6-2022

Finance and Fear: Sentiment, Media, and Financial Markets During the COVID-19 Pandemic

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by

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Submitted in partial fulfillment
of the requirements for
Honors in the Departments of Economics

UNION COLLEGE
June, 2022

ACKNOWLEDGMENT

I would like to express my immense gratitude to Professor Eshragh Motahar. The conception of this thesis sparked in his classroom as a chain reaction from his curiosity. The completion of this thesis was made possible by your guidance and feedback around the clock. Thank you, Professor, for your wisdom, patience, and compassion throughout the entire process. A final thanks, to my family and friends, for always lending an ear and supporting me- I hope you read past my abstract!

ABSTRACT

SOMMERS, ALISON N. Finance and Fear: Sentiment, Media, and Financial Markets During the COVID-19 Pandemic

ADVISOR: Eshragh Motahar

This thesis aims to build on existing research of market psychology and the effect of sentiment on financial markets. The main objective of this study is to determine the ability of investors to make rational decisions during the most recent period of high sentiment. The anomalies that have occurred in the stock market can be better understood by market psychology which focuses on the biases and social factors that influence investors. The media is a newly relevant factor impacting the volume of sentiment present in the market. A review of the literature reveals that many studies of sentiment and financial markets conclude that emotion has a prominent influence on investors' decisions. The current pandemic has had detrimental effects on human life and human livelihood. A unique economic situation has emerged as uncertainty increased and resulted in extreme volatility in financial markets that cannot be explained by mainstream financial theories and rational decision-making alone. This thesis expands on recent literature about the pandemic and attempts to understand the market movements by looking at a range of explanatory data reflecting panic, sentiment, and fake news in the media alongside measures of fundamental economic conditions to assess irrational decisions during the pandemic. I will use these measures to test sentiment and the media's significance on the S&P500 and the 10-year treasury yield in the US for 2020 and 2021. This model identifies when sentiment has the most influence on investment decisions and how. Furthermore, I evaluate how investors treat the bond market differently than the stock market.

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CHAPTER ONE

INTRODUCTION

I. Background Information

Financial markets play a critical role in an economy by properly assessing risk and return and thus allocating resources efficiently. For financial markets to make decisions effectively, the causes of stock market fluctuations are imperative to dissect and analyze. There is no one clear way to evaluate factors that move a stock price. The Efficient Market Hypothesis has been adopted by economists as a popular theory to navigate and explain the stock market. This hypothesis states that share prices reflect all information and trade at their fair price value. The forces that are commonly known to move the stock market are fundamental factors and technical factors. Fundamental factors alter stock prices based on a company's earnings and profitability. A rational investor is concerned about future growth and the perceived risk of the stock. Technical factors affect the supply and demand of a company's stock due to external circumstances. This conventional economic theory assumes that all individuals behave rationally by focusing on fundamental analysis; however, in history, we have often seen market movements that are disconnected from fundamental factors.

Other economic theories of stock market decisions have emerged to acknowledge irrational decisions and explain market movements using psychology. The behavioral theory in finance attributes a portion of predictive power to noise traders. Noise traders, unlike rational arbitrageurs, are subject to sentiment. Sentiment is therefore considered a technical factor that contributes to asset allocation in financial markets in behavioral economics. The anomalies that have occurred in the stock market can be better understood by market psychology which focuses on the biases and social factors that influence investors. Market psychology states that the buying and selling of stocks can be influenced by emotion, particularly during periods of high sentiment (Hayes, 2021). Sentiment's casual power on stock market volatility is to be proven significant in the model created by Baker and Wurgler (2007). Emotions contributing to investment decisions are explained by John Maynard Keynes as "animal spirits" (Friedman, 2009). Common feelings that contribute to sentiment include fear and excitement. Akerlof and Shiller primarily focus on confidence and claim that it is the most crucial force to overheat the economy and vice versa. After an economy unsustainably overheats, financial markets will experience a collapse due to reckless speculative decisions, also known as a 'Minsky Moment' (Friedman, 2009).

The power of sentiment is explicit when reflecting on the decisions creating the housing bubble and subsequent 2008 stock market crash. The financial markets experienced "irrational exuberance" and suffered due to it. (Akerlof and Shiller 2009). The current pandemic has also created a unique economic situation that every country is battling differently. The novel health crisis has taken over five million lives in less than two years and afflicted unquantifiable damage to humans living through it. To prevent the spread of the disease, the world economy was brought to a fierce stop, causing havoc in financial markets. All major and developing stock markets fell at the onset of the pandemic. What makes this crisis different from previous crises is that demand and supply chains were simultaneously interrupted. We are experiencing the decomposition of supply chains due to restrictions on work, travel, et cetera, as well as decreasing demand due to nerves, inability to conduct normal activities, et cetera. The pandemic health emergency is not a familiar event nor a predictable event. Throughout the pandemic, uncertainty increased and the stock market experienced rapid selloffs as well as historic rallies that cannot be explained by conventional financial theories and rational decision making alone.

A more recently developed factor influencing sentiment is the availability and volume of news about investment information and general information. The increase in attention to news, specifically bad news, is heightened now more than ever. Marty et al. (2020) showed evidence for the unarguable use of news in investors' decisions, but there is a debate as to whether it is useful to integrate into strategy. Media coverage during the pandemic has been found to create fear and, in some cases, the fear generated from fake news.

II. Statement of Core Research Question

This paper will adopt an index created by Huynh et al. (2021) called the "Feverish Sentiment Index." This index uses a range of data reflecting panic, sentiment, and fake news in the media to calculate irrational decisions during the pandemic. I will use these measures to test sentiment and the media's significance on financial markets in the US for 2020 and 2021. I will contribute an alternate version of the feverish sentiment index that tests sentiment on the US stock market and bond market in 2020 compared to 2021.

There is conclusive evidence on the impact of sentiment, but there is a gap in research regarding news and its contribution to creating sentiment. To build on existing studies on the presence of sentiment in financial markets, this paper will specifically assess the impact of media on sentiment-based decisions. I will also test the relationships between independent variables to investigate interactions. I predict that the media will not always accurately reflect fundamental measures of financial conditions. I will assess this by comparing fundamental measures of the state of the economy, sentiment measures, and their relationships to US financial markets. The perpetuation of fake news in the media is a new source of concern (Allcott and Gentzkow, 2017). To fill in a gap in research, investors' reaction to fake news is another piece of information I will be identifying in my model.

I will also contribute to the literature by evaluating the effectiveness of irrational investors. The media generates a continuous flow of posts; however, financial news is updated far less frequently. My model assumes that rational investors when making investment decisions, will take fundamental measures into consideration that are not released as frequently as general news. The fundamentals I will draw upon are especially relevant measures of the state of the economy during the pandemic. A few of these factors are unemployment (continued claims), banking tightness, the stock market volatility index, the market price of crude oil. By evaluating the degree of misalignment between fundamentals and sentiment, I predict that decisions during the pandemic did not accurately reflect the condition of the economy. I hypothesize that fake news will be a significant contributor to irrational investment decisions signaling those investors cannot effectively process the news.

III. Significance of Thesis

The implications of financial distress and market volatility are of importance for the physical and mental well-being of individuals and the country. The stock market affects physical livelihood through capital and mental well-being through heightened emotion. This negative feedback loop has the capability of causing harm to financial markets. When the market is inefficiently allocating capital and pricing stocks, it creates financial losses for individuals and firms. Furthermore, an inefficient market deceives buyers and sellers and forges a waste of real resources (Friedman, 2009). Understanding market psychology is crucial because it can deepen the comprehension of economic cycles and potentially be used to improve the productivity and growth of the entire economy. With the end of the pandemic being so uncertain, an understanding of negative influences on the market is pivotal.

This thesis will add more comprehensive insight on exogenous factors that influence sentiment and consequently influence the volatility of the stock market. The evaluation of media and news during the pandemic will broaden the scope of prior knowledge of sentiment. There are many resources contributing to research on this topic. This study will adjust and update the feverish sentiment index to contribute a deeper analysis of the United States economy during the pandemic. The bearer of responsibility for filtering information is currently undefined. I hope that distinguishing the impact of media will raise awareness of the importance of regulating sources of news, a highly debated topic.

IV. Structure of Thesis

This thesis is divided into five chapters. A review of the literature will be presented in chapter two. The third chapter will present the analytical framework of this study and define the variables used in the model. Chapter four provides a report of the results of the model and visually displays them. This will also include an interpretation of their meaning and a discussion of their implications. Finally, chapter five will conclude with the limitations of this study and offer areas for future research.

CHAPTER TWO

LITERATURE REVIEW

I. Introduction

In this chapter, a variety of economic sources of literature pertaining to behavioral finance are reviewed. Presented first is a review of psychological biases that influence investors' decision-making. These are the human factors found to contribute to sentiment present in financial markets. To demonstrate the impact of sentiment in history I review the 2008 stock market crash. Subsequently, I identify the similarities and differences between the housing bubble and the current pandemic. I conclude this section by establishing the significance of sentiment throughout the COVID-19 era. The second section will review the literature about media, sentiment, and financial markets. The relationship between news and investor decisions is a developing, dynamic area of concern. I will review literature that explains the impact of media and sentiment on the stock market and introduce the various theories arguing to what extent the media has power over emotions and decision-making. By drawing on these topics of literature, this paper will build on the limited existing research connecting news, sentiment, and financial markets by focusing on media, fake news, and fundamental measures. Lastly, I will introduce a novel approach to evaluate the rationality of investors' decisions in the U.S. throughout the COVID-19 pandemic.

II. Investor Sentiment

In this section, I review the literature about how investors make financial decisions based on sentiments. The economic human, based on psychology, does not always behave rationally.

