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Can Online Sentiment Help Predict Dow Jones Industrial Average Returns?

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Abstract

In this paper, we explore the relationship between a Global Mood Time Series, provided by Wall Street Birds, and the Dow Jones Industrial Average (DJIA) from April 2011 to December 2011. My econometric results show that there is no long run equilibrium relationship between the level of global mood and the level of the DJIA. These results apply to the whole period, as well as in the six-month subperiods. Furthermore, daily changes in global mood do not Granger cause DJIA returns. However, changes in global mood do appear to be useful in forecasting the volatility of the DJIA, and my results suggest that GARCH models of volatility of large-cap indexes, and potentially the market as a whole, could be strengthened by including online sentiment measures of Big Data. Measuring global mood, and quantifying its impacts, can potentially lead to superior portfolio construction as forecasting volatility is an important input in portfolio optimization. The results, as a whole, suggest that Big Data can have important implications for investment decision-making.

I. Introduction

Big Data is a concept that describes the vast amount of digital information people generate and have an increasing ability to manage, store, and understand. Companies such as Google and the real-time analytics firm Recorded Future have uncovered and utilized the intelligence Big Data provides to accurately forecast events of the future (Chesnire 2011).

One industry that could potentially find great value in this strategy is the financial sector. Since opinions and emotional states influence a person's decision-making process, consolidating the reactions that investors have to a change in the economy could presumably forecast aggregate investment decisions. Social media provides the consolidated intelligence of consumer sentiment. Wall Street Birds is a company that analyzes the data provided by Twitter posts to assess the global "mood" of the economy. The Global Mood Time Series provided by Wall Street Birds is used in this research to assess the predictive ability of social media on returns in the financial stock market.

According to Eugene F. Fama in the Efficient Market Hypothesis, profit opportunities are derived from two sources: superior information and a superior analysis of available information. As Big Data is a relatively new concept, combining it with sophisticated econometric techniques may allow for an opportunity to exploit a profit in the financial markets, in a way researchers have not yet identified.

We will first attempt to construct a Vector Error Correction Model (VECM) that compares the Global Mood Time Series, provided by Wall Street Birds, with the Dow Jones Industrial Average (DJIA). Through this comparison, we can describe any long run equilibrium relationship they may have and the short term departures from this long run equilibrium. Constructing the VECM is possible if both time series follow stochastic trends, their returns are stationary, and evidence of cointegration exists.

Although the Global Mood Time Series and the DJIA follow stochastic trends, and their respective returns are stationary, there is no evidence of cointegration between the two time series. In addition, an attempt to estimate short run dynamics through a Vector Autoregression (VAR) failed the Granger Causality Test. Therefore, the lagged changes in mood do not predict the next day's returns.

While the Efficient Market Hypothesis continues to withstand opposing viewpoints in literature at this time, we should not discount the power social media holds in the realm of Big Data.

Although we could not find any predictive ability of the Global Mood Time Series in forecasting returns on the Dow Jones Industrial Average, we did find that it has an ability to forecast volatility. We constructed an E-GARCH and a standard GARCH model, and found that the change in the Global Mood Time Series has a significant, negative effect on the log return on the Dow Jones Industrial Average. Therefore, when the change in the Global Mood Time Series is positive, it leads to a lower volatility; when the change in the Global Mood Time Series is negative, it leads to a higher volatility. We can speculate that when consumer sentiment is pessimistic and there is uncertainty in the financial markets, investors will respond through erratic behavior, increasing volatility in the stock market. The findings in this paper will be important to financial economics since understanding volatility carries implications for constructing portfolios. Specifically, volatility provides information regarding the predicted variance of returns, which is a key input for portfolio optimization.

As the amount of information shared on the Internet continues to grow, and the intelligence extracted from Big Data becomes more powerful, the greater the impact it will have on the financial industry.

To better assess the predictive ability of Big Data in the scope of social media, a number of important factors must be addressed in future research. This includes using a tradable asset as a proxy for fluctuations in the stock market rather than the DJIA, examining the Global Mood Time Series and the time series of a tradable asset at a lower frequency, and finally, incorporating all information provided on the Internet, not just social media, into the Global Mood Time Series.

II. The Growth of Internet-Based Information

The Internet is a global network. Long gone are the days when people had to wait several days, or even weeks, to exchange letters with a relative or learn of a natural disaster in a remote part of the world. People can now stay connected to one another, and to the world, by recording thoughts on Internet blogs, sharing day-to-day activities on respective social media websites, and by reading online newspapers and magazines.

In just this past decade, there has been an expansion in the amount of data that is generated from the information shared between people across the globe. According to the McKinsey Global Institute, in 2010 alone, people around the world collectively stored more than six exabytes, or six quintillion bytes, of new data on devices like smartphones and notebook computers. Each exabyte contains more than 4,000 times the information stored in the Library of Congress (Freeland 2012). Furthermore, the research firm stated that the amount of data generated globally increases by 40% per year (Wollan 2011). As technology progresses, data will continue to follow an upward trend and accumulate more information with the passing of each year.

It is clear that as the capability of the Internet has grown stronger, information has become more readily available to the public. Data now travels at such a rapid pace that the information shared essentially takes place in *real-time*. In addition, the ability to analyze the accumulated data, which encompasses economic indicators as well as consumer behavior, allows individuals to become objective observers, thereby reducing human error and emotion, which can often influence decision-making (Berman 2012). In an unstructured form, the great amount of data that exists is difficult to manage, much less comprehend. Yet researchers realize the value that lies in the information shared and continue to strive to analyze the large quantity of data acquired through the Web. They have coined the term "Big Data" as one that describes the vast amount of digital information people generate and have an increasing ability to manage, store, and understand (Freeland 2012).

While this conversation of Big Data may seem to be one held exclusively by data experts and research specialists, the concept itself actually applies to and impacts each participant in the economic world. Take for instance the social media websites and blogs that child-raising women around the world engage in to exchange parenting tips and ideas (Laporte 2011). These growing online communities discuss a wide range of topics, which may include the must-have toy of the season. Analyzing the collective motivation and tendency of this particular community can then allow an individual or company to anticipate the future sales activity of that new toy. Through this simple example, it becomes clear that while the surface of online information may seem trivial, a careful analysis of the data uncovers the true value it holds.

Companies from every sector and industry of the economy, ranging from public health to national security, have discovered the power that Big Data holds.

One company that has been able to harness the real-time analytics of Big Data is the Internet search engine, Google. In 2009, Google analyzed flu-related Web searches from

2003 to 2008. Through their research, Google was able to extract the exact location of the people who made these flu-related search entries through the information encrypted in their Internet addresses (Newman 2011). The company was then able to use this data to estimate flu activity across regions in the United States, with a lag of only about a day. This estimation far outstripped the ability of the Center for Disease Control and Prevention, which publishes flu activity one to two weeks after outbreaks occur.

Another company has taken the concept of Big Data and real-time analytics several steps further. Recorded Future, a team of 20 data experts based in Gothenburg, Sweden, has claimed that they have developed a "new tool that allows you to visualize the future" (Chesnire 2011). They process public information provided on the Internet, which includes social media posts, news articles, and government updates on federal websites, and ranks the data according to its credibility and volume of access.

Recorded Future then consolidates events that occur in the same or similar scope, and runs the information through an algorithm they have created to create a "momentum" score. These scores are used to estimate the probability of an event taking place in the future, given the occurrence of past and present information. Recorded Future utilized the predictive qualities of the Internet, in combination with the algorithms they created, to predict the outbreaks of violence and conflict that would eventually occur in 2010 in Yemen -- *one year in advance* (Chesnire 2011).

