ETF's were all captured during the data collection phase, the XLE and XLP ETF's are used to answer the research questions in this study in order to reduce the number of symbols analyzed to a manageable number. A brief listing of some descriptive statistics of the XLE and XLP ETF's and the symbols that make up each ETF is provided in Table 4.9 and Table 4.10.

An item to note in the data is the low values for most symbols for “average Tweets per day.” Due to the low volumes of daily Tweets, it was necessary to consider methods of aggregating daily data into sector data or larger time frames like weekly or monthly data to make it more useful. During this study, aggregated sentiment signals were created to ensure enough Tweets existed each day to provide valid signals.

For the majority of symbols captured, the number of Spam Tweets were generally well below 10% with an average percentage Spam Tweets of 2.67% for XLE and the symbols within XLE but an average of 19.94% for XLP and the symbols that make up XLP. One symbol, $WAG, is a significant outlier from this average percentage with 82.85% of Tweets classified as Spam by the Bayesian Classification algorithm. Reviewing the classified Tweets for $WAG, it became clear that this classification is accurate as it appears many

Twitter users use “$WAG” in place of the word “SWAG”, which is a term used today in popular culture (Johnson & Vasudevan, 2012; Quora.com, 2012; Twitter.com, 2012).

Table 4.9:

Count of collected Tweet sentiment for all symbols in XLE

Symbol	# of Tweets	# of Bearish Tweets	# of Bullish Tweets	# of Neutral Tweets	# of Spam Tweets
$XLE	6645	2197	1541	2861	46
$ANR	3310	750	1425	1015	120
$APA	4089	717	1661	1459	252
$APC	2960	585	1297	925	153
$BHI	3357	524	2138	608	87
$BTU	7428	1595	3157	2507	169
$CAM	1500	272	706	375	147
$CHK	17873	3325	4573	9248	727
$CNX	2282	528	1210	506	38
$COG	2767	693	1097	930	47
$COP	7310	1595	2411	3024	280
$CVX	10751	3688	4309	2566	188
$DNR	1362	452	589	316	5
$DO	1589	210	744	477	158
$DVN	3666	757	1647	1190	72
$EOG	4310	1035	2340	910	25
$EP	1264	265	412	573	14
$EQT	1699	172	477	1041	9
$FTI	1075	406	419	235	15
$HAL	7197	1822	3282	1952	141
$HES	2447	589	875	919	64
$HP	2200	264	767	1054	115
$MPC	739	116	228	377	18
$MRO	2115	412	1038	615	50
$MUR	1491	482	439	541	29
$NBL	1516	381	715	414	6
$NBR	1909	712	688	473	36
$NE	1385	204	521	645	15
$NFX	1333	250	691	378	14
$NOV	2519	308	776	1407	28
$OXY	4306	847	1242	2150	67
$PXD	1810	310	922	551	27
$QEP	647	129	300	207	11
$RDC	1028	280	348	385	15
$RRC	2273	531	1012	706	24
$SE	1358	223	652	351	132

Table 4.9:

Count of collected Tweet sentiment for all symbols in XLE

$SLB	5660	1012	3067	1498	83
$SUN	1320	165	422	708	25
$SWN	2442	508	1112	782	40
$TSO	2491	649	877	926	39
$VLO	3140	689	1272	1122	57
$WMB	1583	281	846	425	31
$XOM	17570	5992	1937	9356	285
Total	**149071**	**34725**	**54641**	**55847**	**3858**

Table 4.10:

Count of collected Tweet sentiment for all symbols in XLP

Symbol	# of Tweets	# of Bearish Tweets	# of Bullish Tweets	# of Neutral Tweets	# of Spam Tweets
$XLP	2443	597	659	1174	13
$ADM	3258	950	484	438	1386
$AVP	3097	667	1107	1251	72
$BEAM	282	44	64	167	7
$BF.B	95	4	20	68	3
$CAG	1725	440	726	521	38
$CCE	1019	170	319	520	10
$CL	4057	656	803	2396	202
$CLX	1106	173	251	641	41
$COST	6131	699	1071	4153	208
$CPB	1438	212	797	406	23
$CVS	3995	925	941	2070	59
$DF	1861	563	692	529	77
$DPS	1056	151	580	307	18
$EL	1778	464	605	539	170
$GIS	2272	311	1367	537	57
$HNZ	2362	766	549	994	53
$HRL	653	178	222	228	25
$HSY	1245	323	369	488	65
$K	4071	522	679	1951	919
$KFT	4688	2169	982	1419	118
$KMB	1928	260	589	1012	67
$KO	11657	1718	1799	7723	417
$KR	1784	391	780	586	27
$LO	1618	460	327	632	199
$MJN	875	296	267	297	15

Table 4.10:

Count of collected Tweet sentiment for all symbols in XLP

$MKC	558	73	214	257	14
$MO	4005	532	640	2614	219
$PEP	6507	1382	1409	3421	295
$PG	8684	2151	1821	4397	315
$PM	3836	1139	800	1822	75
$RAI	1449	332	537	547	33
$SJM	954	150	267	503	34
$SLE	1312	323	743	234	12
$STZ	1271	259	537	438	37
$SVU	9161	857	1089	7121	94
$SWY	3085	606	949	1490	40
$SYY	1321	190	597	513	21
$TAP	1212	382	246	500	84
$TSN	1555	653	459	402	41
$WAG	27171	776	1311	2574	22510
$WFM	1560	298	367	849	46
$WMT	20461	1818	6643	10918	1082
Total	**158153**	**25433**	**35019**	**68473**	**29228**

An additional aspect of this study (found in Research Question 4) relates to the Twitter users who sent the Tweets captured during the data collection stage of this study. For each Tweet captured, the username and a unique Twitter identifier that describes the user who sent the Tweet was also captured. A brief analysis of the Tweets captured for the XLE and XLP ETF's and the symbols within those sectors finds that the majority of Tweets within each sector are sent by a small number of users. Table 4.11 and 4.12 provides an overview of the number of users captured and the amount of Tweet sent by those users.

Reviewing the data given in Tables 4.11 and 4.12 provides some insight into the number of users sending Tweets. For both sectors and the symbols within the sectors about 1.00% of users sent about 50% of the Tweets. Additionally, ranking the users by the number of Tweet allows the building of a top 50 users ranking list. This list highlights that a minority of users send a large number of the Tweets.

With the data set used in this study sufficiently described, the research questions and hypotheses can be presented and analysis. The remainder of this chapter is split into four sections corresponding to the four main research questions put forth for this study. In each section, the research question is provided and the hypotheses related to each question is provided and subsequently discussed.

Table 4.11:

Descriptive Statistics for users who sent Tweets mentioning XLE and all XLE Symbols

Number of Tweets	130,631	*Percentage*
Number of Users	13,067	
Number of Users Sending 80% of Tweets	1,072	8.20%
Number of Users Sending 50% of Tweets	143	1.09%
User with most Tweets	gasoilstocks	-
Number of Tweets Sent by Top User	8,707	6.67%
Number of Tweets Sent by Top 10 Users	27,621	21.14%
Number of Tweets Sent by Top 25 Users	35,890	27.47%
Number of Tweets Sent by Top 50 Users	45,507	34.84%

Table 4.12:

Descriptive Statistics for users who sent Tweets mentioning XLP and all XLP Symbols

Number of Tweets	144,214	*Percentage*
Number of Users	37,607	
Number of Users Sending 80% of Tweets	8,917	23.71%
Number of Users Sending 50% of Tweets	375	1.00%
User with most Tweets	SeekingAlpha	-
Number of Tweets Sent by Top User	4,940	3.43%
Number of Tweets Sent by Top 10 Users	21,642	15.01%
Number of Tweets Sent by Top 25 Users	29,232	20.27%
Number of Tweets Sent by Top 50 Users	38,045	26.38%

RESEARCH QUESTION 1

RQ-1: Using a given sector of the stock market, does the sentiment for that sector match the aggregated sentiment for the stocks that make up that sector? How well does the sentiment predict price / volume movement?

- **H1a**: The sentiment of a sector will match the overall averaged sentiment of all stocks within the sector. The null hypothesis (**H1a$_0$**) states that there will be no noticeable relationship between the sentiment of a sector and the overall averaged sentiment of stocks within the sector.
- **H1b**: The sentiment of a sector can be used to predict the movement of all stocks in that sector. The null hypothesis (**H1b$_0$**) states that the sentiment of a sector will provide no predictive capability.
- **H1c**: The sentiment of a sector or stock on any given day will provide a prediction for the next day's movement in that stock. The null hypothesis (**H1c$_0$**) states that there will be no predictive capability on price and sentiment from day to day.

To answer RQ-1, the Tweets for the XLE and XLP ETF's and the symbols contained within each sector were analyzed for sentiment and Bear/Bull ratios calculated for each symbol for each day from January 1, 2012 to December 30, 2012. Tables 4.13 and 4.14 display the descriptive statistics, the autocorrelation using the Bear/Bull ratio and a correlation study between the Bear/Bull ratio and the symbol's closing price for the XLE, XLP and the symbols within each sector.

Within each sector, there are symbols that have zero collected Tweets. For the XLE sector, SUN and EP show a count of zero. For the XLP sector KFT and SLE both have zero counts for Tweet volume. While this could be a simple matter of no Twitter users mentioning these symbols it might also be due to the fact that these organizations were acquired or removed from public trading. For those symbols with no data, the value 'nan' is displayed for the calculated values because there were no descriptive statistics available for these symbols. Additionally, when looking at the daily collected data, most symbols do not conform to the Central Limit Theorem requirement of having more than 30 observations in a given day.

A review of the number of days that each symbol was captured, identified in the "# Days" column, shows that the majority of symbols within the XLE and XLP ETF's, not every symbol is mentioned every day by Twitter users. For the two sectors, it appears that energy stocks listed in the XLE sector were mentioned on average 270 days and the XLE ETF was mentioned on 317 days while the average for the stocks in the XLP sector is around 222 days with the XLP ETF being mentioned on 244 days.

The “Correlation” column in Tables 4.13 and 4.14 displays the correlation between the daily Bear/Bull ratio and the daily closing price of each symbol. Reviewing each symbol shows little correlation between the daily Bear/Bull ratio and the daily closing price. For the XLE ETF and sector symbols, the symbol with the highest correlation is CHK with a correlation value of -0.288 with a p-value of 0.000 while for XLP and the sector symbols, the symbol with the highest correlation is ADM with a correlation of -0.329 and a p-value of 0.000. In comparison, the XLE ETF Bear/Bull ratio has a -0.133 correlation and p-value of 0.037 with its daily closing price while the XLP ETF Bear/Bull Ratio has a 0.166 correlation and p-value of 0.021with its daily closing price.

For each sector, there are several with significant sentiment and price correlations. These symbols are highlighted in Tables 4.13 and 4.14 with an asterisk (*) for those correlations that are significant to the 95% confidence level and with two asterisks (**) for those correlations that are significant to the 90% confidence level. While the 90% confidence level is displayed, only those symbols with a 95% confidence level were considered.

Table 4.13:

Descriptive Statistics for XLE and symbols making up the XLE Sector (95% Significance described by “” and 90% Significance by “**”)*

Symbol	# Days	Mean	Median	Std Dev.	Var.	Max	Min	Corr.	p-value	
ANR	240.000	0.572	0.357	0.695	0.482	3.000	0.000	0.078	0.229	
APA	250.000	0.587	0.372	0.844	0.713	9.000	0.000	-0.063	0.324	
APC	246.000	0.600	0.333	0.886	0.785	6.000	0.000	0.012	0.849	
BHI	248.000	0.294	0.143	0.504	0.254	4.000	0.000	-0.074	0.249	
BTU	256.000	0.593	0.400	0.672	0.452	6.000	0.000	-0.141	0.024	*
CAM	189.000	0.412	0.000	0.847	0.717	6.000	0.000	0.069	0.346	
CHK	257.000	0.769	0.633	0.599	0.359	4.000	0.000	-0.288	0.000	*
CNX	234.000	0.522	0.250	0.747	0.558	5.000	0.000	-0.017	0.796	
COG	215.000	0.794	0.400	1.108	1.227	7.000	0.000	-0.203	0.003	*
COP	252.000	0.859	0.633	0.848	0.719	7.000	0.000	-0.179	0.004	*
CVX	258.000	1.023	0.862	0.832	0.692	8.000	0.000	-0.131	0.035	*
DNR	172.000	0.804	0.367	1.072	1.150	6.000	0.000	-0.119	0.119	
DO	189.000	0.308	0.000	0.615	0.378	4.000	0.000	0.013	0.858	

Table 4.13:

Descriptive Statistics for XLE and symbols making up the XLE Sector (95% Significance described by "" and 90% Significance by "**")*

DVN	245.000	0.636	0.333	0.887	0.787	8.000	0.000	-0.129	0.043	*
EOG	252.000	0.549	0.392	0.672	0.451	6.000	0.000	0.013	0.841	
EP	0.000	nan	nan	nan	nan	nan	nan	nan	nan	
EQT	154.000	0.357	0.000	0.898	0.806	6.000	0.000	-0.253	0.002	*
FTI	126.000	0.666	0.367	0.877	0.770	4.000	0.000	0.036	0.690	
HAL	256.000	0.737	0.536	0.744	0.554	6.000	0.000	-0.104	0.097	**
HES	214.000	0.851	0.500	1.131	1.279	8.000	0.000	0.039	0.567	
HP	207.000	0.356	0.000	0.660	0.436	5.000	0.000	0.015	0.828	
MPC	107.000	0.353	0.000	0.626	0.392	3.000	0.000	-0.022	0.823	
MRO	227.000	0.528	0.200	0.824	0.679	5.000	0.000	0.051	0.441	
MUR	141.000	0.919	0.500	1.402	1.966	10.000	0.000	0.118	0.162	
NBL	195.000	0.546	0.222	0.856	0.733	6.000	0.000	0.071	0.326	
NBR	192.000	1.230	0.750	1.344	1.806	8.000	0.000	-0.071	0.326	
NE	159.000	0.384	0.000	0.834	0.695	5.000	0.000	-0.015	0.855	
NFX	189.000	0.366	0.000	0.704	0.496	5.000	0.000	0.148	0.042	*
NOV	201.000	0.470	0.000	1.018	1.037	7.000	0.000	0.134	0.058	**
OXY	235.000	0.884	0.571	0.998	0.997	6.000	0.000	-0.199	0.002	*
PXD	211.000	0.391	0.125	0.621	0.386	4.000	0.000	0.065	0.350	
QEP	128.000	0.319	0.000	0.637	0.406	3.000	0.000	0.121	0.175	
RDC	112.000	0.603	0.000	0.946	0.894	4.000	0.000	-0.057	0.554	
RRC	224.000	0.644	0.333	0.974	0.949	7.000	0.000	-0.017	0.806	
SE	181.000	0.430	0.000	1.019	1.039	10.000	0.000	0.102	0.173	
SLB	255.000	0.422	0.286	0.468	0.219	3.000	0.000	-0.022	0.724	
SUN	0.000	nan	nan	nan	nan	nan	nan	nan	nan	
SWN	230.000	0.699	0.250	1.277	1.630	10.000	0.000	-0.196	0.003	*
TSO	213.000	0.848	0.500	1.129	1.275	8.000	0.000	0.003	0.960	
VLO	238.000	0.722	0.500	0.883	0.779	5.000	0.000	-0.134	0.039	*
WMB	199.000	0.440	0.000	0.886	0.784	6.000	0.000	0.039	0.580	
XOM	252.000	4.348	3.125	3.649	13.314	23.000	0.667	-0.011	0.864	
XLE	247.000	1.866	1.273	2.089	4.363	14.000	0.000	-0.133	0.037	*

For the XLE sector, shown in Table 4.13, there are 12 symbols – BTU, CHK, COG, COP, CVX, DVN, EQT, NFX, OXY, SWN, VLO and XLE – that have significant correlations between the price and sentiment. For the XLP sector, shown in Table 4.14, there are 11 symbols – ADM, CCE, COST, GIS, K, KO, KR, STZ, WFM, WMT and XLP - – that have statistically significant correlations between the price and sentiment.

Table 4.14:

Descriptive Statistics for XLP and symbols making up the XLP Sector (95% Significance described by "" and 90% Significance by "**")*

Symbol	# Days	Mean	Median	Std Dev.	Var.	Max	Min	Corr.	p-value	
ADM	146.000	1.968	1.000	2.534	6.423	17.000	0.000	-0.329	0.000	*
AVP	184.000	0.680	0.333	0.989	0.978	5.000	0.000	-0.012	0.876	
BEAM	36.000	0.449	0.000	1.041	1.084	4.000	0.000	-0.112	0.514	
BF.B	9.000	0.222	0.000	0.441	0.194	1.000	0.000	0.516	0.155	
CAG	158.000	0.718	0.333	1.082	1.172	7.000	0.000	-0.136	0.088	**
CCE	107.000	0.419	0.000	0.911	0.829	6.000	0.000	-0.195	0.044	*
CL	199.000	1.092	0.625	1.479	2.187	10.000	0.000	-0.074	0.298	
CLX	111.000	0.493	0.000	0.893	0.797	5.000	0.000	0.014	0.885	
COST	212.000	0.787	0.477	1.159	1.343	8.000	0.000	0.156	0.023	*
CPB	174.000	0.331	0.000	0.862	0.743	7.000	0.000	-0.088	0.250	
CVS	200.000	1.286	0.971	1.446	2.091	9.000	0.000	-0.021	0.768	
DF	154.000	0.819	0.500	1.143	1.307	6.000	0.000	0.101	0.215	
DPS	179.000	0.326	0.000	0.678	0.460	4.000	0.000	-0.092	0.222	
EL	150.000	0.707	0.500	0.999	0.998	7.000	0.000	-0.085	0.299	
GIS	222.000	0.293	0.000	0.629	0.396	4.000	0.000	-0.211	0.002	*
HNZ	134.000	1.474	1.000	1.807	3.267	11.000	0.000	0.148	0.087	**
HRL	100.000	0.487	0.000	0.688	0.473	3.000	0.000	0.074	0.466	
HSY	122.000	0.887	0.450	1.360	1.850	8.000	0.000	0.076	0.404	
K	177.000	0.869	0.333	1.360	1.850	9.000	0.000	-0.151	0.046	*
KFT	0.000	nan	nan	nan	nan	nan	nan	nan	nan	
KMB	164.000	0.481	0.000	0.880	0.774	5.000	0.000	-0.041	0.602	
KO	238.000	1.465	1.000	1.588	2.522	11.000	0.000	-0.210	0.001	*
KR	183.000	0.570	0.250	0.787	0.619	5.000	0.000	-0.150	0.043	*
LO	128.000	1.023	0.586	1.462	2.138	11.000	0.000	-0.052	0.559	
MJN	89.000	0.708	0.400	1.006	1.013	5.000	0.000	-0.178	0.094	**
MKC	98.000	0.244	0.000	0.585	0.342	3.000	0.000	-0.050	0.623	
MO	182.000	0.922	0.500	1.289	1.661	9.000	0.000	0.065	0.385	
PEP	215.000	1.272	0.833	1.484	2.203	10.000	0.000	0.092	0.178	
PG	233.000	1.516	1.000	1.490	2.220	12.000	0.000	-0.062	0.349	
PM	190.000	1.824	1.000	2.154	4.641	15.000	0.000	0.030	0.677	
RAI	164.000	0.730	0.367	1.260	1.588	10.000	0.000	-0.094	0.229	
SJM	91.000	0.388	0.000	0.614	0.377	3.500	0.000	0.020	0.851	
SLE	0.000	nan	nan	nan	nan	nan	nan	nan	nan	
STZ	137.000	0.427	0.000	0.998	0.996	8.000	0.000	-0.220	0.010	*
SVU	194.000	0.947	0.613	1.200	1.439	9.000	0.000	-0.077	0.285	
SWY	186.000	0.733	0.400	1.117	1.248	6.000	0.000	-0.137	0.063	**
SYY	163.000	0.385	0.000	0.919	0.844	7.000	0.000	-0.139	0.078	**
TAP	90.000	0.981	0.278	2.010	4.038	15.000	0.000	-0.188	0.075	**
TSN	139.000	1.192	0.750	1.365	1.862	7.000	0.000	0.001	0.991	
WAG	224.000	0.833	0.500	1.097	1.204	7.000	0.000	-0.061	0.363	
WFM	141.000	0.631	0.200	0.932	0.869	5.000	0.000	0.180	0.032	*
WMT	251.000	0.328	0.250	0.356	0.127	3.000	0.000	0.136	0.032	*

Table 4.14:

Descriptive Statistics for XLP and symbols making up the XLP Sector (95% Significance described by "" and 90% Significance by "**")*

XLP	195.000	1.145	1.000	1.312	1.720	9.000	0.000	0.166	0.021	*

Before addressing RQ-1 and H1a, H1b and H1c directly, the correlation between the daily Bear/Bull ratio for the XLE and XLP ETF's and the symbols that make up each ETF was calculated. This was performed to get a better understanding of the correlations between each symbol and the sector ETF. These correlations are shown in Table 4.15 for XLE and the correlations for XLP are provided later in this section.