Frydman et al. (2020) argue that sentiment alters the weight investors assign to fundamentals depending on the current economic condition. The analysis of this study concludes that when market sentiment aligns with fundamentals the fundamental news has a significant effect on investors' decisions. When market sentiment is neutral or conflicts with fundamental measures, this news does not have a significant effect on investors' decisions. The data also suggests that investor sentiment is largely uncorrelated to fundamental measures of the economy and influences returns irregularly. Overall, different types of investors depend on different factors. Short-term investors are more likely to evaluate technical factors, including market psychology. Sentiment can overwhelm the market in the short run; however, fundamentals are seen to set the stock price in the long run (Tetlock, 2007).

Behavioral finance (behavioral economics) is the field of study that identifies the psychological biases and opinions that influence broad financial decisions. This field of study emerged in the 1980s from the desire to explain illogical decisions, for example, why well-respected investors buy too much or sell too soon. Behavioral finance aims to identify and expose the ideas that cloud investors' brains when evaluating prices and risk. This is important because irrational exchanges can cause volatility or inefficiencies in the financial markets. One example of human error is shown by comparing an investor to an index, "the average investor in equities earned an average annual return of 4.25% in the 20 years between 2000 and 2019. At the same time, the S&P 500 had gone up 6.06%" (Rambow 2021).

Market psychology names counterproductive behaviors biases. Biases culminate from endogenous emotions and exogenous social factors. Common moods that contribute to investor sentiment are fear and excitement. These emotions are explained famously by John Maynard Keynes as "animal spirits". Two economists, George Akerlof and Robert Shiller (2009), more recently expanded on the term “animal spirits” and their irrational influence on decisions. Akerlof and Shiller (2009) identify distinct elements of “animal spirits” as confidence, fear, bad faith, corruption, a concern for fairness, and the stories we tell ourselves about our economic fortune. These internal mental states affect investors and explain certain anomalies and mispricing’s those fundamentals alone cannot account for. Behavioral economics is innately subjective due to the various immeasurable factors that drive irrational decisions. Akerlof and Shiller (2009) state that confidence has the most powerful force on humans. These economists argue that conventional macroeconomic analysis often fails because fluctuations in the economy, and consequently the stock market, are subject to chaotic decisions influenced by sentiment.

Akerlof and Shiller (2009) attributed market psychology as a driving factor to the overheating of the housing market throughout the 2000s. Economists state that blind trust in the continuance of the rise of housing prices defied historic economic fundamentals and arguably had more effect on the economy than monetary policy. The stock market did not reflect the financial downturn in the economy and instead reflected the positive sentiment that numerous sources wrongly forecasted by bankers and investors (Gennaioli and Shleifer 2018). Gennaioli and Sleifer (2018) note the “Kernel of Truth” principle as a behavioral tendency that contributed to sentiment in financial markets. This term states that news pointing to economic growth generates more representation compared to news pointing to economic distress. False representations of reality lead investors to neglect risk and act optimistically. The fragility of the economy was exposed when Lehman declared bankruptcy in September 2008. The following fire sale of assets displays the psychological impact of fear on investors’ decisions. Both the bull and bear reactions of investors to sentiment caused inefficient financial markets (Friedman, 2009).

This housing bubble is most commonly attributed to corruption at all levels of financial markets; however, it is important to understand the role of sentiment. The power of emotion is explicit when reflecting on periods of crisis in history. The COVID-19 pandemic is a very different kind of crisis compared to the 2008 stock market crash. This is important to note because it illuminates the range of effects emotion has on the economy in the United States. The 2008 stock market crash was caused by a period of positive sentiment, fueled by overconfidence. The pandemic is a period of negative sentiment, fueled by fear and uncertainty. Nonetheless, sentiment continues to drive decisions in financial markets and deserves adequate attention.

Robert Shiller is a bold, well-recognized economist who offered a warning about stock market euphoria in 2000 in his book *Irrational Exuberance*. His analysis of factors contributing to the growth is relevant today. He identifies two different anchors for the markets: moral anchors and quantitative anchors. Shiller attributes the amplification of volatility in the market to a positive feedback loop in which investors encourage each other to the point of a collapse of the market. This is identified as herd behavior, which is the tendency for humans to collaborate and consider others' opinions. Rational and irrational investors alike are often persuaded to believe that the majority is accurate.

Shiller also focuses on the role of media during the stock bubble in 2000. Shiller blames newspapers for creating a false vision of the economy by spreading fake news. This occurs due to judgment by representativeness- the tendency for a response to information to be in the correct direction, but as an over or underestimate. Shiller argues that every new era of optimism is followed by extreme pessimism producing economic booms and busts.

Schiller's theory concludes that investors can identify opportunities in the market; however, the EMH theory does not account for mispricing. There are risks to ignoring overpriced stocks. A crash can make an individual or an entity extremely rich and another extremely poor without reason. Shiller notes that there are destructive effects of a large capital loss because the loss will trickle down throughout the economy and lead to inefficient allocation of resources. Shiller's account of sentiment and its implications have built the groundwork for behavioral finance and new studies have extended his theories to the pandemic era.

The COVID-19 virus has cycled in waves and subsequently varied in effect over the past two years. The Fed implemented multiple of the largest stimulus packages in history and lowered interest rates until reaching near zero. Investors have had to digest the changes in regulations for travel, vaccines, and businesses alongside market fundamentals. Throughout the erratic cycles of the pandemic, there have been continuous reports of record-breaking movements. Most notably, in the first half of 2020. The stock market reflected a V-shaped recovery. The S&P 500 fell 34% from February 19th to March 23rd and then shifted to rise 29% by April 17th. The index has fluctuated and experienced volatility throughout the pandemic, but in general, has trended upwards since April 2020 (See figure 1). These movements have spun the heads of economists as we try to understand the root of decisions in financial markets amidst the spread of a deadly virus. At times the financial market's performance has ignored the pilling number of deaths and focused on corporate announcements (Russell and Hadi 2021). Overall, the stability of the economy has relied on both stimulus from the government and the ability to contain the disease. We are now facing the two-year mark since the first case of COVID-19 in the United States and are still experiencing the spread of the disease and severe supply chain issues. Uncertainty persists and the evaluation of the COVID economy thus far is important for future decisions. Research published earlier in the pandemic provided support for the significance of sentiment analysis.

Cox, Greenwald, and Ludvigson (2020) solidified the contribution of sentiment to the fluctuations of the stock market during the first quarter of 2020 during the coronavirus pandemic. This model concludes that the pricing of equity market risk is driven by fluctuations in attitudes toward risk and has the most significant impact on the decline of the stock market before March 23rd, 2020. To dig deeper into the cause of the market rally after March 24th, Cox and Greenwald observed the effect of Federal Reserve Announcements. The study observed the stock market's behavior 10 minutes before and 20 minutes after the announcement and used regression analysis to quantify its influence. The Federal Reserve explains a sizable role in pushing the stock market upward; however, the results do not explain the entire market recovery (Cox et al. 2020).

A sentiment index model developed by Naseem, Mohsin, Hui, Litan, and Penglai supports the research conducted by Cox by theorizing and estimating the effects of sentiment on the mispricing of stock. The SMI index regressed on the stock market volatility series during corona indicated a negative and significant relation to stock returns at a 1% level of significance. The study concludes that the psychological pressure investors faced during the pandemic negatively influenced decisions (Naseem et al. 2021).

The feverish sentiment index constructed by Huynh et al. (2021) uses six behavioral indicators and evaluated a larger range of data, from January 1st, 2020, to February 3rd, 2021. This index shows predictive power on stock returns indicating investor sentiment positively predicts stock volatility and negatively predicts return. Sentiment measures include a range of specific factors contributing to the generation of emotion, including COVID-19 cases, media volume, and fake news. This study will expand on the causal results of the feverish sentiment index by testing the relationship between stock volatility, behavioral indicators, and fundamental measures.

III. Media in the Market

The means by which this health crisis provokes sentiment may be best explained by evaluating the media. Concluding with Shiller's press-as-propagators theory, Baker et al. (2020) and Hanna et al. (2020) attribute the exuberance of sentiment to the explosive volume of news. Hanna et al. (2020) drew this conclusion drawing on the Financial Times as a proxy for the sentiment. Marty et al. (2020) showed evidence for the unarguable use of news in investors' decisions. Media pertaining to traumatic events, like the pandemic, causes heightened anxiety levels; a prominent emotion contributing to sentiment (Collimore et al. 2007).

The investor fear gauge is a term used to relate fear to the market volatility index (VIX). A higher VIX indicates fear in the market. Smales (2014) found a significant relationship between news sentiment and changes in the VIX. The positive news is related to a decrease in VIX and vice versa for negative news. The negative news; however, has a larger effect on the VIX and increases in fear. This relationship was much stronger during the financial crisis period 2007-2009 (Smales, 2014).

More recently, Smales (2021) identifies attention as a scarce resource and explains the direction and magnitude of investment decisions through investor attention. When investors are more attentive to news events, information is more frequently incorporated into prices and subsequently increases the effect of sentiment on asset prices. Smales (2021) uses Google search volume (GSV) as a proxy for investor attention and assumes that GSV indicates the attention of retail investors. There is a negative and statistically significant relationship between GSV and stock market volatility after controlling for the number of COVID-19 cases and macroeconomic effects. The implications of this study are unclear for institutional investors. My thesis will expand on these results by drawing on a wider range of media sources to include institutional investors as well as retail investors.

Cepoi and Cosmin Octavian (2020) investigated the stock market's reaction to coronavirus news in the top six most affected countries by the pandemic. This study uses a panel quantile regression model and concludes that media coverage leads to a decrease in returns across middle and upper quantiles but has no effect on lower ones. This suggests that the media plays a larger role in periods of positive momentum. Cepoi and Cosmin infer investors underreact to macroeconomic news if they are in a bad state. Fake news exerts a statistically significant negative influence on the lower and the middle quartile throughout the distribution of returns. Fake news did not have a statistically significant effect on extreme values; however, its influence appears during transitions from bearish and bullish markets to normal market conditions. The influence of fake news on financial markets is underrepresented in current literature. I will expand on conclusions from Cepoi and Cosmin by including more influential factors that contribute to investment decisions to estimate the relationship of media, fake news, and stock market volatility.