Recorded Future has truly manifested the idea that, "when turned into intelligence, openly available and free information becomes extremely valuable" (Chesnire 2011).

One industry that could potentially find great value in the predictive ability, as well as the objective observations, of Big Data intelligence is, of course, the financial sector. Similar to the concept of Big Data, an investment is the culmination of information as it makes connections across all facets of an economy, be it fashion, energy, technology, or agriculture.

The world and the information we receive are constantly changing, and these changes have an effect on the appetites of consumers, which then have an effect on the movements of the stock market. Since opinions and emotional states influence a person's decision-making process, consolidating the reactions that investors around the world have to an event or a change in the economy could presumably forecast aggregate investment decisions.

Social media websites, such as Twitter or Facebook, provide just that information. Participants "tweet" and post their opinions and advice on matters that can include purchasing decisions about real estate and automobiles, among many other products (The Economist 2010). As the Internet and global network have grown, this information is not only shared between family and friends, but between individuals that have never before met outside of the digital world.

A research study explained through the academic paper "Twitter Mood Predicts the Stock Market," written by Johan Bollen, Huina Mao, and Xiao-Jun Zeng, correlated measurements of collective mood states, derived from large-scale Twitter feeds, with the closing values of the Dow Jones Industrial Average (DJIA). The relationship between these two time series were analyzed from February 28, 2008, to December 19, 2008, and resulted in an accuracy of 87.6% in predicting the daily up and down changes in the closing values of DJIA (Bollen 2010).

At the time this research was carried out, the social media website Twitter had been running live for a mere two years (Carlson 2011). The user-base under this analysis was predominantly English speaking and located in the United States. As the DJIA and other stock markets are comprised of investors not just in the United States but around the world, the research did not adequately represent the "mood" of the global economy. The data was, in other words, limited to a "particular geographical location and a subset of the world's population" (Bollen 2010).

Since then, the demographic of Twitter users has drastically changed. Although the social media Website is based in San Francisco, it now reaches people in countries such as Germany and New Zealand. The online Twitter community continues to expand, and, as of October 2011, the number of tweets per day exceeded 230 million, up more than 100% from the beginning of 2011 (The Economist 2011). It is important to incorporate this expanded demographic of the Twitter user-base to adequately assess the predictive ability of social media.

Similar to previous research, I plan to use measurements of collective mood states derived from large-scale Twitter feeds in my own paper, to answer the question of whether Big Data, in the scope of social media, has a predictive ability in the stock market and the world of finance.

However, I will analyze a global mood index through information provided by Wall Street Birds,* a service through Modulus Informatics, Inc, that captures the expanded demographic of the Twitter user-base by using data from April 9, 2011, to December 23, 2011. I will then correlate the data with the closing values of the Dow Jones Industrial Average to assess the predictive ability of the global mood indicator on changes in the DJIA over time.

**Wall Street Birds is a service that analyzes the data provided by Twitter posts to assess the global "mood" of the economy in order to assist people in making investment decisions* (Wall Street Birds 2011).

III. Literature Review

Financial economic theory has traditionally revolved around the idea that the financial market is composed of "rational and profit-maximizing investors" who make decisions based on information they have obtained through calculated, unemotional logic (Ackert 2003). Behavioral finance contradicts this traditional theory and expands upon psychological research, which has found that under certain circumstances, "emotion-related processes can advantageously bias judgment and reason" (Dolan 2002). For example, Hermalin and Isen show that a change in the emotional state of a decision maker, particularly positive emotion, has a significant effect on decision-making (Hermalin 2000).

Proponents of behavioral finance believe that the market is affected by the behavioral influence of individual investors through the decisions they make in their investments (Ackert 2003). This idea has encouraged further research in the behavior of investors, which is ultimately driven by their respective emotional states. Economists in the field of behavioral finance believe that if they can capture the overall emotional state of these investors, they can make implications for the decisions individual investors make, and, in aggregation, those decisions will affect the changes they see in the financial market.

As early as 2001, companies such as Modulus Financial Engineering, Inc, the sister company of Modulus Informatics, Inc, have worked on creating a system that captures global mood to aid in investing and trading. The current system, which incorporates the valuable information that social media provides, has evolved from one that programmatically crawled through Internet message boards, which at the time served as a proxy for real-time data.

Tumarkin and Whitelaw (2011) describe the primitive model that research companies used in real-time analytics. They examined the relationship between Internet message board activity and abnormal stock returns. At the time of publication, these message boards were believed to capture and “contain new information” that would presumably affect stock prices (Tumarkin 2001). However, research ultimately found that message board activity did not adequately predict industry-adjusted returns.

Since then, the popularization of social media has improved upon earlier models in capturing global mood to create implications for the fluctuation and changes in the financial world.

In 2010, researchers from Harvard University and Northeastern University studied the dynamic ability of Twitter in a project they called “Pulse of the Nation.” The project created a density-preserving cartogram of the United States that depicted the daily progression of global mood through an analysis of 300 million Twitter posts, from September 2006 to August 2009 (Pulse of the Nation 2010). Ideas and projects such as “Pulse of the Nation,” which can visually map global mood from Twitter feeds, served as the foundation for services like Wall Street Birds, which analyze social media information to predict movements in the stock market.

The most relevant research in the scope of social media's current impact on the world of finance is explained by Bollen, Mao, and Zeng (2010). As previously stated, the research investigated whether measurements of collective mood states derived from large-scale Twitter feeds are correlated to the value of the Dow Jones Industrial Average over time (Bollen 2010).

The content of Twitter feeds, which is limited to 140 characters per user-post, was analyzed by using two mood assessment tools. The first assessment tool used was OpinionFinder. According to Wilson et al. (2005), the system aims to identify subjective sentences in written documents and takes into account various aspects of the subjectivity in these sentences. Aspects such as the origin of subjective statements and words, which express a positive or negative tone, are identified (Wilson 2005). The algorithm of this system also weights the ratio of positive and negative words to the total number of words in the document, allowing for an assessment of the post's overall tone.

Systems such as OpinionFinder are frequently used in content analysis research because it transforms descriptive information into quantifiable data, which is easier to manage and analyze. It proved especially helpful to Jegadeesh and Wu when they found that the overall tone of 10-K filings, defined through the ratio of positive to negative words, affected the reactions of markets to information released in document filings (Jegadeesh 2011).

The second assessment tool used was Google-Profile of Mood States (GPOMS), which measures mood in terms of six dimensions: Calm, Alert, Sure, Vital, Kind, and Happy. Since OpinionFinder only makes “binary distinctions between positive and negative sentiment,” the addition of GPOMS incorporates the multi-dimensional quality of human mood and improves the algorithm’s ability to capture an accurate snapshot of public mood (Bollen 2010).

GPMOS is an extension of the Profile of Mood States (POMS), a 65-item adjective rating scale that is designed to measure multiple dimensions of affect. It is widely used in the field of psychology to evaluate the emotional state of psychiatric patients and is administered to assess their overall mood. Patients respond to 65 adjectives on a five-point rating scale, ranging from “Not at All” to “Extremely.” These responses are scored, and the patient is then categorized into his or her respective level across six mood states: Tension-Anxiety, Depression-Dejection, Anger-Hostility, Vigor-Activity, Fatigue-Inertia, and Confusion-Bewilderment (Norcross 1984).

Instead of measuring patient responses across 65 adjectives, GPMOS expanded the range of adjectives to 964. This allows GPMOS to “capture a wider variety of naturally occurring mood terms in Tweets and map them to their respective POMS mood dimensions” (Bollen 2010).