Table 4.15:

Daily Bear/Bull Correlations for XLE sentiment and sentiment of symbols making up the XLE Sector (95% Significance described by "" and 90% Significance by "**")*

Symbol	**Corr with XLE**	**p-value**	**Sig?**	**Symbol**	**Corr with XLE**	**p-value**	**Sig?**
ANR	-0.05	0.44		MPC	0.027	0.786	
APA	-0.06	0.353		MRO	0.084	0.205	
APC	0.032	0.621		MUR	0.019	0.826	
BHI	0.059	0.362		NBL	-0.098	0.175	
BTU	0.032	0.621		NBR	0.169	0.019	
CAM	-0.035	0.628		NE	-0.111	0.166	
CHK	0.039	0.553		NFX	-0.052	0.478	*
CNX	0.006	0.923		NOV	0.071	0.318	
COG	0.029	0.667		OXY	0.011	0.871	
COP	0.076	0.254		PXD	0.026	0.707	
CVX	0.136	0.04	*	QEP	0.021	0.812	
DNR	0.074	0.332		RDC	-0.112	0.238	
DO	-0.017	0.821		RRC	0.079	0.241	
DVN	-0.051	0.428		SE	0.064	0.389	
EOG	-0.038	0.56		SLB	-0.007	0.918	
EP	nan	nan		SUN	nan	nan	
EQT	-0.039	0.628		SWN	0.082	0.218	
FTI	-0.049	0.584		TSO	-0.073	0.286	
HAL	-0.009	0.889		VLO	0.132	0.043	*
HES	-0.087	0.206		WMB	-0.064	0.37	
HP	-0.033	0.639		XOM	-0.002	0.978	

Reviewing the correlations between XLE and each symbol that makes up the sector, there is very little correlation between the daily Bear/Bull ratio of XLE and each symbol that is contained within the sector. The symbol with the highest significant correlation with XLE is BTU with a statistically significant correlation of 0.169 and a p-value of 0.019. Additionally, two other symbols CVX and VLO also have a statistically significant correlation at the 95% significance level between the symbol sentiment and the XLE ETF sentiment.

An interesting outcome from this part of the research is the findings of positive statistically significant correlations between the XLE sentiment and the VCX, NBR and VLO stocks. While correlations are negative on the sentiment and price analysis, correlations between XLE and the symbols within the sector should be positive since the XLE ETF is comprised of the symbols a weighting of each symbol.

Compare these low Bear/Bull correlations with the correlations of daily close price between the XLE ETF and each symbol within the sector. Reviewing these correlations, found in Table 4.16, it is clear that the while the XLE ETF is designed to mimic the movements of a group of stocks, the daily movements of the ETF does not correlate well with each stock making up the ETF with only two symbols – BTU and HES – that have a slightly significant correlation using the 90% Confidence level. From this analysis it is clear that for the XLE ETF and sector, the sentiment of XLE has a much more statistically significant correlation than the correlation of price within the XLE and it's the symbols that make up the sector.

Table 4.16:

Daily Price Correlations for XLE and symbols making up the XLE Sector (95% Significance described by "" and 90% Significance by "**")*

Symbol	**Price Corr with XLE**	**p-value**	**Sig?**	**Symbol**	**Price Corr with XLE**	**p-value**	**Sig?**
ANR	0.034	0.597		MPC	-0.069	0.477	
APA	-0.028	0.671		MRO	0.073	0.274	
APC	-0.005	0.939		MUR	0.027	0.747	
BHI	0.058	0.371		NBL	0.034	0.641	
BTU	-0.12	0.065	**	NBR	0.088	0.223	
CAM	0.004	0.955		NE	-0.114	0.152	

Table 4.16:

Daily Price Correlations for XLE and symbols making up the XLE Sector (95% Significance described by "" and 90% Significance by "**")*

CHK	0.033	0.612		NFX	0.017	0.814	
CNX	0.084	0.202		NOV	0.024	0.73	
COG	0.071	0.302		OXY	0	0.995	
COP	-0.002	0.977		PXD	0.032	0.641	
CVX	0.091	0.167		QEP	-0.015	0.87	
DNR	-0.021	0.786		RDC	-0.031	0.749	
DO	0.026	0.719		RRC	-0.01	0.885	
DVN	-0.058	0.37		SE	0.073	0.327	
EOG	0.058	0.373		SLB	-0.009	0.89	
EP	nan	nan		SUN	nan	nan	
EQT	-0.062	0.445		SWN	0.001	0.993	
FTI	0.097	0.279		TSO	0.097	0.159	
HAL	0.017	0.795		VLO	-0.005	0.943	
HES	0.115	0.093	**	WMB	-0.046	0.519	
HP	0.047	0.497		XOM	0.012	0.85	

The daily Bear/Bull ratio correlations between XLP and the symbols that make up the sector can be found in Table 4.17. Reviewing the correlations between XLP and each symbol that makes up the sector, there is very little correlation between the daily Bear/Bull ratio of XLP and each symbol that is contained within the sector. The symbol with the highest significant correlation with XLP is PM with a statistically significant correlation at the 95% significance level of 0.244 and a p-value of 0.001. Additionally, SJM also has a statistically significant correlation at the 95% significance level between the symbol sentiment and the XLE ETF sentiment.

Table 4.17:

Daily Bear/Bull Correlations for XLP sentiment and sentiment of the symbols making up the XLP Sector (95% Significance described by "" and 90% Significance by "**")*

Symbol	**Price Corr with XLP**	**p-value**	**Sig?**	**Symbol**	**Price Corr with XLP**	**p-value**	**Sig?**
ADM	0.081	0.33		KO	-0.005	0.948	
AVP	0.091	0.221		KR	-0.105	0.159	
BEAM	0.089	0.604		LO	0.015	0.868	
BF.B	-0.532	0.14		MJN	-0.192	0.071	**

Table 4.17:

Daily Bear/Bull Correlations for XLP sentiment and sentiment of the symbols making up the XLP Sector (95% Significance described by "" and 90% Significance by "**")*

CAG	-0.02	0.8		MKC	0.033	0.749	
CCE	-0.02	0.836		MO	0.108	0.147	
CL	0.007	0.925		PEP	0.036	0.624	
CLX	-0.038	0.694		PG	-0.048	0.521	
COST	0.126	0.082	**	PM	0.244	0.001	*
CPB	-0.028	0.714		RAI	0.114	0.144	
CVS	0.11	0.13		SJM	0.218	0.038	*
DF	-0.078	0.336		SLE	nan	nan	
DPS	0.042	0.577		STZ	0.061	0.479	
EL	-0.009	0.915		SVU	-0.007	0.919	
GIS	-0.041	0.577		SWY	0.031	0.678	
HNZ	0.027	0.759		SYY	-0.127	0.106	
HRL	0.1	0.323		TAP	-0.003	0.976	
HSY	0.031	0.734		TSN	0.05	0.562	
K	-0.121	0.108		WAG	-0.057	0.435	
KFT	nan	nan		WFM	0.14	0.098	**
KMB	-0.103	0.188		WMT	0.031	0.678	

Taking a look at the daily close correlations between the XLP ETF and the symbols that make up the sector finds a similar outcome as the XLE correlations in terms of the low correlations, but for XLP there are many more symbols – 18 in all – that have significant correlations between the daily close price and the XLP sector daily close price. Additionally, there are four symbols with significant correlations at the 90% confidence. This is much different than the XLE sector and shows that the movement of the XLP sector and symbols are much more correlated than those of the XLE sector. This data is available in Table 4.18.

Table 4.18:

Daily Price Correlations for XLP and symbols making up the XLP Sector (95% Significance described by "" and 90% Significance by "**")*

Symbol	**Price Corr with XLP**	**p-value**	**Sig?**	**Symbol**	**Price Corr with XLP**	**p-value**	**Sig?**
ADM	-0.109	0.192		KO	0.155	0.034	*
AVP	-0.154	0.037	*	KR	-0.154	0.038	*

Table 4.18:

Daily Price Correlations for XLP and symbols making up the XLP Sector (95% Significance described by "" and 90% Significance by "**")*

BEAM	0.089	0.605		LO	-0.101	0.254	
BF.B	-0.109	0.781		MJN	0.048	0.658	
CAG	0.008	0.924		MKC	0.071	0.49	
CCE	0.324	0.001	*	MO	0.164	0.027	*
CL	0.167	0.018	*	PEP	0.133	0.066	**
CLX	0.193	0.042	*	PG	-0.136	0.065	**
COST	0.194	0.007	*	PM	0.126	0.083	**
CPB	-0.014	0.853		RAI	0.17	0.03	*
CVS	0.056	0.445		SJM	0.188	0.075	**
DF	0.187	0.02	*	SLE	nan	nan	
DPS	0.16	0.033	*	STZ	0.169	0.048	*
EL	0.092	0.262		SVU	-0.104	0.152	
GIS	-0.164	0.023	*	SWY	-0.198	0.007	*
HNZ	0.256	0.003	*	SYY	-0.012	0.882	
HRL	0.117	0.248		TAP	-0.087	0.417	
HSY	0.18	0.047	*	TSN	-0.129	0.129	
K	0.011	0.889		WAG	-0.025	0.732	
KFT	nan	nan		WFM	0.18	0.033	*
KMB	0.234	0.003	*	WMT	0.016	0.834	

Addressing H1a

***H1a**: The sentiment of a sector will match the overall averaged sentiment of all stocks within the sector. The null hypothesis (**$H1a_0$**) states that there will be no noticeable relationship between the sentiment of a sector and the overall averaged sentiment of stocks within the sector.*

In order to test the null hypothesis for H1a, the sentiment for the sector ETF must be shown to be similar to the overall averaged sentiment of all the stocks that make up the sector. To address H1a, a test was run to analyze whether the daily sentiment via the daily Bear/Bull ratio of each symbol could be aggregated in such a way as to make the average be equivalent to the overall sector sentiment. This was accomplished by taking the count of Bearish Tweets and Bullish Tweets for each symbol within both the XLE and XLP sectors and then adding them together to create a daily aggregated Bear/Bull ratio for each sector.

For the XLE ETF and the symbols that make up the sector, descriptive statistics are provided in Table 4.19. Descriptive statistics for the XLP ETF and the symbols that make up that sector can be found in Table 4.20. Reviewing the descriptive statistics for XLE in Table 4.19, the Central Limit Theorem comes into play. The XLE ETF averaged less than 5 Bullish Tweets per day and just over 6 Bearish Tweets per day with the maximum number of both Bullish and Bearish Tweets on any given day at 26 Tweets per day. Compare that to the summation of all symbols that make up the XLE sector where Bullish Tweets averaged almost 150 Tweets per day and Bearish Tweets averaged almost 89 Tweets per day.

Table 4.19:

Descriptive statistics for the Bear/Bull ratios for XLE and symbols making up the XLE Sector

XLE ETF:

	Bear/Bull Ratio	**Bullish Tweet Count**	**Bearish Tweet Count**
count	317	155	162
mean	1.770	4.773	6.189
std	2.078	3.121	4.801
min	0	1	0
max	14.000	26.000	26.000

All symbols within XLE:

	Bear/Bull Ratio	**Bullish Tweet Count**	**Bearish Tweet Count**
count	366	191	175
mean	0.616	148.975	88.954
std	0.207	78.264	49.281
min	0	3	0
max	1.235	500.000	296.000

A correlation analysis comparing the XLE ETF daily Bear/Bull ratio and the combination Bear/Bull ratio finds that there is moderate correlation, but not enough to unequivocally state that the two ratios could be substituted for each other. The correlation between the XLE ETF daily Bear/Bull ratio and the summation of the daily Bear/Bull ratios that make up the XLE ETF is 0.175.

Reviewing the descriptive statistics for XLP in Table 4.20, shows that the XLP ETF averaged less than 3 Bullish Tweets per day and less than 2 Bearish Tweets per day with the maximum number of Bullish Tweets at 10 and Bearish Tweets at 9 Tweets. Compare that to the summation of all symbols that make up the XLP sector where Bullish Tweets averaged almost 90 Tweets per day and Bearish Tweets averaged almost 50 Tweets per day.

A review of the distribution of the XLE ETF sentiment and the XLE Sector sentiment was performed to better understand if the ETF sentiment is similar to the overall sector sentiment so that it could be used in place of the aggregated sentiment. Figure 4.1 and Figure 4.2 below provide a look at the distribution and descriptive statistics of both the ETF and Sector Bear/Bull ratio.

Table 4.20:

Descriptive statistics for the Bear/Bull ratios for XLP and symbols making up the XLP Sector

XLP ETF:

	Bear/Bull Ratio	**Bullish Tweet Count**	**Bearish Tweet Count**
count	244	113	131
mean	1.004	2.631	1.832
std	1.248	1.988	1.787
min	0	1	0
max	9	10	9

All symbols within XLP:

	Bear/Bull Ratio	**Bullish Tweet Count**	**Bearish Tweet Count**
count	360	176	184
mean	0.560	89.194	50.221
std	0.258	58.655	35.281
min	0	1	0
max	1.333	398.000	175.000

Reviewing the statistics and histograms of the XLE ETF and XLE Sector sentiment, it is clear that the distributions are quite different as are the descriptive statistics for each. Based on these histograms and the data presented in Table 4.19, it is clear that the number of Tweets for the XLE ETF were quite low, which resulted in a very wide distribution of Bear/Bull ratios. This outcome was quite different than the aggregated Sector sentiment found by combining sentiment data for all symbols within the sector.

The same argument can be made for the XLP ETF sentiment when compared with the XLP Sector aggregated sentiment, which are shown in Figure 4.3 and Figure 4.4 below. The distribution of the XLP ETF sentiment was similar to the XLE ETF sentiment distribution and showed a good number of observations between zero and 1.5 and occasional measurements found up to a maximum Bear/Bull ratio of 9.0. Compare this distribution with the XLP Sector aggregated sentiment shown in Figure 4.4 and it is clear to see that the aggregated sentiment of both XLE and XLP sectors provides more observations to base a predictive signal on.

The low average daily Tweet count of the symbols within both the XLE and XLP ETF's does cause concern because they do not conform to the Central Limit Theorem requirement of more than 30 observations in a given period. Because the daily observations are less than 30, it is difficult to ascertain whether the sentiment for the XLE and XLP symbols match the averaged sentiment for the sectors.

