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GOOGLE TRENDS DATA AND STOCK PRICE VOLATILITY

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ABSTRACT

Financial markets are consistently trying to find innovative ways to track investors' sentiment and expectations. By doing so, they are able to make investments with more certainty of returns. This paper seeks to determine if potential investment returns can be improved with the use of historical Google Trends data and investor's bounded rationality. To do this, this paper evaluates the link between Google Trends data and the price volatility of individual stocks over a given time period. To evaluate this link, time series regression modeling on the top ten most traded companies since 2008 in the United States is utilized. Google Trends data is then compared with each stock's price volatility on a monthly basis from January 2008 to June 2018 in addition to the aggregate stock price volatility data of all ten companies. The paper finds that there is a consistent, significant correlation between stock price volatility and Google Web data on a monthly basis among a majority of the stocks when evaluated individually. In aggregate form, the paper finds that the correlation between stock price volatility and Google Web data is statistically significant at the 1% level. The results suggest investors begin searching stocks on Google when important news announcements are expected to be released. They also suggest that investors search stocks after large instances of price volatility. As a result, when any investor sees a spike in Google Web data for a particular stock, they could use this information to open a straddle or strangle position in an attempt to profit off of price volatility with greater accuracy.

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Chapter 1

Introduction

One of the most important goals to many individuals is the process of accumulating wealth throughout their lifetime. As a result of this, individuals with excess wealth often seek ways to invest it. In some of these cases, these individuals invest their own money without the help of experienced professionals and thereby become individual investors. In a perfect world, these individual investors would have all of the resources and time they need to make perfectly rational decisions in order to obtain the best returns on their investments. Unfortunately, this is often not the case. Investors, particularly individual investors, are subject to bounded rationality, or the idea that individuals only have access to limited, often unreliable, information regarding alternatives to their decisions, have only a limited capacity to evaluate and process the information at hand, and have only a limited amount of time to make a decision. This bounded rationality can be exploited by financial markets and experienced investors.

Bounded rationality and the time restraint associated with it require investors to condense their investment prospects down to either what they know or what grabs their attention and it leads investors to rely on large sources of data for quick information. This often results in investors simply relying on the Google platform to find all of their needed information before buying, while holding, and before selling a given stock. As a result, this paper seeks to address the following question: Does an increase in Google Trends data precede or follow an increase in stock price volatility?

The Google platform as a search engine is set up to favor Google Web searches. For instance, if an individual types “Google” into an internet search platform, they will be taken to perform a Google Web search. Likewise, when many people refer to “Googling” something, they are most commonly referring to the platform which is easiest to use: the Google Web search. In order for investors, particularly individual investors, to use the Google News platform, they must specifically search for “Google News” within the Google Web platform or type “https://news.google.com/” into their internet search bar as opposed to simply typing “http://google.com” into their internet search bar. In other words, finding Google News requires marginally more work.

Additionally, Google News only provides an investor with news related to a given stock. This means that Google News excludes stock price, market summaries, and other discussions related to a stock. Google Web, however, includes this relevant information in addition to prominent news stories when searching for a stock ticker symbol. Since investors experience bounded rationality and time restraints, they are more likely to use Google Web rather than Google News to search for stock information. This is because Google Web provides a more comprehensive stock report when compared to Google News.

With this information in mind, this paper hypothesizes that Google Trends data will be strongly correlated with price volatility, with a more statistically significant relationship between Google Web data and price volatility as compared with Google News data and stock price volatility. If this hypothesis is true, it presents a potential opportunity for investors and financial markets alike to capitalize on historical Google Trends data in an effort to obtain greater returns on their investments.

Google Trends data was specifically selected over other search engines due to its convenience and the widespread use of Google as a search engine. According to statista.com, Google sites accounted for 63.1% of all searches within the United States in October 2018, which has remained a relatively stable share of all search volume since January 2008 (Share of search queries, 2019, p. 1).

This paper will evaluate the link between the difference in squared percentage returns of individual stocks, also known as a stock's monthly price volatility, and Google Trends data during a given time period with the use of Google News and Google Web data. This will be accomplished by recording the search volume index for a variety of stocks' ticker symbols, a proxy for an individual's search for information related to a given stock. Specifically, this paper hypothesizes that Google Web data will be significantly correlated with stock price volatility. It will expand upon Da et al.'s (2011) study "In Search of Attention Article" in which the authors find that from 2004-2008 Google search volume indexes (SVI) are correlated but different from existing proxies of investor attention, likely measures the attention of retail investors, and that an increase in SVI predicts higher stock market returns in the short run and a reversal of this boost in the long run.

Da et al.'s work was done on a weekly basis from 2004-2008 using Google trends data for all of the stocks listed within the Russel 3000 throughout the duration of the time period studied. In order to expand upon this, this paper will focus on an alternative SVI tracking source: Google Trends data. It will also expand upon the paper by specifically looking at individual stock monthly data from January 2008 to June 2018 as well as aggregate data over the same time period to determine if all stocks experience the same trend individually that can be seen in the aggregate data.

The first chapter of this paper will begin with a literature review of existing scholarly work. This will allow for a better understanding of bounded rationality, investor's limited attention, the link between search volume indexes and stock market returns, and the link between Google Trends data and stock price volatility. The second chapter will detail the methods used to develop the empirical work within this paper, the third chapter will detail the empirical work done, and the fourth chapter will detail the model results. Finally, the paper will conclude with the fifth chapter, a summary and application of the results of this analysis, and offer suggestions for further research.

Chapter 2

Literature Review

Investor's limited attention and bounded rationality is heavily studied in economic research. The traditional approach in finance is based on a rational agent who makes the optimal investment with rational expectations about the future. In this rational world, information is also assumed to be perfectly transmitted. However, according to Hommes, many authors have disproved this traditionalist view. Keynes explained that market psychology plays a large role in financial markets and Simon emphasized that agents are limited in processing capabilities and face costs associated with obtaining news and information (Hommes, 2006, p. 2). This means that individuals are forced to find time saving ways to gather information, which will theoretically affect the individual stock price and overall market via investor psychology.

Liang et al. expands upon the theory of bounded rationality by studying a framework that incorporates investor's limited attention and adjustment sentiment to demonstrate how they affect asset pricing through bounded rationality and market irrationality. They find that investors with lower rationality levels, such as individual investors, are relatively insensitive to market Trends and macroeconomic factors. Therefore, they pay a higher cognitive loss, allocate more wealth to risk-free assets, will promote rapid price declines in combination with bearish sentiment, all of which cannot be cancelled out by aggregation (Liang et al., 2016, p. 100). Furthermore, they also find that "an investor's rising degree of limited attention leads to an underestimated fundamental value" (Liang et al., 2016, p. 100). In other words, individual investors, or those with lower rationality levels, are at a significant disadvantage from their rational peers, or institutional investors. This supports the theory of bounded rationality in which individual investors are limited by time restraints and a lack of information, which as a result leads them to be less rational than they otherwise would be.

Hommes, Liang et al., and Huberman display that investor's bounded rationality drives them towards finding the easiest way to gather a large amount of easily digested information before making a decision. One way individual investor's accomplish the task of finding a large amount of data which is easily digested is by using Google. Google can be used by individual investors to search for a stock's information by inputting its ticker symbol into the search engine.

Home Biases

In addition to the preference to find quick information prior to investing, investors also often exhibit irrationality as a result of bounded rationality via a home bias by investing a majority of their assets in their home nation. For example, "French and Poterba (1991) estimate that U.S., Japan, and U.K. investors hold 93%, 98%, and 82% of their equity investments, respectively, in their home countries, and argue that these numbers are inconsistent with standard models of asset allocation" (Huberman, 2001, p. 661). This is primarily due to a home bias as a result of bounded rationality. Researchers found that "the expected return on U.S. equities is 5.5% in the eyes of U.S. investors, compared with 3.1% and 4.4% in the eyes of Japanese and U.K. investors, respectively" (Huberman, 2001, p. 661). Since the actual return of U.S. equities cannot be 5.5%, 3.1%, and 4.4% simultaneously, the home bias can be considered irrational.

Another instance of investors bounded rationality and investor's limited attention resulting in a home bias can be explained within the analysis of the Regional Bell Operating Company (RBOC). In this analysis, investors in every state but Montana invested more in the local RBOC than in an out-of-state RBOC. In fact, “the typical amount size range[d] between $10,000 and $20,000, a considerable amount to be invested in a single stock in comparison with the typical U.S. household’s net worth and direct and indirect stock holdings” (Huberman, 2001, p. 661). This indicates that investors are primarily invested in just a few stocks that they believe they understand which are close to their residence, likely due to their lack of rationality associated with diversification and their lack of time. As a result of this, they incur an unnecessary amount of risk relative to diversifying their equity portfolios.