In the study by Bollen, Mao, and Zeng, using a combination of two separate mood assessment tools, OpinionFinder and Google-Profile of Mood States, helped to answer the question of whether correlation exists between variation in public mood and changes in the stock market (Bollen 2010). Specifically, the researchers regressed the time series of public mood, captured by OpinionFinder and the six dimensions outlined by GPMOS, against a time series of the Dow Jones Industrial Average, which reflected changes in stock market value between day *t* and day *t-1*. In order to test whether one time series had predictive information about the other, the researchers used *n* lagged values of all time series. The research found that the Calm dimension of the GPMOS was the only time series to prove both significant and predictive of changes in DJIA values, three to four days in advance (Bollen 2010).

The research carried out by Bollen, Mao and Zeng can be classified as data mining, a term used to describe the act of extracting knowledge from large scale data. Furthermore, this intelligence can be used to construct technical trading rules, which provide superior investment performance. When constructing these rules, it is important to evaluate its performance to determine whether the results are, in fact, due to superior economic content, or simply due to luck (Sullivan 1999).

According to Sullivan, Timmermann, and White (1999), data mining does not produce legitimate results unless it has accounted for the biased effects of data mining or "data snooping." These effects can be mitigated by reporting results from all trading strategies, utilizing long data series, and emphasizing the robustness of results across various nonoverlappping subperiods for statistical inference (Sullivan 1999). It is essential to evaluate the Bollen, Mao, and Zeng study to determine if it contains these biased effects before it is established as a technical trading rule.

In creating a Global Mood Time Series, Wall Street Birds uses a similar approach to Bollen, Mao, and Zeng. Specifically, the company uses a mood assessment tool that weights messages based on their positive and negative tone, in addition to a system that sums all individual mood, which includes Love, Joy, Surprise, Anger, Sadness, and Fear.

While the model used by Bollen, Mao, and Zeng was limited to the English language, Wall Street Birds' mood index analyzes Twitter feeds across 10 languages. As the demographic of the Twitter user-base has expanded internationally, the incorporation of an analysis through several languages allows for a more accurate representation of global mood and presumably becomes a better predictor of changes in the stock market (Wall Street Birds 2011).

In my own research, I will expand on the study by Bollen, Mao, and Zeng to assess the predictive ability of global mood indicators on changes in the Dow Jones Industrial Average from April 9, 2011, to December 23, 2011, using an improved Global Mood Time Series provided by Wall Street Birds.

IV. Theory

The Efficient Market Hypothesis, proposed by Eugene F. Fama, states that securities, which incorporate all freely available information, are priced correctly and will reflect their intrinsic value at any point in time (Fama 1965).

In an efficient market, many rational and profit maximizing investors compete with one another through the use of computer software and research to identify a stock they feel is underpriced or overpriced. They all try to identify and exploit a discrepancy between price and intrinsic value, based on both past and current public information. These attempts prove futile, as the world is full of trained investors. The resulting ongoing competition between these investors allows the market to instantaneously and correctly value each stock (Fama 1965).

Furthermore, Fama states that predicting the future behavior of stocks is impossible as they follow a "random walk." Changes in the price of securities are independent of past history and therefore, "the future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers" (Fama 1965).

Since the publication of Fama's doctoral dissertation, "The Behavior of Stock-Market Prices," in the Journal of Business in January 1965, the Efficient Market Hypothesis, and its accompanying assumption that stock market prices follow a random walk, has survived challenges presented by opposing viewpoints in literature (Fama 1998).

For example, DeBondt and Thaler (1985) presented a proposal contrary to the Efficient Market Hypothesis in which long-term return anomalies and reversals were attributed to investor overreaction. However, the proposition did not hold as the researchers placed too much emphasis on the past performance of firms" (Fama 1998).

Despite attempts by many economists, including those in the field of behavioral finance, none have had such a resounding effect as to dismantle the Efficient Market Hypothesis. In "Market Efficiency, Long-Term Returns, and Behavioral Finance," Fama asserts the fact that a behavioral model that captures the menu of anomalies better than market efficiency does not yet exist (Fama 1998).

It is important to note that Andrew Lo (2004) has proposed an alternative to the Efficient Market Hypothesis with his Adaptive Markets Hypothesis. In this qualitative analysis, Lo incorporates an evolutionary perspective into market efficiency. Due to the principles of evolution, which include competition, adaptation, and natural selection, investors are forced to adapt to a constantly changing financial environment. As a result, his behavioral approach suggests that investors are "often, if not always, irrational and exhibit predictable as well as financially ruinous behavior" (Lo 2004). According to Lo, profit opportunities are present in financial markets.

With the growth and analysis of Big Data, and the consolidation of consumer sentiment into a Global Mood Time Series through services such as Wall Street Birds, we can attempt to construct a predictive model through which an investor can exploit a profit.

Following the Efficient Market Hypothesis, profit opportunities are derived from two sources: superior information and superior analysis of available information. As the intelligence extracted from Big Data and social media is relatively new data, combining it with sophisticated econometric techniques may allow for an opportunity to exploit a profit in the financial markets, in a way that researchers have not yet identified.

Comparing the relationship between two financial time series, which independently follow a stochastic process, can result in a combined predictive relationship. It is possible to construct a model through this comparison, which allows an investor to describe long run equilibrium relations between two time series. In addition, short term departures from this long run equilibrium create predictable long run movements toward equilibrium.

I propose that constructing a model that describes the relationship between the Global Mood Time Series, provided by Wall Street Birds, and the Dow Jones Industrial Average will present an investor the opportunity to exploit a profit by uncovering the predictive ability of Big Data, in the scope of social media, on the stock market.

V. Data Description

The Global Mood Time Series was provided by Wall Street Birds, a service that analyzes the data provided by Twitter posts to assess the global "mood" of the economy. They use this information to assist people in making investment decisions. The data used in this study illustrates global mood from April 9, 2011, to December 23, 2011. Although data was provided until January 9, 2012, the extended time series contained an abnormal trend following New Years Eve, a socio-cultural event that has a unique and complex effect on public mood. Therefore, we will analyze data leading up to December 23, 2011, to avoid this abnormal event.

The company uses a mood assessment tool that weights messages based on their positive and negative tone. Wall Street Birds also uses a system that sums all individual mood, which includes Love, Joy, Surprise, Anger, Sadness, and Fear. The Global Mood Time Series consolidates consumer sentiment across these dimensions in a dynamic fashion. In addition, it analyzes Twitter feeds presented in 10 different languages, which include English, Chinese (Mandarin), Spanish, Arabic, Hindi, Bengali, Portuguese, Russian, Japanese, and German.

The Dow Jones Industrial Average is one of the most well-known indices among stock market observers in the world. The DJIA is a price-weighted measure of 30 U.S. blue chip companies, which not only attracts investors in the United States, but across the globe. It was selected for its comparable characteristics to the demographics encompassed by the Global Mood Time Series. Although the Global Mood Time Series is based in the United States, as Twitter was founded in San Francisco, it incorporates data from Twitter feeds all around the world.

I will analyze the relationship between the Global Mood Time Series and the Dow Jones Industrial Average by comparing the closing values of each index over time. Specifically, the closing value of the Global Mood Time Series will be the value at hour 16:00, which represents the 4:00 p.m. EST closing time of the U.S. Stock Market. In addition, the closing values of both time series will only be observed on trading days, as the DJIA is unavailable in a closed market. This restriction resulted in a total of 166 observations.

In order to assess the predictive ability of global mood indicators on changes in the Dow Jones Industrial Average, it is essential to first find and describe the relationship between the two time series. This allows for the construction of a model in which a long run equilibrium relationship between these two financial time series is described. This description, in combination with an explanation for short run deviations from this long run equilibrium, provides an opportunity to map long run movements toward equilibrium, which may be exploited for profit.

