QATAR UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

# ANALYSIS OF CLIMATE CHANGE NEWS SENTIMENT'S IMPACT ON GCC STOCK MARKETS

BY

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# ABSTRACT

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Title: Analysis of Climate Change News Sentiment's Impact on GCC Stock Markets.

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Climate change imposes severe pressure on the world's financial and economic systems. Commencing from altering the natural ecosystem and weather patterns to eventually affecting the public health. The climate change threats have notably extended to economic activities and financial markets, which will be thoroughly investigated in this study and precisely its impact on Qatar's and UAE stock market's performance. To showcase the considerable impact of climate change, this study will denote news related to climate change, environmental issues, and natural disasters sourced from Thomson Reuters' news monitor. A set of climate change news indices with distinctive classifications were then constructed. The classification of climate change news is centered on the region of publication (Global, GCC, Local news sources) and whether natural disaster news is included. For the period spanning from June 2016 to June 2023, the study compiled a total of 8,314 and 27,193 daily news headlines for Qatar and UAE, respectively. Climate change news undergoes a preprocessing for tidying the news text corpus to obtain a sentiment score utilizing widely used lexicons in this field. The scope of this analysis includes the use of both the Valence Aware Dictionary for Sentiment Reasoning (VADER) as well as the Loughran and McDonald (LM) sentiment approaches. Empirically, the study shows that the climate change news sentiment has varying impacts on Qatar and UAE's general and ESG indices. This research uncovers patterns of behavior that can help investors and regulators assess, recognize, and mitigate climate change-associated risks.

# DEDICATION

*I dedicate this achievement to my loved ones- family, friends, and workmates: Your kindness, prayers, and unconditional love have been an inspiration to me and have kept me going ... for that, I am appreciative.*

# ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my supervisor, Prof. Lanouar Cherfedinne, whose generosity in sharing his experience, dedication, patience, and invaluable guidance has made this journey both enjoyable and rewarding. My sincere gratitude goes out to my dearest professors and members of the college faculty for their support and encouragement over the past two years. I am also grateful for the inspiration I received and the moral support I received from my classmates. My family, friends, and workmates have been a constant source of support throughout my life. Words cannot express how grateful I am for them. I have been able to cope with many difficult days due to their prayers, understanding, and unconditional support.

"It has always been a pleasure to have you by my side."

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## 1. INTRODUCTION

Climate change poses one of humanity's greatest challenges since it threatens biodiversity, food security, economic growth, and financial system stability (Nordhaus, 1977; Sheffield & Landrigan, 2011; Giglio, Kelly & Stroebel, 2021; Santi, 2023). For example, in response to climate change's multi-faceted effects on the global assets market, the capital market will likely undergo an accelerated reallocation of assets. This is due to climate change's escalating severity (Lin & Wu, 2023). Despite standard futures or insurance contracts in which one party promises to compensate another in the event of a catastrophe, climate risk is inherent and non-diversifiable. Investors must self-insure against climate risks by seeking alternative investment vehicles that offer climate risk protection (Engle et al., 2020).

Although opinions diverge on how climate change impacts the financial markets, there is consensus on the significant risks it poses. The physical and transition risks are two major risks associated with climate change (Grippa, Schmittmann & Suntheim, 2019; Faccini et al., 2021; Ozturk et al., 2022; Zhang, 2022). The physical risk brings damage to property, land, and infrastructure. These global disasters brought by extreme weather could affect the companies' level of production business operations and diminish the value of their assets. The more extreme weather's uncertainty, the greater the financial consequences. Therefore, the prices of stocks whose performance is more vulnerable to climate physical risk could shift than their fundamentals (Bee-Hoong, 2023). Meanwhile, the transition risk occurs due to changes in technology, climate topology, and consumer and market mood over the transformation to a lower-carbon economy. Countries face various transition risks to transform into a lower-carbon economy since it entails higher corporate expenses and undermines the profitability of existing goods and services (Blackrock, 2016). The adverse effects of climate change on the global economy must therefore be mitigated through corrective measures.

Climate change's corrective measures will likely be dependent on changes in market sentiment, regulations, and future weather forecasts (Pachauri et al., 2014). The implementation of climate change's corrective measures, however, may affect the stock market. For instance, professional investors and asset managers should be capable of determining whether a company could manage climate relevant risk and align its strategy for long-term return. One such indicator for determining a company's vulnerability to climate change threats is to consider firm's ESG-related information. Therefore, companies should include ESG considerations in their long-term growth strategies to offer an opportunity for growth. The goal of making ESG investments is to not only generate profit but have a positive environmental change. This has made ESG equities more appealing, especially when climate change threats are increasingly affecting investment decisions (Giglio, Kelly & Stroebel, 2021; Bee-Hoong, 2023).