Limited Attention

Madsen and Niessner (2014) and Lou (2014) take this notion of bounded rationality and a home bias a step further within their respective papers. Madsen and Niesser find that an increase in advertisements is highly correlated to an increase in search volume index on Google. Lou finds that these advertisements are highly correlated to a short term increase in stock price and also finds that managers take advantage of this connection and exploit it to profit on their own stock holdings.

Madsen and Neissner specifically hypothesize that due to attention constraints, investors’ attention jumps on days of advertisement, which generates increased interest in financial performance. After analyzing MediaRadar advertising data from February 2008 to October 2013, which included brand advertisements, publication, parent company, ad size, location within the publication, and estimated cost, they find “significant increases in investor attention on ad days, consistent with ads generating spillover effect from consumers to financial markets. [They] also find that ads trigger significant increases in quoted depths, indicating improved liquidity for large trades on ad days" (Madsen and Neissner, 2014, p. 27). Using Google Trends data, they find that ads trigger a 13.1% increase in name search volume index (SVI) and a 5% increase in ticker SVI on days of advertising (Madsen and Niessner, 2014, p. 1-3).

Doug Lou (2014) in his paper, "Attracting Advertising Expenditure Through Advertising", expands upon this concept. Lou finds that an increase in advertising expenditure is accompanied by an increase in retail spending and higher, abnormal stock returns, which are followed by decreased future returns. Lou argues that investors with limited attention or processing capabilities overact to advertising due to being overly optimistic, thus causing stock prices to overshoot their true value. Lou then supports this claim with statistical evidence. He finds that "firms in the top decile ranked by year to year changes in advertising spending outperform those in the bottom decile by 12.85% (t =6.72) in the ranking year, and yet underperform by 6.96% (t= –3.53) and 9.84% (t= –4.52) in the following two years" (Lou, 2014, p. 1797-1798).

Lou then tests to see if managers, or insiders within the firm, are aware of this irrational stock price movement as a result of increased advertising. If they are aware of it, Lou attempts to determine if they exploit it for their own personal gain. Lou uses data on firm advertising expenditures, total assets, and capital expenditures from the Compustat annual tape for the period between 1974 and 2010. This data is then merged with advertising-spending information from the sample, CRSP monthly stock file, quarterly institutional holdings, and monthly small order imbalances. Lou argues that firm managers intentionally exploit investors' bounded rationality. He determines this by finding a high increase in advertising expenditure shortly before insider sales and a significant decrease in advertising expenditure the following year. Lou then states that, "Further evidence suggests that this inverted V-shaped pattern is most consistent with managers' opportunistically adjusting advertising to exploit its temporary return effect" despite this action being considered illegal insider trading (Lou, 2014, p. 1802 and 1825-1826).

If transitivity holds with respect to these two papers, it would be true that search volume indices are highly correlated with stock price movements. Da et al. (2014) indeed prove that search volume indices are correlated with short term stock price movements in their paper, "In Search of Attention." Da et al. examine the weekly search volume index (SVI) for all of the 3606 stocks ever included within the Russell 3000 index between January 2004 and June 2008 based on their ticker symbol. They exclude weekly stock observations which were lower than three dollars and also excluded and any stock which had a "noisy" ticker symbol. Noisy tickers are defined as those which experience irrational behavior relative to other ticker symbols. These stocks included tickers with a generic meaning such as "BABY", "A", "B", etc. They support the idea that investor attention impacts stock price on a weekly basis, but did not expand their selection to include either monthly or daily data. However, Da et al. did find that stocks which experience an SVI increase in one week have an outperformance of more than thirty basis points in the subsequent two weeks. That positive price pressure is then almost entirely reversed by the end of the year. Therefore Da et al. concludes that SVI is "correlated with but different from existing proxies for investor attention [therefore] SVI is a direct measure of individual [investor] attention" (Da et al. 2011, p. 1463-1466, and 1497).

Chapter 3

Data Description

To examine the relationship between search volume indexes and stock price movements, data from Google Trends and The Center for Research in Security Prices (CRSP) from Wharton Research Data Services was obtained. In order to expand upon Da et al.'s work, data was gathered on a monthly basis from January 2008 until June 2018. Monthly data was used based on the assumption of bounded rationality constraints. The specific timeframe was used due to the restrictions imposed by the way Google Trends data is reported and the available data from The Center for Research in Security Prices (CRSP) from Wharton Research Data Services. In an effort to condense the search volume index, exclude noise associated with cultural searches throughout the world, control for the home bias found by Huberman (2001), and focus on a specific grouping of stocks, only U.S. traded stocks from the Russell 3000 were used and the Google Trends data was limited to searches within the United States.

Google Trends data is presented in a relative scale from 0 to 100. It reports the number of times individuals in a given area search for a given letter, group of letters, words, and or phrases. A relative value of 100 indicates that on that given day or over that given period, the inputted search term was searched for with the most frequency relative to other days, weeks, or months in the time frame. Therefore, the measure of frequency is only based on same inputted string of characters (in this case ticker symbols) over the given time frame. However, since Google Trends data is relative, researchers are only able to download the available data based on the given time frame restraints.

Google Trends data is given on a daily basis for roughly a 250 day time period, a weekly basis for roughly a 60 month timeframe, and on a monthly basis for anything greater than a 60 month period. Due to the relative values, it is extremely difficult to obtain Google Trends data for smaller time periods than Google data provides. As a result, this paper focuses only on monthly Google Trends data.

Since Google Trends has a variety of platforms including Youtube, Google Shopping, Google Images, Google Web, and Google News, search volume index data is available for all of the different platforms on the Google Trends database. For the use of this paper, Google News and Google Web data were selected for data collection because they are the two outlets that provide the most easily accessible news and stock market information to a given investor. In order to obtain searches on the Google platform that are most likely to be related to movements within the stock market, the ticker symbols for companies were used. By doing so, it helps to avoid consumer searches. For instance, a consumer may search “Walmart” if they want to find a Walmart store near them to shop at. While this may impact a stock’s long term returns due to increased revenue, it is less likely to impact short term stock price movements. However, an individual is presumably less likely to search “WMT” in an effort to consume Walmart’s products. Instead, they are more likely to be searching for short term stock data or news, which this paper seeks to correlate with stock price movements.

In order to compare the relative Google Trends data to stock market returns, monthly stock market returns were obtained. The Center for Research in Security Prices (CRSP) from Wharton Research Data Services was used to obtain this data within the associated time frame. Price volatility in the form of returns squared is used for a more accurate comparison to Google Trends data, which does not reflect negative or positive search history.

To track both large and small cap stocks and to limit the scope of this paper primarily to the United States, the top ten most traded stocks since 2008 within the Russell 3000 were selected. The Russell 3000 index is a market-capitalization-weighted equity index maintained by the FTSE Russell that tracks the performance of the 3,000 largest U.S. traded stocks based on market capitalization. As a result, it represents approximately 98% of all U.S incorporated equity securities. The top ten most traded stocks with their respective ticker symbols utilized in this paper were the following: Citigroup Inc. (C), Bank of America Corporation (BAC), General Electric Company (GE), Wells Fargo & Company (WFC), Microsoft Corporation (MSFT), JP Morgan and Chase Company (JPM), Intel Corporation (INTC), Cisco System Inc. (CSCO), Facebook Inc. (FB), Pfizer Inc. (PFE), and Alphabet Inc. (GOOGL). Since “C” is a “noisy” ticker symbol because it is a single primary letter, it was replaced with GOOGL.

Possible Measurement Issues

There are various measurement issues that could results with this specific data being used for analysis. Since the entire model is based primarily on data obtained from Google Trends in a relative scale, this data could be misleading in a variety of ways. First and foremost, the data obtained from Google Trends is, as previously explained, based entirely on the searched keyword, or in this case key letters in the form of a ticker symbol, that individuals input into either Google News or Google Web. Therefore, individuals could be typing the symbols into the Google platforms for reasons other than stock market information. This paper attempts to control for this potential measurement issue by omitting ticker symbols which it deems as noisy. However, there could be acronyms, cultural references, or other explanations that impact the motivation for individuals to input a given grouping of letters that happen to also resemble the ticker symbols which this paper evaluates. This could lead to bias that is nearly impossible to detect when downloading Google Trends data associated with the ticker symbols. Furthermore since the scale is relative, if there was a specific time period in which a large number of individuals researched a grouping of letters that resemble a stock's ticker symbol for information other than stock data, it will skew the entire data set for that specific stock. This could lead to significant bias in the overall results of this paper.