Many economic time series follow a deterministic trend and/or a stationary process, which is mean reverting. In contrast, many financial time series follow stochastic trends. One example of a stochastic trend is the random walk:

$$y_t = y_{t-1} + \varepsilon_t$$

The variable y_{t-1} represents yesterday's log price, while ε_t describes "white noise" or a random element. In the random walk, the impact of shocks does not diminish over time and any changes are made permanent. Therefore, y_t is stochastic and is said to have a unit root.

While the DJIA has been determined a stochastic process, the characteristics of the Global Mood Time Series are unknown. The Global Mood Time Series must be tested using the Unit Root Test, in which the null hypothesis is that a unit root is present and the trend is stochastic. Unit Root Tests for financial time series include the Phillips-Perron, as well as the Augmented Dickey Fuller (ADF) Tests.

If the Global Mood Time Series is determined to follow a stochastic trend, it is possible to proceed to the next step in constructing the model. This includes testing the returns on both the Global Mood Time Series and the DJIA for stationarity. To model the return on the DJIA, we will take the log return of its time series. To model the return on the Global Mood Time Series, we will simply take the difference between today's level of mood and yesterday's level of mood. If the returns on the respective time series are indeed stationary, the Global Mood Time Series and the DJIA can then be tested for cointegration. Cointegration states that even when two or more series are individually integrated, some linear combination of them has a lower order of integration. In other words, the two series have unit roots and their linear combination is stationary.

The Johansen Trace Test is typically used to determine if cointegration exists between two variables. If the Global Mood Time Series and the DJIA have a common stochastic trend, then they are indeed cointegrated and a Vector Error Correction Model (VECM) can be estimated.

Even when two or more financial time series follow stochastic trends, the VECM allows one to model a relationship between them. With the VECM, it is possible to estimate the long run equilibrium relationship between two asset prices, or in this case, the level of an index and the level of global mood. In addition, it describes the short run dynamics that move two variables toward the long run equilibrium. Assuming the Global Mood Time Series and the DJIA are cointegrated, and the VECM model is constructed, an investor would have the ability to make predictions on the convergence of the two time series in order to make a profit.

VI. Empirical Findings

After testing the Global Mood Time Series and the log of the Dow Jones Industrial Average for stationarity through the Phillips-Perron and Augmented Dickey Fuller (ADF) Unit Root Tests, both time series were found to follow a stochastic trend, as seen in *Figures 5* through *8*. Moreover, the returns on the respective time series were found to be stationary, as seen in *Figures 9* through *12*, which allowed us to proceed to the next step in constructing a model.

The Global Mood Time Series and the log of the DJIA were tested for cointegration through the Johansen Trace Test. However, the time series were found to follow separate stochastic trends and no evidence of cointegration was found, as seen in *Figures 13* through *15*. In addition, the sample was split into two separate time periods, for the first half of trading days and the second half, and tested for cointegration, but there was again no evidence of cointegration. This can be seen in *Figures 16* and *17*. Although this means that a Vector Error Correction Model cannot be estimated, and no long run equilibrium relationship can be found between the Global Mood Time Series and the DJIA, it is possible to find explanatory power in the short run.

Given the lack of a cointegration relation, the correct approach to understanding short run dynamics between the time series is to estimate a stationary Vector Autoregression (VAR) using the first differences of the Global Mood Time Series and the log of the DJIA. The Granger Causality Test will be used to determine the effect lag returns of each time series have on one another. This will allow us to see if changes in the Global

Mood Time Series have any ability to forecast returns on the DJIA. In addition, we can see if the returns on the DJIA have any ability to forecast changes in the Global Mood Time Series.

In estimating a stationary Vector Autoregression (VAR), lagged values of one and three were used for the returns on the log of the DJIA and Global Mood Time Series. These lagged values of one and three were selected as they yielded results that could not reject the null hypothesis of no autocorrelation in the Lagrange-Multiplier Test. Refer to *Figures 18* and *19* for the results of this test.

The Granger Causality Test was then used to determine the effect these lagged returns of each time series have on one another. However, as seen in *Figure 20*, the high chi-squared values in each case of the Granger Causality Test indicate that the coefficients on the lags of the change in the Global Mood Time Series, in the equation for the return on the log of the DJIA, are jointly zero. This also applies to the coefficients on the lags of the return on the log of the DJIA, in the equation for the change in the Global Mood Time Series. Therefore, we fail to reject the null hypothesis that the change in the Global Mood Time Series does not Granger cause the return on the log of the DJIA, and vice versa.

With the results of the Johansen Trace Test and the Granger Causality Test, we cannot yet determine a long run equilibrium relationship or understand any short run dynamics.

At this time, there appears to be no predictive ability of the Global Mood Time Series in forecasting returns on the Dow Jones Industrial Average.

Although the Global Mood Time Series does not appear to have the ability to forecast returns on the Dow Jones Industrial Average, it may still have a predictive ability in forecasting volatility. High frequency returns, such as the return on the daily closing values of the Global Mood Time Series, exhibit clustered volatility, in which periods with a high variance tend to cluster together.

Understanding clustered volatility is important in financial economics as it carries implications for constructing portfolios. In particular, volatility provides information regarding the predicted variance of returns, which is a key input for portfolio optimization.

To determine the predictive ability of the Global Mood Time Series in forecasting volatility, we will need to construct a volatility equation. We will first estimate an exponential, Generalized Autoregressive Conditional Heteroskedasticity model (E-GARCH) and include the exogenous variable of the change in the Global Mood Time Series. This exponential model facilitates a superior method to the standard GARCH model in capturing movements in volatility. While the GARCH model restricts its coefficients to a positive value, and establishes that positive and negative shocks have similar impacts on volatility, the E-GARCH model relaxes these constraints. With the E-

GARCH model, large shocks, either positive or negative, will increase volatility more than small shocks.

As seen in *Figure 21*, the change in the Global Mood Time Series has a significant, negative effect on the volatility equation with a p-value of 0.011. Therefore, when the change in the Global Mood Time Series is positive, it leads to a lower volatility in the log return on the Dow Jones Industrial Average. Conversely, when the change in the Global Mood Time Series is negative, it leads to a higher volatility in the log return on the DJIA. By interpreting these results, we can speculate that when consumer sentiment is pessimistic, and there is uncertainty in the financial markets, investors will respond through erratic behavior. This notion corresponds with the increase in volatility that we see in the log return on the Dow Jones Industrial Average through the E-GARCH model, when the change in the Global Mood Time Series is negative.

We can also extend the E-GARCH model with an assumption that the residuals will follow a *t* distribution rather than a normal distribution. Using a *t* distribution may be more appropriate in modeling returns rather than using a normal distribution. As seen in *Figure 22*, the change in the Global Mood Time Series becomes more significant under the assumption that the E-GARCH model follows a *t* distribution, with a p-value of 0.005.

The results of the E-GARCH model, under the assumption of a *t* distribution, remain valid through checks for robustness. Specifically, under different parameters, the change in the Global Mood Time Series continues to negatively affect the volatility equation. As seen in *Figure 23*, the change in the Global Mood Time Series remains significant in a standard GARCH model with a p-value of 0.009.

The significant values of the change in the Global Mood Time Series in the E-GARCH and the standard GARCH models indicate that the change in the Global Mood Time Series has a predictive ability in forecasting volatility in the log return on the Dow Jones Industrial Average.

VII. Conclusion

Through this research, we tried to assess the predictive ability of a global mood indicator on changes in the Dow Jones Industrial Average over time. A Global Mood Time Series was provided by Wall Street Birds, a service that analyzes the data provided by Twitter posts to assess the global "mood" of the economy, in order to assist people in making investment decisions.