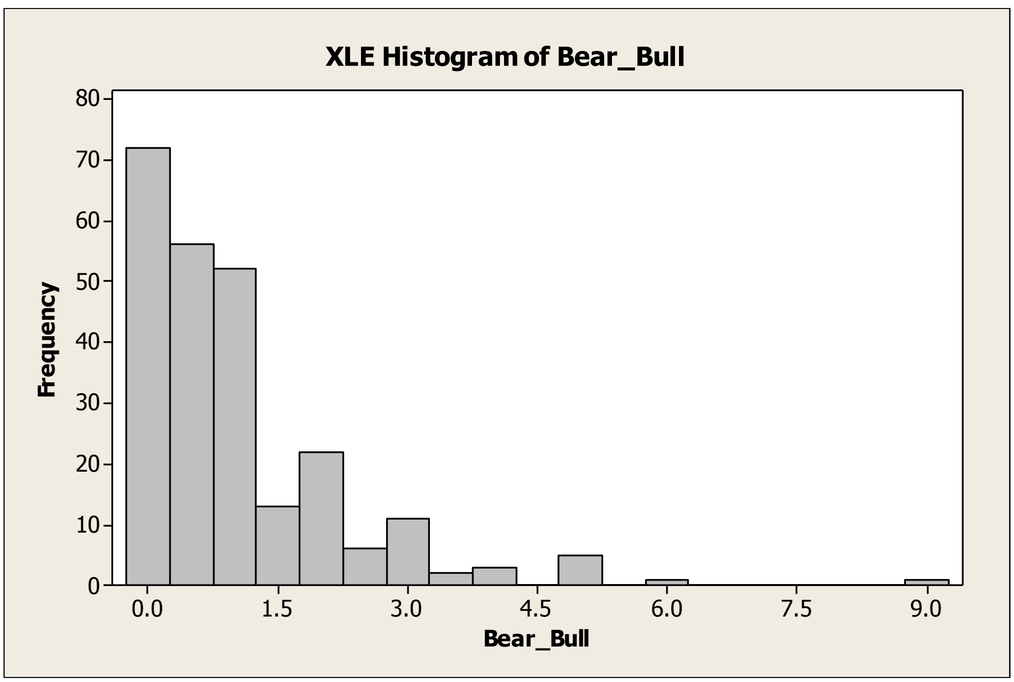

Figure 4.1 - XLE ETF Histogram

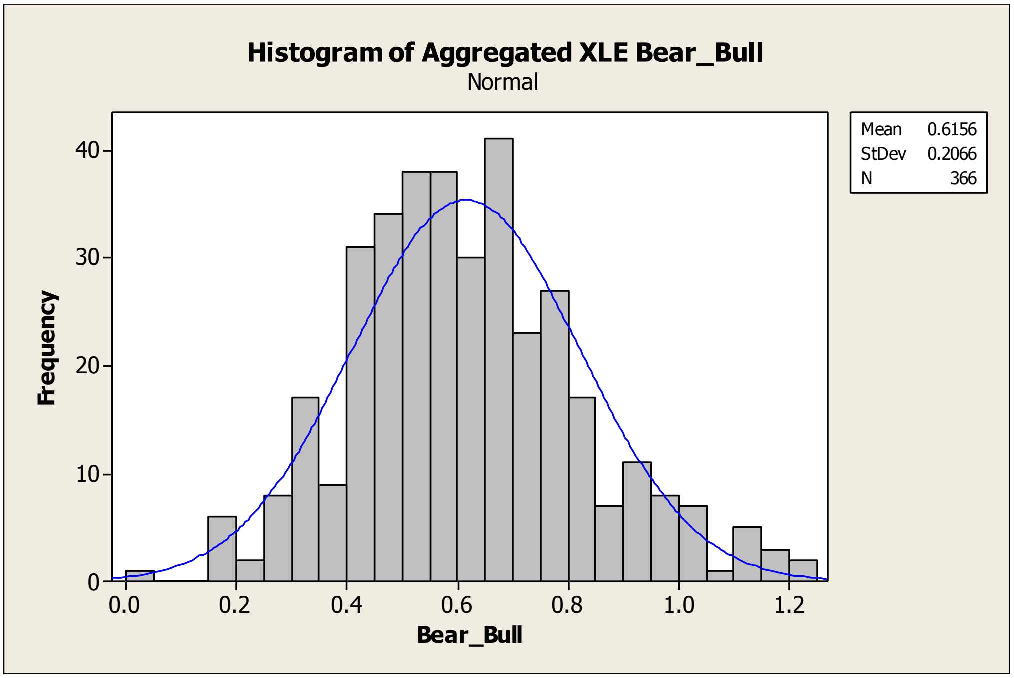

Figure 4.2: XLE Sector Distribution

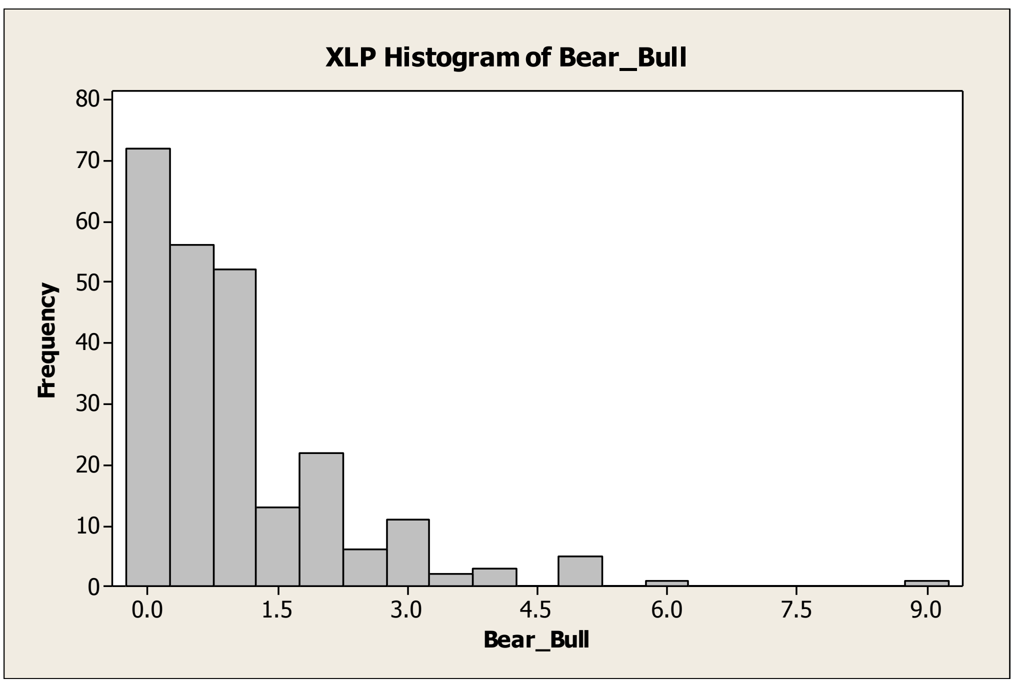

Figure 4.3: XLP ETF Distribution

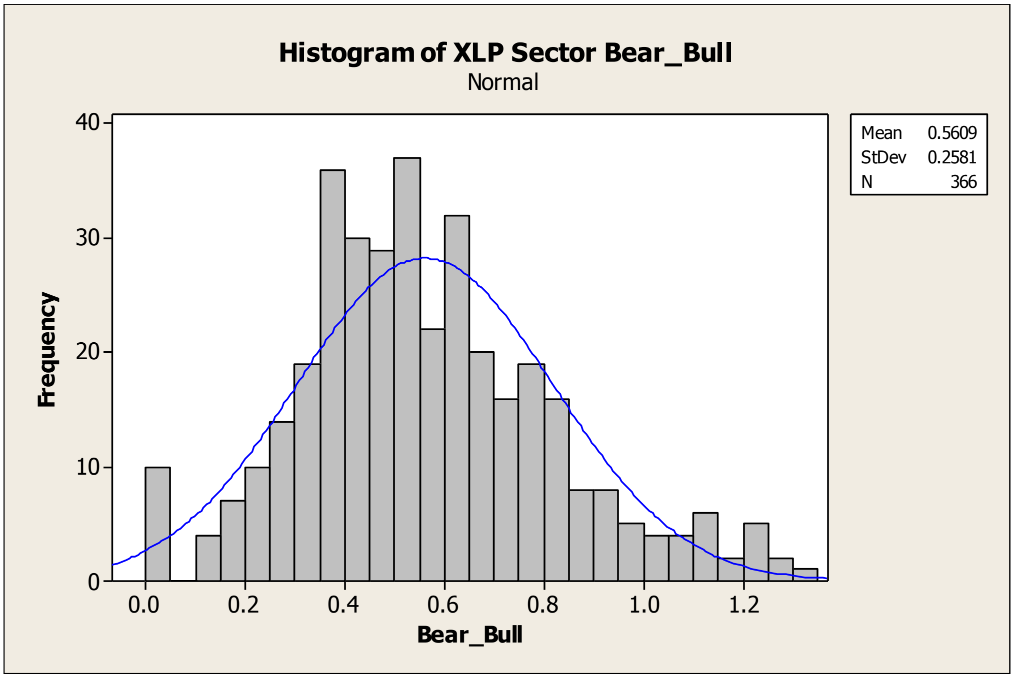

Figure 4.4: XLE Sector Histogram and Statistics

Based on the very low average daily Tweet count, which is less than the Central Limit Theorem recommendation of 30 observations, along with the skewed ETF sentiment distributions when compared to the Sector sentiment distributions, it can be claimed that the distributions are quite different. That said, there was not enough evidence available on a daily basis for the XLE and XLP ETF sentiment to reject the null hypothesis for H1a.

Addressing H1b & H1c

H1b*: The sentiment of a sector can be used to predict the movement of all stocks in that sector. The null hypothesis (**$H1b_0$**) states that there will be no noticeable relationship between the sentiment of a sector and the overall averaged sentiment of stocks within the sector.*

H1c*: The sentiment of a sector or stock on any given day will provide a prediction for the next day's movement in that stock. The null hypothesis (**$H1c_0$**) states that the sentiment of a sector will provide no predictive capability.*

The low observation numbers found with the XLE and XLP ETF's do not allow the daily Bear/Bull ratios for those ETF's to be used without ignoring the Central Limit Theorem.

With this in mind, it is inappropriate to use the XLE ETF and XLP ETF daily Bear/Bull ratios to predict the movement of the ETF's or the stocks within the sectors. Therefore, it can be stated, based on the work for H1a, that there is insufficient evidence available to reject the null hypothesis for H1b and H1c.

With this in mind, a new definition of the sentiment of a sector was developed. This new definition allowed for the sentiment of a sector to be defined as the aggregation of the daily Bear/Bull ratio for all the symbols within a sector. By aggregating the data, the concerns about the Central Limit Theorem requirement of 30 observations per period should be removed and additional research can be performed. With this new definition in mind, a review of the use of the aggregated Bear/Bull ratio for predictability was performed.

Using the aggregated Bear/Bull ratio for the sectors covered by XLE and XLP, a regression analysis was performed to analyze how well the aggregated Bear/Bull ratio could be used to predict daily price movement for the XLE and XLP ETF's and the symbols within each sector. In order to use regression analysis on time-series data like that found in stock market daily closing prices, the time-series must be transformed from a non-stationary series to a stationary series (Arroyo, Espinola, & Mate, 2011). To create a stationary series, the daily closing price was transformed into a percentage change value from one day to the next. This approach created a stationary time-series with daily values being the percentage change from the previous day.

Using standard linear regression analysis techniques, an analysis was performed for both the XLE and XLP ETF's and the symbols within the sectors using the aggregated sentiment and the daily closing prices transformed into daily percentage change values. Additionally, the values for daily closing price and subsequent percentage change values were shifted by one day to that the regression analysis regresses the current day's Bear/Bull Ratio with the next day's change in price.

For the purposes of this regression analysis, the data set was split into two parts to create an in-sample and out-of-sample data set. The in-sample data set was used to run the regression analysis on and the out-of-sample data set was used to run predictions of price movement to determine how well the models work. The in-sample data set consisted of 188 days of data while the out-of-sample data set consisted of 90 days of data.

For the regression analysis in this research, the regression equation is shown in Equation 1 below. The outcome of the regression analysis for both sectors is provided in Tables 4.21 and 4.22 below outputs from both correlation analysis and the regression analysis.

$$P_i = a + b * i_i + \varepsilon_i \qquad (1)$$

The fields in Tables 4.21 and 4.22 that describe the correlation analysis are the correlation and p-values columns and the fields below describe the outputs from the regression analysis:

- R-Squared
- F-Statistic
- Coefficient of Independent variable
- T-Value
- 95% Confidence Intervals
- Durbin Watson value

Additionally, both Tables 4.21 and 4.22 provide a value called 'beta' which is a comparison of the movement of the stock when compared to the S&P 500 SPY ETF. Beta is a measure of risk of one stock versus another, which is normally an index used to measure the markets. A beta of 1.0 equates to a stock moving in line with the underlying index while a beta greater than 1.0 means the stock has more volatility than the comparison stock or index. A beta less than 1.0 means the stock has less volatility than the comparison stock or index.

While correlations are low, these results are somewhat promising. For starters, the Durbin-Watson values for all symbols are between 1.7 and 2.3 which points to little to no autocorrelations in the samples. A very positive outcome for both regression analysis studies shows the sign of the correlations and coefficients within both the XLE and XLP sectors to be the appropriate sign, meaning that the Bear/Bull ratio should be considered a contrarian signal and trades should be taken in the opposite direction of the sentiment.

The regression analysis for the XLE sector provides seemingly good correlations and p-values at reasonable levels while the XLP sector analysis shows very high p-values for most symbols. Out of the 43 symbols that make up the sector, 36 symbols have significant correlations at the 95% confidence level.

While the XLE sector regression analysis shows promising results, the majority of the symbols within the XLP sector show high p-values and low F-Statistics. Out of the 43 symbols for XLP, only 5 have significant correlation at the 95% confidence level. Additionally, unlike the XLE sector and symbols, most symbols in the XLP sector have a beta of less than 1.0, which highlights the fact that these symbols are much less volatile then the S&P SPY ETF.

While the analysis presented in Tables 4.21 and 4.22 provides some insight into using sentiment for predicting next day price movements, the correlations and R-Squared values are quite small. One thing to note from this analysis is that the symbols with a higher beta seem to have a better correlation and tend to fall into the category of acceptable regression analysis output. While it cannot be said that stocks with higher volatility can be predicted more accurately with sentiment, it does point to volatility playing a role in how well sentiment predicts movements.

A quick review of the XLE ETF regression analysis with the XLE Sector aggregated sentiment will highlight that while sentiment does seem to provide some insight into next day movement correctly, the effect of sentiment on price is minimal. The XLE ETF has a beta of 1.234 and regression analysis shows a correlation of -0.306 with p-value of 0.000, which shows that the correlation is statistically significant. Additionally, the XLE ETF has an F-Statistic of 16.129, an R-Squared value of 9.04% and regression coefficient of -0.012. While the correlation of the sentiment signal with the daily percentage change is not considered high, the output of the regression analysis points to the fact that sentiment could be used to describe change in price of the XLE ETF.

Based on the regression analysis performed, it appears that the sentiment of a sector can be used to predict the price movements of the sector ETF and the stocks within the sector but there are questions of how well the predictions would do in generating actual returns from the investments. Additionally, it appears that predictions using sentiment are more appropriate for those stocks and ETF's with higher volatility measures when compared with the S&P 500 ETF.

To understand how well these models actually work in predicting price movements, the out-of-sample data set was used as input into the regression models for each symbol to attempt to find an accuracy rating of the prediction model. To find this accuracy measurement, after the regression prediction was performed, the directional prediction of the Bear/Bull ratio was compared to the direction of the actual percentage change of the stock using those symbols with significant correlations as identified in Table 4.21 and 4.22. The results are shown in Tables 4.23 and 4.24 for XLE and XLP sectors respectively.

Reviewing the XLE sector in Table 4.23, the average accuracy is 51.79%, the median accuracy is 51.67% and a standard deviation is 4.726%. While the accuracy is better than 50%, the standard deviation of 4.726% highlights the fact that accuracy has the possibility of swinging between 56.52% and 47.06% approximately two-thirds of the time.

A look at the XLP sector in Table 4.24 shows a similar accuracy of 51.57% and a median accuracy of 52.22% with a standard deviation of 3.950%. Again, while the accuracy is better than 50%, the fact that there are only 5 symbols must be recognized. Additionally, the standard deviation of 3.950% highlights the fact that accuracy has the possibility of swinging between 55.51% and 47.61% approximately two-thirds of the time.

Table 4.21:

Aggregated Sentiment Regression Analysis Results for XLE and Symbols within the Sector

(95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	Coefficient	TValue	Durbin-Watson
ANR	2.414	-0.148	0.064	**	0.022	3.487	-0.033	-1.867	2.051
APA	1.368	-0.287	0.000	*	0.082	13.953	-0.025	-3.735	2.095
APC	1.635	-0.173	0.029	*	0.030	4.838	-0.018	-2.200	2.133
BHI	1.258	-0.347	0.000	*	0.120	21.349	-0.037	-4.621	1.855
BTU	1.962	-0.240	0.002	*	0.058	9.536	-0.038	-3.088	1.866
CAM	1.745	-0.279	0.000	*	0.078	13.187	-0.031	-3.631	1.921
CHK	1.758	-0.086	0.282		0.007	1.165	-0.015	-1.079	2.221
CNX	1.432	-0.191	0.016	*	0.036	5.900	-0.024	-2.429	1.988
COG	1.369	-0.154	0.054	**	0.024	3.776	-0.023	-1.943	2.070
COP	0.983	-0.087	0.276		0.008	1.194	-0.005	-1.093	2.175
CVX	1.042	-0.210	0.008	*	0.044	7.203	-0.012	-2.684	2.033
DNR	2.041	-0.230	0.004	*	0.053	8.675	-0.031	-2.945	2.176
DO	1.074	-0.345	0.000	*	0.119	21.024	-0.027	-4.585	2.194
DVN	1.255	-0.327	0.000	*	0.107	18.709	-0.029	-4.325	1.916
EOG	1.780	-0.230	0.004	*	0.053	8.719	-0.026	-2.953	2.410
EP	0.453	-0.367	0.371		0.135	0.936	-0.022	-0.967	1.606
EQT	1.094	-0.232	0.003	*	0.054	8.904	-0.024	-2.984	2.062
FTI	1.472	-0.258	0.001	*	0.066	11.113	-0.025	-3.334	1.871
HAL	1.276	-0.329	0.000	*	0.108	18.958	-0.032	-4.354	1.833
HES	1.568	-0.212	0.008	*	0.045	7.314	-0.024	-2.704	1.978
HP	1.789	-0.238	0.003	*	0.057	9.400	-0.029	-3.066	1.854
MPC	1.122	-0.198	0.013	*	0.039	6.352	-0.021	-2.520	1.857
MRO	1.498	-0.263	0.001	*	0.069	11.617	-0.025	-3.408	2.088

Table 4.21:

Aggregated Sentiment Regression Analysis Results for XLE and Symbols within the Sector

(95% Significance described by "*" and 90% Significance by "**")

MUR	1.488	-0.296	0.000	*	0.087	14.927	-0.027	-3.863	2.045
NBL	1.401	-0.170	0.033	*	0.029	4.630	-0.015	-2.152	2.225
NBR	2.207	-0.237	0.003	*	0.056	9.274	-0.036	-3.045	1.989
NE	1.563	-0.333	0.000	*	0.111	19.458	-0.037	-4.411	2.135
NFX	1.742	-0.212	0.007	*	0.045	7.371	-0.028	-2.715	1.963
NOV	1.555	-0.237	0.003	*	0.056	9.273	-0.025	-3.045	2.057
OXY	1.488	-0.241	0.002	*	0.058	9.642	-0.021	-3.105	2.165
PXD	2.108	-0.276	0.000	*	0.076	12.846	-0.037	-3.584	2.248
QEP	1.664	-0.251	0.001	*	0.063	10.464	-0.032	-3.235	1.907
RDC	1.458	-0.274	0.000	*	0.075	12.665	-0.031	-3.559	2.049
RRC	1.243	-0.258	0.001	*	0.066	11.086	-0.033	-3.330	2.320
SE	0.685	-0.127	0.113		0.016	2.547	-0.007	-1.596	1.912
SLB	1.441	-0.273	0.001	*	0.075	12.592	-0.025	-3.549	1.898
SUN	0.353	-0.071	0.482		0.005	0.497	-0.009	-0.705	1.847
SWN	1.231	-0.233	0.003	*	0.054	8.955	-0.030	-2.992	2.144
TSO	1.083	-0.162	0.042	*	0.026	4.186	-0.021	-2.046	2.070
VLO	1.284	-0.259	0.001	*	0.067	11.191	-0.029	-3.345	2.152
WMB	1.166	-0.190	0.017	*	0.036	5.839	-0.015	-2.416	2.056
XOM	0.926	-0.175	0.028	*	0.031	4.946	-0.009	-2.224	1.945
XLE	1.234	-0.306	0.000	*	0.094	16.129	-0.019	-4.016	2.065

Table 4.22:

Aggregated Sentiment Regression Analysis Results for XLP and Symbols within the Sector

(95% Significance described by "*" and 90% Significance by "**")

Symbol	**Beta**	**Correlation**	**p-value**	**Sig?**	**RSquared**	**F-Stat**	**Coefficient**	**TValue**	**DurbinWatson**
ADM	0.939	-0.065	0.414		0.004	0.672	-0.004	-0.819	2.023
AVP	1.256	-0.052	0.515		0.003	0.426	-0.006	-0.653	2.086
BEAM	0.950	-0.046	0.567		0.002	0.328	-0.002	-0.573	2.041
BF.B	0.777	-0.073	0.359		0.005	0.846	-0.003	-0.920	2.013
CAG	0.445	-0.067	0.401		0.005	0.709	-0.002	-0.842	2.047
CCE	1.103	-0.050	0.534		0.002	0.389	-0.003	-0.623	2.056
CL	0.608	-0.169	0.034	*	0.028	4.563	-0.005	-2.136	1.970
CLX	0.359	-0.107	0.180		0.012	1.818	-0.003	-1.348	1.993
COST	0.646	-0.175	0.028	*	0.031	4.918	-0.007	-2.218	1.777
CPB	0.430	0.023	0.771		0.001	0.085	0.001	0.291	1.711
CVS	0.605	-0.104	0.195		0.011	1.694	-0.005	-1.302	2.199
DF	0.514	0.041	0.608		0.002	0.264	0.006	0.514	2.040
DPS	0.475	-0.028	0.730		0.001	0.119	-0.001	-0.346	2.027
EL	1.100	-0.019	0.810		0.000	0.058	-0.001	-0.241	1.813
GIS	0.389	-0.031	0.697		0.001	0.152	-0.001	-0.390	1.750
HNZ	0.479	-0.032	0.687		0.001	0.163	-0.001	-0.404	2.056
HRL	0.572	-0.064	0.426		0.004	0.637	-0.002	-0.798	1.786
HSY	0.466	-0.113	0.156		0.013	2.029	-0.004	-1.425	2.103
K	0.392	-0.052	0.515		0.003	0.427	-0.002	-0.653	1.865
KFT	0.529	-0.304	0.002	*	0.092	9.678	-0.010	-3.111	1.997
KMB	0.425	-0.110	0.168		0.012	1.918	-0.003	-1.385	1.743
KO	0.648	-0.137	0.085	**	0.019	2.995	-0.004	-1.731	1.906

Table 4.22:

Aggregated Sentiment Regression Analysis Results for XLP and Symbols within the Sector

(95% Significance described by "*" and 90% Significance by "**")

KR	0.576	-0.151	0.058	**	0.023	3.651	-0.007	-1.911	2.206
LO	0.417	-0.091	0.255		0.008	1.307	-0.006	-1.143	1.989
MJN	0.520	-0.155	0.052	**	0.024	3.847	-0.009	-1.961	2.214
MKC	0.569	-0.110	0.170		0.012	1.904	-0.003	-1.380	1.831
MO	0.508	-0.132	0.098	**	0.017	2.775	-0.004	-1.666	2.393
PEP	0.438	-0.130	0.104		0.017	2.675	-0.004	-1.636	1.810
PG	0.486	-0.029	0.719		0.001	0.130	-0.001	-0.360	1.760
PM	0.706	-0.110	0.171		0.012	1.896	-0.005	-1.377	1.871
RAI	0.488	-0.095	0.233		0.009	1.432	-0.004	-1.197	2.103
SJM	0.502	-0.030	0.705		0.001	0.144	-0.001	-0.380	1.816
SLE	0.578	0.205	0.260		0.042	1.317	0.014	1.148	2.065
STZ	1.192	-0.028	0.724		0.001	0.125	-0.003	-0.354	1.711
SVU	0.916	-0.157	0.048	*	0.025	3.962	-0.035	-1.990	1.799
SWY	0.797	-0.083	0.301		0.007	1.076	-0.006	-1.037	2.182
SYY	0.595	-0.146	0.068	**	0.021	3.382	-0.005	-1.839	1.657
TAP	0.796	-0.101	0.206		0.010	1.612	-0.005	-1.270	1.802
TSN	0.888	0.058	0.469		0.003	0.528	0.004	0.727	2.146
WAG	0.697	-0.101	0.209		0.010	1.592	-0.007	-1.262	1.731
WFM	1.133	-0.041	0.609		0.002	0.262	-0.003	-0.512	1.942
WMT	0.413	-0.187	0.019	*	0.035	5.650	-0.008	-2.377	1.891
XLP	0.604	-0.153	0.054	**	0.024	3.764	-0.004	-1.940	2.064

The outcome of the research for RQ1 and H1b and H1c shows that while sentiment provides a slight edge in predicting the directional movement of the next day's closing price, the accuracy and standard deviation of that accuracy isn't significantly different from taking signals from a coin flip. It appears that, for many stocks, the sector sentiment can be used to predict daily movements in the sector and individual stocks, the accuracy of the predictions are slightly higher than 50%. The R-Squared values for each stock and ETF show that only a small variance of the daily percentage change is described by the daily sentiment values.