There is also the potential bias of uncontrolled macroeconomic Trends that impact the stock market which are independent of searches and information which is associated with an individual stock. For instance if the global economy's anticipated growth is adjusted or trade war tensions escalate, it will likely impact the entire stock market. This information would presumably not be captured in search volume indexes for a specific stock. As a result, it could lead to a bias that the overall model cannot explain. This paper attempts to control for this issue by averaging the monthly data returns on a twelve month rolling basis. However, these macroeconomic events are difficult to control for and could lead to an issue of bias within the results. Additionally, the data obtained within this paper, specifically the search volume index via Google Trends, is only gathered from the United States. Since the stocks within the analysis are globally traded, this could also bias the results.

Finally, the sample sized used for this paper is relatively small. Ideally, all three thousand stocks within the Russell index would be utilized. However, due to the lack of fluid Google Trends data available, this paper chooses to focus on the top ten most traded companies within the index since 2008. As a result, this could skew the overall results.

The Models and Regressions

General Model Descriptions

There will be three main variables studied within this paper: price volatility, or squared stock price returns (returnsq), Google Trends Web data (Google_web), and Google Trends News data (Google_news). The three variables will be evaluated for the top 10 most traded stocks within the Russell three thousand on a monthly basis from January 2008 to June 2018 for each stock individually as well as an aggregate group using performing panel data estimation. All of the models, tests, and empirical results will be evaluated using the EViews software platform.

In order to further expand upon Da et al.'s work, this paper will perform a variety of tests. To do so, the three variables will be tested in all three of the following types of tests: ordinary least squares (OLS), granger causality, and vector auto regressions (VAR). In the initial model, returnsq will be the dependent variable and historical Google Trends will be the independent variables. This initial model seeks to determine if historical searches for a stock's ticker symbol on Google Web and Google News has any impact on price volatility, controlling for historical price volatility (lags of the dependent variable). Reverse causality will then be tested by reversing the equations' orders. In this case, Google News and Google Web data will be tested as dependent variables separately, and the independent variable will be returnsq. This model will seek to determine if there is a link between a stock's price volatility and searches on Google News and Google Web. In other words, do people search a stock's ticker symbol more if the stock has larger expected swings in price? In each scenario, two lags will be used to evaluate each model. Two lags were selected for the data because throughout the models, two lags consistently provided the lowest Akaike information criterion (AIC) values, a generally accepted way to determine the appropriate number of lags to use. Since we are not concerned with present data, present independent variables will be omitted. As a result the general models will be:

$$returnsq = \alpha + \beta 1 returnsq(-1) + \beta 2 returnsq(-2) + \beta 3\ google_{news}(-1) + \beta 4 google_{news}(-2) + \beta 5\ google_{web}(-1) + \beta 6 google_{web}(-2) + \varepsilon$$

$$google_{web} = \alpha + \beta 1 returnsq(-1) + \beta 2 returnsq(-2) + \beta 3\ google_{news}(-1) + \beta 4 google_{news}(-2) + \beta 5\ google_{web}(-1) + \beta 6 google_{web}(-2) + \varepsilon$$

$$google_{news} = \alpha + \beta 1 returnsq(-1) + \beta 2 returnsq(-2) + \beta 3\ google_{news}(-1) + \beta 4 google_{news}(-2) + \beta 5\ google_{web}(-1) + \beta 6 google_{web}(-2) + \varepsilon$$

Please note that all the designated (-1) and (-2) coefficients stand for lagged time variables. For instance, $\text{Google}_{\text{News}}$(-1) represents the Google News Data from one month ago, or Google News with a one month lag. Likewise, GoogleNews(-2) represents the Google News Data from two months ago, or Google News with with a two month lag. The individual variables will also be pooled together to determine the overall company results. For these results, the intercepts will be allowed to vary accordingly across all the evaluated stocks.

Test One Description: OLS

Ordinary least squares (OLS) is a standard test used to estimate unknown parameters in a linear regression test. It uses parameters of a linear function to attempt to show the relationship of explanatory variables on a given dependent variable using the principle of least squares. This results in a simple linear regression that is relatively easily understood. This estimation is important for this paper because it will potentially provide evidence if a significant correlation between a stock's price volatility (returnsq) over a given period and Google News and/or Google Web data over the same period exists.

An example of OLS regression output within the Eview's software appears in figure 1 below:

Dependent Variable: RETURNSQ
Method: Least Squares
Date: 02/24/19 Time: 13:45
Sample (adjusted): 2008M03 2018M06
Included observations: 124 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RETURNSQ(-1)	0.140736	0.086121	1.634158	0.1049
RETURNSQ(-2)	0.362261	0.087495	4.140357	0.0001
GOOGLE_NEWS(-1)	-4.215950	4.103052	-1.027516	0.3063
GOOGLE_NEWS(-2)	5.633143	4.038220	1.394957	0.1657
GOOGLE_WEB(-1)	41.06504	8.350018	4.917958	0.0000
GOOGLE_WEB(-2)	-36.16609	7.971022	-4.537196	0.0000
C	-167.3125	255.0312	-0.656047	0.5131

R-squared	0.438679	Mean dependent var	211.9949
Adjusted R-squared	0.409893	S.D. dependent var	589.6132
S.E. of regression	452.9316	Akaike info criterion	15.12416
Sum squared resid	24002208	Schwarz criterion	15.28336
Log likelihood	-930.6976	Hannan-Quinn criter.	15.18883
F-statistic	15.23945	Durbin-Watson stat	2.262134
Prob(F-statistic)	0.000000		

Figure 1: BAC Monthly OLS Regression

With an F-statistic of 15.23945, this OLS test as a whole is a statistically significant predictor of BAC price volatility. Individually only returnsq(-2), Google_web(-1), and Google_web(-2) are statistically significant at the 95% confidence interval. This implies that there is useful information in lagged Google Web data, in addition to the lagged retrunsq data, that helps explain the variation in the variance of BAC (returnsq).

Test Two Description: Granger Causality Test

The granger causality test is a hypothesis test for determining if the lags of one variable are useful in forecasting another variable and vice versa. It also allows researchers to investigate the direction of causality in a Granger sense. Granger causality tests employ the OLS framework and seek to predict the future value of a time series using prior values of the same series (lags of the dependent variable) as well as lags of the chosen independent variable(s). Using the test, researchers seek to determine if the past values X are a significant predictor of the value of Y in addition to the included past values of Y. The null hypothesis of the Granger causality test is that the coefficient values of the past values of X are jointly equal to zero, or not significant in determining the value of Y. In other words, Granger causality is not truly testing causality as we know it. Instead, it tests if shocks to one variable consistently (with statistical significance) precede shocks to another within a time series.

For the purposes of this paper, Granger Causality testing can be used to determine if increases in Google Trends data precedes increased stock price volatility. Likewise, it can also be used to determine if increased stock price volatility precedes increased Google Trends data. If this test rejects the joint null hypothesis that prior monthly Google Trends data is not significant in preceding increased stock price volatility, it would imply that individuals could use Google Trends data to predict stock price volatility. An example of a Granger Causality test within figure 2 below.

Pairwise Granger Causality Tests
Date: 02/24/19 Time: 13:43
Sample: 2008M01 2018M06
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GOOGLE_NEWS does not Granger Cause RETURNSQ	124	1.58271	0.2097
RETURNSQ does not Granger Cause GOOGLE_NEWS		8.62124	0.0003
GOOGLE_WEB does not Granger Cause RETURNSQ	124	14.5546	2.E-06
RETURNSQ does not Granger Cause GOOGLE_WEB		2.64204	0.0754
GOOGLE_WEB does not Granger Cause GOOGLE_NEWS	124	4.37651	0.0147
GOOGLE_NEWS does not Granger Cause GOOGLE_WEB		0.13984	0.8696

Figure 2: BAC Monthly Grange Cuasality Test

The information in the table above implies that we can reject the null hypothesis of no Granger causality for the following pairs respectively: BAC price volatility (RETURNSQ) precedes Google News Data, Google Web data precedes BAC price volatility, and Google Web data precedes Google News data. The most significant result, with an F-statistic of 14.5545, is that Google Web data precedes BAC price volatility. This implies that a spike in Google Web data will precede a spike in BAC stock price volatility. Again if you are a trader who bets on volatility, this information would be very useful since you might be able to profit off of the signal from Google Web data.

Test Three Description: Vector Auto Regression

Vector auto regressions are multivariable time-series tests in which endogenous variables in the system are functions of lagged values of all endogenous variables within the function and a selected independent variable(s). The VAR test, like the Granger Causality tests, is another way to utilize OLS estimation. VAR analysis is an excellent way to evaluate the dynamic responses of a series to an unexpected shock to another series. These are referred to as impulse response functions. For example, from the Granger results above, VAR tests allows us to examine the response of price volatility (RETURNSQ) to one unexpected, positive standard deviation shock to Google News and vice versa. For the purposes of this paper, VAR tests and the associated impulse response functions will be analyzed.