The closing values of the data, which ran over a period from April 9, 2011, to December 23, 2011, were compared to the closing values of the Dow Jones Industrial Average. We made an attempt to construct a model to describe a relationship between the two time series and to explain any short run deviations from this long run equilibrium. Although each time series follows a stochastic trend, and their returns are stationary, there is no evidence of cointegration between the Global Mood Time Series and the DJIA.

Since a long run equilibrium relationship could not be found, we proceeded to estimate a stationary Vector Autoregression (VAR) to understand any short term dynamics. However, after running the Granger Causality Test, no predictive power between the two returns series was established. This may be due to the fact that the Global Mood Time Series, provided by Wall Street Birds, consolidates consumer sentiment across the multiple dimensions of individual mood in a dynamic fashion. Unlike the research carried out by Bollen, Mao, and Zeng, the mood metric was not disaggregated. It may be necessary to construct a time series that models individual mood to find the predictive ability of global mood in forecasting returns. Nevertheless, we fail to construct a trading rule or model to exploit a profit opportunity in the financial markets by using the predictive power of Big Data in the scope of social media.

The Efficient Market Hypothesis is one that has withstood decades of testing and opposing viewpoints in literature, and it continues to do so today. Although we could not find any predictive ability of the Global Mood Time Series on changes in the Dow Jones Industrial Average, we must not discount the power social media holds in the realm of Big Data.

By extending research on the Global Mood Time Series, we did find evidence of its ability to forecast volatility in the Dow Jones Industrial Average. By estimating an E-GARCH and a standard GARCH model, we found the change in the Global Mood Time Series has a significant, negative effect on volatility. In other words, when the change in the Global Mood Time Series is positive, it leads to a lower volatility in the log return on the Dow Jones Industrial Average. When the change in the Global Mood Time Series is negative, it leads to a higher volatility in the log return on the DJIA. With these results, we can infer that when consumer sentiment is pessimistic, and there is uncertainty in the financial markets, investors will react through erratic behavior, which will increase volatility.

Understanding volatility is very important in financial economics as it carries implications for constructing portfolios. It provides information pertaining to the predicted variance of returns, which is a key input for portfolio optimization. Future research can expand on the models constructed in this paper by incorporating additional lagged changes in the Global Mood Time Series and examining regimes of the Global Mood Time Series by creating threshold values in the volatility equation.

In order to fully understand the impact of social media on aggregate investment decisions made in the stock market, further research in the field of behavioral finance and the role emotions play on decision-making must continue. As the amount of information shared on the Internet continues to grow, and the intelligence extracted from Big Data becomes more powerful, the greater the impact it will have on the financial industry.

The vast amount of information the Internet provides will become even more valuable when researchers fully understand and are able to harness the true potential and capability of Big Data. We must keep in mind that we are just on the cusp of the Digital Age and there is still much to learn. Given the success of companies such as Google and Recorded Future in turning information into intelligence, and our finding that the Global Mood Time Series has a predictive ability in forecasting volatility, the future remains bright.

To better assess the predictive ability of Big Data in the scope of social media, a number of important factors must be addressed in future research.

First, future research should measure the relationship between the Global Mood Time Series and a tradable asset, rather than the Dow Jones Industrial Average, to assess social media's ability to forecast returns on the financial stock market. The Dow Jones may not be the best representation of the stock market as a whole, as it ignores dividends. According to Shoven, an index that ignores dividends, such as the Dow Jones Industrial Average, dramatically underestimates the long run returns earned by stock market investors (Shoven 2000). One alternative to the Dow Jones Industrial Average is the Vanguard 500 ETF, which invests in the S&P 500 Index and represents 500 of the largest companies in the United States (Vanguard 2012). As the fund incorporates dividends, and is a tradable asset, the Vanguard 500 ETF could prove to be a superior proxy for the fluctuations in the stock market.

Second, it may be beneficial to examine the Global Mood Time Series, as well as the time series of a tradable asset, at a lower frequency. For example, Global Mood should be observed at the market close on Fridays of each week, as opposed to daily closing values, to provide consistent observations of changes in consumer sentiment. This would allow us to see the overall trend of each time series more clearly by eliminating intra-day, abnormal variations. A weekly observation would be a superior assessment of the change in mood, and thus better capture the predictive ability of social media on the financial markets. If a lower frequency is used, the time series will need to capture a wider range of trading dates to increase the sample size and number of observations.

Finally, social media is just one facet of Big Data. Although Twitter posts have the ability to capture consumer sentiment, which influences a person's decision-making process, an investment decision is the culmination of multiple emotional and cognitive processes. Similar to the methods of the real-time analytics firm Recorded Future, future research should incorporate all information provided on the Internet. This may include international news articles, searches made in Internet search engines, government updates on federal websites, among many other sources, in addition to social media posts. Big Data carries valuable indicators for future economic events, and it is important to attempt to consolidate all the intelligence it provides in future research.

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IX. Tables and Graphs

Figure 1: Line Graph of Log Dow Jones Industrial Average
This figure shows the stochastic trend that the log of the Dow Jones Industrial Average follows over trading days.

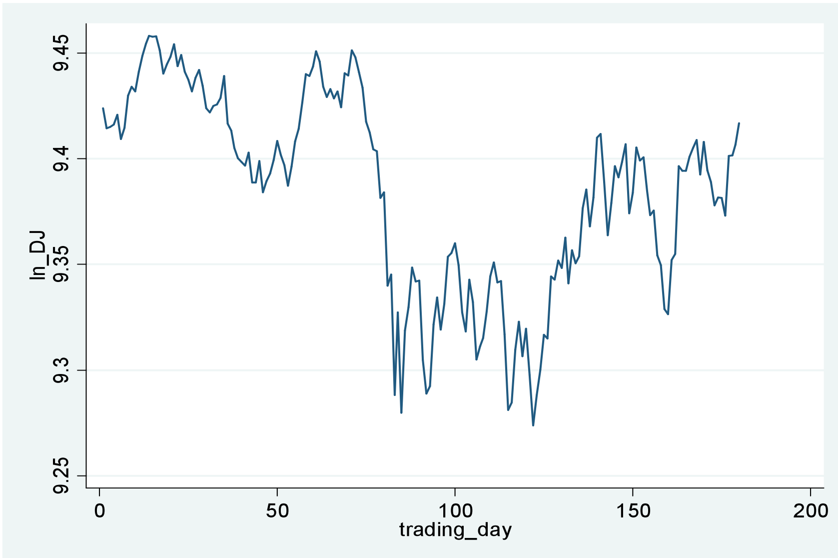

Figure 2: Line Graph of Global Mood Time Series
This figure shows the stochastic trend that the Global Mood Time Series follows over trading days.

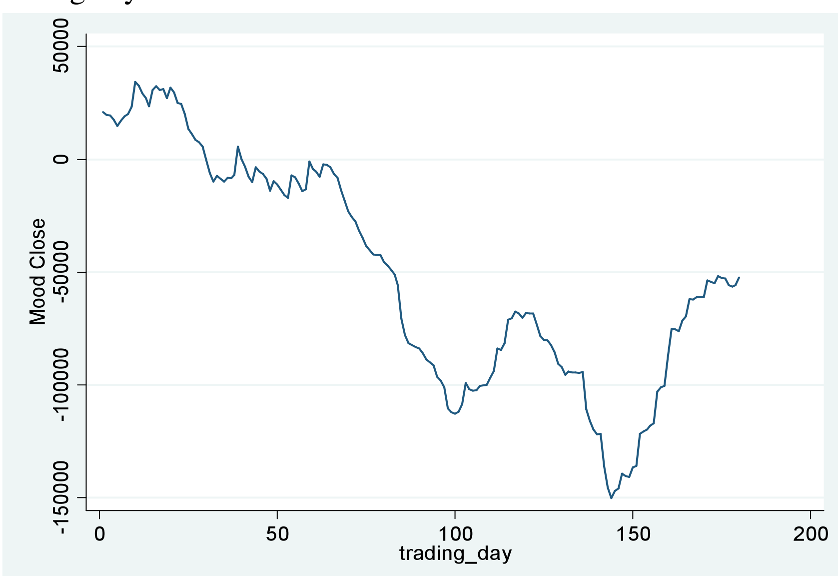

Figure 3: Line Graph of Log Return on Dow Jones Industrial Average
This figure shows the stationary trend that the log return on the Dow Jones Industrial Average follows over trading days.