Table 4.23:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50%**	**Symbol**	**Beta**	**Accuracy**	**≥ 50%**
APA	1.368	63.333	*	MUR	1.488	42.222	
APC	1.635	54.444	*	NBL	1.401	41.111	
BHI	1.258	52.222	*	NBR	2.207	54.444	*

Table 4.23:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

BTU	1.962	48.889		NE	1.563	52.222	*
CAM	1.745	50.000	*	NFX	1.742	52.222	*
CNX	1.432	55.556	*	NOV	1.555	52.222	*
CVX	1.042	53.333	*	OXY	1.488	56.667	*
DNR	2.041	48.889		PXD	2.108	42.222	
DO	1.074	51.111	*	QEP	1.664	51.111	*
DVN	1.255	53.333	*	RDC	1.458	45.556	
EOG	1.780	51.111	*	RRC	1.243	50.000	*
EQT	1.094	53.333	*	SLB	1.441	52.222	*
FTI	1.472	58.889	*	SWN	1.231	51.111	*
HAL	1.276	44.444		TSO	1.083	48.889	
HES	1.568	48.889		VLO	1.284	50.000	*
HP	1.789	43.333		WMB	1.166	53.333	*
MPC	1.122	56.667	*	XOM	0.926	52.222	*
MRO	1.498	44.444		XLE	1.234	48.889	
		Average	**51.790**				
		Median	**51.667**				
		Standard Deviation	**4.726**				

For testing purposes, the SPY ETF and all symbols within the sector were analyzed in the same manner as XLE and XLP to determine if the accuracies seen in Tables 4.23 and Table 4.24 are valid or are flukes. The outcome of the analysis of the SPY ETF and the 500 symbols in the ETF provides a similar outcome with an average accuracy of 52.69%, a median accuracy of 52.22% and a standard deviation of 4.36 with 369 symbols having significant correlation at the 95% confidence level with the aggregated sentiment for all symbols making up the SPY ETF.

Table 4.24:

Model Accuracy for XLP Aggregated Sentiment and XLP ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50**
CL	0.608	54.444	*
COST	0.646	48.889	
KFT	0.529	45.556	
SVU	0.916	56.667	*
WMT	0.413	52.222	*
	Average	**51.556**	
	Median	**52.222**	
	Standard Deviation	**3.950**	

The Bear/Bull ratio is modeled after the Put/Call ratio. With this in mind, a similar analysis to the above was performed to determine how well the Put/Call ratio works for predicting daily price movements. To perform this study, the Chicago Board of Exchange's (CBOE) Total Put/Call Ratio, which calculates a ratio of the total volume of Put options and the total volume of Call options for all stocks and indexes, and the CBOE Equity Put/Call Ratio, which calculates a ratio of the total volume of Put options and the total volume of Call options for all stocks without indexes (*Chicago Board of Exchange, 2012)*.

Using the CBOE Total Put/Call ratio, regression analysis was performed to determine if the Put/Call ratio of today could predict the directional price movement of a stock tomorrow using percentage change of the daily closing price of the stock. In the same manner as before, the regression analysis was performed on XLE and XLP with the following findings:

- **XLE**: 25 significant correlations between Daily Closing Percentage Change and Put/Call Ratio with a prediction accuracy average of 49.156%, a median of 48.889% and a standard deviation of 5.031%.
- **XLP**: 4 significant correlations between Daily Closing Percentage Change and Put/Call Ratio with a prediction accuracy average of 53.3330%, a median of 54.444% and a standard deviation of 3.271%.

- **SPY**: 195 significant correlations between Daily Closing Percentage Change and Put/Call Ratio with a prediction accuracy average of 50.826%, a median of 51.111% and a standard deviation of 4.772%.

Using the CBOE Equity Put/Call ratio, regression analysis was performed to determine if the Put/Call ratio of today could predict the directional price movement of a stock tomorrow using percentage change of the daily closing price of the stock. In the same manner as before, the regression analysis was performed on XLE and XLP with the following findings:

- **XLE**: 26 significant correlations between Daily Closing Percentage Change and Put/Call Ratio with a prediction accuracy average of 51.795%, a median of 52.778% and a standard deviation of 4.066%.
- **XLP**: 7 significant correlations between Daily Closing Percentage Change and Put/Call Ratio with a prediction accuracy average of 53.492%, a median of 53.333% and a standard deviation of 5.089%.
- **SPY**: 273 significant correlations between Daily Closing Percentage Change and Put/Call Ratio with a prediction accuracy average of 53.415%, a median of 53.333% and a standard deviation of 4.150%.

Comparing the Total Put/Call Ratio with the Equity Put/Call ratio, it can be seen that the Equity ratio provides for a better predictor across the board with better accuracies and slightly significant correlations. It is claimed that this is the case due to the fact that the Total Put/Call ratio includes index options, which are normally used for hedging rather than directional trades (StockCharts.com, 2012). This causes the Total Put/Call ratio to be slightly skewed, which can be seen in the regression analysis when compared to the Equity Put/Call ratio.

Comparing these results with the results found using Twitter Sentiment Bear/Bull ratio finds a very similar outcome of accuracy greater than 50% with a fairly high standard deviation. While a prediction accuracy over 50% is considered good in the world of investing and trading, the ability to make money with these predictions hinges more on money and risk management than on accuracy of predictions and trades. The use of proper risk management and money management techniques are key to successfully investing over the long term. Additionally, it may prove difficult to implement a trading strategy to take advantage of this outcome due to trading costs such as slippage and commissions.

With this in mind, one approach considered during this study is the contrarian trading approach made popular by investors like Warren Buffet and others. This type of signal is regularly used by contrarian investors to signal a trade in the opposite direction than that expressed by the extreme value of the Put/Call ratio. For example, if the Put/Call ratio is an extreme value to the bearish side, a contrarian investor might take a long entry into the market.

With this contrarian model in mind, a quick study was performed to determine if extreme values of the Bear/Bull ratio work as a contrarian signal. To find extremes, a simple approach was used that takes the top 90% of values as Bearish Extremes and the bottom 10% of values as Bullish Extremes. For both the XLE and XLP sectors, the 90th and 10th percentiles were calculated and the values used as extreme values. A trading signal would be generated if the Bear/Bull ratio closes above the Bearish Extreme value or below the Bullish Extreme value. The extreme values for XLE, XLP are:

- XLE:
  - Bearish Extreme: 0.90
  - Bullish Extreme: 0.43
- XLP:
  - Bearish Extreme: 0.90
  - Bullish Extreme: 0.33

Using these extreme values and Tradestation, a simple strategy was developed that used the Bear/Bull ratio as a prediction mechanism. The aggregated daily Bear/Bull ratio was imported into Tradestation and used as an entry signal for buying a stock or shorting a stock. The investing strategy used for this test uses the following rules:

- Date Range: August 21 2012 to December 31 2012
- Entry criteria (If not already in a trade):
  - Bearish Extreme = Buy

  - Bullish Extreme = Short

- Direction: Long & Short
- Number of Shares: 500
- Holding period: 2 days
- Commission: $5 per trade
- Slippage: $0.10 per trade

For this strategy, when an extreme is identified, a position was taken when the market opened on the next day using a market order to enter the position. The position was held overnight and sold on the market close on day 2. This strategy was applied to the symbols with significant correlation with the aggregated sector sentiment as listed in Table 4.23 for XLE and Table 4.24 for XLP. The outcome of the strategy is provided in Table 4.25.

Table 4.25:

Investing strategy outcomes

XLE		**All Symbols in XLE (Average)**	
Bear/Bull Sentiment Return	4.85%	Bear/Bull Sentiment Return	3.86%
Bear/Bull Extreme Accuracy	54.55%	Bear/Bull Extreme Accuracy	54.16%
Buy and Hold Return	-1.07%	Buy and Hold Return	1.09%
Random Entry Return	-3.62%	Random Entry Return	-2.61%
XLP		**All Symbols in XLP (Average)**	
Bear/Bull Sentiment Return	-1.39%	Bear/Bull Sentiment Return	-2.19%
Bear/Bull Extreme Accuracy	33.33%	Bear/Bull Extreme Accuracy	34.60%
Buy and Hold Return	-2.10%	Buy and Hold Return	-1.87%
Random Entry Return	-2.52%	Random Entry	-1.64%

Comparing the returns in Table 4.25 shows promise for the XLE sentiment signal with a 54.55% win rate and a very nice return of 4.58% when compared to both the buy and hold return of -1.07% and random entry return of -3.62% when using the XLE aggregated Bear/Bull ratio with the XLE ETF or the 35 selected symbols within the sector. The signal does not seem to provide much value for the XLP sector, but given that there were only 5 stocks tested, the results could not be considered conclusive.

As previously mentioned, based on the original definition of sentiment and the original hypotheses, there is insufficient evidence to reject the null hypothesis but when utilizing the modified definition of sentiment, there appears to be limited evidence to support rejecting the null for both **H1b** and **H1c**.

RESEARCH QUESTION 2

RQ-2: Are there specific stocks within a given sector that supply the majority of the sentiment for that sector? If so, do these stocks supply sentiment in correlation to the weighting given to them by ratings agencies such as the Standard & Poor's rating agency?

- **H2a:** The sentiment of a stock within a given sector will affect the sentiment of the overall sector based on the relative market cap weighting of that stock assigned to that stock within the sector. The null hypothesis (**H2a$_0$**) states that the sentiment of a stock is not correlated with the market cap weighting of the stock in that sector.
- **H2b**: The stocks that provide the most weight toward the sentiment of a sector are also the stocks with the highest number of mentions on Twitter. The null hypothesis (**H2b$_0$**) states that there is no relationship between the number of mentions on Twitter and the affect those stocks have on the sector sentiment.

Each sector ETF within the stock market is designed to track that sector's performance by creating a bucket of stocks and assign an appropriate weight based on the size of the underlying company in market capital size is assigned to the stock (Shreck & Antoniewicz, 2012). For the XLE and XLP ETF's, the weighting given to each symbol is shown in Tables 4.26 and 4.27.

Reviewing the weights given to each symbol, it is clear that some symbols, for example XOM, within the XLE sector, should contribute considerably to the movement and price within the XLE sector while other symbols like ANR should contribute minimally overall to price and movement within the sector.

Table 4.26:

Index weightings for XLE sector given in percentage

Symbol	Index Weighting	Symbol	Index Weighting	Symbol	Index Weighting
XOM	17.82	SE	1.74	MUR	1.02
CVX	14.93	CHK	1.7	MPC	0.92
SLB	7.16	HES	1.58	DNR	0.88
COP	4.93	PXD	1.53	TSO	0.83
OXY	4.59	MRO	1.52	RDC	0.79
APC	3.21	NBL	1.46	SUN	0.67
APA	2.98	VLO	1.38	EQT	0.66
HAL	2.78	FTI	1.36	NBR	0.64
NOV	2.63	CAM	1.32	NE	0.64
BHI	2.21	SWN	1.3	DO	0.52
DVN	2.15	COG	1.26	QEP	0.44
EP	2.14	RRC	1.24	HP	0.39
EOG	2.01	BTU	1.14	NFX	0.37
WMB	1.74	CNX	1.06	ANR	0.37

Table 4.27:

Index weightings for XLP sector

Symbol	Index Weighting	Symbol	Index Weighting	Symbol	Index Weighting
PG	14.13	HNZ	1.71	WFM	0.89
PM	10.11	SYY	1.52	TAP	0.88
WMT	8.21	RAI	1.4	MKC	0.88
KO	7.51	KR	1.33	AVP	0.77
KFT	5.14	K	1.25	TSN	0.75
MO	4.63	LO	1.24	SJM	0.73
CVS	4.57	MJN	1.18	CPB	0.72
PEP	4.06	EL	1.09	SWY	0.68
CL	3.82	CAG	1.07	DPS	0.67
COST	3.35	SLE	1.06	BEAM	0.63
WAG	2.55	CCE	0.98	STZ	0.43
KMB	2.43	HSY	0.93	HRL	0.34
GIS	2.35	CLX	0.89	SVU	0.21
ADM	1.87	BF.B	0.89	DF	0.15

Addressing H2a

H2a: *The sentiment of a stock within a given sector will affect the sentiment of the overall sector based on the relative market cap weighting of that stock assigned to that stock within the sector. The null hypothesis (**H2a$_0$**) states that the sentiment of a stock is not correlated with the market cap weighting of the stock in that sector.*

To test H2a, the index weightings given in Tables 4.26 for XLE and Table 4.27 for XLP were compared with the number of Tweets found within the collected data. In order to reject H2a$_0$, those symbols that have the largest index weighting should be proven to be the symbols that provide the majority of Tweets and, in effect, provide the largest amount of sentiment toward the sector.

Running a simple analysis of Tweet volume with the collected data for each sector showed that the index weighting has little to do with the number of Tweets captured for each symbol. Table 4.28 displays the top 15 symbols by Tweet volume with associated ranking by index weighting for both the XLE and XLP sectors.

Table 4.28:

Ranking of Top 15 symbols by Tweet volume

XLE					XLP				
Symbol	**Bear Count**	**Bull Count**	**Total Count**	**Rank**	**Symbol**	**Bear Count**	**Bull Count**	**Total Count**	**Rank**
CVX	3542	4194	7736	2	WMT	1603	5721	7324	3
CHK	3057	4409	7466	17	PG	1854	1717	3571	1
XOM	5441	1885	7326	1	KO	1517	1737	3254	4
HAL	1732	3206	4938	9	PEP	1106	1322	2428	8
BTU	1507	3075	4582	28	WAG	662	1278	1940	11
SLB	954	2999	3953	3	SVU	728	1063	1791	41
COP	1478	2339	3817	4	PM	882	782	1664	2
EOG	970	2309	3279	14	CVS	721	921	1642	7
BHI	491	2090	2581	11	AVP	576	1057	1633	32
APA	688	1623	2311	8	COST	579	1037	1616	10
DVN	696	1611	2307	12	GIS	270	1344	1614	13
ANR	668	1372	2040	42	SWY	496	930	1426	36
OXY	744	1226	1970	5	CL	565	785	1350	9
VLO	591	1240	1831	21	DF	454	672	1126	42
APC	536	1281	1817	6	HNZ	523	533	1056	15

If the index weighting and market cap of the symbols were highly correlated with the number of Tweets that were sent by Twitter users, then the ranking of symbols with the highest volume of Tweets would be much more closely aligned with the index weigh ranking, which in this case is not the case.

Because the sentiment measurement used in this study is a ratio, total Tweet volume is not the only factor to consider. Since a ratio can equate to the same calculated value whether there are 1,000 Tweets or 10,000 Tweets, a review of the effect of each stock on the daily sentiment is in order. To test this, the daily sentiment reading for each symbol was calculated then multiplied by the index weighting given in Tables 4.26 and 4.27 and a weighted aggregated sector sentiment was built. This aggregated sentiment was then compared to the aggregated sentiment without weightings applied. Using this approach, In order to reject the null hypothesis in H2a, the weighted sentiment measures should provide a similar or better outcome to that found in the research for RQ1.

Table 4.29 provides the output of regression analysis for XLE using the weighted aggregated sector sentiment. From this analysis it is clear that the number of symbols with significant correlations have drastically decreased from 36 found previously to only 4 with the weighted aggregated sentiment. Using the significant correlations found in Table 4.29 to run a prediction accuracy test leads to the accuracy findings in Table 4.30 for XLE.

Table 4.29:

Weighted Aggregated Sentiment Regression Analysis Results for XLE and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	Coefficient	TValue	Durbin-Watson
ANR	2.414	-0.080	0.316		0.006	1.010	-0.010	-1.005	2.044
APA	1.368	-0.039	0.626		0.002	0.238	-0.002	-0.488	1.934
APC	1.635	0.036	0.651		0.001	0.205	0.002	0.453	2.021
BHI	1.258	-0.130	0.104		0.017	2.670	-0.008	-1.634	1.746
BTU	1.962	-0.118	0.140		0.014	2.205	-0.010	-1.485	1.846
CAM	1.745	-0.100	0.213		0.010	1.567	-0.006	-1.252	1.822
CHK	1.758	0.019	0.816		0.000	0.054	0.002	0.233	2.205
CNX	1.432	-0.124	0.121		0.015	2.435	-0.009	-1.560	1.989
COG	1.369	0.005	0.951		0.000	0.004	0.000	0.062	2.062
COP	0.983	-0.018	0.823		0.000	0.050	-0.001	-0.224	2.133
CVX	1.042	-0.103	0.196		0.011	1.687	-0.003	-1.299	1.945
DNR	2.041	-0.002	0.982		0.000	0.001	0.000	-0.023	2.081
DO	1.074	-0.165	0.038	*	0.027	4.391	-0.007	-2.096	2.024
DVN	1.255	-0.169	0.034	*	0.028	4.563	-0.008	-2.136	1.764

Table 4.29:

Weighted Aggregated Sentiment Regression Analysis Results for XLE and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

EOG	1.780	-0.057	0.473		0.003	0.516	-0.004	-0.719	2.314
EP	0.453	-0.482	0.227		0.232	1.814	-0.010	-1.347	1.940
EQT	1.094	-0.059	0.462		0.003	0.543	-0.003	-0.737	2.015
FTI	1.472	-0.090	0.262		0.008	1.265	-0.005	-1.125	1.825
HAL	1.276	-0.164	0.039	*	0.027	4.338	-0.009	-2.083	1.732
HES	1.568	-0.076	0.343		0.006	0.906	-0.005	-0.952	1.880
HP	1.789	-0.020	0.800		0.000	0.065	-0.001	-0.254	1.801
MPC	1.122	0.008	0.918		0.000	0.011	0.000	0.103	1.738
MRO	1.498	-0.102	0.204		0.010	1.626	-0.005	-1.275	1.916
MUR	1.488	-0.048	0.550		0.002	0.359	-0.002	-0.599	1.882
NBL	1.401	0.020	0.803		0.000	0.062	0.001	0.249	2.144
NBR	2.207	-0.094	0.240		0.009	1.391	-0.008	-1.180	1.889
NE	1.563	-0.179	0.024	*	0.032	5.171	-0.011	-2.274	1.986
NFX	1.742	-0.093	0.246		0.009	1.356	-0.007	-1.164	1.891
NOV	1.555	-0.075	0.350		0.006	0.877	-0.004	-0.937	1.960
OXY	1.488	-0.053	0.507		0.003	0.442	-0.003	-0.665	2.050
PXD	2.108	-0.097	0.226		0.009	1.479	-0.007	-1.216	2.106
QEP	1.664	-0.078	0.330		0.006	0.954	-0.006	-0.977	1.821
RDC	1.458	-0.076	0.341		0.006	0.914	-0.005	-0.956	1.967
RRC	1.243	-0.087	0.276		0.008	1.195	-0.006	-1.093	2.237
SE	0.685	-0.026	0.743		0.001	0.108	-0.001	-0.328	1.835
SLB	1.441	-0.120	0.132		0.014	2.287	-0.006	-1.512	1.767
SUN	0.353	0.009	0.927		0.000	0.008	0.001	0.091	1.863
SWN	1.231	-0.071	0.377		0.005	0.786	-0.005	-0.887	2.044
TSO	1.083	-0.050	0.531		0.003	0.393	-0.004	-0.627	2.005
VLO	1.284	-0.088	0.270		0.008	1.224	-0.005	-1.107	2.008
WMB	1.166	-0.056	0.487		0.003	0.484	-0.002	-0.696	1.991
XOM	0.926	-0.104	0.192		0.011	1.719	-0.003	-1.311	1.919
XLE	1.234	-0.107	0.182		0.011	1.798	-0.004	-1.341	1.897

While the accuracy of the predictions shows in Table 4.30 are slightly better than those found for the standard XLE sector aggregated sentiment, the fact that the number of symbols with significant correlations is much lower highlights that the use of the index weighting does little more than harm the sentiment signal for the sector.

The outcome of the regression analysis and prediction testing for XLP and the XLP weighted aggregated sentiment is provided in Tables 4.31 and 4.32 respectively. Similar results are found with XLP as was found within the analysis of the XLE data. The number of symbols with significant correlations dropped from 5 to 2 and the prediction accuracy actually dropped to an average of 49.44%, a median of 49.44% and a standard deviation of 0.556%.