Example output of impulse response functions from Eviews software appears as the following:

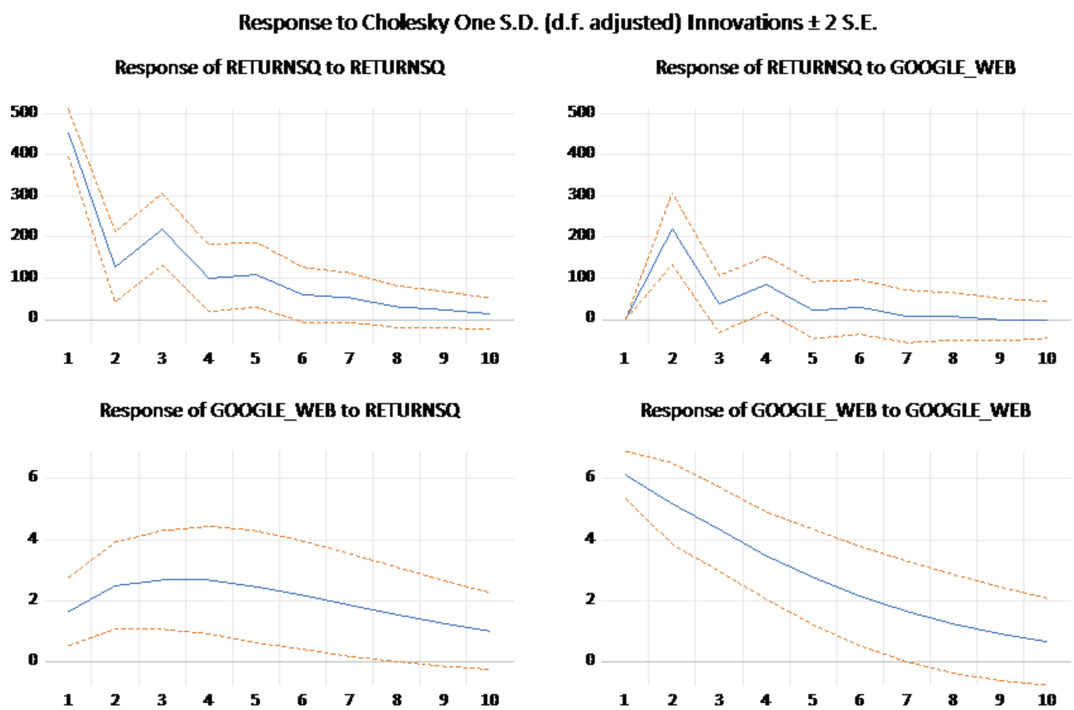

Figure 3: BAC Monthly VAR Output

The above VAR test results imply that a one standard deviation shock to Google Web data will significantly increase BAC stock price volatility for about 4 months at the 95% confidence intervals as shown. The peak influence occurs in month 2 - two months after the one standard deviation shock to Google Web (upper right hand panel). However, this shock will dissipate over approximately 5 months. Similarly, consistent with our Granger causality tests above, a one standard deviation shock to BAC stock price volatility (RETURNSQ) will increase Google Web data by with the effects dissipating over approximately 9 months.

Chapter 4

Model and Test Results

The individual and overall company results indicate that Google Web data is significantly correlated with stock price volatility due to the predicted investor tendencies with respect to Google Web data. All of the previously discussed tests were repeated for each individual company. All of the companies had 124 observations excluding FB (Facebook), which had 71 observations due to going public in May 2012. The overall results combined all of the observations within the individual results and therefore had 1205 observations.

Individual Company Results

Within the results related to Google Web data, table one (below) displays that nine of the ten company results demonstrate that Google Web data Granger causes stock price volatility by rejecting the null at the 5% significance level. The only company which did not have significant results for this variable was Facebook (FB), likely because it was the only company which did not span the entire timeframe due to becoming publically traded in 2012. Furthermore, seven of the ten company results reject the null the 1% significance level. However, just six of the ten companies show that stock price volatility Granger causes Google Web data by rejecting the null at the 10% significance level. In other words, Google Web data (Google_Web) more robustly precedes stock price volatility (Returnsq) than stock price volatility precedes Google Web data. This means that lagged Google Web data specifically provides information over and above lagged stock price volatility when predicting current stock price volatility. This is particularly difficult to do with respect to the implied information within stock price volatility as explained by the efficient market theory.

Company Ticker Symbol	Google_News does not Granger Cause Returnsq	Returnsq does not Granger Cause Google_News	Google_Web does not Granger Cause Returnsq	Returnsq does not Granger Cause Google_Web
BAC	0.2097	0.0003***	0.0000***	0.0754*
CSCO	0.6594	0.1274	0.0000***	0.0003***
FB	0.2729	0.6464	0.6065	0.8826
GE	0.1892	0.4329	0.0005***	0.3141
GOOGL	0.0349**	0.7852	0.0325**	0.8024
INTC	0.0214**	0.1837	0.0013***	0.0027***
JPM	0.1345	0.3029	0.0000***	0.0288**
MSFT	0.0065***	0.0508*	0.0000***	0.0021***
PFE	0.8137	0.9957	0.0133**	0.7477
WFC	0.2577	0.0454**	0.0000***	0.0537*

Table 1: Monthly Granger Probabilities
Significance: *(1% level), ** (5% level), *(10% level)**

The table above also displays that of the ten companies which were evaluated, a majority, or six of the ten companies, demonstrate that Google Web data granger causes stock price volatility and that stock price volatility Granger causes Google Web data at the 10% percent significance level. Meanwhile, just one company, MSFT, demonstrates that Google News data Granger causes stock price volatility and stock price volatility Granger causes Google News data at the 10% significance level. The data, listed in table one below, suggests that Google Web data is more significant in Granger causing stock price volatility than Google News data. The hypothesis expected these results due to investors' bounded rationality. This is specifically important to investors who bet on volatility and could be used to reduce their associated risk or increase their returns. Meanwhile, the other granger causation tests were applicable to just a few companies, suggesting that they are insignificant as a whole.

The results imply that as stock price increases or decreases, individuals begin searching the individual stock on Google Web in an effort to determine what is happening with the stock price. As a result, an increase or decrease in stock price volatility precedes an increase or decrease in searches on Google Web. On the other hand, as investors anticipate large news developments related to stocks, such as earnings announcements, they begin to search for the information on Google Web before the announcements are released. After the anticipated news is released, the individual stock price increases. Hence, an increase or decrease in Google Web data precedes an increase or decrease in stock price. The results suggest that the latter of these two examples is more statistically significant than the first. This is particularly important for investors who bet on volatility. It implies that investors can track monthly Google Web data for a given stock and more accurately make bets on volatility. Therefore, they could use these results to generate increased profits.

Specific companies which emulate these Granger results are Cisco Systems, Inc. (CSCO) and General Electric (GE). CSCO exhibits the Granger causation between stock price volatility and Google Web data in both directions as displayed by the output in the middle panel of figure 4 below.

Pairwise Granger Causality Tests
Date: 02/24/19 Time: 15:58
Sample: 2008M01 2018M06
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GOOGLE NEWS does not Granger Cause RETURNSQ	124	0.41795	0.6594
RETURNSQ does not Granger Cause GOOGLE NEWS		2.09617	0.1274
GOOGLE WEB does not Granger Cause RETURNSQ	124	10.8923	5.E-05
RETURNSQ does not Granger Cause GOOGLE WEB		8.81692	0.0003
GOOGLE WEB does not Granger Cause GOOGLE NEWS	124	0.35400	0.7026
GOOGLE NEWS does not Granger Cause GOOGLE WEB		0.25774	0.7732

Figure 4: CSCO Monthly Granger Causality Test

Figure 4 demonstrates that CSCO is one of the six companies in which Google Web data Granger causes stock price volatility in addition to stock price volatility granger causing Google Web data at the 1% significance level. Again, the overall data suggests, stock price volatility granger causing Google Web data is less significant relative to Google Web data Granger causing stock price volatility.

On the other hand, GE is one of the three companies out of nine in which only Google Web data Granger causes stock price volatility at the 1% significance level. This is shown in the middle panel of figure 5 below.

Pairwise Granger Causality Tests
Date: 02/24/19 Time: 14:05
Sample: 2008M01 2018M06
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GOOGLE NEWS does not Granger Cause RETURNSQ	124	1.68852	0.1892
RETURNSQ does not Granger Cause GOOGLE NEWS		0.84307	0.4329
GOOGLE WEB does not Granger Cause RETURNSQ	124	8.08233	0.0005
RETURNSQ does not Granger Cause GOOGLE WEB		1.16923	0.3141
GOOGLE WEB does not Granger Cause GOOGLE NEWS	124	0.09118	0.9129
GOOGLE NEWS does not Granger Cause GOOGLE WEB		0.82996	0.4386

Figure 5: GE Monthly Granger Causality Test

Notice that all other results are insignificant. As the overall data suggests, Google Web data is very significant in granger causing stock price volatility.