## 1.2. Background

### 1.2.1. Defining Climate Change

Climate change is a change in the earth's weather patterns that impacts all living creatures (Hunt and Watkiss, 2011; Bálint et al., 2011; Tai et al., 2014; Li et al., 2019; Calel et al., 2020; Nijhawan and Howard, 2021; Forzieri et al., 2021; Gao et al., 2021). Climate change has become an integral part of our contemporary culture and goes beyond mere trends. It is necessary to consider the global energy balance and emission scenarios to understand the evolution of climate change in the context of finance. During the industrial revolution in the early nineteenth century, the concentration of greenhouse gases (GHG) in the atmosphere and the planet's temperature experienced an unprecedented increase (Mukhopadhyay et al., 2018). A marked increase in atmospheric concentrations of GHG 150 years ago has become a major concern for society, business operations, and others. Therefore, climate change has raised a number of issues that are interconnected in terms of their economic, social, and environmental dimensions. By understanding these concerns in the current capital market, we can avoid future stock price crashes (Bose et al., 2023). To address these concerns, a step toward transitioning to a low-carbon, sustainable economy and green finance instruments is necessary. Transition can indeed be viewed as a means of mimicking human-induced climate change threats and avoiding future stock price crashes.

#### *1.2.1.1 Climate Physical Risk*

Increasing community awareness has led to a surge in climate change-related research in finance. In the field of climate finance, researchers have primarily examined methods for quantifying the risks posed by climate change. There is also an emphasis on green finance, green financial systems, and sustainable finance (Giglio et al., 2020; Hong et al., 2020). However, research relevant to quantifying climate change uncertainty has been an area of great concern to parties in the financial markets. In general, the known quantifiable risks associated with climate change are physical and transitional risks. Physical climate risk, first-order risks, refers to the potential loss, damage, or adverse effects caused by natural disasters, extreme weather conditions, and similar events (Bua et al., 2021; Zhang, 2022). It encompasses a wide range of potential risks that may have adverse effects on investors, corporations, and society as a whole. Investors can be adversely affected by physical climate risks. An example would be a company whose performance is highly susceptible to physical risks, which would result in financial losses and a decline in its asset value. There is a possibility that investors, especially those who own shares in these companies, will see a decline in the value of their investments.

#### *1.2.1.2 Responses of Stock Markets to Climate Physical Risk*

The threats posed by climate physical risk have gained the attention of financial regulators, who are concerned about how climate physical risk is reflected in asset prices. To gain a better understanding of how climate physical risk impacts the stock market, it is useful to review some published cases concerning its impact on global financial markets.

It is worth noting that physical risks influence assets or factors of production directly or indirectly, which in turn influence the value of stocks. The results from previous studies indicate that the effects of physical climate change risks depend on their timing and to the extent of their influence on production factors. Garbarino & Guin (2021) investigated the effects of a critical flood event in England between 2013 and 2014 on the credit risk. They found that banks considered this flood event as a temporary risk and therefore did not include a flood risk in valuating mortgage or lending decisions. In this case, the climate change physical risk was acute and did not have significant effect on financial stability or stock prices. It is arguable that if this flood event was chronic, there would have been significant rise in credit risk, disrupting firm financial stability and hence decreasing stock prices.

Flori, Pammolli and Spelta (2021) analyzed the impact of financial stability with regard to commodity price mobility during extended physical climate change risks such as strenuous temperature and rainfall. They found an empirical correlation between extended climate-related variables and financial stability. Their study found that changes in commodity prices correlated inversely with changes in climate-related variables. Similar findings were established by Faccini Matin and Skiadopoulos (2023), who found similar changes in commodity prices due to physical climate change risks. In this study, Faccini et al. (2023) investigated whether the changes in stock prices due to climate change risks were caused by physical risks or imposed government regulations to mitigate the risks- transition risks in the United States of America. Despite physical risks influencing financial stability, this study concluded that transition risks were the most important factor responsible for stock price changes caused by climate change.