The relationship between the media, sentiment, and the stock market is clearly significant; however, there is contradicting evidence as to whether attention to news is an effective investment strategy. EMH assumes all available information is incorporated into market prices; however, full information is impossible to achieve by any person in the financial market. This sparks the question: is including media a reliable source for information to make decisions for allocating capital?

One view identifies media coverage as a cost-reducing tool for information gathering. Reputable news hubs can enable investors to effectively analyze stocks and allocate capital more quickly and frequently. An opposing view argues that media coverage exacerbates bias in investment decisions and causes inefficiencies in the market.

Tantaopas, Padungsaksawasdi, and Treepongkaruna (2016, 107-124) provide evidence that attention to news increases efficiency in the equity market. The study concludes that attention reduces predictability in the return and return volatility. Using the Google search volume index, the model states that the average efficiency improvement in developed equity markets was 33.2% for return and 29.1% for volatility when using news sources for research. Investor attention was not found to have a significant relationship to trading volume (Tantaopas, Padungsaksawasdi, and Treepongkaruna 2016).

Tetlock (2007) evaluated the relationship between the stock market and a popular *Wall Street Journal* column that reports on investor sentiment. Tetlock uses PCA analysis and finds evidence that negative sentiment predicts a decline in market prices, followed by a reversion to fundamentals. Tetlock et al. (2008) use a quantitative measure of language in news to measure the predictive power of new information on earnings. The paper concludes that negative words in firm-specific news stories precede low firm earnings. The data also suggests that the predictive power from negative words is stronger for fundamental information. This paper's model will vary from both of Tetlock's evaluations by applying different quantitative variables investors utilize, different sentiment measures, and looking at media more broadly.

Haroon and Rizvi (2020) provide evidence that media coverage could predict stock returns at the onset of the pandemic. The study observed unprecedented news coverage and disparate opinions that caused volatility in the equity market. Furthermore, the sectors perceived to be most affected by the pandemic experienced more volatility (Haroon and Rizvi 2020).

There is conflicting evidence that suggests the continuous flow of information reduces efficiency in the market and negatively affects investor decisions. Barber and Odean (2008) claim choice asymmetry exists in the market. This theory explains that investors can only be aware of so many opportunities. Stocks that are more present in the media are more likely to be purchased and can cause unsustainable increases in the stock price. Unknown stocks may be more attractive, but due to choice asymmetry, will not receive capital or resources.

Curme et. al (2015) investigated the directional relationship between financial market movements and the news. The model collected daily data for market news sentiment and returns of major stock indices from 40 countries for the period 2002-2012. The results conclude that financial markets precede news more frequently than news items precede movements in the market. This suggests that an investor relying on the news to make decisions will lag the market.

Solomon et. al (2014) draw similar findings to Curme et. al (2015) when evaluating mutual funds. The paper concludes that investor bias is exacerbated by the media. When there is a fund's performance present in the media, the subsequent quarter shows investors allocate more capital to funds with high past returns. Furthermore, a prominent fund with low past returns will experience a larger outflow than an identical low-return fund without media coverage. The effect on media-covered funds is larger for rewarding winners compared to penalizing losers. Solomon et. al (2015) suggests that media coverage increases the salience of prominent stocks instead of increasing valuable information and signaling those investors are not evaluating news effectively.

Fang and Peress (2009) use a cross-sectional analysis to evaluate media coverage and expected stock returns. They control for numerous well-known risk factors and the results conclude that stocks with no media coverage earn higher returns than stocks with high media coverage. The no-media premium may be explained by two hypotheses. First, the "impediments-to-trade" argues that the no-media premium exists due to mispricing and therefore offers an opportunity for traders. Savvy investors who are willing to dissect a company themselves prefer a unique stock. The second theory "investor recognition hypothesis" proposes that investors who are not aware of all securities and unknown stocks must offer higher returns to compensate for their increased risk (Fang and Peress 2009).

Xu et. al (2020) evaluate the efficiency of investors during the pandemic. The paper investigates the relationship between stock price sensitivity and firm-specific information on the Chinese stock market during COVID-19. Firm-specific news and infection scale are identified as fundamental measures incorporated in investing decisions. The impact of the outbreak on public attention is identified as a non-fundamental factor. The results show the pandemic reduces stock returns and inhibits investors' ability to process firm-specific information. The public attention to the pandemic weakens the stock market's reaction to firm-specific news. The infection scale increases stock price sensitivity to firm-specific information. The effect of the infection scale on stock price sensitivity to firm-specific information is greater for negative news. The paper also observed a return reversal in the market following public attention about the pandemic confirming that shocks caused by public attention are non-fundamental. Xu et. al (2020) suggests this is evidence that the COVID-19 outbreak distorts information discovery in the stock market and causes inefficient price discovery.

IV. Conclusion

The psychological factors that contribute to investor decisions are well-established by numerous economists including Akerlof and Shiller. During the current pandemic, fear and uncertainty are the main contributors to sentiment-driven decisions in financial markets. The 'feverish sentiment' index shows the significant impact of sentiment on stock market volatility during the pandemic. Media is a dynamic factor contributing to the volume of sentiment present in financial markets. The incorporation of news in investment decisions is regarded by some as an effective information collecting technique. Others claim the media distorts investors' fundamental processing strategy and causes inefficiencies in the market. My thesis will regard news as a potential source of sentiment and its effect on pricing. I will contribute a novel approach that incorporates fundamental measures alongside the feverish sentiment indices created specifically for the COVID-19 era. Prior research incorporates fundamental measures that are infrequently published, like quarterly earnings and federal announcements. New information during the pandemic was flooding the minds of investors daily. To display the relationship more accurately between daily news, sentiment measures, fundamentals, and the stock market during the pandemic my model will draw on prominent data during the health crisis that is published weekly. Previous models have also chosen a narrow scope for media, for example, Twitter posts or a singular news column. The literature lacks the viewpoint of a broad range of media sources and data. This model will include a broad array of news outlets that encompasses fed announcements and firm-specific information alongside fake news, sentiment, and pandemic updates. My model will evaluate a variety of frequently published fundamental measures, major market indices, sentiment measures, and broad media data.

CHAPTER THREE

THE ANALYTICAL FRAMEWORK

I. INTRODUCTION

This chapter explains the analytical framework and model that will be utilized to quantify the contribution of sentiment, fundamentals, and media to the changes in the US financial market during the pandemic. In the first section, I will present the literature that provoked the formation of my model. I explain the quantitative mechanism for evaluating sentiment and fundamentals influence on financial markets and compare it to other models. In the second section, I will introduce the dependent and independent variables chosen for the model. I hypothesize that the COVID-19 virus generated investor sentiment, specifically fear, and subsequently harmed financial markets. I also predict that the media will be a large contributor to provoking sentiment.

II. CREATING THE MODEL

After reviewing the literature on investor sentiment during the COVID-19 pandemic, I was inspired by the work done by Huynh et al. (2021) and curious to expand their use of the 'feverish Sentiment index'. Huynh et al. explored data on global financial markets and tested 6 behavioral indicators of investor sentiment. Huynh et al. tested transmission of shock using the TVP-VAR framework. This estimation concluded that the United States was at the epicenter of pandemic sentiment and the second largest contributor to shock. This study will focus on the United States and utilize the robust sentiment indexes sourced from RavenPack to take a closer look at what has happened to the US economy.

This paper focuses on the United States financial markets during the pandemic. The data collected ranges from January 1, 2020, to December 31, 2021. To evaluate the condition of the economy a variety of sentiment and fundamental indicators were chosen as independent variables. The dependent variables devoted to reflecting the state of the US economy are the S&P 500 and the 10-year market treasury yield. Prior literature has lacked information on the bond market, so the estimation of the 10-year market treasury yield as an independent variable is valuable.

The model is constructed to evaluate the US markets at a larger scale while also at a frequent level to analyze investors' ability to allocate capital efficiently. A rational investor includes various numeric economic indicators to assess the condition of the market before deciding. In the COVID-19 pandemic economic conditions are also influenced by the spread of the disease. This study utilizes economic measures pertinent to the pandemic and assumes that rational investors will include them in decisions in financial markets alongside media and news. During the pandemic, updates regarding policy, health recommendations, and the economy were broadcasted continuously throughout every day. Among these news postings are fear-provoking titles and outright fake news. The rational investor in this model is defined as an individual who evaluates fundamental indicators and media simultaneously to effectively analyze covid news. To represent the relationship most accurately between fundamental and sentiment measures I have chosen to estimate the regression at a weekly frequency. Daily data has been averaged to weekly.

Huynh et al. (2021) used a principal component analysis (PCA) to aggregate 6 sentiment indexes. Instead of using PCA analysis to generate a single index, this study individually tests the same 6 sentiment indicators. The advantage of keeping every variable separate is the ability to identify the effects of each index in the US economy and no loss of information. One benefit of PCA analysis is the removal of correlated figures. To control for this adverse effect, I have tested the correlations of all sentiment measures and will take them under consideration when reflecting on the results.

I utilize 6 variations of OLS regression to test the relationships between sentiment indices, fundamental indices, and media indices on US stock market returns and 10-year treasury yields. The SP500 is used as a proxy for the US stock market. Treasury securities are core to financial markets, provide more representation for institutional investors, and are seen as safe, liquid investments. Daily covid cases are estimated in various regressions; however, it is not included in either independent variable category because of its contribution to both measures.

To compare the effects of sentiment measures and fundamentals measures on financial markets I utilize a log-log regression model that normalizes every variable using a log transformation (Equation 1). To compute a log transformation on every variable, I converted the data sources containing negative numbers to contain all positive numbers. I did this by finding the largest negative number, assigning it an arbitrary positive number, and executing a transformation (see chart enter that here). I checked these transformations for correctness by plotting the original and converted values together and normalizing the data. Estimating the regression using a log transformation allows the relationship between various units of values to be interpreted. The coefficient in the regression of a log-log regression is understood as a percentage.