Since vector auto regressions are based upon the same OLS framework as Granger causality, the VAR output is very similar to the results obtained in the Granger causality tests. CSCO results are similar to the Granger causality test as displayed in figure six below.

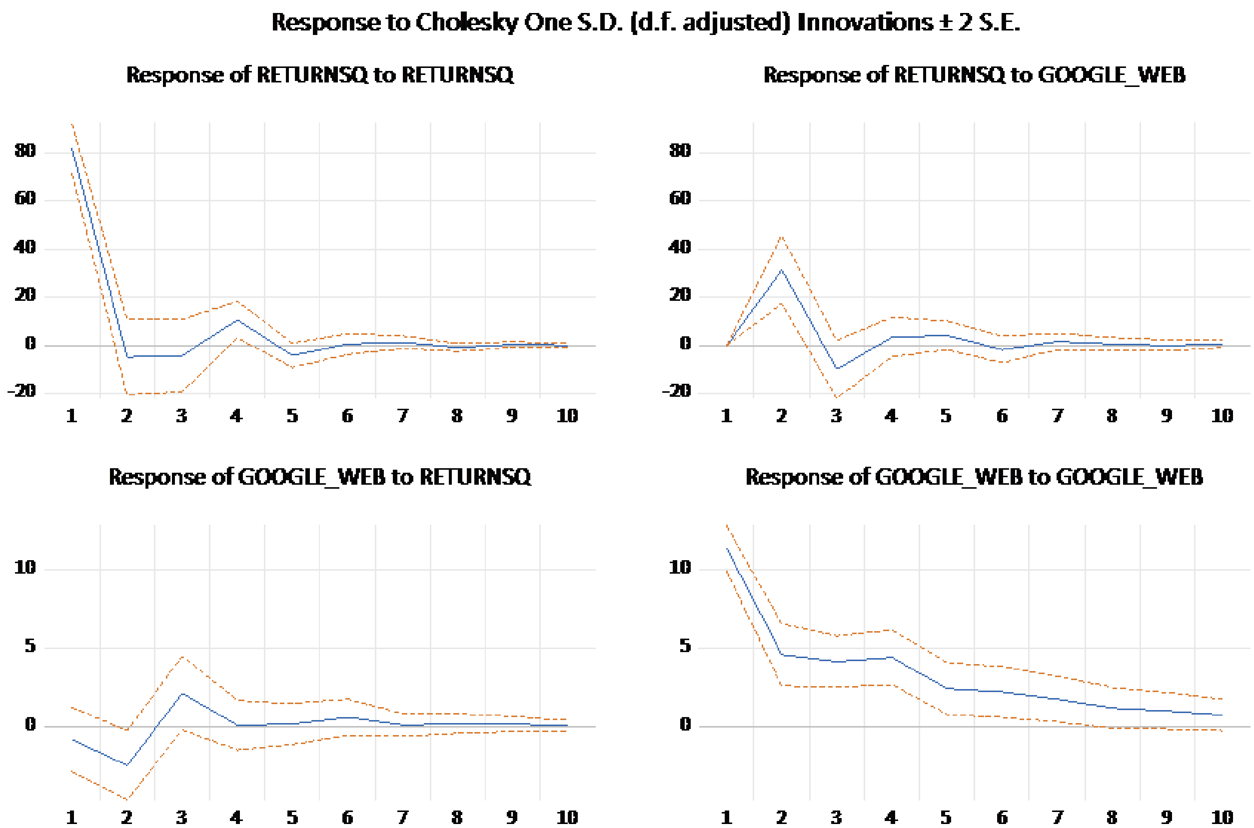

Figure 6: CSCO Monthly Google_Web Output

The output implies that a one standard deviation shock to Google Web data will significantly increase CSCO stock price volatility for about 2 months at the 95% confidence interval with the peak influence occurring in month 2 - two months after the one standard deviation shock to Google Web (upper right hand panel). However, this shock will dissipate over approximately 3 months. Consistent with our Granger causality tests above, a one standard deviation shock to CSCO stock price volatility (RETURNSQ) has less of an impact on Google Web data. In fact, the VAR test demonstrates that a shock to Returnsq is not statistically significant at the 95% confidence interval to Google Web (bottom left panel). The results of the VAR test with respect to Google News data show no significant results as expected and demonstrated by the Granger causality test. This is displayed in figure eleven in the appendix.

The same results are found with respect to GE as shown in figure 8.

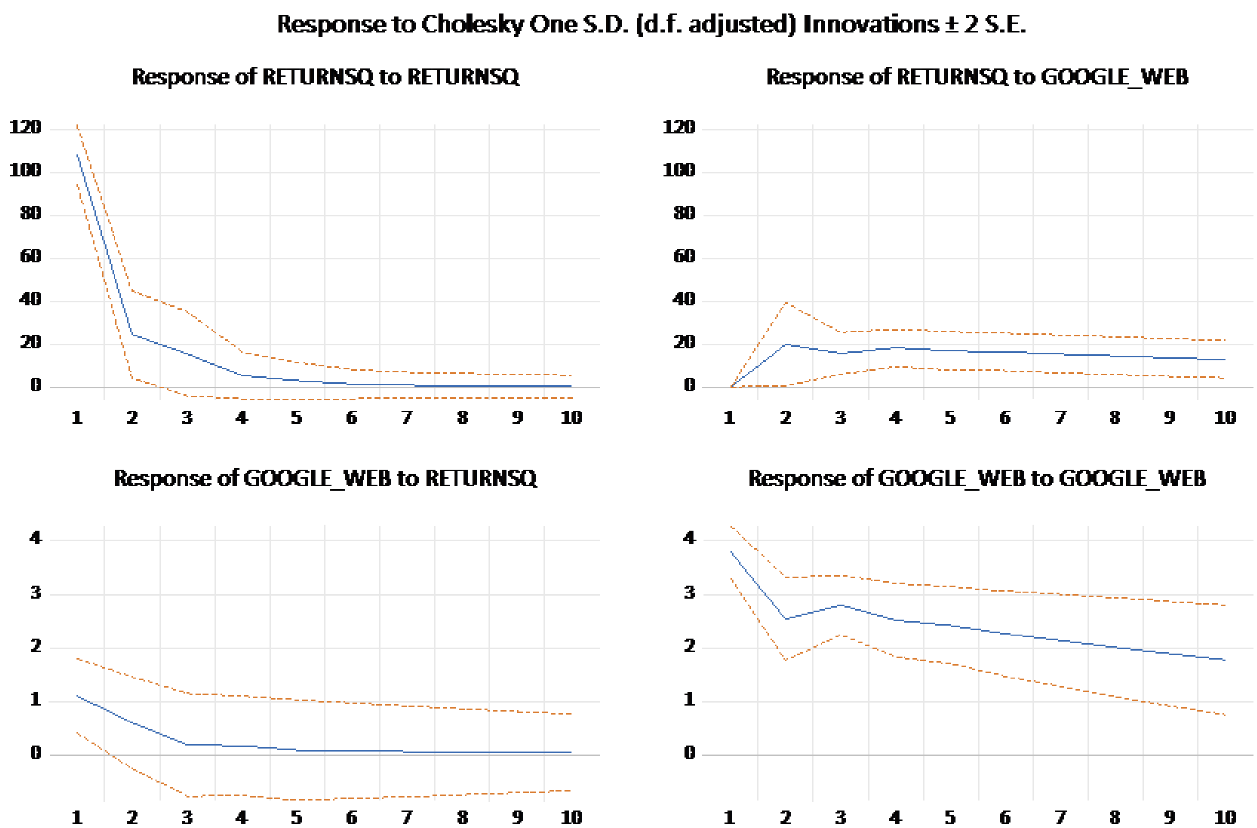

Figure 7: GE Monthly Google_Web Output

The output implies that a one standard deviation shock to Google Web data will significantly increase GE stock price volatility for over 10 months at the 95% confidence interval with the peak influence occurring in month 2 - two months after the one standard deviation shock to Google Web (upper right hand panel). However, consistent with our Granger causality tests above, a one standard deviation shock to GE stock price volatility (RETURNSQ) has no impact on Google Web data. As expected, the shock associated with the results of the VAR test with respect to Google News data show no significant results, as demonstrated by the Granger causality test. This is displayed in figure twelve in the appendix.

The obtained results and trends within the individuals stocks are found to be similar and even more robust in the overall results after combining the observations of all individual stocks which were evaluated.

Overall Company Results

The overall company results echo the individual company results and continue to the support the original hypothesis; however, the overall results are more robust than the individual company results. In the overall company results, the individual company data is pooled together to determine overall effects. Thus, 1205 observations are observed. The OLS test displays this from the beginning; particularly the OLS test in which the variable of main interest, Returnsq, is the dependent variable.