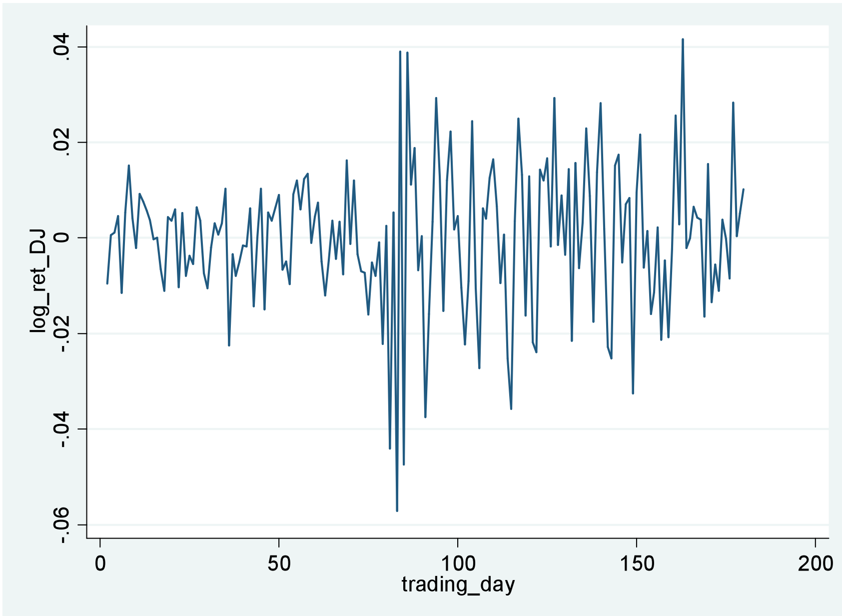

Figure 4: Line Graph of Change in Global Mood Time Series
This figure shows the stationary trend that the change in the Global Mood Time Series follows over trading days.

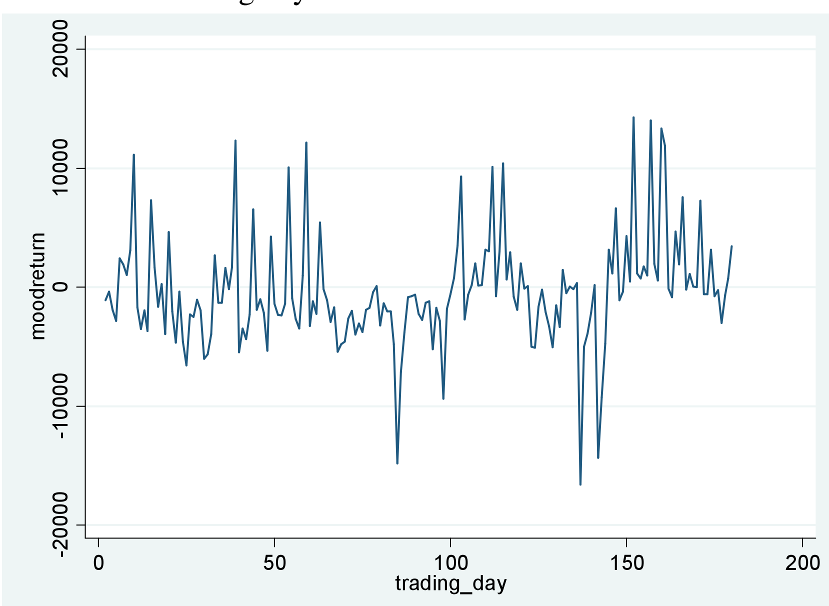

Figure 5: Augmented Dickey Fuller Test Results for Log Dow Jones Industrial Average
This figure shows the Augmented Dickey Fuller Unit Root Test results for log of the Dow Jones Industrial Average. With exception to the second lag value, the log of the DJIA fails to reject the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 1, log of the DJIA follows a stochastic trend.

DF-GLS for ln_DJ   Number of obs = 166
Maxlag = 13 chosen by Schwert criterion

[lags]	DF-GLS mu Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
13	-1.453	-2.589	-1.964	-1.657
12	-1.402	-2.589	-1.972	-1.664
11	-1.525	-2.589	-1.979	-1.672
10	-1.433	-2.589	-1.987	-1.679
9	-1.288	-2.589	-1.995	-1.686
8	-1.354	-2.589	-2.002	-1.693
7	-1.457	-2.589	-2.009	-1.700
6	-1.369	-2.589	-2.016	-1.706
5	-1.379	-2.589	-2.023	-1.712
4	-1.594	-2.589	-2.029	-1.718
3	-1.571	-2.589	-2.035	-1.724
2	-1.824	-2.589	-2.041	-1.729
1	-1.624	-2.589	-2.047	-1.734

Opt Lag (Ng-Perron seq t) = 5 with RMSE .0147992
Min SC = -8.30415 at lag 1 with RMSE .0152547
Min MAIC = -8.340398 at lag 5 with RMSE .0147992

Figure 6: Augmented Dickey Fuller Test Results for Global Mood Time Series
This figure shows the Augmented Dickey Fuller Unit Root Test results for the Global Mood Time Series. It fails to reject the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 2, the Global Mood Time Series follows a stochastic trend.

DF-GLS for moodclose   Number of obs = 166
Maxlag = 13 chosen by Schwert criterion

[lags]	DF-GLS mu Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
13	-0.856	-2.589	-1.964	-1.657
12	-0.771	-2.589	-1.972	-1.664
11	-0.780	-2.589	-1.979	-1.672
10	-0.765	-2.589	-1.987	-1.679
9	-0.837	-2.589	-1.995	-1.686
8	-0.814	-2.589	-2.002	-1.693
7	-0.866	-2.589	-2.009	-1.700
6	-0.894	-2.589	-2.016	-1.706
5	-0.948	-2.589	-2.023	-1.712
4	-0.551	-2.589	-2.029	-1.718
3	-0.488	-2.589	-2.035	-1.724
2	-0.402	-2.589	-2.041	-1.729
1	-0.328	-2.589	-2.047	-1.734

Opt Lag (Ng-Perron seq t) = 5 with RMSE 4092.341
Min SC = 16.81852 at lag 5 with RMSE 4092.341
Min MAIC = 16.70543 at lag 5 with RMSE 4092.341

Figure 7: Phillips-Perron Test Results for Log Dow Jones Industrial Average
This figure shows the Phillips-Perron Unit Root Test results for log of the Dow Jones Industrial Average. The DJIA fails to reject the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 1 and Figure 5, log of the DJIA follows a stochastic trend.

Phillips-Perron test for unit root — Number of obs = 179; Newey-West lags = 4

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-0.001	-13.458	-7.953	-5.653
Z(t)	-0.048	-2.589	-1.950	-1.615

ln_DJ	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ln_DJ L1.	.9999945	.0001201	8325.15	0.000	.9997575	1.000232

Figure 8: Phillips-Perron Test Results for Global Mood Time Series
This figure shows the Phillips-Perron Unit Root Test results for the Global Mood Time Series. It fails to reject the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 2 and Figure 6, the Global Mood Time Series follows a stochastic trend.