1. $log(Y) = \beta_0 + \beta_1 log(X_1) + \beta_2 log(X_2)...$

After testing my variables with logarithmic estimations, I found that the Durbin-Watson results were lower than satisfactory. In an attempt to strengthen my results, I also apply the log-

log regression model in differences (Equation 2). The difference of log decreases the influence of stationarity in the results and improves the Durbin-Watson statistic. I have included variations of both equations in my results where necessary. This equation is used to evaluate the influences of sentiment measures compared to fundamental measures present in the US financial market.

$$2. \quad d(log(Y)) = \beta_0 + \beta_1 d(log(X_1)) + \beta_2 d(log(X_2))...$$

To evaluate the relationships between sentiment and fundamentals I utilize two-way interactions in the differences of the log-log regression model (Equation 3) and a regular log-log regression model (Equation 4). Interaction terms are used to display the interplay between independent variables on a dependent variable. An interaction effect is significant when the presence of one independent variable changes the value of another independent variable. An interaction is represented by the product of two or more variables. My model evaluates two-way interactions. Before choosing interaction terms to test, it is important to evaluate the relationship between the independent variables. If the independent variables are parallel, there is no interaction. After testing the interaction, I have observed the statistical significance and coefficients of the interaction term.

$$3. \quad log(Y) = \beta_0 + \beta_1 log(X_1) + \beta_2 log(X_2) + \beta_3 log(X_1) * log(X_2)$$

$$4. \quad d(log(Y)) = \beta_0 + \beta_1 d(log(X_1)) + \beta_2 d(log(X_2)) + \beta_3 d(log(X_1)) * d(log(X_2))$$

I created two dummy variables to further investigate the US financial markets. Dum2020 is a dummy variable created to evaluate the effect of 2020 and 2021 on sentiment and fundamentals when making investment decisions. 1 is printed for every week in 2020 and 0 is printed for every week in 2021. The second dummy variable was generated to display the weekly change in the panic index during the first stock market crash and the subsequent rapid recovery. This dummy variable, dum1 is used to test the reaction of investors during the period of the initial stock market crash in 2020 with the time range represented by 0 being 2/19/2020 - 4/22/2020.

In order to interpret the coefficients of the interaction terms, I have used two different derivatives. For the dummy variables, I take the derivative with respect to the explanatory variable. The dummy variable represents a 1 or a 0; so, the dependent variable regressed on the interaction term either includes β_2 or it does not.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_1 * Dummy$$

$$\partial Y / \partial X_1 = \beta_1 + \beta_2 * Dummy$$

To evaluate the coefficients of two independent variables' interactions I use a slightly different equation and interpretation. The derivative is taken with respect to one of the independent variables. The coefficient of the interaction term is interpreted after multiplying β_2 by the mean of the second term. This number is then added to β_1 to evaluate Y in respect to X_1 when X_2 is present and absent. The second independent variable is therefore identified as an important factor to the first independent variable and the dependent variable. The interaction term indicates how the dependent variable responds to the first independent variable given the state of the second independent variable. Without the interaction of the second independent variable, we evaluate the influence of the first independent variable alone as β_1 .

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_1 * X_2$$

$$\partial Y / \partial X_1 = \beta_1 + B_2 * X_2$$

The last equation utilized is a distributed lag regression model (Equation 5). The lag regression model is used for three periods to evaluate the time series component of the relationship between the economy and the explanatory variables. The reversal effect can be used to demonstrate investors' inability to make rational decisions in periods of high sentiment. If momentum in the market is caused by fundamentals, we infer that investment decisions to buy (sell) will not be reversed (Xu et. al, 2020). A theory of momentum and reversal explains that flows are initiated by a change in opinion of the market. Momentum occurs if the new trend in the market persists. Reversal occurs if the bear or bull view is temporary (Vayanos and Woolley 2013, 1087-1145). The reversal effect can be evaluated using a lag of y in the regression. If the coefficients exhibit a change in sign over lagged periods, we can infer those prices have pushed away from fundamentals.

5. $$log(Y) = \beta_0 + \beta_1 log(X)) + \beta_2 log(X_{t-1})) + \beta_3 log(X_{t-2})) + \beta_4 log(X_{t-3}))$$

6. $$d(log(Y)) = \beta_0 + \beta_1 d(log(X)) + \beta_2 d(log(X_{t-1})) + \beta_3 d(log(X_{t-2})) + \beta_4 d(log(X_{t-3}))$$

III. SENTIMENT MEASURES

The RavenPack is a website created to track media during the pandemic with the goal of identifying key trends around the world. The website tracks thousands of news sources pertaining to the Coronavirus and generates a collection of indexes by country. See table for the definitions of each index.

Sentiment Measures
Fake News Index The Coronavirus Fake News Index measures the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19. Values range between 0 and 100 where a value of 2.00 indicates that 2 percent of all news globally is talking about fake news and COVID-19.

The higher the index value, the more references to fake news found in the media. The index is computed as the daily count of distinct stories that co-mention fake news related keywords and the Coronavirus, divided by the total daily count of distinct stories. The daily percentage change value represents the change from the latest index value against the value from midnight local time.
Infodemic Index The Coronavirus Infodemic Index calculates the percentage of all entities (places, companies, organizations, etc.) that are reported in the media alongside COVID-19. Values range between 0 and 100 where a value of 60.00 means that 60 percent of all entities covered by the media are being co-mentioned with COVID-19. The index is computed as the daily count of distinct entities that are co-mentioned with the Coronavirus, divided by the total daily count of distinct entities. The daily percentage change value represents the change from the latest index value against the value from midnight local time.
Media Coverage Index The Coronavirus Media Coverage Index calculates the percentage of all news sources covering the topic of the novel Coronavirus. Values range between 0 and 100 where a value of 60.00 means that 60 percent of all sampled news providers are currently covering stories about COVID-19. The index is computed as the daily count of distinct sources of news that mention the Coronavirus, divided by the total daily count of distinct sources. The daily percentage change value represents the change from the latest index value against the value from midnight local time.
Media Hype Index The Coronavirus Hype Index measures the percentage of news talking about the novel Coronavirus. Values range between 0 and 100 where a value of 75.00 indicates that 75 percent of all news globally is talking about COVID-19. The index is computed as the daily count of distinct stories that mention the Coronavirus, divided by the total daily count of distinct stories. The daily percentage change value represents the change from the latest index value against the value from midnight local time.
Panic Index The Coronavirus Panic Index measures the level of news chatter that makes reference to panic or hysteria alongside the Coronavirus. Values range between 0 and 100 where a value of 7.00 indicates that 7 percent of all news globally is talking about panic related terms and COVID-19. The higher the index value, the more references to panic found in the media. The index is computed as the daily count of distinct stories that co-mention panic keywords and Coronavirus, divided by the total daily count of distinct stories. The daily percentage change value represents the change from the latest index value against the value from midnight local time.
Sentiment Index The Coronavirus Sentiment Index measures the level of sentiment across all entities mentioned in the news alongside the Coronavirus. The index ranges between -100 and 100 where a value of 100 is the most positive sentiment, -100 is the most negative, and 0 is neutral. The index is computed as the difference between the daily median of the RavenPack's Event Sentiment Score (ESS) of all detected news events co-mentioned with the Coronavirus and the daily median of the ESS for all detected events that are not co-mentioned with the Coronavirus. This difference is then averaged over the previous 7 calendar days. We only take into account non-neutral events (with ESS different than zero) and events with an Event Relevance Score greater than 20 (out of 100) and that have not been detected within the last week - where we have not seen a similar event in the previous 7 days (Event Similarity Days greater than 7 days). The daily percentage change value represents the

change from the latest index value against the value from midnight local time.

Source: RavenPack

IV. FUNDAMENTAL MEASURES

The fundamental measures were specifically chosen due to their high frequency and relevance. Other papers have included less frequent or irregular sources of measures. For example, Tetlock (2008) uses quarterly earnings reports to evaluate the rationality of market decisions. Corporate updates are crucial to evaluating individual stocks effectively; however, during the pandemic different economic measures have become significant.

The pandemic created an abrupt increase in unemployment and subsequent inflation (Figure 2). The US government also provided historic levels of assistance for those unable to work due to the virus. Tracking unemployment is therefore a key indicator of the recovery of the economy. This study chose continued claims to measure unemployment levels due to their weekly frequency.

A consequence of the close of the economy is a disruption of supply chains. The corona economy has experienced a fluctuation of demand for certain commodities, but overall prices have increased, and inflation has become a growing concern. The CPI is a measure used to evaluate the cost of goods, but it is recorded monthly. Oil prices have historically correlated to levels of inflation; if oil prices are rising inflationary expectations also rise. Crude oil prices are recorded daily and evaluated by investors as an overall indicator of inflationary pressure.

There are countless indicators of the economy that investors, economists, and media outlets track. In order to accurately estimate the fundamental changes in the economy throughout the pandemic, this model has also tested various established indexes summarized below.