Dependent Variable: RETURNSQ
Method: Panel Least Squares
Date: 03/17/19 Time: 17:25
Sample (adjusted): 2008M03 2018M06
Periods included: 124
Cross-sections included: 10
Total panel (unbalanced) observations: 1187

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.840416	16.00202	0.364980	0.7152
RETURNSQ(-1)	0.232952	0.026860	8.672775	0.0000
RETURNSQ(-2)	0.349788	0.026789	13.05724	0.0000
GOOGLE_NEWS(-1)	-0.185178	0.380151	-0.487115	0.6263
GOOGLE_NEWS(-2)	0.201236	0.379517	0.530243	0.5960
GOOGLE_WEB(-1)	4.697138	0.694635	6.762023	0.0000
GOOGLE_WEB(-2)	-4.087684	0.689272	-5.930433	0.0000

R-squared	0.273590	Mean dependent var	79.27016
Adjusted R-squared	0.269896	S.D. dependent var	238.5601
S.E. of regression	203.8404	Akaike info criterion	13.47843
Sum squared resid	49030055	Schwarz criterion	13.50838
Log likelihood	-7992.449	Hannan-Quinn criter.	13.48972
F-statistic	74.07103	Durbin-Watson stat	2.039056
Prob(F-statistic)	0.000000		

Figure 8: Overall Returnsq OLS Test Results

The OLS test above is statistically significant overall with a F-Statistic of 74.07 and a p-vale of 0.0000. The test has an adjusted R-squared value of 0.269896. Furthermore, Returnsq with both one and two month lags in addition to Google_Web with both one and two month lags are statistically significant at the 1% significance level. Again, this implies that lagged Google Web data is statistically significant above and beyond lagged stock price volatility. Meanwhile, neither lagged Google News data is statistically significant.

This, as the hypothesis suggests, implies that Google Web data is highly correlated with stock price volatility (Returnsq) while Google News data is not. This data is very similar to the individual stock data. The coefficient on the one month lagged Google Web data (Google_Web (-1)) is positive. However, the coefficient on the two month lagged Google Web (Google_Web (-2)) data is negative. With this information in mind, if an investor is attempting to bet on volatility, they can use this information to find stocks which experience large Google Web data searches in the past month relative to few Google Web searches two months ago. This will result in the potential for the largest profits based on associated coefficients within the OLS output.

It is important to note that when an omitted variable test is run, Google Web and Google News are both statistically significant. However, the Google News data results are less significant and, as shown above, are not significant individually. These results can be found in the appendix in figures 14 and 15.

These results are also reiterated with the Granger Causality test as shown in figure 9 below.

Pairwise Granger Causality Tests
Date: 03/17/19 Time: 17:19
Sample: 2008M01 2018M06
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
GOOGLE WEB does not Granger Cause RETURNSQ	1187	26.5811	5.E-12
RETURNSQ does not Granger Cause GOOGLE WEB		0.93982	0.3910
GOOGLE NEWS does not Granger Cause RETURNSQ	1187	3.70434	0.0249
RETURNSQ does not Granger Cause GOOGLE NEWS		4.73987	0.0089
GOOGLE NEWS does not Granger Cause GOOGLE WEB	1187	9.30385	0.0001
GOOGLE WEB does not Granger Cause GOOGLE NEWS		1.13982	0.3202

Figure 9: Overall Granger Causality Test Results

The granger test reiterates the results found in the OLS test. The test demonstrates that Google Web data Granger causes stock price volatility (Returnsq), Google News data Granger causes stock price volatility, stock price volatility Granger causes Google News data, and that Google News data Granger causes Google Web data by rejecting the associated null hypotheses. Unlike the individual company results, stock price volatility does not Granger cause Google Web data. Similar to the hypothesis, the individual company results, and the basic OLS regression above, the most statistically significant result is that Google Web data Granger causes stock price volatility with a T-statistic of 26.5811. These results are outlined in red in figure 9 above. These results are also demonstrated in the VAR tests shown below.

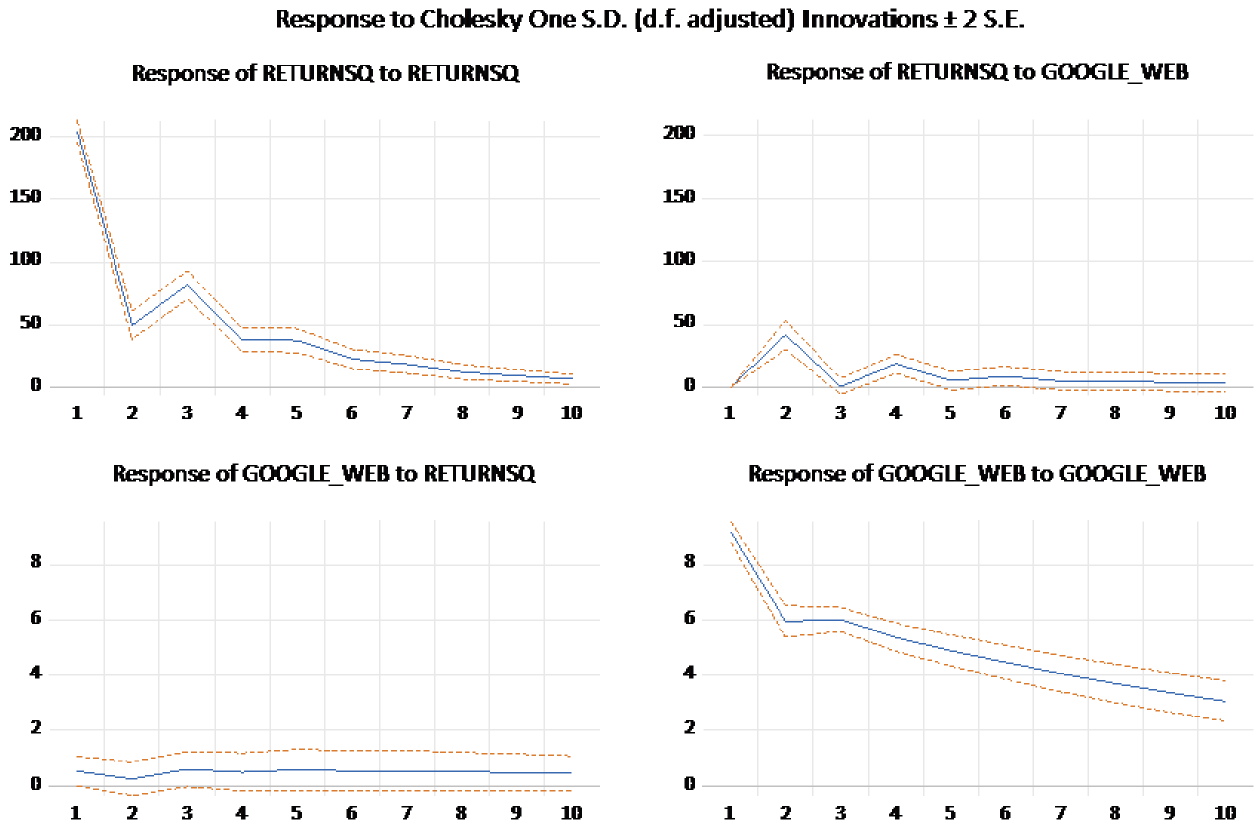

Figure 10: Overall VAR Results; Google Web and Returnsq

The output in figure nine implies that a one standard deviation shock to Google Web data will significantly increase overall stock price volatility for over 10 months at the 95% confidence interval with the peak influence occurring in month 2 - two months after the one standard deviation shock to Google Web (upper right hand panel). These results also exhibit the largest magnitude and remain statistically significant for the entire ten month period. A shock to Google News data also demonstrates an impact on stock price volatility, as displayed below.