Table 4.30:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50%**
DO	1.074	54.444	*
DVN	1.255	55.556	*
HAL	1.276	46.667	
NE	1.563	56.667	*
	Average	**53.333**	
	Median	**55.000**	
	Standard Deviation	**3.928**	

Both the XLE and XLP sector analysis shows much worse performance of correlations and accuracy when using index-weighted sentiment versus non-weighted sentiment. An analysis of the SPY ETF and the 500 symbols that make up the ETF shows a slightly better performance with respect to prediction accuracy but there are much fewer symbols with significant correlations. The prediction accuracy has an accuracy of 54.29% with a median accuracy of 54.44% and a standard deviation of 4.26% with 231 symbols having significant correlations, down from 369 symbols with the standard aggregated sentiment.

It is clear from the analysis for XLE and XLP, that using index weightings does not generate similar or better results than using a non-weighted sentiment signal. Additionally, the fact that only 5 symbols in XLE and 2 symbols in XLP have significant correlations is troubling. While the analysis with SPY shows some improvement over the non-weighted sentiment, the fact that almost half the symbols in the SPY ETF are missing due to not being significantly correlated makes this approach less than ideal.

Table 4.31:

Weighted Aggregated Sentiment Regression Analysis Results for XLP and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	Coefficient	TValue	Durbin-Watson
ADM	0.939	-0.018	0.819		0.000	0.053	-0.001	-0.229	2.026
AVP	1.256	-0.026	0.741		0.001	0.110	-0.002	-0.331	2.094
BEAM	0.950	-0.058	0.473		0.003	0.518	-0.002	-0.720	2.048
BF.B	0.777	-0.065	0.419		0.004	0.656	-0.002	-0.810	2.000
CAG	0.445	-0.016	0.839		0.000	0.041	0.000	-0.204	2.033
CCE	1.103	0.002	0.975		0.000	0.001	0.000	0.031	2.054
CL	0.608	-0.107	0.180		0.012	1.816	-0.003	-1.348	1.960
CLX	0.359	-0.056	0.486		0.003	0.488	-0.001	-0.698	1.976
COST	0.646	-0.184	0.020	*	0.034	5.496	-0.005	-2.344	1.758
CPB	0.430	0.055	0.489		0.003	0.480	0.001	0.693	1.711
CVS	0.605	-0.056	0.483		0.003	0.494	-0.002	-0.703	2.184
DF	0.514	0.042	0.598		0.002	0.280	0.005	0.529	2.043
DPS	0.475	0.037	0.642		0.001	0.217	0.001	0.465	2.018
EL	1.100	-0.016	0.841		0.000	0.040	-0.001	-0.201	1.814
GIS	0.389	-0.020	0.801		0.000	0.064	0.000	-0.253	1.748
HNZ	0.479	-0.014	0.861		0.000	0.031	0.000	-0.175	2.050
HRL	0.572	-0.011	0.893		0.000	0.018	0.000	-0.135	1.791
HSY	0.466	-0.044	0.582		0.002	0.304	-0.001	-0.552	2.092
K	0.392	-0.006	0.944		0.000	0.005	0.000	-0.070	1.869
KFT	0.529	-0.289	0.004	*	0.084	8.661	-0.007	-2.943	2.013
KMB	0.425	-0.065	0.417		0.004	0.663	-0.001	-0.814	1.716
KO	0.648	-0.108	0.178		0.012	1.831	-0.003	-1.353	1.888
KR	0.576	-0.137	0.085	**	0.019	3.000	-0.004	-1.732	2.183
LO	0.417	-0.073	0.363		0.005	0.833	-0.003	-0.913	1.990
MJN	0.520	-0.105	0.188		0.011	1.752	-0.005	-1.323	2.205
MKC	0.569	-0.015	0.847		0.000	0.037	0.000	-0.193	1.829
MO	0.508	-0.126	0.114		0.016	2.531	-0.003	-1.591	2.369
PEP	0.438	-0.135	0.091	**	0.018	2.888	-0.003	-1.699	1.811
PG	0.486	-0.095	0.233		0.009	1.435	-0.002	-1.198	1.783
PM	0.706	-0.084	0.295		0.007	1.103	-0.003	-1.050	1.887
RAI	0.488	-0.068	0.394		0.005	0.731	-0.002	-0.855	2.093
SJM	0.502	-0.057	0.480		0.003	0.500	-0.002	-0.707	1.828
SLE	0.578	-0.009	0.962		0.000	0.002	0.000	-0.048	2.210
STZ	1.192	-0.080	0.317		0.006	1.006	-0.007	-1.003	1.705
SVU	0.916	-0.046	0.562		0.002	0.338	-0.008	-0.581	1.783
SWY	0.797	-0.028	0.728		0.001	0.121	-0.002	-0.348	2.168
SYY	0.595	-0.072	0.370		0.005	0.808	-0.002	-0.899	1.647
TAP	0.796	-0.065	0.414		0.004	0.671	-0.002	-0.819	1.802
TSN	0.888	0.110	0.169		0.012	1.911	0.005	1.382	2.151
WAG	0.697	-0.093	0.246		0.009	1.357	-0.005	-1.165	1.737
WFM	1.133	0.028	0.726		0.001	0.123	0.002	0.350	1.930
WMT	0.413	-0.123	0.124		0.015	2.391	-0.004	-1.546	1.867
XLP	0.604	-0.131	0.102		0.017	2.713	-0.002	-1.647	2.053

For comparison purposes, Tradestation was used to compare the weighted index signal with the un-weighted signal previously reported. The extreme values for XLE, XLP were found to be :

- XLE:
    - Bearish Extreme: 0.90
    - Bullish Extreme: 0.43
- XLP:
    - Bearish Extreme: 1.08
    - Bullish Extreme: 0.28

Table 4.32:

Model Accuracy for XLP Aggregated Sentiment and XLP ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50 %**
COST	0.646	50.000	*
KFT	0.529	48.889	
	Average	**49.444**	
	Median	**49.444**	
	Standard Deviation	**0.556**	

Comparing the results in Table 4.33 with the results from the un-weighted aggregated Bear/Bull ratio found in Table 4.25, it could be seen that the index weight sentiment signal delivers significantly poorer performance for XLE and slightly poorer performance for XLP. Based on the analysis above, there is not enough evidence available to fail to reject the null hypothesis.

Table 4.33:

Investing strategy outcomes

XLE		**All Symbols in XLE (Average)**	
Bear/Bull Sentiment Return	0.82%	Bear/Bull Sentiment Return	1.24%
Bear/Bull Extreme Accuracy	35.00%	Bear/Bull Extreme Accuracy	46.14%
Buy and Hold Return	-1.07%	Buy and Hold Return	1.09%
Random Entry Return	-3.62%	Random Entry Return	-2.61%

Table 4.33:

Investing strategy outcomes

XLP		**All Symbols in XLP (Average)**	
Bear/Bull Sentiment Return	-2.76%	Bear/Bull Sentiment Return	-2.69%
Bear/Bull Extreme Accuracy	27.27%	Bear/Bull Extreme Accuracy	35.91%
Buy and Hold Return	-2.10%	Buy and Hold Return	-1.87%
Random Entry Return	-2.52%	Random Entry	-1.64%

Addressing H2b

H2b: *The stocks that provide the most weight toward the sentiment of a sector are also the stocks with the highest number of mentions on Twitter. The null hypothesis (**$H2b_0$**) states that there is no relationship between the number of mentions on Twitter and the affect that those stocks have on the sector sentiment.*

To address H2b, similar analysis as that in H2a was performed. Rather than use the index weightings for each symbol, a weighting mechanism was developed to weight each symbol by its contribution to the number of Tweets per day. This weighted contribution was then used to build the aggregated sentiment signal, which was then used for regression analysis as described previously.

Table 4.34 provides the output of this analysis for the XLE sector. This approach provides more symbols with significant correlations at the 95% confidence level when compared to the index weighted approach, but the total number of symbols with at 95% confidence is still less than the number found in the standard non-weighted sentiment analysis.

Table 4.34:

Tweet Count Weighted Aggregated Sentiment Regression Analysis Results for XLE and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	Coefficient	TValue	Durbin-Watson
ANR	2.414	-0.102	0.201		0.010	1.649	-0.019	-1.284	2.050
APA	1.368	-0.095	0.237		0.009	1.410	-0.007	-1.187	1.975
APC	1.635	-0.031	0.696		0.001	0.154	-0.003	-0.392	2.046

Table 4.34:

Tweet Count Weighted Aggregated Sentiment Regression Analysis Results for XLE and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

BHI	1.258	-0.224	0.005	*	0.050	8.216	-0.020	-2.866	1.786
BTU	1.962	-0.177	0.026	*	0.031	5.052	-0.023	-2.248	1.881
CAM	1.745	-0.172	0.031	*	0.029	4.736	-0.016	-2.176	1.861
CHK	1.758	-0.008	0.922		0.000	0.010	-0.001	-0.099	2.203
CNX	1.432	-0.161	0.043	*	0.026	4.163	-0.017	-2.040	2.005
COG	1.369	-0.045	0.577		0.002	0.313	-0.006	-0.559	2.060
COP	0.983	-0.020	0.800		0.000	0.064	-0.001	-0.254	2.142
CVX	1.042	-0.106	0.185		0.011	1.769	-0.005	-1.330	1.987
DNR	2.041	-0.075	0.349		0.006	0.884	-0.008	-0.940	2.114
DO	1.074	-0.254	0.001	*	0.065	10.777	-0.016	-3.283	2.129
DVN	1.255	-0.216	0.007	*	0.046	7.602	-0.016	-2.757	1.834
EOG	1.780	-0.108	0.176		0.012	1.849	-0.010	-1.360	2.346
EP	0.453	-0.398	0.328		0.159	1.132	-0.013	-1.064	1.804
EQT	1.094	-0.127	0.111		0.016	2.564	-0.011	-1.601	2.035
FTI	1.472	-0.153	0.055	**	0.023	3.747	-0.012	-1.936	1.845
HAL	1.276	-0.229	0.004	*	0.052	8.634	-0.018	-2.938	1.775
HES	1.568	-0.154	0.053	**	0.024	3.795	-0.014	-1.948	1.944
HP	1.789	-0.142	0.076	**	0.020	3.199	-0.014	-1.789	1.824
MPC	1.122	-0.133	0.095	**	0.018	2.813	-0.011	-1.677	1.805
MRO	1.498	-0.130	0.104		0.017	2.681	-0.010	-1.638	1.970
MUR	1.488	-0.140	0.078	**	0.020	3.141	-0.010	-1.772	1.946
NBL	1.401	-0.017	0.831		0.000	0.046	-0.001	-0.214	2.154
NBR	2.207	-0.141	0.077	**	0.020	3.177	-0.018	-1.782	1.929
NE	1.563	-0.256	0.001	*	0.066	10.977	-0.023	-3.313	2.094
NFX	1.742	-0.143	0.072	**	0.021	3.275	-0.015	-1.810	1.942
NOV	1.555	-0.168	0.035	*	0.028	4.522	-0.014	-2.126	2.023
OXY	1.488	-0.112	0.162		0.013	1.978	-0.008	-1.406	2.093
PXD	2.108	-0.155	0.052	**	0.024	3.821	-0.017	-1.955	2.171
QEP	1.664	-0.155	0.052	**	0.024	3.830	-0.016	-1.957	1.863
RDC	1.458	-0.169	0.033	*	0.029	4.607	-0.016	-2.146	2.009
RRC	1.243	-0.148	0.064	**	0.022	3.482	-0.015	-1.866	2.268
SE	0.685	-0.051	0.522		0.003	0.411	-0.002	-0.641	1.853
SLB	1.441	-0.194	0.014	*	0.038	6.125	-0.014	-2.475	1.833
SUN	0.353	-0.007	0.941		0.000	0.005	-0.001	-0.074	1.860
SWN	1.231	-0.121	0.130		0.015	2.314	-0.013	-1.521	2.066
TSO	1.083	-0.098	0.223		0.010	1.497	-0.011	-1.224	2.030
VLO	1.284	-0.197	0.013	*	0.039	6.307	-0.018	-2.511	2.091
WMB	1.166	-0.108	0.179		0.012	1.824	-0.007	-1.351	2.029
XOM	0.926	-0.153	0.056	**	0.023	3.718	-0.006	-1.928	1.956
XLE	1.234	-0.179	0.024	*	0.032	5.177	-0.009	-2.275	1.975

Using the regression analysis model with the symbols with significant correlation, a prediction accuracy of 53.08%, a median accuracy of 53.33% and a standard deviation of 4.14% was found and is displayed in Table 4.35. This accuracy is greater than the 51.79%

found using the standard non-weighted signal, but with only 10 out of 43 symbols providing greater than 50% accuracy, the possibility of profitably using this approach is limited.

Table 4.35:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50%**
BHI	1.258	54.444	*
BTU	1.962	51.111	*
CAM	1.745	55.556	*
CNX	1.432	57.778	*
DO	1.074	57.778	*
DVN	1.255	53.333	*
HAL	1.276	45.556	
NE	1.563	57.778	*
NOV	1.555	57.778	*
RDC	1.458	47.778	
SLB	1.441	53.333	*
VLO	1.284	47.778	
XLE	1.234	50.000	*
	Average	**53.077**	
	Median	**53.333**	
	Standard Deviation	**4.138**	

Table 4.36 provides the output of the same analysis for the XLP sector and symbols. This approach provides the same number of symbols with significant correlations at the 95% confidence level when compared to the index weighted approach. Additionally, the symbols are the same for this approach when compared to the index weighted analysis shown in Table 4.31.

Using the regression analysis model with the symbols with significant correlation, for XLP finds a prediction accuracy of 51.667%, a median accuracy of 51.667% and a standard deviation of 0.556% as shown in Table 4.37. This accuracy is greater than the 49.44% found using the standard non-weighted signal and both symbols provide accuracies greater than 50%.

Table 4.36:

Tweet Count Weighted Aggregated Sentiment Regression Analysis Results for XLP and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	Coefficient	TValue	Durbin-Watson
ADM	0.939	-0.044	0.580		0.002	0.308	-0.002	-0.555	2.035
AVP	1.256	-0.055	0.490		0.003	0.479	-0.006	-0.692	2.082
BEAM	0.950	-0.040	0.618		0.002	0.249	-0.002	-0.499	2.037
BF.B	0.777	-0.069	0.386		0.005	0.755	-0.003	-0.869	1.995
CAG	0.445	-0.052	0.518		0.003	0.420	-0.001	-0.648	2.035
CCE	1.103	-0.022	0.782		0.000	0.077	-0.001	-0.277	2.051
CL	0.608	-0.125	0.117		0.016	2.489	-0.004	-1.578	1.954
CLX	0.359	-0.062	0.436		0.004	0.609	-0.002	-0.780	1.982
COST	0.646	-0.191	0.016	*	0.036	5.905	-0.007	-2.430	1.745
CPB	0.430	0.063	0.433		0.004	0.617	0.002	0.786	1.719
CVS	0.605	-0.064	0.425		0.004	0.639	-0.003	-0.799	2.186
DF	0.514	0.018	0.821		0.000	0.052	0.003	0.227	2.038
DPS	0.475	0.027	0.737		0.001	0.114	0.001	0.337	2.022
EL	1.100	-0.056	0.481		0.003	0.500	-0.004	-0.707	1.818
GIS	0.389	0.007	0.935		0.000	0.007	0.000	0.081	1.745
HNZ	0.479	0.012	0.878		0.000	0.024	0.000	0.154	2.043
HRL	0.572	0.018	0.818		0.000	0.053	0.001	0.231	1.790
HSY	0.466	-0.073	0.362		0.005	0.837	-0.003	-0.915	2.085
K	0.392	-0.028	0.722		0.001	0.127	-0.001	-0.356	1.864
KFT	0.529	-0.263	0.009	*	0.069	7.067	-0.009	-2.658	2.012
KMB	0.425	-0.075	0.346		0.006	0.894	-0.002	-0.945	1.713
KO	0.648	-0.119	0.137		0.014	2.235	-0.003	-1.495	1.889
KR	0.576	-0.148	0.063	**	0.022	3.515	-0.006	-1.875	2.195
LO	0.417	-0.058	0.469		0.003	0.526	-0.003	-0.725	1.989
MJN	0.520	-0.106	0.185		0.011	1.773	-0.006	-1.331	2.202
MKC	0.569	-0.011	0.886		0.000	0.021	0.000	-0.144	1.827
MO	0.508	-0.103	0.197		0.011	1.681	-0.003	-1.297	2.355
PEP	0.438	-0.112	0.160		0.013	1.997	-0.003	-1.413	1.811
PG	0.486	-0.121	0.129		0.015	2.325	-0.004	-1.525	1.771
PM	0.706	-0.068	0.397		0.005	0.722	-0.003	-0.850	1.862
RAI	0.488	-0.067	0.404		0.004	0.699	-0.002	-0.836	2.090
SJM	0.502	-0.069	0.386		0.005	0.755	-0.003	-0.869	1.824
SLE	0.578	0.023	0.901		0.001	0.016	0.001	0.125	2.205
STZ	1.192	-0.014	0.862		0.000	0.030	-0.001	-0.174	1.706
SVU	0.916	-0.057	0.479		0.003	0.503	-0.012	-0.709	1.795
SWY	0.797	-0.063	0.433		0.004	0.619	-0.005	-0.787	2.184
SYY	0.595	-0.105	0.189		0.011	1.743	-0.004	-1.320	1.654
TAP	0.796	-0.061	0.450		0.004	0.574	-0.003	-0.758	1.802
TSN	0.888	0.107	0.182		0.011	1.794	0.007	1.339	2.143
WAG	0.697	-0.096	0.230		0.009	1.450	-0.006	-1.204	1.741
WFM	1.133	-0.054	0.501		0.003	0.455	-0.004	-0.674	1.944
WMT	0.413	-0.127	0.112		0.016	2.559	-0.005	-1.600	1.888
XLP	0.604	-0.139	0.082	**	0.019	3.063	-0.003	-1.750	2.051

Table 4.37:

Model Accuracy for XLP Aggregated Sentiment and XLP ETF and Sector Symbols. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	Beta	Accuracy	≥ 50%
COST	0.646	52.222	*
KFT	0.529	51.111	*
Average		**51.667**	
Median		**51.667**	
Standard Deviation		**0.555556**	

Although the total number of symbols with statistically significant correlations for XLE and XLP are small, the prediction accuracy using a signal created by weighting the sentiment based on the stocks with the most mentions seems to increase accuracy when compared to the signal created from the index weighting of the stocks. That said, this accuracy is not universal across all symbols so it would be difficult to say that using this approach for any symbol would provide any positive expectations in predicting price movement in the market. There is limited evidence to support rejecting the null.

RESEARCH QUESTION 3

RQ-3: Are there times of the day or days of the week that provide a more accurate and informative sentiment for a stock or sector?

- ***H3:*** *There is a difference in the effect that Tweets sent during non-market hours (i.e., evenings and weekends) and Tweets sent during market hours have on sentiment and price. The null hypothesis (**$H3_0$**) states that there is no difference in the effect of Tweets sent during market hours and non-market hours.*

To address H3, analysis was performed on all Tweets received for XLE and XLP and the symbols that make up the sectors. The Tweets were split into two categories to describe whether the Tweets were received during trading hours or non-trading hours. These two categories are described as:

- **Trading hours**: For equity and index markets in the U.S., trading hours are defined as 8:30 AM to 3:00 PM Central Time from Monday through Friday. Any Tweets captured with a timestamp between these two times will be considered to have been sent during trading hours.
- **Non-trading hours**: For equity and index markets in the US, non-trading hours are defined as any time outside of the 8:30 AM to 3:00 PM Central time. This includes evenings and weekends. Additionally, market holidays are included into the non-trading hour's category. Any Tweet captured with a timestamp that falls outside of the Trading Hours are classified as having been sent during non-trading hours.

Similarly to the analysis performed in previous sections, the sentiment captured during both trading hours and non-trading hours was used to predict the movement in the market on the following day. The comparison of accuracies of Tweets sent during trading hours and non-trading hours will assist with providing insight into H3.

Table 4.38 provides the output of the regression analysis for XLE for trading hours. It is worth highlighting that out of the 43 symbols in the XLE sector, 39 symbols fall within the 95% significance level. Using the regression analysis model with the symbols with significant correlation, a prediction accuracy of 51.07%, a median accuracy of 51.11% and a standard deviation of 3.09 was found and is displayed in Table 4.39. Additionally, 27 out of the 43 symbols had accuracy ratings greater than or equal to 50%. Table 4.40 provides the output of the regression analysis for XLE for non-trading hours. It is worth highlighting that out of the 43 symbols in the XLE sector, 35 symbols fall within the 95% significance level.