Fundamental Measures
Continued Claims (Insured Unemployment) Units: Number, Seasonally Adjusted Frequency: Weekly, Ending Saturday Continued claims, also referred to as insured unemployment, is the number of people who have already filed an initial claim and who have experienced a week of unemployment and then filed a continued claim to claim benefits for that week of unemployment. Continued claims data are based on the week of unemployment, not the week when the initial claim was filed.
Chicago Fed National Economic Conditions Units: Index, Not Seasonally Adjusted Frequency: Weekly, Ending Friday The Chicago Fed's National Financial Conditions Index (NFCI) provides a comprehensive weekly update on U.S. financial conditions in money markets, debt and equity markets and the traditional and "shadow" banking systems. Positive values of the NFCI indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average.
Crude Oil Price Units: Dollars per Barrel, Not Seasonally Adjusted Frequency: Daily Definitions, Sources and Explanatory Notes
Lewis-Mertens Stock Index Units: Index, Not Seasonally Adjusted Frequency: Weekly, Ending Saturday The WEI is an index of real economic activity using timely and relevant high-frequency data. It represents the common component of ten different daily and weekly series covering consumer behavior, the labor market, and production. The WEI is scaled to the four-quarter GDP growth rate; for example, if the WEI reads -2 percent and the current level of the WEI persists for an entire quarter, one would expect, on average, GDP that quarter to be 2 percent lower than a year previously. The WEI is a composite of 10 weekly economic indicators: Redbook same-store sales, Rasmussen Consumer Index, new claims for unemployment insurance, continued claims for unemployment insurance, adjusted income/employment tax withholdings (from Booth Financial Consulting), railroad traffic originated (from the Association of American Railroads), the American Staffing Association Staffing Index, steel production, wholesale sales of gasoline, diesel, and jet fuel, and weekly average US electricity load (with remaining data supplied by Haver Analytics). All series are represented as year-over-year percentage changes. These series are combined into a single index of weekly economic activity.
St. Louis Financial Stress Index Units: Index, Not Seasonally Adjusted Frequency: Weekly, Ending Friday

The STLFSI2 measures the degree of financial stress in the markets and is constructed from 18 weekly data series, all of which are weekly averages of daily data series: seven interest rates, six yield spreads, and five other indicators. Each of these variables captures some aspect of financial stress. Accordingly, as the level of financial stress in the economy changes, the data series are likely to move together. How to Interpret the Index: The average value of the index, which begins in late 1993, is designed to be zero. Thus, zero is viewed as representing normal financial market conditions. Values below zero suggest below-average financial market stress, while values above zero suggest above-average financial market stress.
CBOE Volatility Index: VIX (VIXCLS) Units: Index, Not Seasonally Adjusted Frequency: Daily, Close VIX measures market expectation of near term volatility conveyed by stock index option prices. Copyright, 2016, Chicago Board Options Exchange, Inc. Reprinted with permission.

Source: Fred

V. CONCLUSION

A unique and focused analytical framework is used in this research to develop the current understanding of sentiment analysis on the corona economy in the United States. In the following chapter, I will discuss my data sources, present my regression estimations, and provide explanations for my results. I test 6 different equations and identify specific relationships contributing to the dynamic financial markets during the pandemic. By using this method, I am able to include sentiment measures and fundamental measures that broadly cover the media, emotions, and technicals. The meticulous analysis of each source of information individually enables me to evaluate specific cause and effect relationships that prior literature has lacked.

CHAPTER FOUR

DATA AND RESULTS

I. INTRODUCTION

In this chapter, I first explore the data utilized in this model. In the second section, I will present my estimations. My model will first compare the effect of sentiment and fundamentals on two indicators of the US financial markets. The next part of the analysis will interpret interaction terms to identify the interplay between independent variables and curated dummy variables. The last variation of my model will evaluate a lag regression model to look for reversals or momentum in the market.

II. DATA SOURCES

The variables tested in this model vary in unit measure and size greatly. For reference, I have provided a table of the mean and median statistics for each variable for the observed time 1/1/2020 to 12/21/2021. Please note that the variables transformed to include only positive values are reflecting the transformed data. All data are averaged to a weekly frequency for every estimation in this paper. Where applicable, the mean of log transformation and the mean of difference of log transformation have been calculated.

TABLE 1

Variables	Mean	Median	Log(mean)	D(log(mean))
S&P 500	3748.81	3728.91	8.22	0.00
10 Year Treasury Market Yield	1.17	1.26	0.07	0.00
Continued Claims	6820308.00	3761000.00		
Chicago Index*	4.94	4.83	1.59	0.00
Crude Oil ($/Barrel)	53.77	53.33		
Fake News Index	0.74	0.64	-0.49	0.00
Infodemic Index	48.32	48.34		
Lewis-Mertens Stock Index*	16.83	17.00	2.71	0.01
Market Yield on 10 Year Treasury	1.17	1.26		
Media Coverage Index	69.64	71.11		
Media Hype Index	31.37	29.66	3.34	0.00
Panic Index	2.90	2.67	0.94	0.00
Sentiment Index*	53.24	56.03	3.95	0.00
S&P 500 Index	3744.59	3727.04		
St. Louis Financial Stress Index *	10.04	9.72		
CBOE Volatility Index	19.66	18.69		

*Indicates that the data was transformed and originally included negative values

III. REGRESSION ANALYSIS

In an effort to identify the effect of sentiment in comparison to fundamentals I tested various combinations of the explanatory variables. My goal was to identify specific variables and relationships that contribute to the condition of the US economy during the pandemic.

Equation 1 estimations were useful in finding the significant indices that would be most interpretable. I tested numerous combinations of sentiment and fundamental measures in Equation 1 and then if the results were strong, I then tested the variables in Equation 2. Reference Table 2 for one version of Equation 1 that includes the variables I found the most insightful. For both dependent variables, I found that the equation resulted in a Durbin-Watson test statistic that indicated serial correlation among error terms. Whereas the difference-in-logs specification substantially addressed this issue. In general, the dependent variable S&P 500 equations provide clearer results compared to the 10-year treasury yield. The explanatory variables coefficients in relation to the S&P 500 are as expected for Equation 1 and variations of Equation 2. The 10-year Treasury yield as the dependent variable in the regression model was more difficult to find significant results. This difficulty may be due to the unique nature of the Corona Economy. Treasury securities are seen as the safe-haven asset; so, when the stock market is unstable investors often flock to the bond market. During the pandemic, we saw individuals pulling their money out of all investments and into savings. The bond market experienced extreme volatility and treasuries were subject to panic as well. (Cheng et al. 2020)

I will interpret two significant equations with the S&P 500 and the 10-year treasury yield to compare the influence of sentiment measures and fundamental measures (Table 2). For the regression on the S&P 500 closing price, the increase of positive sentiment in the news by 1%

increases the S&P 500 by 4.5%. The increase of the Chicago fed index by 1% decreases the S&P 500 by almost 15%. The effect of the fundamental financial conditions represented by the Chicago Fed index is much higher; however, the influence of sentiment is notable. On the residual plot, we see that the points stray from the fitted regression line significantly on 3/11/2020 and 3/25/2020 (Figure 4). These are significant dates due to the extreme volatility in the stock market. The sentiment index may better explain the change in the stock market prices on those dates.

The 10-year Treasury yield had the most significant results with the explanatory variables panic index and the adjusted Lewis-Mertens index (Table 2). I expected the 10-year Treasury yield to reflect less influence of sentiment; however, these results show that the panic index and Lewis Mertens index were not weighted very differently. A 1% increase in the panic index decreased the 10-year treasury yield by 6.9%. The Lewis Mertens index is related to a 26.9% increase in the 10-year treasury. In the corona economy, the treasury market is seen here to be a safe-haven asset because the treasury yield indicates the price of bonds increases as panic increases. The residual table of this regression shows that the bond market has a point off the fitted line one week prior to the stock market's march crash (Figure 5). This may indicate the treasury market anticipated the crash before the stock market.

We can see that sentiment measures do not have as large an impact on financial markets compared to fundamental measures overall. When looking closer at specific times, we can see where sentiment may have influenced the market more heavily. The treasury market was still a safe-haven asset for some investors as panic increased.

TABLE 2

Variables	**SP500** Equation 1	Equation 2	Equation 2	**10 Year Treasury Yield** Equation 1	Equation 2	Equation 2
Panic Index	-0.081***	-0.016**		-0.296***	-0.059**	-0.079***
	(-0.025)	(0.007)		(0.051)	(0.026)	(0.025)
Sentiment Index	0.090***	0.035***	0.045***	-0.108*	-0.028	
	(0.031)	(0.008)	(0.008)	(0.066)	(0.032)	
Chicago Fed	-0.888***	-1.476***	-1.266***	0.477	-2.293**	
	(0.322)	(0.264)	(0.252)	(-0.657)	(0.990)	
Lewis-Mertens	0.152***	-0.087***		0.476***	0.151	0.269***
	(0.029)	(0.031)		(0.476)	(0.115)	(0.105)
Durbin-Watson	0.15	2.10	2.02	0.35	2.31	2.18
R - Squared	0.81	0.46	0.38	0.83	0.16	0.11

Notes: 102 Observations, standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*).

The interactions in Table 2 are dummy variables with both dependent variables in respect to independent variables. The dummy variable 2020 was used to reflect the years 2020 and 2021 separately in the regression model. I found significant relationships between the sentiment index and the panic index for each respective year. The sentiment index is seen to have less of an influence on the S&P 500 market pricing in 2020 compared to 2021. This result indicates that investors' decisions were less aligned with the sentiment in the media in 2020. Investors during the early months of the pandemic were very uncertain and we know that emotion was high (Collimore et al. 2007). This result is consistent with other literature including Russell and Hadi (2021) who found that investors were often ignoring bad news. An example of this is the market's V-shaped recovery from February 19th to April 17th that occurred in misalignment with fundamental indicators. In figure 3 you can see the rise in panic, stark decline in the S&P 500, the covid cases remaining low. Subsequently, you can see COVID cases rise as the S&P climbs again and panic in the news remains high.

The result of the interaction regression resulted in an increase in the S&P 500 when the panic index increased in 2020. In 2021, when panic increased, the S&P 500 decreased. The relationship between panic and the stock market we expect is a negative relationship and that is what the model estimated for the relationship between panic and the S&P 500 without the dummy variable. This result is consistent with the interpretation of sentiment in 2020 compared to 2021. It appears that market participants did not pay attention to panic in the media in 2020. This is not to say that decisions were not made of fear. We can only speculate here that investors chose to ignore the current panic in the media pertaining to COVID-19 and the pricing of stocks in 2020. The stock market is reflective of the future economy and in 2020 the future economy was very uncertain. Investors in the stock market were seen as optimistic, in many economists' opinions, too optimistic. In other views, investors were smart not to let emotions drive decisions. In 2020 there were numerous Federal Reserve initiatives to support individuals and the economy. These efforts are seen to explain the positive stock market sentiment and may explain why covid panic in the news was not as important to investors (Cox et al. 2020). To investigate the rationale of investors I look further into the interactions between sentiment measures and fundamental indexes during the initial stock market crash in 2020.