Phillips-Perron test for unit root — Number of obs = 179; Newey-West lags = 4

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-0.475	-13.458	-7.953	-5.653
Z(t)	-0.401	-2.589	-1.950	-1.615

moodclose	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
moodclose L1.	.9991497	.0048622	205.49	0.000	.9895548	1.008745

Figure 9: Augmented Dickey Fuller Test Results for Log Return on the Dow Jones Industrial Average

This figure shows the Augmented Dickey Fuller Unit Root Test results for the log return on the Dow Jones Industrial Average. With exception to the lagged values of 8-13, the log return on the DJIA rejects the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 3, the log return on DJIA follows a stationary trend.

```
DF-GLS for log_ret_DJ                                    Number of obs =   165
Maxlag = 13 chosen by Schwert criterion
```

[lags]	DF-GLS mu Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
13	-1.556	-2.589	-1.964	-1.657
12	-1.628	-2.589	-1.972	-1.664
11	-1.799	-2.589	-1.980	-1.672
10	-1.788	-2.589	-1.987	-1.679
9	-2.052	-2.589	-1.995	-1.686
8	-2.528	-2.589	-2.002	-1.693
7	-2.727	-2.589	-2.010	-1.700
6	-2.883	-2.589	-2.017	-1.707
5	-3.628	-2.589	-2.023	-1.713
4	-4.411	-2.589	-2.030	-1.719
3	-4.641	-2.589	-2.036	-1.724
2	-6.052	-2.589	-2.042	-1.729
1	-6.657	-2.589	-2.047	-1.734

```
Opt Lag (Ng-Perron seq t) =  9 with RMSE  .0153601
Min SC   = -8.174384 at lag  1 with RMSE  .0162748
Min MAIC = -8.060769 at lag 13 with RMSE  .0151321
```

Figure 10: Augmented Dickey Fuller Test Results for Change in the Global Mood Time Series

This figure shows the Augmented Dickey Fuller Unit Root Test results for the change in the Global Mood Time Series. With exception to the lagged values of 12 and 13, it rejects the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 4, the change in the Global Mood Time Series follows a stationary trend.

```
DF-GLS for moodreturn                                    Number of obs =   165
Maxlag = 13 chosen by Schwert criterion
```

[lags]	DF-GLS mu Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
13	-2.513	-2.589	-1.964	-1.657
12	-2.525	-2.589	-1.972	-1.664
11	-2.803	-2.589	-1.980	-1.672
10	-2.861	-2.589	-1.987	-1.679
9	-2.999	-2.589	-1.995	-1.686
8	-2.938	-2.589	-2.002	-1.693
7	-3.079	-2.589	-2.010	-1.700
6	-3.020	-2.589	-2.017	-1.707
5	-3.031	-2.589	-2.023	-1.713
4	-2.963	-2.589	-2.030	-1.719
3	-4.571	-2.589	-2.036	-1.724
2	-5.391	-2.589	-2.042	-1.729
1	-6.899	-2.589	-2.047	-1.734

```
Opt Lag (Ng-Perron seq t) =  4 with RMSE   4099.88
Min SC   =  16.79215 at lag  4 with RMSE   4099.88
Min MAIC =  16.97926 at lag  4 with RMSE   4099.88
```

Figure 11: Phillips-Perron Test Results for Log Return on the Dow Jones Industrial Average

This figure shows the Phillips-Perron Unit Root Test results for the log return on the Dow Jones Industrial Average. The log return on the DJIA rejects the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 3 and Figure 9, the log return on the DJIA follows a stationary trend.

Phillips-Perron test for unit root — Number of obs = 178; Newey-West lags = 4

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-199.219	-13.456	-7.952	-5.652
Z(t)	-14.833	-2.590	-1.950	-1.615

Figure 12: Phillips-Perron Test Results for Change in the Global Mood Time Series

This figure shows the Phillips-Perron Unit Root Test results for the change in the Global Mood Time Series. It rejects the null hypothesis of a stochastic trend. Therefore, in congruence with Figure 4 and Figure 10, the change in the Global Mood Time Series follows a stationary trend.

Phillips-Perron test for unit root — Number of obs = 178; Newey-West lags = 4

	Test Statistic	Interpolated Dickey-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-132.810	-13.456	-7.952	-5.652
Z(t)	-9.939	-2.590	-1.950	-1.615

Figure 13: Johansen Trace Test (rconstant) Results for Log Dow Jones Industrial Average and Global Mood Time Series

This figure shows the Johansen Trace Test results for cointegration between the Dow Jones Industrial Average and Global Mood Times Series, under the assumption that there are no deterministic trends and there is no drift in daily returns (daily returns are on average zero). It fails to reject the null hypothesis, and the two time series follow separate stochastic trends. Therefore, there is no evidence of cointegration between the DJIA and the Global Mood Time Series.

```
                      Johansen tests for cointegration
Trend: rconstant                                      Number of obs =     176
Sample:  5 - 180                                               Lags =       4
-------------------------------------------------------------------------------
maximum                                      trace    5% critical  1% critical
  rank    parms      LL       eigenvalue  statistic      value        value
    0      12    -1231.0867                11.2565*1*5  19.96        24.60
    1      16    -1226.5105     0.05067     2.1043        9.42        12.97
    2      18    -1225.4584     0.01189
-------------------------------------------------------------------------------
```

Figure 14: Johansen Trace Test (rtrend) Results for Log Dow Jones Industrial Average and Global Mood Time Series

This figure shows the Johansen Trace Test results for cointegration between the Dow Jones Industrial Average and Global Mood Times Series, under the assumption that a deterministic trend is only in the cointegration relation and constants are in both series. It fails to reject the null hypothesis, and the two time series follow separate stochastic trends. Therefore, there is no evidence of cointegration between the DJIA and the Global Mood Time Series.

```
                      Johansen tests for cointegration
Trend: rtrend                                         Number of obs =     176
Sample:  5 - 180                                               Lags =       4
-------------------------------------------------------------------------------
maximum                                      trace    5% critical  1% critical
  rank    parms      LL       eigenvalue  statistic      value        value
    0      14    -1230.8572                13.4919*1*5  25.32        30.45
    1      18    -1225.3563     0.06060     2.4900       12.25        16.26
    2      20    -1224.1113     0.01405
-------------------------------------------------------------------------------
```

Figure 15: Johansen Trace Test (constant) Results for Log Dow Jones Industrial Average and Global Mood Time Series

This figure shows the Johansen Trace Test results for cointegration between the Dow Jones Industrial Average and Global Mood Times Series, under the assumption that no deterministic trends exist but there are constants in both series. It fails to reject the null hypothesis, and the two time series follow separate stochastic trends. Therefore, there is no evidence of cointegration between the DJIA and the Global Mood Time Series.

Johansen tests for cointegration

Trend: constant Number of obs = 176
Sample: 5 - 180 Lags = 4

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	1% critical value
0	14	-1230.8572		10.7977*1*5	15.41	20.04
1	17	-1226.3266	0.05018	1.7363	3.76	6.65
2	18	-1225.4584	0.00982			

Figure 16: Johansen Trace Test (rconstant) Results for Log Dow Jones Industrial Average and Global Mood Time Series for First Half of Trading Days

This figure shows the Johansen Trace Test results for cointegration between the Dow Jones Industrial Average and Global Mood Times Series under the rconstant assumption, for the first half of trading days. It fails to reject the null hypothesis, and the two time series follow separate stochastic trends. Therefore, there is no evidence of cointegration between the DJIA and the Global Mood Time Series.