Table 4.38:

Regression Analysis output for Tweets captured during Trading Hours for XLE and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	Coefficient	TValue	Durbin-Watson
NBL	1.401	-0.188	0.021	*	0.035	5.461	-0.010	-2.337	2.233
ANR	2.414	-0.229	0.005	*	0.052	8.255	-0.031	-2.873	2.064
EP	0.453	0.389	0.389		0.151	0.889	0.019	0.943	0.989
CAM	1.745	-0.328	0.000	*	0.108	18.018	-0.023	-4.245	1.973
EQT	1.094	-0.318	0.000	*	0.101	16.716	-0.020	-4.089	2.088
APC	1.635	-0.182	0.025	*	0.033	5.126	-0.011	-2.264	2.108
TSO	1.083	-0.193	0.018	*	0.037	5.757	-0.016	-2.399	1.968
BHI	1.258	-0.336	0.000	*	0.113	18.966	-0.022	-4.355	1.789
HP	1.789	-0.317	0.000	*	0.101	16.679	-0.024	-4.084	1.882
XOM	0.926	-0.166	0.042	*	0.027	4.209	-0.005	-2.052	1.937
APA	1.368	-0.291	0.000	*	0.085	13.797	-0.015	-3.714	2.024
HAL	1.276	-0.354	0.000	*	0.125	21.366	-0.021	-4.622	1.801
COP	0.983	-0.161	0.048	*	0.026	3.983	-0.006	-1.996	2.199
SLB	1.441	-0.316	0.000	*	0.100	16.584	-0.017	-4.072	1.876
WMB	1.166	-0.267	0.001	*	0.071	11.473	-0.013	-3.387	2.190
BTU	1.962	-0.304	0.000	*	0.093	15.197	-0.029	-3.898	1.843
VLO	1.284	-0.278	0.001	*	0.077	12.512	-0.019	-3.537	2.072
HES	1.568	-0.293	0.000	*	0.086	14.002	-0.020	-3.742	1.935
CNX	1.432	-0.239	0.003	*	0.057	9.024	-0.018	-3.004	1.957
RRC	1.243	-0.292	0.000	*	0.085	13.872	-0.022	-3.724	2.340
COG	1.369	-0.207	0.011	*	0.043	6.670	-0.019	-2.583	2.085
CVX	1.042	-0.213	0.009	*	0.045	7.062	-0.007	-2.657	1.997
DO	1.074	-0.331	0.000	*	0.109	18.284	-0.016	-4.276	2.094
OXY	1.488	-0.307	0.000	*	0.094	15.463	-0.017	-3.932	2.160
SE	0.685	-0.117	0.151		0.014	2.085	-0.004	-1.444	1.983
MUR	1.488	-0.271	0.001	*	0.073	11.792	-0.015	-3.434	1.992
DVN	1.255	-0.300	0.000	*	0.090	14.745	-0.016	-3.840	1.897
NBR	2.207	-0.326	0.000	*	0.106	17.676	-0.030	-4.204	1.976
SUN	0.353	-0.129	0.209		0.017	1.601	-0.010	-1.265	1.881
DNR	2.041	-0.260	0.001	*	0.068	10.828	-0.021	-3.291	2.147
QEP	1.664	-0.324	0.000	*	0.105	17.440	-0.025	-4.176	1.912
NE	1.563	-0.344	0.000	*	0.118	19.969	-0.023	-4.469	2.082
NFX	1.742	-0.285	0.000	*	0.081	13.136	-0.023	-3.624	1.981
CHK	1.758	-0.112	0.171		0.013	1.896	-0.013	-1.377	2.260
MRO	1.498	-0.220	0.007	*	0.049	7.595	-0.013	-2.756	2.024
XLE	1.234	-0.334	0.000	*	0.112	18.743	-0.013	-4.329	2.065
SWN	1.231	-0.333	0.000	*	0.111	18.547	-0.026	-4.307	2.110
PXD	2.108	-0.272	0.001	*	0.074	11.874	-0.022	-3.446	2.190
RDC	1.458	-0.312	0.000	*	0.097	16.049	-0.021	-4.006	2.023
NOV	1.555	-0.300	0.000	*	0.090	14.786	-0.019	-3.845	2.032
EOG	1.780	-0.235	0.004	*	0.055	8.747	-0.016	-2.958	2.389
FTI	1.472	-0.266	0.001	*	0.071	11.362	-0.016	-3.371	1.879
MPC	1.122	-0.242	0.003	*	0.058	9.255	-0.016	-3.042	1.925

Table 4.39:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols for Tweets captured during trading hours. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	Beta	Accuracy	≥ 50%	Symbol	Beta	Accuracy	≥ 50%
ANR	2.414	55.556	*	MRO	1.498	44.444	
APA	1.368	52.222	*	MUR	1.488	42.222	
APC	1.635	51.111	*	NBL	1.401	44.444	
BHI	1.258	50.000	*	NBR	2.207	54.444	*
BTU	1.962	48.889		NE	1.563	52.222	*
CAM	1.745	48.889		NFX	1.742	52.222	*
CNX	1.432	50.000	*	NOV	1.555	52.222	*
COG	1.369	51.111	*	OXY	1.488	53.333	*
COP	0.983	53.333	*	PXD	2.108	48.889	
CVX	1.042	54.444	*	QEP	1.664	46.667	
DNR	2.041	51.111	*	RDC	1.458	54.444	*
DO	1.074	53.333	*	RRC	1.243	47.778	
DVN	1.255	44.444		SLB	1.441	53.333	*
EOG	1.780	51.111	*	SWN	1.231	53.333	*
EQT	1.094	46.667		TSO	1.083	53.333	*
FTI	1.472	56.667	*	VLO	1.284	51.111	*
HAL	1.276	50.000	*	WMB	1.166	53.333	*
HES	1.568	50.000	*	XLE	1.234	51.111	*
HP	1.789	46.667		XOM	0.926	55.556	*
MPC	1.122	55.556	*				
			Average		**51.056**		
			Median		**51.111**		
		Standard	**Deviation**		**3.093**		

Table 4.40:

Regression Analysis output for Tweets captured during non-trading hours for XLE and Symbols within the Sector (95% Significance described by “*” and 90% Significance by “**”)

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	FStatProb	Coefficient	TValue	Durbin-Watson
NBL	1.401	-0.239	0.003	*	0.057	9.193	0.003	-0.017	-3.032	2.293
ANR	2.414	-0.160	0.047	*	0.026	3.994	0.047	-0.027	-1.998	2.025
EP	0.453	-0.305	0.505		0.093	0.514	0.505	-0.023	-0.717	1.312
CAM	1.745	-0.277	0.001	*	0.077	12.649	0.001	-0.024	-3.557	1.937
EQT	1.094	-0.213	0.008	*	0.045	7.201	0.008	-0.017	-2.683	2.055
APC	1.635	-0.192	0.017	*	0.037	5.788	0.017	-0.015	-2.406	2.108
TSO	1.083	-0.115	0.154		0.013	2.052	0.154	-0.012	-1.433	1.999
BHI	1.258	-0.258	0.001	*	0.066	10.827	0.001	-0.022	-3.291	1.736
HP	1.789	-0.216	0.007	*	0.047	7.458	0.007	-0.021	-2.731	1.879
XOM	0.926	-0.195	0.015	*	0.038	6.037	0.015	-0.008	-2.457	1.904
APA	1.368	-0.268	0.001	*	0.072	11.741	0.001	-0.018	-3.427	2.078
HAL	1.276	-0.282	0.000	*	0.080	13.134	0.000	-0.021	-3.624	1.729
COP	0.983	-0.071	0.379		0.005	0.779	0.379	-0.003	-0.883	2.193
SLB	1.441	-0.248	0.002	*	0.061	9.953	0.002	-0.017	-3.155	1.802
WMB	1.166	-0.191	0.018	*	0.036	5.735	0.018	-0.011	-2.395	2.095
BTU	1.962	-0.221	0.006	*	0.049	7.810	0.006	-0.027	-2.795	1.791
VLO	1.284	-0.236	0.003	*	0.056	8.933	0.003	-0.020	-2.989	2.034
HES	1.568	-0.197	0.014	*	0.039	6.124	0.014	-0.017	-2.475	1.916
CNX	1.432	-0.181	0.025	*	0.033	5.134	0.025	-0.018	-2.266	1.941
RRC	1.243	-0.259	0.001	*	0.067	10.968	0.001	-0.025	-3.312	2.282
COG	1.369	-0.155	0.055	**	0.024	3.752	0.055	-0.019	-1.937	2.063
CVX	1.042	-0.171	0.034	*	0.029	4.593	0.034	-0.008	-2.143	1.939
DO	1.074	-0.343	0.000	*	0.118	20.283	0.000	-0.021	-4.504	2.161
OXY	1.488	-0.285	0.000	*	0.081	13.459	0.000	-0.020	-3.669	2.169
SE	0.685	-0.068	0.403		0.005	0.703	0.403	-0.003	-0.839	1.917
MUR	1.488	-0.266	0.001	*	0.071	11.608	0.001	-0.019	-3.407	1.995
DVN	1.255	-0.279	0.000	*	0.078	12.852	0.000	-0.020	-3.585	1.881
NBR	2.207	-0.196	0.015	*	0.038	6.082	0.015	-0.023	-2.466	1.940
SUN	0.353	-0.068	0.504	**	0.005	0.450	0.504	-0.007	-0.671	1.839
DNR	2.041	-0.242	0.003	*	0.058	9.425	0.003	-0.025	-3.070	2.183
QEP	1.664	-0.252	0.002	*	0.064	10.349	0.002	-0.025	-3.217	1.882
NE	1.563	-0.292	0.000	*	0.085	14.170	0.000	-0.025	-3.764	2.047
NFX	1.742	-0.167	0.038	*	0.028	4.367	0.038	-0.017	-2.090	1.973
CHK	1.758	-0.091	0.262		0.008	1.268	0.262	-0.013	-1.126	2.262
MRO	1.498	-0.266	0.001	*	0.071	11.603	0.001	-0.020	-3.406	2.094
XLE	1.234	-0.296	0.000	*	0.088	14.606	0.000	-0.014	-3.822	1.991
SWN	1.231	-0.230	0.004	*	0.053	8.464	0.004	-0.023	-2.909	2.079
PXD	2.108	-0.270	0.001	*	0.073	11.978	0.001	-0.029	-3.461	2.292
RDC	1.458	-0.257	0.001	*	0.066	10.780	0.001	-0.023	-3.283	2.022
NOV	1.555	-0.251	0.002	*	0.063	10.195	0.002	-0.021	-3.193	2.003
EOG	1.780	-0.246	0.002	*	0.061	9.795	0.002	-0.022	-3.130	2.407
FTI	1.472	-0.228	0.004	*	0.052	8.318	0.004	-0.018	-2.884	1.858
MPC	1.122	-0.217	0.007	*	0.047	7.523	0.007	-0.018	-2.743	1.858

Using the regression analysis model with the symbols with significant correlation, a prediction accuracy of 49.85%, a median accuracy of 50.00% and a standard deviation of 4.159% was found and is displayed in Table 4.41. Additionally, 20 symbols out of the 43 symbols had accuracy ratings greater than or equal to 50%.

Table 4.41:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols for Tweets captured during non-trading hours. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50**	**Symbol**	**Beta**	**Accuracy**	**≥ 50**
ANR	2.414	50.000	*	MRO	1.498	44.444	
APA	1.368	54.444	*	MUR	1.488	43.333	
APC	1.635	52.222	*	NBL	1.401	44.444	
BHI	1.258	53.333	*	NBR	2.207	50.000	*
BTU	1.962	52.222	*	NE	1.563	47.778	
CAM	1.745	55.556	*	NFX	1.742	55.556	*
CNX	1.432	58.889	*	NOV	1.555	51.111	*
CVX	1.042	50.000	*	OXY	1.488	51.111	*
DNR	2.041	45.556		PXD	2.108	46.667	
DO	1.074	45.556		QEP	1.664	47.778	
DVN	1.255	48.889		RDC	1.458	42.222	
EOG	1.780	51.111	*	RRC	1.243	54.444	*
EQT	1.094	50.000	*	SLB	1.441	53.333	*
FTI	1.472	54.444	*	SWN	1.231	53.333	*
HAL	1.276	50.000	*	VLO	1.284	48.889	
HES	1.568	48.889		WMB	1.166	44.444	
HP	1.789	47.778		XLE	1.234	47.778	
MPC	1.122	56.667	*	XOM	0.926	42.222	
			Average	**49.846**			
			Median	**50.000**			
		Standard	**Deviation**	**4.159**			

By reviewing the data from the XLE, it does appear that there could be a bit of an edge found in using Tweets during trading hours when compared to those captured during non-trading hours. There is evidence to support rejecting the null hypothesis.

Performing this same analysis on XLP provides similar results. Table 4.42 provides the output of the regression analysis for XLP for trading hours. It is noted that out the 43 symbols in the XLP sector, 5 symbols fall within the 95% significance level.

Table 4.42:

Regression Analysis output for Tweets captured during trading hours for XLP and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	FStatProb	Coefficient	TValue	Durbin-Watson
TAP	0.796	-0.044	0.593		0.002	0.288	0.593	-0.001	-0.536	1.779
MJN	0.520	-0.263	0.001	*	0.069	11.115	0.001	-0.006	-3.334	2.267
SWY	0.797	-0.087	0.291		0.007	1.125	0.291	-0.003	-1.061	2.210
PG	0.486	0.135	0.100	**	0.018	2.746	0.100	0.002	1.657	1.793
LO	0.417	-0.078	0.343		0.006	0.905	0.343	-0.002	-0.951	2.039
DF	0.514	0.037	0.652		0.001	0.204	0.652	0.002	0.452	2.033
HNZ	0.479	0.094	0.251		0.009	1.326	0.251	0.001	1.152	2.036
ADM	0.939	-0.105	0.201		0.011	1.649	0.201	-0.002	-1.284	2.094
CPB	0.430	-0.018	0.830		0.000	0.046	0.830	0.000	-0.215	1.686
RAI	0.488	0.032	0.700		0.001	0.149	0.700	0.000	0.386	2.098
SVU	0.916	-0.132	0.105		0.018	2.658	0.105	-0.012	-1.630	1.880
HSY	0.466	-0.049	0.547		0.002	0.365	0.547	-0.001	-0.604	2.112
EL	1.100	-0.212	0.009	**	0.045	7.014	0.009	-0.005	-2.648	2.004
PEP	0.438	-0.022	0.787		0.000	0.074	0.787	0.000	-0.271	1.813
WAG	0.697	0.032	0.700		0.001	0.149	0.700	0.001	0.386	1.731
MKC	0.569	-0.098	0.230		0.010	1.453	0.230	-0.001	-1.205	1.885
KO	0.648	-0.062	0.447		0.004	0.581	0.447	-0.001	-0.762	1.897
GIS	0.389	0.015	0.857		0.000	0.032	0.857	0.000	0.180	1.766
PM	0.706	-0.046	0.573		0.002	0.318	0.573	-0.001	-0.564	1.871
STZ	1.192	0.177	0.030	*	0.031	4.798	0.030	0.008	2.190	1.704
CCE	1.103	-0.148	0.071	*	0.022	3.314	0.071	-0.003	-1.821	2.092
HRL	0.572	-0.189	0.020	*	0.036	5.519	0.020	-0.002	-2.349	1.897
KMB	0.425	0.021	0.801		0.000	0.064	0.801	0.000	0.253	1.687
KR	0.576	0.048	0.559		0.002	0.344	0.559	0.001	0.586	2.174
MO	0.508	-0.004	0.960		0.000	0.003	0.960	0.000	-0.050	2.339
AVP	1.256	-0.094	0.253		0.009	1.319	0.253	-0.004	-1.148	2.062
CVS	0.605	-0.055	0.501		0.003	0.455	0.501	-0.001	-0.675	2.219
CL	0.608	-0.077	0.347		0.006	0.889	0.347	-0.001	-0.943	1.960
DPS	0.475	0.038	0.641		0.001	0.219	0.641	0.001	0.468	2.018
TSN	0.888	-0.050	0.544		0.002	0.370	0.544	-0.001	-0.608	2.125
CLX	0.359	0.071	0.386		0.005	0.757	0.386	0.001	0.870	1.979
SLE	0.578	-0.087	0.640		0.008	0.223	0.640	-0.003	-0.472	2.267
K	0.392	-0.021	0.802		0.000	0.063	0.802	0.000	-0.252	1.813
SJM	0.502	-0.026	0.752		0.001	0.100	0.752	0.000	-0.316	1.933
BF.B	0.777	0.015	0.857		0.000	0.033	0.857	0.000	0.181	1.978
XLP	0.604	-0.010	0.905		0.000	0.014	0.905	0.000	-0.120	2.056
SYY	0.595	-0.007	0.928		0.000	0.008	0.928	0.000	-0.091	1.560
COST	0.646	-0.046	0.571		0.002	0.322	0.571	-0.001	-0.568	1.699
WMT	0.413	0.016	0.849		0.000	0.036	0.849	0.000	0.190	1.826
KFT	0.529	-0.243	0.019	*	0.059	5.735	0.019	-0.005	-2.395	2.074
WFM	1.133	-0.023	0.782		0.001	0.077	0.782	-0.001	-0.277	1.973
BEAM	0.950	0.027	0.744		0.001	0.107	0.744	0.001	0.327	2.042
CAG	0.445	-0.021	0.795		0.000	0.068	0.795	0.000	-0.261	2.092

Using the regression analysis model with the symbols with significant correlation, a prediction accuracy of 49.33%, a median accuracy of 51.11% and a standard deviation of 5.560% was found and is displayed in Table 4.43. Additionally, 3 symbols out of the 43 symbols had accuracy ratings greater than or equal to 50%.

Table 4.43:

Model Accuracy for XLP Aggregated Sentiment and XLP ETF and Sector Symbols for Tweets captured during trading hours. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50**
CCE	1.103	55.556	*
STZ	1.192	54.444	*
HRL	0.572	51.111	*
MJN	0.519	43.333	
KFT	0.529	42.222	
	Average	**49.333**	
	Median	**51.111**	
Standard	**Deviation**	**5.560**	

Table 4.44 provides the output of the regression analysis for XLP for non-trading hours. It is worth highlighting that out of the 43 symbols in the XLP sector, 4 symbols fall within the 95% significance level.