The regression estimations using dum1 confirm the increased influence of sentiment during periods of high sentiment for the S&P 500 (Table 3). When testing the S&P 500 as the dependent variable, the coefficient of the panic index for the stock market crash period is -0.130. The coefficient of the panic index for all other time periods is -0.034. This indicates that the panic index was more prominent to the investment decisions made during the major market movements early in the pandemic when uncertainty was raging. The fundamental measure of the economy in this estimation is insignificant. In prior estimations without the dummy variable, the Lewis-Mertens and Chicago Fed indexes were significant to the changes in the S&P 500. This suggests that financial conditions were not important to investors during this period. A slightly different result is found with the 10-year treasury yield as the dependent variable of Equation 3 with dum1. The panic index and Lewis-Mertens index are both significant and coefficients are as expected; however, both the independent variables' interaction terms with dum1 are not significant. This indicates that during this period the 10-year treasury yield did not experience a change in investment decisions based on these factors. This result is conclusive with Cox et al. (2020) test of the GLL model. The paper concludes that the V-shaped recovery of the stock market is near impossible to explain by fundamentals alone and that attitude toward risk had the most significant impact on the stock market's sell-off and subsequent turnaround. In this model, the news was also found to contribute to increasing fear and uncertainty as did Cox et al. (2020).

Investors' decisions were not rational when looking at the S&P 500 in 2020, specifically during the first quarter of the year. When looking at the entire period, the model was not able to identify the adverse effects of sentiment on the stock market. This model identified the increase of panic in the media as the most significant factor to investment decisions during the V-shaped recovery period in 2020. The treasury market did not experience the same irrational exuberance during 2020. Naseem et al. (2020) argues that during this period the effects of sentiment caused mispricing of stock and negatively influenced decisions. Investors appear to make irrational decisions at the start of the pandemic, but as the market progresses investors are better able to digest the news.

TABLE 3	**SP500**		**10 Year Treasury Yield**
Variables	Equation 3	Equation 3	Equation 3
Panic Index	-0.128***	0.130***	-0.174***
	(0.024)	(0.025)	(0.064)
Sentiment Index	0.096***		
	(0.020)		
Chicago Fed	-1.676***		
	(0.204)		
Lewis-Mertens		-0.060	0.421***
		(0.052)	(0.136)
Sentiment*Dum2020	-0.067***		
	(0.007)		
Panic*Dum2020	0.138***		
	(0.033)		
Panic*Dum1		0.097***	0.109
		(0.029)	(0.078)
Lewis-Mertens*Dum1		0.139	-0.387
		(0.096)	(0.249)
Durbin-Watson	0.42	2.68	2.36
R - Squared	0.90	0.28	0.15

Notes: 100 Observations, standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*).

The interaction between fundamental and sentiment measures is an area of research that economic literature has not developed sufficiently. I have tested different interactions among all the fundamental and sentiment variables identified in my data sources (Table 4). The interactions tested with the dependent variable 10-year treasury yield were inconclusive. Here I present the most significant findings with the S&P 500 market value as the dependent variable. The interaction of the panic index given the Chicago index with respect to the S&P 500 is significant (Table 4). The panic index reflects the panic present in the media pertaining to covid-19 news. When the panic index declines with respect to the Chicago index, the reaction is more negative. This indicates that investors' decisions in the S&P 500 are more severe in response to the panic index when the underlying conditions of the financial markets represented by the Chicago index are worse. Without the presence of the Chicago index, investors' reaction to panic is smaller. These results suggest that investors can effectively process sentiment in the news alongside positive fundamentals. This may support the findings from Tantaopas, Padungsaksawasdi, and Treepongkaruna (2016, 107-124) that provide evidence that attention to news can increase efficiency in the stock market. One could also argue that panic in the media impairs investors' evaluation of the stock market. This is because when panic is present, investors react stronger to negative fundamental news.

The next notable interaction is the Chicago index given the fake news index with respect to the S&P 500 (Table 4). The fake news index was found to have a statistically significant negative influence on stock market returns during the pandemic in a study conducted by Cepoi and Cosmin Octavian (2020). My regression estimation indicates that investors' decisions in the stock market are not largely affected by the presence of fake news when evaluating financial conditions. The interaction between fake news and the Chicago index only accounts for a 1% difference in the change in the S&P 500. The Chicago index alone accounts for an 8.8% decrease in the S&P 500 when financial conditions decrease by 1%.

The volume of news during the pandemic and the psychological factors of asymmetric information and the kernel of truth principle can greatly affect the decisions of investors as seen in the 2008 stock market crisis. To look for the presence of over or underreaction to the volume of news pertaining to the covid pandemic in the market I have tested the interaction between the sentiment index and the media hype index in relation to the S&P 500 (Table 4). I found that the stock market was not affected a significant amount by the interplay of sentiment given the media hype index. This suggests that investors were ignoring the volume of news pertaining to COVID. The regression shows investors were able to price in the overall sentiment effectively. This interpretation extends on results from Fang and Peress (2009) who measured those stocks with no media coverage earn higher expected returns.

TABLE 4 **S&P 500**

Variables	Equation 4	Equation 4	Equation 4
Panic Index			-0.024***
			(0.007)
Sentiment Index		0.051***	
		(0.009)	
Fake News	-0.02***		
	(0.004)		
Media Hype Index		-0.663***	
		(0.017)	
Chicago Fed	-0.879***		-0.625**
	(0.277)		(0.288)
Panic*Chicago			-3.073***
			(0.680)
Sentiment*Media Hype		-0.111	
		(0.035	
Fake News*Chicago	-2.778***		
	(0.639)		
Durbin-Watson	2.12	1.78	2.34
R - Squared	0.38	0.32	0.41

Notes: 102 Observations, standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*).

The analysis of the lag of the panic index for three periods is estimated on the dependent variables to evaluate the effectiveness of evaluating a sentiment measure (Table 5). If a reversal is observed, we can conclude that investors may have irrationally responded to sentiment in the market. The estimation of the three lagged terms shows that a significant reversal occurs between the second and third lagged periods. A reversal also occurs between the first and second lag; however, the first lag period is not statistically significant. Like findings from Huynh et al. (2021), we can interpret this change in decision-making in the market in response to panic as an indication that these decisions were not based on fundamentals. Investors tend to overreact to panic feelings, especially during a financial crisis (Smales, 2014). In order to correct irrational decision-making investors, revert their actions, as seen by the change in sign of the coefficients. This is often seen when looking at short-term periods; however, Tecklock (2007) argues that in the long run fundamentals will set the price of stocks.

The results from the estimation of three lag periods of panic regression on the 10-year treasury yield reveal momentum instead of reversal (Table 5). The coefficient of the first lag continues to remain negative, and the equation is significant. Although the second lag is positive; the coefficient is very small, and the probability is insignificant. This estimation suggests that the treasury market was not subject to an overreaction to panic. Investors appear to be more rational in the treasury market compared to the stock market; this might be explained by the many retail traders present in the stock market, especially during the pandemic. Overall, the media may not have as much of an effect on financial markets in the US as we think.

TABLE 5

	SP500			10 Year Treasury Yield		
Variables	Equation 5	Equation 5	Equation 5	Equation 6	Equation 6	Equation 6
Panic Index	-0.226***	-0.234***	-0.268***	-0.084**	-0.078**	-0.078**
	(0.046)	(0.046)		(0.036)	(0.037)	(0.037)
Panic Index (-1)	-0.083*	-0.019	0.002	-0.078**	-0.081**	-0.084**
	(0.083)	(0.065)	(0.064)	(0.035)	(0.036)	(0.037)
Panic Index (-2)		-0.063	-0.596**		0.021	0.028
		(0.045)	(0.059)		(0.027)	(0.887)
Panic Index (-3)			0.115***			-0.011
			(0.030)			(0.025)
Durbin-Watson	0.24	0.19	0.44	2.10	2.09	2.11
R - Squared	0.68	0.69	0.7	0.11	0.11	0.11

Notes: 100 Observations, standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*).

IV. CONCLUSION

My regression model utilizes explanatory variables individually to test relationships that previous literature has tested using a different method. My model identifies a significant influence of sentiment indices and fundamental indices on both the 10-year treasury yield and the S&P 500. The influence of sentiment measures did not have as much of an effect on S&P valuation or the 10-year treasury yield. During specific periods in the pandemic, sentiment had a much larger effect on investment decisions than the present financial conditions. Treasuries are seen to be safe-haven assets during the pandemic. When looking at interaction terms with dum2020 we found that the stock market reflected the sentiment index and the panic index more accurately in 2021 compared to 2020. Many investors bet on the fast recovery of the economy in a time when uncertainty and fear were very high. Another interesting relationship was found between the panic index and the Chicago index on the stock market. Investors' decisions when the panic index increases, are larger when the Chicago index increases as well. This indicates that investors do take fundamentals alongside sentiment. The interaction tested with the fake news index and the Chicago index supports this finding as well. The Chicago index when tested with the fake new index does not have a sizable impact on the evaluation of the S&P 500. The last interaction term tests the ability of investors to digest a large volume of news. The estimation of the interplay of the sentiment index and the media hype index suggests that the S&P 500 reflects the sentiment index and is not affected by asymmetric information. The estimation of a three-period lag is also used to evaluate the rationale of investors. The three-period lag of the panic index regressed on the S&P 500 suggests that investors do experience the reversal effect in the short term.

The three periods of lags of the panic index did not experience a reversal but instead experienced momentum when evaluating the 10-year treasury yield as the dependent variable. This suggests that investors in the stock market are less rational compared to the treasury market because we see the reversion of stock market valuations.