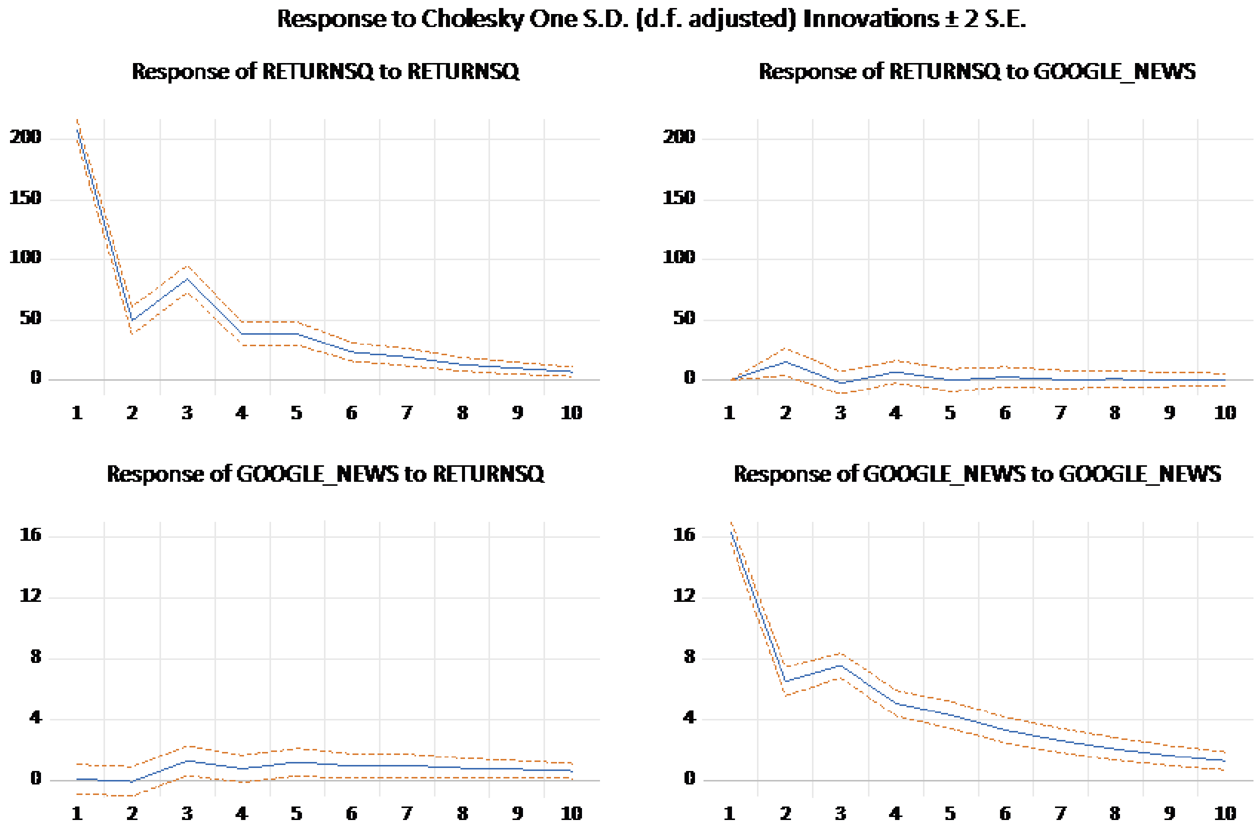

Figure 11: Figure 9: Overall VAR Results; Google News and Returnsq

The output above implies that a one standard deviation shock to Google News data will significantly increase stock price volatility for about 2.5 months at the 95% confidence interval with the peak influence occurring in month 2 - two months after the one standard deviation shock to Google News (upper right hand panel). However, this shock will dissipate over approximately 3 months. With respect to the impact on Returnsq, the magnitude and duration of this shock is inferior relative to a shock to Google Web data. These results support the original hypothesis that Google Trends data will be strongly correlated with price volatility, with a more statistically significant relationship between Google Web data and price volatility as compared with Google News data and stock price volatility. It is also reiterates the findings of the individual company data in a more robust, statistically significant way.

Chapter 5

Conclusion

Cumulative investor information is a powerful tool which can help any individual or financial company profit when making bets on market movements. This paper hypothesized that Google Trends would be strongly correlated with stock price volatility, with a more statistically significant relationship between Google Web data and stock price volatility as compared with Google News data and stock price volatility. The results imply that this hypothesis is correct on both an individual company and aggregate data scale.

Of the 10 companies evaluated, 9 demonstrate that Google Web data Granger causes stock price volatility by rejecting the null at the 5% significance level. Additionally, 6 of the 10 companies show that stock price volatility Granger causes Google Web data by rejecting the null at the 10% significance level. The strongest results, as hypothesized, are associated with Google Web data Granger causing stock price volatility. These individual results are reiterated with the OLS and VAR test framework for the corresponding stocks.

The aggregate data provides even more robust results. The overall OLS test is statistically significant with a T-Statistic of 74.07 and a p-vale of 0.0000, and it finds that Google Web data at both one and two month lags are statistically significant at the 1% significance level. Google Web data lagged one month has a positive coefficient of 4.697138. Google Web Data lagged two months has a negative coefficient of 4.087684. Meanwhile, neither lagged Google News data is statistically significant.

. This Granger Causality test finds that Google Web data Granger causes stock price volatility (Returnsq), Google News data Granger causes stock price volatility, stock price volatility Granger causes Google News data, and that Google News data Granger causes Google Web data by rejecting the associated null hypotheses at the 5% significance level.

Finally, the VAR test also helps to reiterate these overall results. The output implies that a one standard deviation shock to Google Web data will significantly increase overall stock price volatility for over 10 months at the 95% confidence interval with the peak influence occurring in month 2 - two months after the one standard deviation shock to Google Web (upper right hand panel). These results also exhibit the largest magnitude. Meanwhile a one standard deviation shock to Google News data implies an increase in stock price volatility for about 2.5 months at the 95% confidence interval with the peak influence occurring in month 2 - two months after the one standard deviation shock to Google News (upper right hand panel). However, this shock will dissipate over approximately 3 months.

These results suggest that investors begin searching for stock tickers ahead of large news announcements or predicted events in a company's annual business cycle. However, they are less likely to search a company's ticker symbol after a large deviation in price. These searches primarily occur on the Google Web platforms as opposed to the Google News platform, likely due to convenience and the information provided.

With this statistically significant information in mind, investors could use it to make bets on volatility by using bets such as strangle or straddle options, explained graphically in figures 16 and 17. By using this information, investors will potentially be able to increase their overall profits. The data suggests this will be particularly true if the company has large Google Web searches in the previous month relative to the number of Google searches two months ago.

Future areas of research for this topic could evaluate the link between stock price and other search indexes in an attempt to determine if these results can be replicated on other platforms. Furthermore, more stocks could be evaluated on a monthly or daily basis to determine if the results are similar. Finally, links between search volume indices could be used to determine correlation or ultimately causality between other variables such as bond prices, consumer spending, real estate purchases, and so on. Google trends provides a unique way to track individual behavior as an aggregate, which means it is a great tool for a variety of potential economic studies.