Table 4.44:

Regression Analysis output for Tweets captured during non-trading hours for XLP and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig?	RSquared	F-Stat	FStatProb	Coefficient	TValue	Durbin-Watson
TAP	0.796	-0.016	0.840		0.000	0.041	0.840	0.000	-0.202	1.801
MJN	0.520	-0.198	0.014	*	0.039	6.171	0.014	-0.004	-2.484	2.232
SWY	0.797	-0.138	0.087	**	0.019	2.964	0.087	-0.004	-1.722	2.184
PG	0.486	0.017	0.832		0.000	0.045	0.832	0.000	0.212	1.761

Table 4.44:

Regression Analysis output for Tweets captured during non-trading hours for XLP and Symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

LO	0.417	-0.026	0.751		0.001	0.101	0.751	-0.001	-0.318	2.056
DF	0.514	-0.058	0.473		0.003	0.518	0.473	-0.003	-0.719	2.043
HNZ	0.479	0.014	0.860		0.000	0.031	0.860	0.000	0.176	2.042
ADM	0.939	-0.282	0.000	*	0.080	13.153	0.000	-0.006	-3.627	2.148
CPB	0.430	0.025	0.754		0.001	0.098	0.754	0.000	0.314	1.730
RAI	0.488	0.097	0.231		0.009	1.446	0.231	0.001	1.202	2.124
SVU	0.916	-0.048	0.558		0.002	0.344	0.558	-0.004	-0.586	1.799
HSY	0.466	0.053	0.514		0.003	0.429	0.514	0.001	0.655	2.097
EL	1.100	-0.059	0.470		0.003	0.525	0.470	-0.001	-0.725	1.854
PEP	0.438	-0.050	0.537		0.003	0.383	0.537	-0.001	-0.619	1.781
WAG	0.697	-0.092	0.257		0.008	1.292	0.257	-0.002	-1.137	1.728
MKC	0.569	-0.015	0.857		0.000	0.033	0.857	0.000	-0.180	1.853
KO	0.648	-0.068	0.404		0.005	0.700	0.404	-0.001	-0.837	1.842
GIS	0.389	0.049	0.547		0.002	0.364	0.547	0.000	0.603	1.748
PM	0.706	0.054	0.506		0.003	0.444	0.506	0.001	0.666	1.866
STZ	1.192	0.247	0.002	*	0.061	9.898	0.002	0.010	3.146	1.772
CCE	1.103	-0.040	0.624		0.002	0.241	0.624	-0.001	-0.491	2.073
HRL	0.572	-0.086	0.286		0.007	1.145	0.286	-0.001	-1.070	1.822
KMB	0.425	0.065	0.422		0.004	0.647	0.422	0.001	0.805	1.702
KR	0.576	-0.131	0.106		0.017	2.641	0.106	-0.002	-1.625	2.115
MO	0.508	0.015	0.850		0.000	0.036	0.850	0.000	0.189	2.330
AVP	1.256	-0.030	0.712		0.001	0.137	0.712	-0.001	-0.370	2.089
CVS	0.605	0.003	0.975		0.000	0.001	0.975	0.000	0.031	2.199
CL	0.608	-0.029	0.720		0.001	0.129	0.720	0.000	-0.360	1.951
DPS	0.475	-0.015	0.851		0.000	0.035	0.851	0.000	-0.188	2.026
TSN	0.888	-0.089	0.270		0.008	1.224	0.270	-0.002	-1.106	2.161
CLX	0.359	-0.023	0.775		0.001	0.082	0.775	0.000	-0.286	1.972
SLE	0.578	0.040	0.832		0.002	0.046	0.832	0.002	0.214	2.181
K	0.392	-0.043	0.594		0.002	0.285	0.594	-0.001	-0.534	1.859
SJM	0.502	-0.017	0.836		0.000	0.043	0.836	0.000	-0.207	1.931
BF.B	0.777	-0.067	0.410		0.004	0.683	0.410	-0.001	-0.826	2.016
XLP	0.604	-0.042	0.603		0.002	0.272	0.603	0.000	-0.521	2.030
SYY	0.595	-0.052	0.524		0.003	0.409	0.524	-0.001	-0.639	1.624
COST	0.646	-0.043	0.593		0.002	0.287	0.593	-0.001	-0.536	1.699
WMT	0.413	-0.071	0.379		0.005	0.780	0.379	-0.001	-0.883	1.782
KFT	0.529	-0.383	0.000	*	0.146	15.947	0.000	-0.008	-3.993	2.118
WFM	1.133	-0.063	0.441		0.004	0.597	0.441	-0.002	-0.773	1.973
BEAM	0.950	-0.118	0.145		0.014	2.146	0.145	-0.002	-1.465	2.022
CAG	0.445	-0.058	0.474		0.003	0.515	0.474	-0.001	-0.717	2.076

Using the regression analysis model with the symbols with significant correlation, a prediction accuracy of 50.28%, a median accuracy of 49.44% and a standard deviation of 4.80 was found and is displayed in Table 4.45. Additionally, 2 symbols out of the 43 symbols had accuracy ratings greater than or equal to 50%.

Table 4.45:

Model Accuracy for XLP Aggregated Sentiment and XLP ETF and Sector Symbols for Tweets captured during trading hours. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	Beta	Accuracy	≥ 50
ADM	0.939	57.778	*
MJN	0.520	50.000	*
KFT	0.529	48.889	
STZ	1.192	44.444	
	Average	50.278	
	Median	49.444	
Standard Deviation		4.803	

Reviewing the XLP analysis, the prediction average for non-trading hours are a bit better than the trading hours predictions, but the number of symbols adding to that predictability has decreased. With the low number of symbols participating in the XLP analysis it is difficult to say how the trading hours versus non-trading hours analysis compares with each other. With the XLP data, there is not enough evidence to support rejecting the null hypothesis.

From the analysis, it appears that for XLE the Tweets captured during trading hours provide more of an edge in predicting market movements versus non-trading hours. For the XLP sector and symbols, there was not enough evidence to support rejecting the null hypothesis. Additionally, this categorization of Tweets does not seem to provide an edge over previous analysis using Tweets from trading hours and non-trading hours combined as shown in H1 above.

RESEARCH QUESTION 4

RQ-4: Are there specific users that provide more ‘weight’ to a sentiment of a stock or sector based on the users’ reputation?

- **H4**: The number of followers of a Twitter user determines the effect that users' Tweets will have on sentiment for a stock or sector. The null hypothesis (**$H4_0$**) states that there is no relationship between the number of followers and sentiment on a stock or sector.

Addressing RQ-4 was challenging since the Twitter API makes it time-consuming to get information on a Twitter user. Twitter's API forces a limit on accessing user information to keep unscrupulous developers from taking an enormous amount of Twitter user profile data in a short amount of time. At the time of this study, the Twitter API had a request limit of 350 requests per hour for authorized users with a request being defined as a call to the API for any form of information (Twitter, 2011a).

There were 13,067 unique users captured in the XLE sector and 37,760 users captured in the XLP sector. The information gathered on each user consisted of basic user information including number of followers, number of people the user is following and total number of Tweets sent by the user. With the user information for each user captured, regression analysis was performed to evaluate RQ-4. The regression equation used for this analysis was the same as previously used and is provided in Equation 1.

Addressing H4

H4: *The number of followers of a Twitter user determines the effect that users' Tweets will have on sentiment for a stock or sector. The null hypothesis (**$H4_0$**) states that there is no relationship between the number of followers and sentiment on a stock or sector*

The first step in addressing H4 was to review the number of followers that each user has by accessing the Twitter API. This was performed using an automated script that ran over the course of several weeks to download user information for each user captured during the data collection phase.

Recall that from the initial data analysis shown in tables 4.2 and 4.3, XLE had 130,611 Tweets and XLP had 144,214 Tweets captured. Additionally, XLE had 13,067 unique users and XLP had 37,760 unique users captured. While it was impossible to review each user's Tweets and each user's follower numbers during this study, users could be ranked by number of followers to determine if those users with a high number of followers provide an edge in predicting movement in then markets, should provide some insights into H4.

To begin the analysis the Top 50 users ranked by number of followers were identified for both the XLE and XLP sectors and symbols. The Top 50 users are highlighted in Table 4.46 for XLE and Table 4.47 for XLP. This list of Top 50 users was generated in December 2012.

Table 4.46:

Top 50 users ranked by number of followers in XLE

Rank	User	Number of Tweets	Followers	Rank	User	Number of Tweets	Followers
1	BloombergNews	14	1382581	26	SquawkStreet	3	57857
2	MarketWatch	33	966839	27	stockhaven	23	55624
3	CMEGroup	2	756499	28	stockguy22	174	53760
4	jimcramer	267	735608	29	IBDinvestors	15	53585
5	CBOE	139	727694	30	Bong8242CO	21	53416
6	CNNMoney	46	681439	31	SeekingAlpha	4534	53193
7	businessinsider	125	487486	32	ritholtz	6	51733
8	themotleyfool	33	475329	33	alphatrends	10	51329
9	StockTwits	463	344489	34	optionmonster	35	48860
10	YahooFinance	57	308958	35	AnneMarieTrades	6	41732
11	howardlindzon	61	243581	36	ReutersInsider	22	39985
12	BloombergTV	98	212865	37	terranovajoe	227	39079
13	FoxBusiness	18	194320	38	abnormalreturns	64	38908
14	HamzeiAnalytics	20	150588	39	Benzinga	515	35500
15	russian_market	11	132253	40	MarketBeat	37	35313
16	TheAroraReport	11	104276	41	LaMonicaBuzz	275	35129
17	TheStreet	857	97681	42	clusterstock	207	34681
18	MadMoneyOnCNBC	265	85814	43	KeithMcCullough	323	33628
19	cnbcfastmoney	401	77086	44	alaidi	6	33613
20	DougKass	14	72380	45	themoneygame	213	33155
21	ReformedBroker	87	71355	46	bespokeinvest	68	32517
22	pensionpartners	83	70217	47	Convertbond	35	32203
23	carlquintanilla	20	67063	48	WALLSTJESUS	32	32196
24	TheStalwart	18	63317	49	WallStJesus	893	32196
25	herbgreenberg	16	59510	50	Street_Insider	82	29868

Tables 4.46 and 4.47 clearly highlight a disparity between number of followers and the number of Tweets captured by that Twitter user during the data collection phase. For the XLE sector and symbols, the Top 50 users ranked by number of followers contributed 10,985

Tweets out of 130,611 total Tweets, which is 8.41% of total Tweets. For the XLP sector the same ranking approach found that the Top 50 users contributed 13,071 Tweets out of the total 144,214 Tweets, which is 9.06% of total Tweets captured.

Table 4.47:

Top 50 users ranked by number of followers in XLP

Rank	User	Number of Tweets	Followers	Rank	User	Number of Tweets	Followers
1	BloombergNews	32	1382581	26	stockhaven	19	55624
2	MarketWatch	30	966839	27	stockguy22	61	53760
3	jimcramer	246	735608	28	IBDinvestors	38	53585
4	CBOE	77	727694	29	SeekingAlpha	4985	53193
5	CNNMoney	108	681439	30	ritholtz	14	51733
6	businessinsider	203	487486	31	alphatrends	12	51329
7	themotleyfool	48	475329	32	optionmonster	13	48860
8	StockTwits	627	344489	33	infamous_SODM G	608	42155
9	YahooFinance	205	308958	34	JamieSaettele	2	41797
10	howardlindzon	70	243581	35	AnneMarieTrades	2	41732
11	BloombergTV	199	212865	36	ReutersInsider	70	39985
12	FoxBusiness	60	194320	37	terranovajoe	103	39079
13	HamzeiAnalytics	46	150588	38	abnormalreturns	110	38908
14	russian_market	10	132253	39	Benzinga	357	35500
15	TheAroraReport	18	104276	40	MarketBeat	49	35313
16	TheStreet	1323	97681	41	LaMonicaBuzz	533	35129
17	MadMoneyOnCNBC	447	85814	42	clusterstock	164	34681
18	cnbcfastmoney	286	77086	43	KeithMcCullough	184	33628
19	DougKass	44	72380	44	alaidi	4	33613
20	ReformedBroker	94	71355	45	themoneygame	159	33155
21	pensionpartners	104	70217	46	bespokeinvest	41	32517
22	carlquintanilla	101	67063	47	Convertbond	16	32203
23	TheStalwart	24	63317	48	WALLSTJESUS	9	32196
24	herbgreenberg	73	59510	49	WallStJesus	871	32196
25	SquawkStreet	8	57857	50	Street_Insider	164	29868

Reviewing the lists of the Top 50 users in Tables 4.46 and 4.47 shows most users to be well known stock market organizations, news outlets and other accounts associated with stock market related companies. For example, the user ‘howardlindzon’ is the founder of StockTwits, the company that started the use of the ‘$’ nomenclature used during this study.

Table 4.48 provides a summary of analysis of the Top 50 users ranked by number of followers. Reviewing this data, it is clear that in both the XLE and XLP sectors, the Top 50 users ranked by number of followers is the minimum ranking that can be used to ensure the average number of Tweets per day is above the central limit recommendation of 30 observations per period. For this reason, regression analysis was performed only on the Top 50 users to ensure the central limit recommendations are considered.

Table 4.48:

Summary of the Top 50 users ranked by number of followers for XLE and XLP

XLE				**XLP**			
Ranking	**Number of Tweets**	**Percentage of Total**	**Average Tweets per Day**	**Ranking**	**Number of Tweets**	**Percentage of Total**	**Average Tweets per Day**
Top 50	10,985	8.41%	30.096	Top 50	13,071	9.06%	35.811

Similarly to the other sections of this chapter, the sentiment signals for each symbol and sector were run through a regression analysis test using the same regression model used throughout the study and shown in Equation 1. For this particular analysis, Tweets sent by the Top 50 users ranked by number of followers were used. Table 4.49 provides the output of the regression analysis for the XLE sector and symbols. Using the Top 50 users ranked by number of follower's results in 38 out of 43 symbols with p-values in the 95% significance range. Compare that to the original regression analysis for H1a where 36 out of 43 were in the 95% significance range and we see a slight increase in correlated and significant results.

Table 4.49:

Regression Analysis output for the Top 50 users ranked by number of followers for the XLE and symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig ?	RSquared	F-Stat	FStatProb	Coefficient	TValue	Durbin-Watson
NBL	1.401	-0.253	0.002	*	0.072	5.876	0.003	0.000022	1.152	2.324
ANR	2.414	-0.193	0.017	*	0.039	3.036	0.051	0.000023	0.499	2.049
EP	0.453	0.110	0.815		0.612	3.155	0.150	0.000140	2.487	1.358
CAM	1.745	-0.367	0.000	*	0.135	11.799	0.000	-0.000006	-0.257	1.962
EQT	1.094	-0.261	0.001	*	0.070	5.718	0.004	-0.000014	-0.637	2.056
APC	1.635	-0.225	0.005	*	0.058	4.684	0.011	-0.000024	-1.107	2.134
TSO	1.083	-0.194	0.016	*	0.081	6.655	0.002	-0.000074	-2.669	2.160

Table 4.49:

Regression Analysis output for the Top 50 users ranked by number of followers for the XLE and symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

BHI	1.258	-0.354	0.000	*	0.127	10.935	0.000	-0.000010	-0.441	1.790
HP	1.789	-0.296	0.000	*	0.100	8.367	0.000	-0.000036	-1.415	1.926
XOM	0.926	-0.223	0.005	*	0.051	4.083	0.019	0.000006	0.515	1.921
APA	1.368	-0.322	0.000	*	0.106	8.940	0.000	-0.000012	-0.648	2.124
HAL	1.276	-0.384	0.000	*	0.148	13.091	0.000	-0.000003	-0.168	1.767
COP	0.983	-0.162	0.045	*	0.044	3.447	0.034	-0.000022	-1.663	2.288
SLB	1.441	-0.333	0.000	*	0.113	9.571	0.000	0.000010	0.519	1.859
WMB	1.166	-0.286	0.000	*	0.087	7.216	0.001	0.000015	0.933	2.112
BTU	1.962	-0.291	0.000	*	0.085	7.017	0.001	-0.000006	-0.183	1.791
VLO	1.284	-0.288	0.000	*	0.095	7.950	0.001	-0.000033	-1.448	2.089
HES	1.568	-0.275	0.001	*	0.079	6.476	0.002	-0.000017	-0.717	1.974
CNX	1.432	-0.210	0.009	*	0.047	3.733	0.026	-0.000019	-0.707	1.944
RRC	1.243	-0.279	0.000	*	0.078	6.356	0.002	-0.000001	-0.052	2.316
COG	1.369	-0.192	0.017	*	0.040	3.151	0.046	-0.000023	-0.692	2.077
CVX	1.042	-0.246	0.002	*	0.063	5.054	0.008	-0.000007	-0.608	1.982
DO	1.074	-0.367	0.000	*	0.137	11.961	0.000	-0.000009	-0.564	2.173
OXY	1.488	-0.366	0.000	*	0.135	11.760	0.000	-0.000007	-0.390	2.189
SE	0.685	-0.138	0.087	**	0.019	1.493	0.228	0.000002	0.212	1.965
MUR	1.488	-0.350	0.000	*	0.123	10.564	0.000	-0.000004	-0.190	2.067
DVN	1.255	-0.326	0.000	*	0.106	8.959	0.000	-0.000001	-0.033	1.889
NBR	2.207	-0.312	0.000	*	0.099	8.313	0.000	-0.000017	-0.549	1.991
SUN	0.353	-0.079	0.439		0.031	1.502	0.228	0.000057	1.546	1.882
DNR	2.041	-0.297	0.000	*	0.093	7.783	0.001	0.000026	0.946	2.220
QEP	1.664	-0.318	0.000	*	0.101	8.502	0.000	0.000006	0.241	1.870
NE	1.563	-0.384	0.000	*	0.148	13.088	0.000	-0.000006	-0.264	2.108
NFX	1.742	-0.258	0.001	*	0.067	5.430	0.005	0.000007	0.237	1.997
CHK	1.758	-0.113	0.163	**	0.027	2.102	0.126	-0.000059	-1.490	2.284
MRO	1.498	-0.305	0.000		0.096	8.020	0.000	-0.000014	-0.719	2.142
XLE	1.234	-0.374	0.000	*	0.142	12.476	0.000	-0.000007	-0.549	2.059
SWN	1.231	-0.295	0.000	*	0.088	7.269	0.001	-0.000008	-0.318	2.083
PXD	2.108	-0.329	0.000	*	0.108	9.184	0.000	0.000006	0.221	2.365
RDC	1.458	-0.323	0.000	*	0.107	9.025	0.000	-0.000015	-0.648	2.045
NOV	1.555	-0.311	0.000	*	0.099	8.287	0.000	-0.000012	-0.566	2.024
EOG	1.780	-0.284	0.000	*	0.084	6.922	0.001	-0.000018	-0.764	2.472
FTI	1.472	-0.269	0.001	*	0.077	6.313	0.002	-0.000018	-0.880	1.897
MPC	1.122	-0.267	0.001	*	0.072	5.869	0.004	0.000007	0.331	1.885

Table 4.50 provides the accuracy output of the analysis performed using the regression models. For the Top 50 user Tweets, 21 out of 43 symbols had accuracy greater than or equal to 50%, which is slightly less than the outcome of the analysis in H1a, which included Tweets from all users. Additionally, using Tweets from the Top 50 users results in an average accuracy of 49.386% with a standard deviation of 4.787%.

Table 4.50:

Model Accuracy for XLE Aggregated Sentiment and XLE ETF and Sector Symbols for Tweets from the Top 50 users ranked by number of followers.. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	**Beta**	**Accuracy**	**≥ 50**	**Symbol**	**Beta**	**Accuracy**	**≥ 50**
BTU	1.962	58.889	*	NOV	1.555	50.000	*
MPC	1.122	58.889	*	FTI	1.472	50.000	*
APA	1.368	56.667	*	NBL	1.401	48.889	
CNX	1.432	55.556	*	CAM	1.745	48.889	
OXY	1.488	55.556	*	CVX	1.042	48.889	
EQT	1.094	53.333	*	QEP	1.664	48.889	
EOG	1.780	53.333	*	HES	1.568	47.778	
BHI	1.258	52.222	*	DO	1.074	47.778	
SLB	1.441	52.222	*	XOM	0.926	46.667	
VLO	1.284	52.222	*	WMB	1.166	46.667	
NBR	2.207	52.222	*	COG	1.369	45.556	
ANR	2.414	51.111	*	PXD	2.108	45.556	
APC	1.635	51.111	*	COP	0.983	44.444	
NE	1.563	51.111	*	DNR	2.041	44.444	
NFX	1.742	51.111	*	XLE	1.234	44.444	
SWN	1.231	51.111	*	HAL	1.276	43.333	
TSO	1.083	50.000	*	RDC	1.458	42.222	
RRC	1.243	50.000	*	HP	1.789	37.778	
DVN	1.255	50.000	*	MUR	1.488	37.778	
		Average	**49.386**				
		Median	**50.000**				
		Standard Deviation	**4.787**				

Table 4.51 provides the output of the regression analysis for the XLP sector and symbols. Using the Top 50 users ranked by number of followers results in 4 out of 43 symbols with p-values in the 95% significance range, which is the same output found in the original regression analysis for H1a.