CHAPTER FIVE

CONCLUSION

I. SUMMARY OF FINDINGS

In summary, the regression model and specified equations in this study captured the effect of sentiment, the media, and fundamental variables on US financial markets during the COVID-19 pandemic. This study employed a new approach by individually testing a variety of sentiment measures based on media presence and frequently updated fundamental variables. The model evaluates the independent variables in relation to the S&P 500 and the 10-year Treasury yield. This model produced statistically significant results that are consistent with intuition and prevailing literature surrounding the role of uncertainty causing financial instability. The results are robust for certain specifications that are identified and interpreted with consideration of limitations. The use of the difference of log transformations compared to log transformations improves the Durbin-Watson statistic and lowers the detection of endogeneity. The correlation coefficients between variables were estimated and considered when choosing variables to test to lower the adverse effect of correlating variables in estimations. In general, this model confirms the presence of sentiment in investors' decisions in financial markets. More specifically, this model can draw new inferences on the factors influencing market participants throughout the pandemic.

The empirical results lead to the conclusion that sentiment during the onset of the pandemic can be seen as an intrinsic risk factor in US financial markets. The S&P 500 experienced much more vulnerability to sentiment-driven decisions compared to 10-year Treasuries. After the initial shock to the economy, investors were less susceptible to sentiment in the media. Panic and sentiment in the media were most influential on investors' evaluation of the S&P 500 during the first stock market crash in 2020. In 2020, when panic increased it caused the S&P 500 to increase as well. Economic conditions were insignificant when tested on the initial crash in the stock market; however, the 10-year Treasury did not exhibit the effects of irrational exuberance. The treasury market also experienced a quicker reaction at the onset of the pandemic, suggesting that the bond market was able to anticipate the crash before the stock market and make more rational decisions. In 2021, we conclude that investors were more cautious. In 2020, Investors were less influenced by the sentiment in the media for the S&P 500. This is indicative of the V-shaped recovery and explains the rise of the stock market. The S&P 500's rapid growth was misaligned with unemployment and the spread of the disease. There were few COVID winners in the economy, but there were far more losers. The stock market displayed optimism in a very uncertain time, pre-vaccine. Some of the stock market gains can be explained by the aggressive policy implementations by the Federal Reserve. We can interpret that at times early in the pandemic, the stock market movements appear to be random because they do not follow fundamentals or sentiment measures reflected in the media.

When testing the effect of independent variables on the S&P 500 interesting results were found. We can see that investors' reaction to negative fundamentals is stronger when panic is also present in the media. This indicates the media intensifies investors' adversity to risk when fundamental news is negative. Fake news does not have a notable effect on investors' decisions in the stock market or treasury market. The volume of news was also not found to influence the pricing of US financial markets. This suggests that investors were able to digest a high volume of news rationally and identify fake news.

When estimating a three-period lag regression of the panic index, the reversal effect was observed for the S&P 500, and momentum was observed for the 10-year treasury. The reversal effect indicates that decisions made in response to panic were not based on fundamentals. Panic in the media can be seen as an irrational factor included in pricing risk in the stock market. Overall, investment decisions in the 10-year treasury market are more efficient. Panic in the media is the most influential factor contributing to sentiment-driven decisions.

II. LIMITATIONS OF MODEL

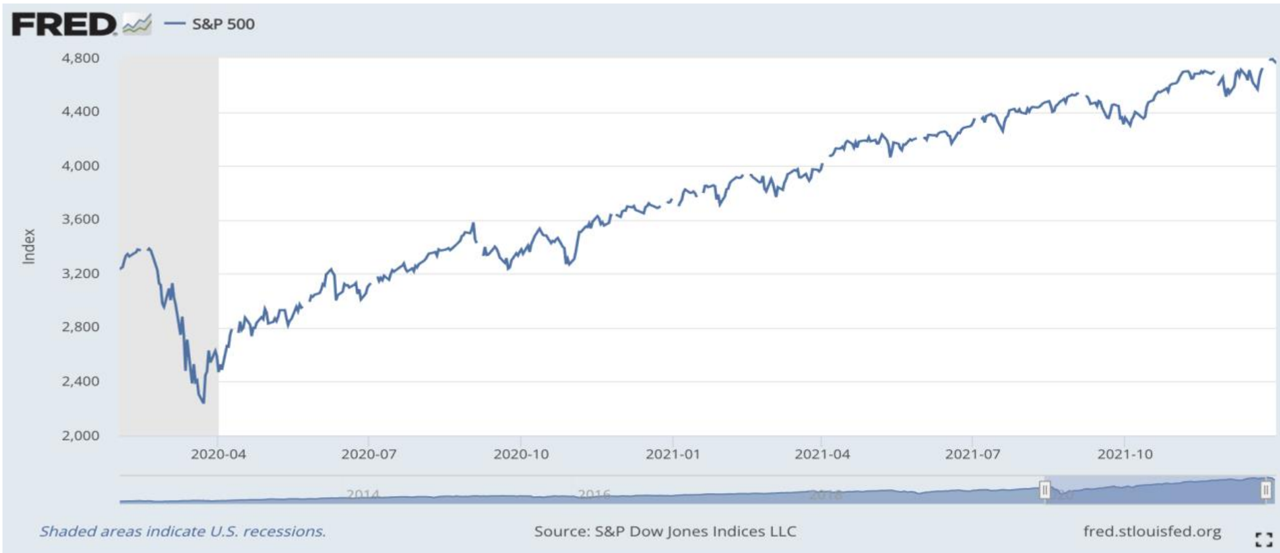
There will always be winners and losers in an economy. Investors, bankers, and entrepreneurs could be lucky, or they could be savvy. In the Corona economy, many participants in the market got lucky. Future research should focus on which type of investors were affected by the volatility in the market and which type of entities were affected by the dismantling of the economy. Investors have been known to experience FOMO- fear of missing out. Recently the market has been described as having FOBI- fear of being in. Paulsen (2022) claims the market participants are the majority “fearful bulls.” The panic in the news is a cause of concern that has shifted the attitudes of investors who once ignored risks. Further research should be done to conclusively evaluate the efficiency of investment decisions over time more closely and identify if financial markets have improved in the pandemic world. This model estimated sentiment variables by evaluating the type of news in the media. The sentiment analysis of an individual's direct feelings would be an area of future research that can expand on market psychology. As the Coronavirus adapts, updated literature will consistently be needed to understand the effect it has on the economy. Lastly, building on potential policy implementations to control the media and news broadcasts to limit the effect of sentiment-driven decisions.

III. CONCLUDING REMARKS

Uncertainty generates emotions that affect investment decisions and cause fluctuations in the market. Large booms and busts in valuations occur because stocks are being mispriced. When the market is inefficiently allocating capital and pricing stocks, it forges a waste of real resources and financial losses for individuals and firms. Behavioral economics can better inform investors of their influences and augment decision-making in times of uncertainty. The coronavirus is here to stay, and the economy, businesses, and individuals need to continuously adjust to the new normal. Currently, we are experiencing a correction in the stock market and a flock to treasuries as inflation rises to historic highs. The market's fears have shifted away from the virus itself and pivoted to the recovery of supply chains and political discourse. Emotions and mental health are intrinsic factors that were once taboo have now become common topics of conversation. The fear present in the minds of participants in financial markets is as important to discuss as anyone else's. Sentiment in the media can negatively skew investors' decisions and cause inefficiencies in the US market and therefore the economy. The male-dominated finance industry should continue to embrace societal moves to acknowledge and improve mental health in larger ways.

APPENDIX

Figure 1



S&P Dow Jones Indices LLC, S&P 500 [SP500], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/SP500, January 30, 2022.