Johansen tests for cointegration

Trend: rconstant Number of obs = 79
Sample: 5 - 83 Lags = 4

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	1% critical value
0	12	-513.16161		11.3033*1*5	19.96	24.60
1	16	-508.76444	0.10535	2.5089	9.42	12.97
2	18	-507.50998	0.03126			

Figure 17: Johansen Trace Test (rconstant) Results for Log Dow Jones Industrial Average and Global Mood Time Series for Second Half of Trading Days

This figure shows the Johansen Trace Test results for cointegration between the Dow Jones Industrial Average and Global Mood Times Series under the rconstant assumption, for the second half of trading days. It fails to reject the null hypothesis, and the two time series follow separate stochastic trends. Therefore, there is no evidence of cointegration between the DJIA and the Global Mood Time Series.

Johansen tests for cointegration

Trend: rconstant   Number of obs = 97

Sample: 84 - 180   Lags = 4

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	1% critical value
0	12	-695.49488		7.4790*1*5	19.96	24.60
1	16	-692.1403	0.06683	0.7698	9.42	12.97
2	18	-691.75538	0.00791			

Figure 18: Estimate for a Stationary Vector Autoregression (VAR)
This figure shows the estimate for a stationary Vector Autoregression using the log return on the Dow Jones Industrial Average and the change in the Global Mood Time Series. This is used to find any explanatory power of the time series in the short run.

Vector autoregression

Sample: 5 - 180		No. of obs	= 176
Log likelihood	= -1234.21	AIC	= 14.13875
FPE	= 4736.356	HQIC	= 14.21181
Det(Sigma_ml)	= 4227.459	SBIC	= 14.31889

Equation	Parms	RMSE	R-sq	chi2	P>chi2
log_ret_DJ	5	.014973	0.0509	9.439406	0.0510
moodreturn	5	4482.41	0.1010	19.76804	0.0006

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
log_ret_DJ						
log_ret_DJ						
L1.	-.094634	.0747928	-1.27	0.206	-.2412253	.0519572
L3.	-.173218	.0742171	-2.33	0.020	-.3186809	-.0277551
moodreturn						
L1.	2.75e-07	2.43e-07	1.13	0.258	-2.01e-07	7.50e-07
L3.	-2.70e-07	2.44e-07	-1.10	0.269	-7.49e-07	2.09e-07
_cons	-.000023	.0011209	-0.02	0.984	-.0022199	.002174
moodreturn						
log_ret_DJ						
L1.	-1618.516	22390.63	-0.07	0.942	-45503.35	42266.32
L3.	-19624.47	22218.29	-0.88	0.377	-63171.52	23922.58
moodreturn						
L1.	.2740564	.0726174	3.77	0.000	.1317289	.416384
L3.	.1131978	.0731474	1.55	0.122	-.0301685	.2565641
_cons	-232.8558	335.5711	-0.69	0.488	-890.5631	424.8516

.

Figure 19: The Lagrange-Multiplier Test for Autocorrelation
This figure shows the test results of using lagged values of one and three in estimating the Vector Autoregression in Figure 18. Lagged values of one and three were selected as they yielded results that could not reject the null hypothesis of no autocorrelation in this Lagrange-Multiplier Test.

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	7.7106	4	0.10277
2	7.6973	4	0.10332
3	6.8404	4	0.14457
4	1.3307	4	0.85614

H0: no autocorrelation at lag order

Figure 20: The Granger Causality Test
This figure shows the results of the Granger Causality Test. The high chi-squared values in each case indicate that the coefficients on the lags of the change in the Global Mood Time Series in the equation for the log return on the DJIA are jointly zero. This also applies to the coefficients on the lags of the log return on the DJIA in the equation for the change in the Global Mood Time Series. Therefore, we fail to reject the null hypothesis that the change in the Global Mood Time Series does not Granger cause the log return on the DJIA, and vice versa.

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
log_ret_DJ	moodreturn	2.1694	2	0.338
log_ret_DJ	ALL	2.1694	2	0.338
moodreturn	log_ret_DJ	.81345	2	0.666
moodreturn	ALL	.81345	2	0.666

Figure 21: The E-GARCH Model Under the Normal Distribution Assumption
This figure shows the results of estimating an E-GARCH model by including the exogenous variable of the change in the Global Mood Time Series. This model is under the assumption of a normal distribution. The change in the Global Mood Time Series has a significant, negative effect on the volatility equation with a p-value of 0.011.

```
ARCH family regression -- multiplicative heteroskedasticity

Sample: 3 - 180                                   Number of obs   =       178
Distribution: Gaussian                            Wald chi2(.)    =         .
Log likelihood =  502.3538                        Prob > chi2     =         .
```

log_ret_DJ	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
log_ret_DJ						
_cons	.0004666	.0012562	0.37	0.710	-.0019955	.0029288
HET						
moodreturn L1.	-.0000449	.0000177	-2.54	0.011	-.0000795	-.0000102
_cons	-16.84055	.247279	-68.10	0.000	-17.3252	-16.35589
ARCH						
earch L1.	-.0565122	.0251856	-2.24	0.025	-.1058751	-.0071492
earch_a L1.	-.0573248	.0398911	-1.44	0.151	-.1355099	.0208602
egarch L1.	-.9801465	.0222492	-44.05	0.000	-1.023754	-.9365389

Figure 22: The E-GARCH Model Under the t Distribution Assumption
This figure shows the results of estimating an E-GARCH model by including the exogenous variable of the change in the Global Mood Time Series. This model is under the assumption of a *t* distribution. The change in the Global Mood Time Series has a significant, negative effect on the volatility equation with a p-value of 0.005.

```
ARCH family regression -- multiplicative heteroskedasticity

Sample: 3 - 180                                   Number of obs   =       178
Distribution: t                                   Wald chi2(.)    =         .
Log likelihood =  508.6296                        Prob > chi2     =         .
```

log_ret_DJ	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
log_ret_DJ						
_cons	.0008809	.0008886	0.99	0.322	-.0008608	.0026226
HET						
moodreturn L1.	-.0000591	.0000212	-2.79	0.005	-.0001007	-.0000175
_cons	-17.0051	.3710982	-45.82	0.000	-17.73244	-16.27776
ARCH						
earch L1.	-.0639694	.0399492	-1.60	0.109	-.1422684	.0143295
earch_a L1.	-.1614574	.0916522	-1.76	0.078	-.3410924	.0181776
egarch L1.	-1.002723	.0255428	-39.26	0.000	-1.052786	-.9526604
/lndfm2	1.047039	.7471084	1.40	0.161	-.4172663	2.511345
df	4.849203	2.128663			2.658845	14.32149

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Figure 23: Checking for Robustness Under the t Distribution Assumption
This figure shows that the change in the Global Mood Time Series continues to have a significant, negative effect on volatility through checks for robustness. Under a standard GARCH model, the change in the Global Mood Time Series has a significant p-value of 0.009.

```
ARCH family regression -- multiplicative heteroskedasticity

Sample: 3 - 180                                 Number of obs   =        178
Distribution: t                                 Wald chi2(.)    =          .
Log likelihood =  504.2602                      Prob > chi2     =          .
```

log_ret_DJ	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
log_ret_DJ						
_cons	.0011779	.00099	1.19	0.234	-.0007625	.0031183
HET						
moodreturn						
L1.	-.0000493	.0000188	-2.63	0.009	-.000086	-.0000125
_cons	-7.945824	.3037245	-26.16	0.000	-8.541113	-7.350535
ARCH						
arch						
L1.	-.0077359	.0340309	-0.23	0.820	-.0744353	.0589636
garch						
L1.	-.5194934	.2397747	-2.17	0.030	-.9894432	-.0495435
/lndfm2	.9091022	.8426739	1.08	0.281	-.7425083	2.560713
df	4.482093	2.091595			2.475919	14.94504