Table 4.51:

Regression Analysis output for the Top 50 users ranked by number of followers for the XLP and symbols within the Sector (95% Significance described by "*" and 90% Significance by "**")

Symbol	Beta	Correlation	p-value	Sig ?	RSquared	F-Stat	FStatProb	Coefficient	TValue	Durbin-Watson
TAP	0.796	0.015	0.851		0.002	0.180	0.835	-0.000009	-0.570	1.806
MJN	0.520	-0.253	0.002	*	0.071	5.791	0.004	-0.000020	-1.077	2.297
SWY	0.797	-0.089	0.274		0.008	0.599	0.551	0.000000	-0.016	2.198
PG	0.486	0.038	0.637		0.004	0.306	0.737	-0.000007	-0.624	1.762
LO	0.417	-0.074	0.362		0.010	0.735	0.481	-0.000015	-0.798	2.030
DF	0.514	-0.040	0.623		0.004	0.273	0.761	-0.000027	-0.552	2.049
HNZ	0.479	0.019	0.817		0.002	0.164	0.849	-0.000005	-0.524	2.048
ADM	0.939	-0.227	0.005	*	0.053	4.188	0.017	0.000007	0.403	2.169
CPB	0.430	0.021	0.797		0.001	0.080	0.923	0.000003	0.308	1.727
RAI	0.488	0.072	0.373		0.023	1.753	0.177	-0.000019	-1.643	2.147
SVU	0.916	-0.114	0.159		0.013	1.002	0.369	-0.000010	-0.136	1.797
HSY	0.466	0.001	0.987		0.000	0.016	0.984	0.000002	0.178	2.102
EL	1.100	-0.088	0.279		0.008	0.589	0.556	0.000001	0.063	1.863
PEP	0.438	-0.034	0.679		0.005	0.375	0.688	-0.000007	-0.761	1.796
WAG	0.697	-0.026	0.745		0.001	0.068	0.934	0.000004	0.177	1.728
MKC	0.569	-0.022	0.787		0.002	0.188	0.829	-0.000005	-0.551	1.854
KO	0.648	-0.070	0.390		0.005	0.386	0.681	0.000002	0.179	1.857
GIS	0.389	0.072	0.377		0.007	0.519	0.596	-0.000005	-0.507	1.745
PM	0.706	-0.017	0.832		0.001	0.039	0.961	-0.000002	-0.185	1.865
STZ	1.192	0.328	0.000	*	0.108	9.165	0.000	-0.000011	-0.310	1.689
CCE	1.103	-0.080	0.322		0.012	0.948	0.390	0.000017	0.954	2.088
HRL	0.572	-0.082	0.312		0.007	0.517	0.598	0.000001	0.097	1.820
KMB	0.425	0.035	0.664		0.004	0.312	0.732	0.000006	0.661	1.705
KR	0.576	-0.023	0.773		0.005	0.413	0.662	-0.000012	-0.862	2.172
MO	0.508	-0.023	0.777		0.006	0.452	0.637	-0.000008	-0.907	2.338
AVP	1.256	-0.016	0.847		0.005	0.380	0.685	0.000031	0.850	2.108
CVS	0.605	-0.035	0.663		0.002	0.117	0.890	-0.000003	-0.210	2.206
CL	0.608	-0.038	0.639		0.004	0.271	0.763	-0.000006	-0.568	1.958
DPS	0.475	-0.042	0.605		0.005	0.351	0.705	-0.000008	-0.659	2.041
TSN	0.888	-0.082	0.309		0.007	0.569	0.567	-0.000007	-0.323	2.174
CLX	0.359	0.018	0.822		0.014	1.062	0.348	-0.000012	-1.440	1.998
SLE	0.578	-0.044	0.813		0.095	1.461	0.249	0.000149	1.692	2.296
K	0.392	-0.046	0.573		0.021	1.592	0.207	-0.000021	-1.692	1.885
SJM	0.502	-0.023	0.778		0.001	0.079	0.924	-0.000004	-0.279	1.932
BF.B	0.777	-0.014	0.863		0.003	0.202	0.818	-0.000008	-0.611	2.021
XLP	0.604	-0.035	0.670		0.005	0.351	0.705	-0.000005	-0.721	2.053
SYY	0.595	-0.074	0.359		0.021	1.624	0.201	-0.000018	-1.547	1.686
COST	0.646	0.015	0.849		0.013	0.984	0.376	-0.000017	-1.390	1.758
WMT	0.413	0.001	0.995		0.033	2.601	0.078	-0.000029	-2.281	1.926
KFT	0.529	-0.368	0.000	*	0.139	7.447	0.001	0.000008	0.623	2.174
WFM	1.133	-0.039	0.629		0.004	0.267	0.766	-0.000013	-0.549	1.985
BEAM	0.950	-0.062	0.445		0.007	0.528	0.591	-0.000011	-0.687	2.037
CAG	0.445	-0.023	0.781		0.004	0.281	0.756	-0.000007	-0.696	2.098

Table 4.52 provides the accuracy output of the analysis performed using the regression models. For the Top 50 users, 3 out of 43 symbols had accuracy greater than or equal to 50%, which is similar to the outcome of the analysis in H1a that included Tweets from all users. Additionally, using Tweets from the Top 50 users resulted in an average accuracy of 49.727%

with a standard deviation of 3.179%, which is less than the average accuracy found with the complete signal.

Table 4.52:

Model Accuracy for XLP Aggregated Sentiment and XLP ETF and Sector Symbols for Tweets from the Top 50 users ranked by number of followers. Accuracy presented in Percentage. Asterisk denotes Accuracy greater than or equal to 50%

Symbol	Beta	Sig ?	Accuracy	≥ 50
ADM	0.939	*	52.222	*
KFT	0.529	*	52.222	*
STZ	1.192	*	50.000	*
MJN	0.520	*	44.444	
	Average	**49.722**		
	Median	**51.111**		
	Standard Deviation	**3.179**		

Based on the analysis performed, there does not appear to be any significant correlation between the number of followers that a Twitter user has and that user's Tweets affect on sentiment of a sector or stock. Using the Top 50 user list does not provide any additional value over using all Tweets. In fact, limiting the data in to only the Tweets from Top 50 users removes more than 90% of the data from the analysis data set, which is not ideal when the initial data set is already limited.

For H4, there is insufficient evidence available to be able reject the null hypothesis for individual users. Studying the Top 50 user list provides some information but there is still insufficient evidence to support rejecting the null hypothesis.

Chapter Summary

This chapter has discussed the data analysis for this study and revealed the results of the tests of the hypothesis testing for the main research questions and hypotheses. A summary of the outcome of the hypothesis tests is shown in Table 4.53 and a discussion of the results follow the table.

Table 4.53:

Hypothesis Summary Table

Hypothesis	Null Hypothesis	Outcome
H1a: The sentiment of a sector will match the overall averaged sentiment of all stocks within the sector	**H1a$_0$**: That there will be no noticeable relationship between the sentiment of a sector and the overall averaged sentiment of stocks within the sector.	Insufficient evidence to reject the null hypothesis.
H1b: The sentiment of a sector can be used to predict the movement of all stocks in that sector.	**H1b$_0$**: The sentiment of a sector will provide no predictive capability.	For the original definition, there is insufficient evidence to reject the null hypothesis. For the modified definition of sentiment, there is limited evidence to support rejecting the null.
H1c: The sentiment of a sector or stock on any given day will provide a prediction for the next day's movement in that stock	**H1c$_0$**: There will be no predictive capability on price and sentiment from day to day.	For the original definition, there is insufficient evidence to reject the null hypothesis.

Table 4.53:

Hypothesis Summary Table

		For the modified definition of sentiment, there is limited evidence to support rejecting the null.
H2a: The sentiment of a stock within a given sector will affect the sentiment of the overall sector based on the relative market cap weighting of that stock assigned to that stock within the sector	$H2a_0$: The sentiment of a stock is not correlated with the market cap weighting of the stock in that sector	Insufficient evidence to reject the null hypothesis.
H2b: The stocks that provide the most weight toward the sentiment of a sector are also the stocks with the highest number of mentions on Twitter.	$H2b_0$: There is no relationship between the number of mentions on Twitter and the affect that the stocks have on the sector sentiment.	There is limited evidence to support rejecting the null.
H3: There is a difference in the effect that Tweets sent during non-market hours (i.e., evenings and weekends) and Tweets sent during market hours have on sentiment and price.	$H3_0$: There is no difference in the effect of Tweets sent during market hours and non-market hours.	Evidence exists to reject the null hypothesis for XLE but not for XLP.
H4: The number of followers of a Twitter user determines the effect that users' Tweets will	$H4_0$: There is no relationship between	Insufficient evidence to reject

Table 4.53: *Hypothesis Summary Table*		
have on sentiment for a stock or sector.	the number of followers and sentiment on a stock or sector.	the null hypothesis.

While there was not insufficient evidence to reject the null hypothesis for some of the hypotheses, there were significant findings within this research project. There are a large number of Twitter users sending Tweets related to the stock market each day, there is generally not enough data on a daily basis to be able to analyze most individual symbols. Due to this limitation, aggregating data for multiple symbols in a sector allows analysis to be performed using an aggregated sentiment signal for each sector. Using the aggregation approach provided enough data to perform this study.

A very important finding from this study is found within the XLE sector analysis throughout the research. During the analysis, it was found that there was a statistically significant correlation between many of the symbols that comprise the XLE sector. The statistically significant correlation between price and sentiment sets the stage for future research into why the significant correlations existed with the XLE analysis but not with the XLP analysis.

One of the most intriguing outcomes from this research is found with the analysis of using the Bear/Bull ratio extreme values. Taking the 90% and 10% percentiles of the Bear/Bull ratio and using those values as extreme readings shows a great deal of promise for investing strategies. With this contrarian approach to extreme readings with the XLE ETF resulted in a 578 basis point improvement over buy and hold returns and a 723 basis point improvement over random entry returns. Using this extreme contrarian approach with the XLP ETF resulted in a 71 basis point improvement over the buy and hold strategy and a 113 basis point improvement over random entry returns. From this research, it is clear that using a trading strategy that uses a contrarian approach to Bear/Bull sentiment extreme signals provides a very interesting research path for the future. In the next chapter, a review of this research is provided along with more avenues for future research.

CHAPTER 5: CONCLUSIONS AND FUTURE RESEARCH

The goal of this study was to analyze Twitter sentiment to determine if it might be a useful predictor for movement in the stock market. To perform this study, Tweets were captured over the course of one year and the sentiment of each Tweet was analyzed using an automated Bayesian Classifier. This sentiment was then used to attempt to predict movements in the market.

At the beginning of this study, a number of topical areas and questions were to be studied. These topical areas and the planned outcomes for each are provided below:

- To understand how the Twitter sentiment of a sector affects or responds to the Twitter sentiment of the stocks that make up that sector.
- To understand whether there are times of day or days of the week that provides more useful sentiment information for a stock or sector.
- To gain a better understanding of how Twitter is being used to share information about the stock market and how that information is disseminated via ReTweets and further sharing.
- To gain an understanding of how users and groups of users impact the movement of specific stocks or financial instruments.
- To gain a better understanding of whether a stock or sector's sentiment has predictive capabilities for price or volume action

To address these topical areas, four main research questions were developed and hypothesis tests were performed. The four research questions were:

- **RQ-1:** Using a given sector of the stock market, does the sentiment for that sector match the aggregated sentiment for the stocks that make up that sector? How well does the sentiment predict price / volume movement?
- **RQ-2**: Are there specific stocks within a given sector that supply the majority of the sentiment for that sector? If so, do these stocks supply sentiment in correlation to the weighting given to them by ratings agencies such as the Standard & Poor's rating agency?

- **RQ-3:** Are there times of the day or days of the week that provide a more accurate and informative sentiment for a stock or sector?
- **RQ-4**: Are there specific users that provide more 'weight' to a sentiment of a stock or sector based on the users' reputation?

To address each research question, hypothesis tests were performed. While the majority of hypotheses in this study failed to reject the null hypothesis, the questions were answered and the initially stated outcomes were addressed. While most of the null hypotheses of this study were not rejected, the study still delivered a great deal of knowledge on Twitter sentiment analysis, how sentiment is correlated with price movement in the market and how users with large numbers of followers affect the market.

In addition to answering the initial research questions, there are import findings from this study worth highlighting again. These highlights are provided below:

- Regression analysis showed a negative correlation between sentiment and next day price movement. This points toward future analysis of using sentiment as a contrarian indicator using the Bear/Bull ratio construct.
- Regression analysis highlighted that stocks with a higher Beta value appear to be better candidates for using Twitter Sentiment. It is assumed that this is due to having more investors watching these stocks as they tend to more move than the S&P 500 index, which could deliver higher returns to investors if they are able to make accurate predictions on price movement.
- Tweets sent during market hours appear to provide more valuable information relating to market movements than those sent during market hours.
- During this study, the idea of a sentiment 'extreme' was shown to be an interesting approach to using sentiment as a predictor for price movement. When an extreme occurs, a contrarian trade can be taken. Using this approach on XLE and XLP results in the following results:
    - Using an extreme contrarian approach with the XLE ETF resulted in 54.55% accuracy and a 578 basis point improvement over buy and hold returns and a 723 basis point improvement over random entry returns.

- The average return for all symbols in the XLE sector with the extreme contrarian approach resulted in averages of 54.16% accuracy and a 277 basis point improvement over buy and hold returns and a 511 basis point improvement over random entry returns.
- Using an extreme contrarian approach with the XLP ETF resulted in a 71 basis point improvement over buy and hold returns and 113 basis point improvement over random entry returns.
- The average return for all symbols in the XLP sector with the extreme contrarian approach resulted in averages of 34.60% accuracy and a 32 basis point decrease in performance over buy and hold returns and a 55 basis point decrease in performance over random entry returns.

- The number of followers a user has on Twitter does not appear to have any correlation with how that user's Tweets affect price on the symbols studied.
- Due to the lower volume of Tweets for most symbols, it is recommended to look at methods to aggregate sentiment rather than use individual symbol sentiment for those symbols with a small number of Tweets.
- Stocks that exhibit high trading volume on a regular basis also exhibit high Tweet volume on a regular basis.
- Comparing the Bear/Bull ratio with the Put/Call ratio provides very similar results in similar numbers of statistically significant results.
- A small number of users send the majority of Tweets discussing stocks and ETF's.

Future Research

There are numerous areas available for future research using Twitter sentiment and other forms of sentiment from social media.

The first area for additional research can be found with the idea that Twitter sentiment appears to have a negative correlation with price movement on the daily timeframe. This area of research would expand upon the idea of using extreme sentiment measures to attempt to predict movement in the market. In this study, the idea of using sentiment extremes was introduced as part of the study exploration process, but a more detailed and thorough research project could be undertaken to explore this idea further.

An additional avenue for future research is the use of additional classification methods to determine if there are more accurate classification approaches. While the Bayesian Classifier is considered to have 'good' accuracy, additional tests with different classification methods should be undertaken to understand if there are other approaches that deliver more accurate results.

Additional research into the correlations between market volume and Tweet volume should be undertaken. This research might identify methods of selecting only those symbols with high Tweet volume for analysis, which would remove many of the Central Limit Theorem constraints found within this study.

Another avenue of research can be found in reviewing the use of aggregated sentiment. Due to the low volume of Tweets for many symbols, it was necessary to aggregate sentiment to build a useful signal. Further research into methods of aggregating sentiment to determine how best to combine sentiment or whether aggregated sentiment is useful for all sectors or symbols.

Conclusions

While the research questions in this study have not been answered in the affirmative, there has been a great of knowledge gained in how Tweets can be analyzed for sentiment, how investors and traders are using Twitter to share ideas and how those ideas might be used to build trading decision models. Much more research is needed to find useful decision support models for trading and investing based on sentiment.

APPENDICES

Appendix A – S&P 500 ETF Symbols

$MMM	$BMC	$CTAS	$EQT	$GR	$K	$MOLX	$PDCO	$CRM	$TSS
$ACE	$BHI	$CSCO	$EMN	$GT	$KEY	$TAP	$PAYX	$SNDK	$TRV
$AES	$BLL	$C	$ETN	$GOOG	$KMB	$MON	$BTU	$SLE	$TYC
$AFL	$BAC	$CTXS	$ECL	$GWW	$KIM	$MWW	$JCP	$SLB	$TSN
$AKS	$BCR	$CLF	$EIX	$HCP	$KSS	$MCO	$PBCT	$SCHW	$USB
$T	$BAX	$CLX	$EP	$HAL	$KFT	$MS	$POM	$SNI	$UNP
$ABT	$BDX	$COH	$ERTS	$HOG	$KR	$MMI	$PEP	$SEE	$UPS
$ANF	$BBBY	$KO	$EMR	$HAR	$LLL	$MSI	$PKI	$SHLD	$X
$ADBE	$BMS	$CCE	$ETR	$HRS	$LSI	$MUR	$PFE	$SRE	$UTX
$AMD	$BRK/B	$CTSH	$EFX	$HIG	$LH	$MYL	$PM	$SHW	$UNH
$AET	$BBY	$CL	$EQR	$HAS	$LM	$GAS	$PNW	$SIAL	$UNM
$A	$BIG	$CMCSA	$EL	$HCN	$LEG	$NKE	$PXD	$SPG	$URBN
$APD	$BIIB	$CMA	$EXC	$HNZ	$LEN	$NRG	$PBI	$SJM	$VFC
$ARG	$HRB	$CSC	$EXPE	$HP	$LUK	$NYX	$PCL	$SNA	$VLO
$AKAM	$BA	$CPWR	$EXPD	$HSY	$LXK	$NBR	$RL	$SO	$VAR
$AA	$BXP	$CAG	$ESRX	$HES	$LIFE	$NDAQ	$PX	$LUV	$VTR
$AYE	$BSX	$COP	$XOM	$HPQ	$LLY	$NOV	$PCP	$SWN	$VRSN
$ATI	$BMY	$ED	$FFIV	$HD	$LTD	$NSM	$PCLN	$SE	$VZ
$AGN	$BRCM	$STZ	$FLIR	$HON	$LNC	$NTAP	$PFG	$S	$VIA/B
$ALL	$BF/B	$CEG	$FMC	$HRL	$LLTC	$NFLX	$PG	$STJ	$V
$ALTR	$CA	$GLW	$FTI	$DHI	$LMT	$NWL	$PGN	$SWK	$VNO
$MO	$CBG	$COST	$FDO	$HSP	$L	$NFX	$PGR	$SPLS	$VMC
$AMZN	$CBS	$CVH	$FAST	$HST	$LO	$NEM	$PLD	$SBUX	$WMT
$AEE	$CF	$CMI	$FDX	$HCBK	$LOW	$NWSA	$PRU	$HOT	$WAG
$AEP	$CHRW	$DTV	$FII	$HUM	$MTB	$NEE	$PEG	$STT	$DIS
$AXP	$CI	$DTE	$FIS	$HBAN	$WFR	$NI	$PSA	$SRCL	$WPO
$AIG	$CMS	$DHR	$FITB	$ITT	$M	$NE	$PHM	$SYK	$WM
$AMT	$CNX	$DRI	$FHN	$ITW	$MRO	$NBL	$QEP	$STI	$WAT
$AMP	$CSX	$DVA	$FSLR	$IR	$MAR	$JWN	$QCOM	$SUN	$WPI
$ABC	$CVS	$DV	$FE	$TEG	$MMC	$NSC	$PWR	$SVU	$WLP
$AMGN	$CVC	$DF	$FISV	$INTC	$MI	$NU	$DGX	$SYMC	$WFC
$APH	$COG	$DE	$FLS	$ICE	$MAS	$NTRS	$Q	$SYY	$WDC
$APC	$CAM	$DELL	$FLR	$IPG	$MEE	$NOC	$RSH	$TROW	$WU
$ADI	$CPB	$DNR	$F	$IBM	$MA	$NOVL	$RRC	$TE	$WY
$AON	$COF	$XRAY	$FRX	$IFF	$MAT	$NVLS	$RTN	$TJX	$WHR
$APA	$CAH	$DVN	$FO	$IGT	$MFE	$NUE	$RHT	$TGT	$WFMI
$AIV	$CFN	$DO	$BEN	$IP	$MKC	$NVDA	$RF	$TLAB	$WMB

$APOL	$KMX	$DFS	$FCX	$INTU	$MCD	$ORLY	$RSG	$THC	$WIN
$AAPL	$CCL	$DISCA	$FTR	$ISRG	$MHP	$OKE	$RAI	$TDC	$WEC
$AMAT	$CAT	$D	$GME	$IVZ	$MCK	$OXY	$RHI	$TER	$WYN
$ADM	$CELG	$RRD	$GCI	$IRM	$MJN	$OMC	$ROK	$TSO	$WYNN
$AIZ	$CNP	$DOV	$GPS	$JDSU	$MWV	$ORCL	$COL	$TXN	$XL
$AN	$CTL	$DOW	$GD	$JPM	$MHS	$OI	$ROP	$TXT	$XEL
$AZO	$CEPH	$DPS	$GE	$JBL	$MDT	$PCAR	$ROST	$BK	$XRX
$ADSK	$CERN	$DD	$GIS	$JEC	$MRK	$PCG	$RDC	$TMO	$XLNX
$ADP	$CHK	$DUK	$GPC	$JNS	$MET	$PNC	$R	$TIF	$YHOO
$AVB	$CVX	$DNB	$GNW	$JNJ	$PCS	$PPG	$SAI	$TWC	$YUM
$AVY	$CME	$ETFC	$GENZ	$JCI	$MCHP	$PPL	$SCG	$TWX	$ZMH
$AVP	$CB	$EMC	$GILD	$JNPR	$MU	$PLL	$SLM	$TIE	$ZION
$BBT	$CINF	$EOG	$GS	$KLAC	$MSFT	$PH	$SWY	$TMK	$EBAY

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