Figure 2

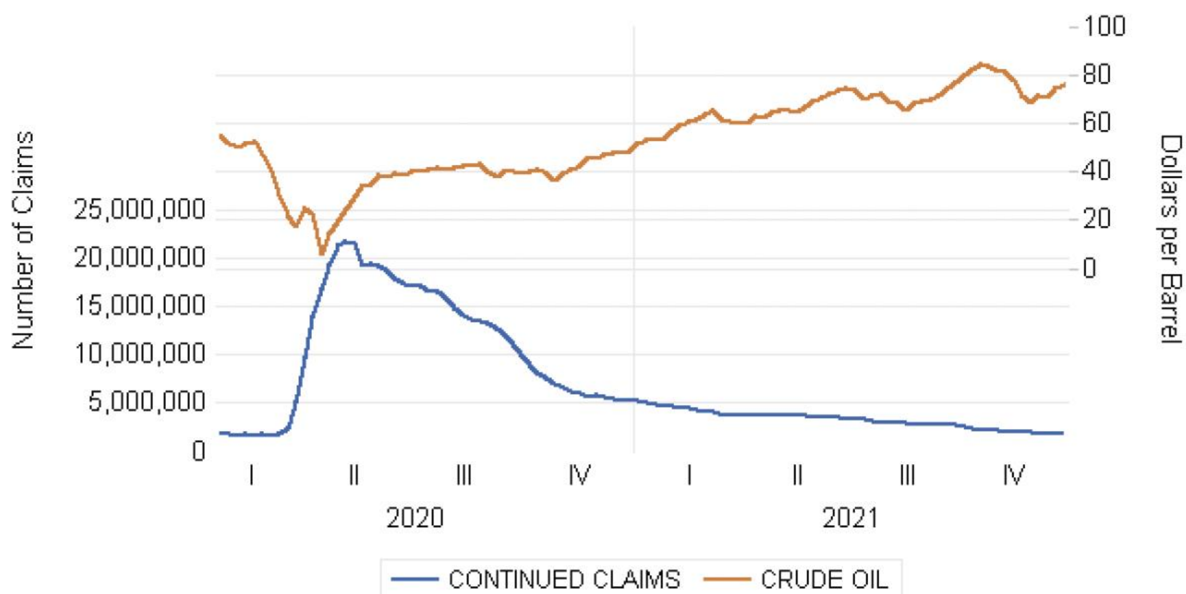


Figure 3

Normalized Plot of S&P 500, Panic Index, and Daily COVID-19 Cases in the US 2020

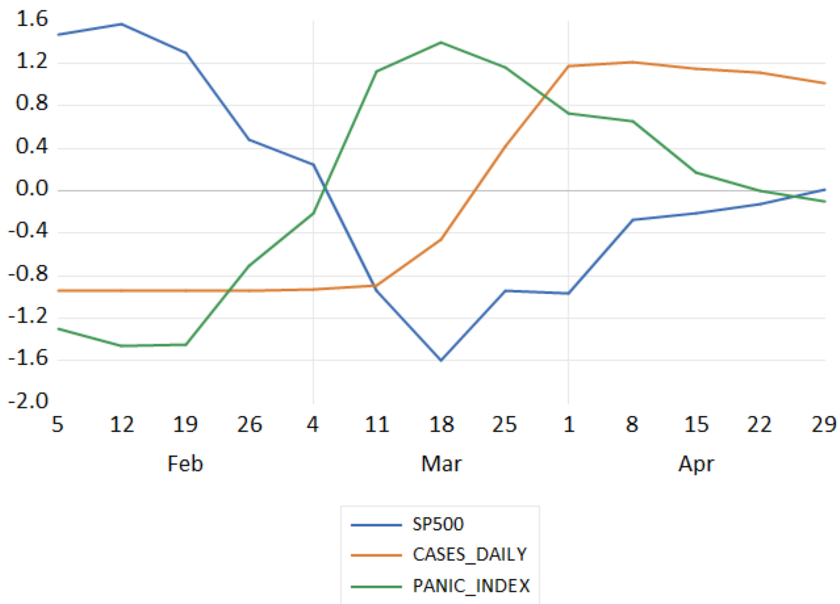


Figure 4

Residual Table: (DV:S&P 500 IV: Chicago & Sentiment indexes)

1/22/2020	-0.00654	-0.01358	0.00704
1/29/2020	-0.00814	0.02323	-0.03137
2/05/2020	0.02354	0.02252	0.00102
2/12/2020	0.00963	-0.01171	0.02134
2/19/2020	-0.02572	-0.02686	0.00114
2/26/2020	-0.08286	-0.03158	-0.05129
3/04/2020	-0.02594	-0.04285	0.01691
3/11/2020	-0.13838	-0.05626	-0.08212
3/18/2020	-0.08536	-0.07372	-0.01164
3/25/2020	0.08614	0.01599	0.07015
4/01/2020	-0.00383	-0.02218	0.01834
4/08/2020	0.08420	0.02780	0.05640
4/15/2020	0.00593	0.01678	-0.01086
4/22/2020	0.01125	0.02535	-0.01410
4/29/2020	0.01527	0.02193	-0.00666
5/06/2020	0.00458	0.03057	-0.02599
5/13/2020	-0.00324	0.02878	-0.03202
5/20/2020	0.02880	0.03548	-0.00668
5/27/2020	0.02743	0.02722	0.00021
6/03/2020	0.03999	0.01266	0.02733
6/10/2020	-0.02837	0.00962	-0.03799
6/17/2020	0.00973	0.00603	0.00371
6/24/2020	-0.01808	0.00017	-0.01825
7/01/2020	0.02689	0.00710	0.01980
7/08/2020	0.00926	0.00399	0.00527
7/15/2020	0.01974	-0.00039	0.02013
7/22/2020	0.00057	0.00793	-0.00736

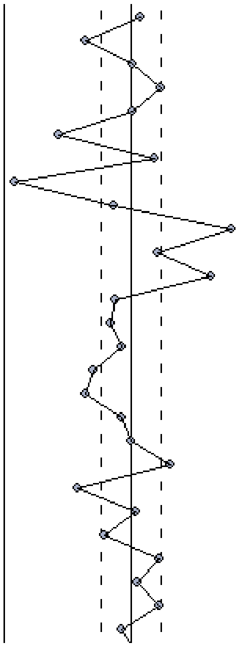


Figure 5

Residual Plot (DV: 10-year Treasury yield, IV: Panic and Lewis-Mertens Index)

1/22/2020	-0.06347	-0.13819	0.07472
1/29/2020	-0.07857	-0.02272	-0.05585
2/05/2020	0.02771	0.00480	0.02291
2/12/2020	-0.01093	0.01877	-0.02970
2/19/2020	-0.09374	-0.00634	-0.08740
2/26/2020	-0.20944	-0.06769	-0.14176
3/04/2020	-0.39027	-0.02550	-0.36477
3/11/2020	0.09805	-0.04419	0.14224
3/18/2020	0.09344	-0.03938	0.13283
3/25/2020	-0.22991	-0.08025	-0.14966
4/01/2020	-0.15198	-0.07555	-0.07643
4/08/2020	0.13751	-0.07222	0.20973
4/15/2020	-0.19700	-0.04944	-0.14756
4/22/2020	0.00963	-0.01189	0.02152
4/29/2020	0.02524	0.00037	0.02486
5/06/2020	0.07500	0.02233	0.05267
5/13/2020	-0.03530	0.03182	-0.06712
5/20/2020	0.01412	0.01591	-0.00179
5/27/2020	-0.00518	0.02698	-0.03216
6/03/2020	0.22492	0.02378	0.20114
6/10/2020	-0.16447	0.01919	-0.18366
6/17/2020	0.00000	0.02069	-0.02069
6/24/2020	-0.07841	0.00662	-0.08504
7/01/2020	0.02314	0.00700	0.01615

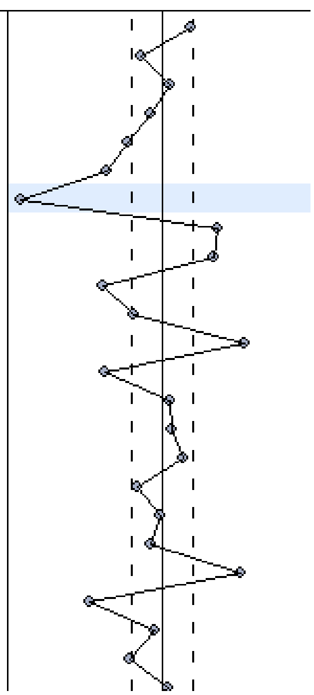


Figure 6

Correlation Coefficients

Correlation Coefficients	CHICAGO	CONTINUED CLAIMS	CRUDEOIL	FAKE NEWS INDEX	INFODEMIC INDEX	LEWIS-MARTENS	MEDIA COVERAGE INDEX	PANIC INDEX	MEDIA HYPE INDEX	SENTIMENT INDEX	SPLAST PRICE	ST. LOUIS	TEN YEAR LAST PRICE	VIXCLS
CHICAGO	1	0.053048515	-0.39065931	-0.046100272	0.305934199	-0.65270133	0.281182453	0.284185409	0.319241843	-0.092177318	-0.122354876	0.72888116	-0.400936681	0.62522139
CONTINUED CLAIMS	0.05304852	1	-0.85125856	0.333275401	0.886887833	-0.578632565	0.905641984	0.738439162	0.859557631	-0.099492815	-0.959282475	0.35257424	-0.37707331	0.40899495
CRUDE OIL	-0.39065931	-0.851258565	1	-0.276186094	-0.900994961	0.549502195	-0.914884552	-0.841275822	-0.892984965	0.143088419	0.837948929	-0.59442479	0.438440777	-0.5627357
FAKE NEWS INDEX	-0.04610027	0.333275401	-0.27618609	1	0.278191024	-0.261784924	0.320002627	0.454787169	0.399830119	-0.232419786	-0.259300758	0.05527227	-0.501044885	0.15988131
INFODEMIC INDEX	0.3059342	0.886887833	-0.90099496	0.278191024	1	-0.660692175	0.983679659	0.789730567	0.940004716	-0.101946516	-0.889753521	0.52988799	-0.355469719	0.48101705
LEWIS-MARTENS	-0.65270133	-0.578632565	0.549502195	-0.261784924	-0.660692175	1	-0.644334763	-0.506164488	-0.635248155	0.153722263	0.637172872	-0.61797075	0.51714325	-0.6553788
MEDIA COVERAGE INDEX	0.28118245	0.905641984	-0.91488455	0.320002627	0.983679659	-0.644334763	1	0.833233604	0.961966562	-0.14579905	-0.909428766	0.53885793	-0.36554953	0.48779031
PANIC INDEX	0.28418541	0.738439162	-0.84127582	0.454787169	0.789730567	-0.506164488	0.833233604	1	0.872349029	-0.163176011	-0.753518295	0.57138348	-0.394030531	0.54043476
MEDIA HYPe INDEX	0.31924184	0.859557631	-0.89298496	0.399830119	0.940004716	-0.635248155	0.961966562	0.872349029	1	-0.186180651	-0.848883939	0.54405039	-0.478045459	0.47710672
SENTIMENT INDEX	-0.09217732	-0.099492815	0.143088419	-0.232419786	-0.101946516	0.153722263	-0.14579905	-0.163176011	-0.186180651	1	0.091744117	-0.01228982	0.256661753	-0.0216668
SPLAST PRICE	-0.12235488	-0.959282475	0.837948929	-0.259300758	-0.889753521	0.637172872	-0.909428766	-0.753518295	-0.848883939	0.091744117	1	-0.48809962	0.255464023	-0.5239816
ST. LOUIS	0.72888116	0.352574242	-0.59442479	0.055272272	0.529887988	-0.617970748	0.538857933	0.571383476	0.544050387	-0.012289819	-0.488099616	1	-0.231350211	0.79097876
TEN YEAR LAST PRICE	-0.40093668	-0.37707331	0.438440777	-0.501044885	-0.355469719	0.51714325	-0.36554953	-0.394030531	-0.478045459	0.256661753	0.255464023	-0.23135021	1	-0.4245576
VIXCLS	0.62522139	0.408994955	-0.56273574	0.159881311	0.481017053	-0.655378756	0.487790307	0.540434759	0.477106725	-0.021666751	-0.523981599	0.79097876	-0.42455763	1

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