Appendix A

Supporting Graphs

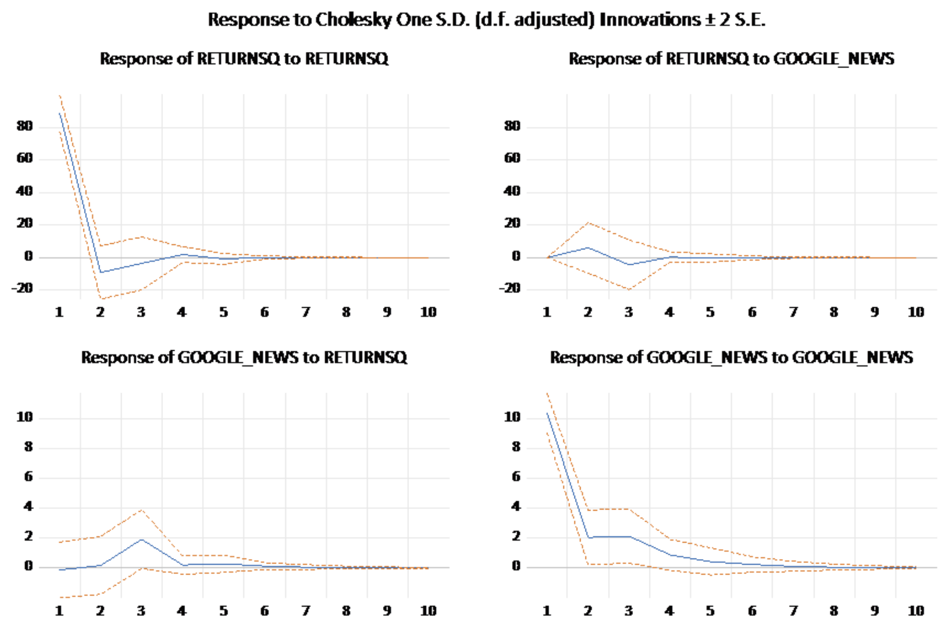

Figure 12: CSCO Monthly VAR Google_News

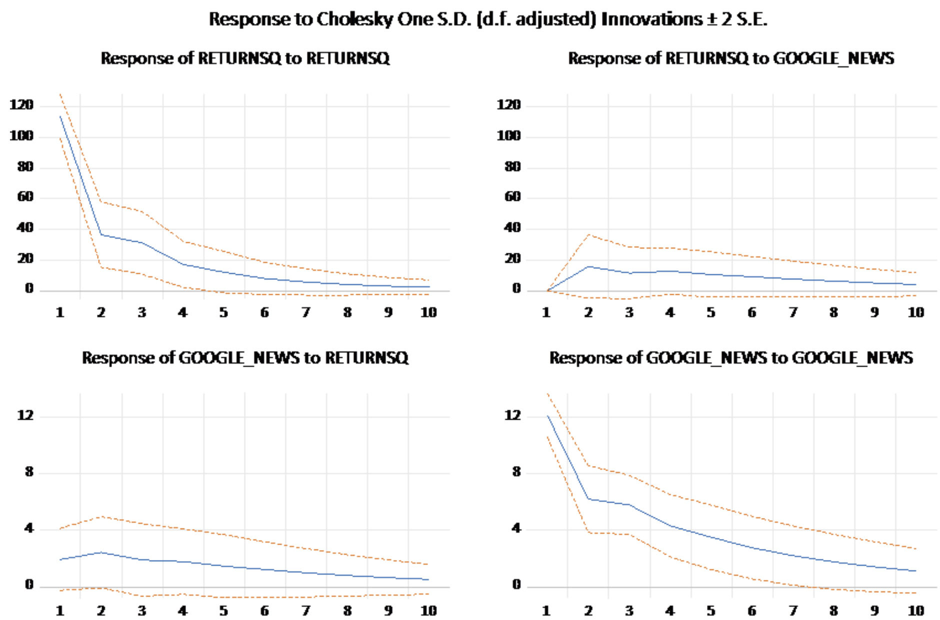

Figure 13: GE Monthly VAR Google_News

Omitted Variables Test
Null hypothesis: GOOGLE_NEWS(-1) GOOGLE_NEWS(-2)
Equation: RETURNSQ_REGRESSED
Specification: RETURNSQ C RETURNSQ(-1) RETURNSQ(-2)
Omitted Variables: GOOGLE_NEWS(-1) GOOGLE_NEWS(-2) are jointly insignificant

	Value	df	Probability
F-statistic	3.704344	(2, 1182)	0.0249
Likelihood ratio	7.416809	2	0.0245

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	319226.0	2	159613.0
Restricted SSR	51249314	1184	43284.89
Unrestricted SSR	50930088	1182	43088.06

LR test summary:

	Value
Restricted LogL	-8018.722
Unrestricted LogL	-8015.014

Unrestricted Test Equation:
Dependent Variable: RETURNSQ
Method: Panel Least Squares
Date: 03/17/19 Time: 17:28
Sample: 2008M03 2018M06
Periods included: 124
Cross-sections included: 10
Total panel (unbalanced) observations: 1187

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	27.46699	10.81155	2.540522	0.0112
RETURNSQ(-1)	0.237258	0.027147	8.739693	0.0000
RETURNSQ(-2)	0.349880	0.027133	12.89491	0.0000

R-squared	0.245439	Mean dependent var	79.27016
Adjusted R-squared	0.242886	S.D. dependent var	238.5601
S.E. of regression	207.5766	Akaike info criterion	13.51308
Sum squared resid	50930088	Schwarz criterion	13.53448
Log likelihood	-8015.014	Hannan-Quinn criter.	13.52115
F-statistic	96.11870	Durbin-Watson stat	2.006547
Prob(F-statistic)	0.000000		

Figure 14: Overall Google News Omitted Variables Test

Omitted Variables Test
Null hypothesis: GOOGLE WEB(-1) GOOGLE WEB(-2)
Equation: RETURNSQ REGRESSED
Specification: RETURNSQ C RETURNSQ(-1) RETURNSQ(-2)
Omitted Variables: GOOGLE WEB(-1) GOOGLE WEB(-2) are jointly insignificant

	Value	df	Probability
F-statistic	26.58112	(2, 1182)	0.0000
Likelihood ratio	52.22136	2	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	2205806.	2	1102903.
Restricted SSR	51249314	1184	43284.89
Unrestricted SSR	49043508	1182	41491.97

LR test summary:

	Value
Restricted LogL	-8018.722
Unrestricted LogL	-7992.612

Unrestricted Test Equation:
Dependent Variable: RETURNSQ
Method: Panel Least Squares
Date: 03/17/19 Time: 17:29
Sample: 2008M03 2018M06
Periods included: 124
Cross-sections included: 10
Total panel (unbalanced) observations: 1187

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.204970	15.38108	0.403416	0.6867
RETURNSQ(-1)	0.233187	0.026831	8.690775	0.0000
RETURNSQ(-2)	0.349562	0.026759	13.06326	0.0000

R-squared	0.273390	Mean dependent var	79.27016
Adjusted R-squared	0.270931	S.D. dependent var	238.5601
S.E. of regression	203.6958	Akaike info criterion	13.47534
Sum squared resid	49043508	Schwarz criterion	13.49673
Log likelihood	-7992.612	Hannan-Quinn criter.	13.48340
F-statistic	111.1833	Durbin-Watson stat	2.039699
Prob(F-statistic)	0.000000		

Figure 15: Overall Google Web Omitted Variables Test

Figure 16: Strangle Bet

Source: https://www.optionsbro.com/long-strangle-option-strategy-example/

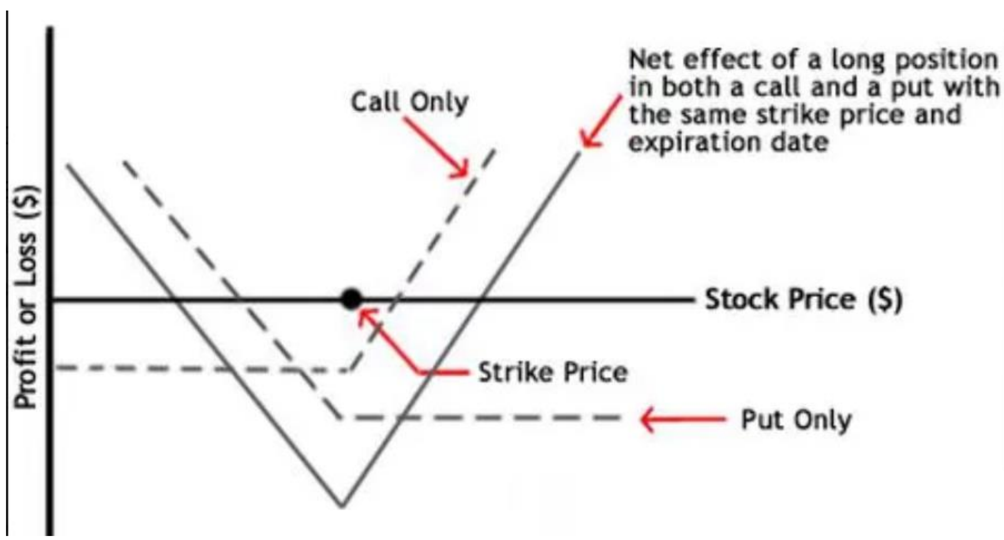

Figure 17: Straddle Bet

Source: https://www.investopedia.com/terms/s/straddle.asp

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ACADEMIC VITA

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Research Assistant

Research Experiences for Undergraduates Program, University Park, PA 8/2018- 12/2018

- Worked with distinguished faculty, Russell Chuderewicz, in the Economics Department
- Evaluated the effect of Google Trends data on stock market returns
- Completed research in conjunction with my undergraduate thesis
- Conducted literature reviews and empirical work with Stata regressions

Intern

Farm Credit East, Flemington, NJ 5/2018- 8/2018

- Researched, developed, and implemented a new social media marketing strategy
- Interviewed 6 managers and surveyed 91 employees to create branch oriented social media pages
- Created 3 original reports, totaling 68 pages, based on findings for employees to reference
- Presented social media findings and recommendations to top executives

Entrepreneurial Business Owner, Kutztown, PA 3/2012- 6/2018

T and T Farms Greenhouses

- Managed employees, predicted future pricing, and selected inventory
- Obtained an average profit of $7.62 per square foot and a 21% profit margin
- Developed marketing strategies to promote products
- Tracked, recorded, and evaluated annual finances and market trends with excel

Mentor 7/2017-8/2017

Pennsylvania School for Excellence in the Agricultural Sciences, University Park, PA

- Mentored, led, and educated a group of six students at Penn State
- Developed, organized, and collaborated with a team to create events and kept students engaged
- Analyzed and problem solved in diverse situations
- Gained exposure to and learned about the agribusiness industry

LEADERSHIP/ EXTRACURRICULAR ACTIVITIES:

The Pennsylvania State University

University Park Allocation Committee; *Member* 8/2017- Present

Economics Association; *Member* 8/2017- Present

Habitat For Humanity; *Member* 8/2018- Present

Agriculture and Environmental Club; *Vice President* 8/2016-5/2017

- Helped established club, coordinated activities, budgeted, and presided over meetings

TECHNICAL SKILLS:

Stata, Microsoft Excel