*1.2.1.3 Climate Transition Risk*

In response to the increased global momentum towards environmental sustainability, governments nationwide have enacted aggressive measures to combat climate change, exerting pressure on businesses (Zhang, 2022). These developments are viewed by companies as a climate-related transition risk. Risks associated with climate transition can also be defined as risks that arise from a country's transition to a greener economy (Collender et al., 2023). There are both risks and opportunities associated with climate transition risk, including policy changes, potential reputational damage, and shifts in consumer preferences, customs, and technological advances. Transition opportunities exist due to the utilization of resources and the development of technologies, new products and services that are capable of capturing potential markets and financing sources. This risk and opportunity spectrum vary across regions, industries, timelines, and on the basis of government and business commitments for better environmental outcomes.

*1.2.1.4 Responses of Stock Markets to Climate Transition Risk*

In response to actions intended to mitigate and adapt to the paradigm shift in environmental sustainability, climate transition risk can offer some companies a unique opportunity. In contrast, companies with a high degree of vulnerability to the climate transition risk would suffer losses. To gain a better understanding of how climate transition risk impacts the stock market, it is useful to review some published cases concerning its impact on global financial markets.

The common theme from transitional risks influence stock market is due to disruptions of financial stability as firms attempt to conform to policies and regulations established to prevent excessive toll of production on environmental factors. Dafermos and Nikolaidi (2021) investigated the impact of transition fiscal policies and regulations on firm capital requirements. They found that these policies reduced long run financial stability especially when “dirty penalizing” and “green supporting” occurred simultaneously. “Dirty penalizing” in this case refers to transition policies that impose penalties on firms whose productions are construed to contribute to climate change. “Green supporting,” on the other hand, refers to the transition benefits credited to firms participating in green production- non pollutive production. Dafermos and Nikolaidi (2021) demonstrated that banks are financially vulnerable due to reduced credit risks from green instrument adaptation. Meanwhile, they found that dirty penalization had the opposite effect.

Analyzing the impact of climate transition risks on bank lending behavior, Dunz, Naqvi and Monasterolo (2021) found that banks and other credit firms implement appropriate climate sentiments in the lending behavior during climate change risks. The interest rates accrued by banks on firms varied greatly between high-carbon and low-carbon firms. Similar findings were reported by Alessi, Ossola and Panzica (2021) who found an increased tendency for investors to accept lower compensations for stocks of firms disclosing environmental data and with low carbon emissions. The stock prices of such firms therefore increased. Alessi et al, (2021) also found that the stock market tended to relocate assets to green assets as a way of mitigating losses.

Through a case study of the Mexican stock market, Roncoroni et al. (2021) investigated how climate transition policies influenced financial valuation and stability. Their study utilized a climate stress-test framework to predict firm and asset valuation amidst transition changes. They found that the greatest impact from transition risks occurred when implemented policies were met by weak market conditions. These findings collaborate the capital recycling techniques among banks, investors and credit firms highlighted by Alessi et al. (2021) and Dunz et al. (2021). This suggests a critical financial determinism by banks on the trajectory of the financial stability and hence the stock market during climate transition risks.

*1.2.1.5 Hedging Climate Change Risks*

The multifaceted impacts of climate change threats on the stock markets have led studies to explore the possibility of hedging against climate change threats (Andersson et al., 2016; Engle et al., 2020; Bua et al., 2021; Çepni et al., 2022; Li et al., 2023; and others). Hedging climate change risks is not only considered from the standpoint of corporations but also considers the possibility of hedging to other participants in the market. When it comes to the possibility of hedging by firms, companies may be able to mitigate some climate change risks if they disclose their sustainability and environmental responsibility patterns (Clarkson et al., 2008; Park et al., 2023). Climate-relevant disclosures serve as a signal to attract investment, especially as advances in climate reporting and sustainability reporting become more widespread. Environmental, social, and governance (ESG) disclosure is one of the most widely used tools for assessing a firm's vulnerability to climate change risk. Firms' reputations and capital costs were found enhanced through high-quality ESG disclosure (Dhaliwal et al., 2011; Ryou et al., 2022; Yang et al., 2023). An organization's ESG disclosures should describe its environmental impact, social responsibilities, and governance practices (Van Duuren et al., 2015). Therefore, ESG disclosure can be regarded as an indication of a company's commitment to corporate responsibility, the measures it takes to overcome environmental and social issues, the risks posed by climate change, and its long-term sustainability strategies.

Meanwhile, from an investment perspective, investors can hedge climate change risks by allocating capital to investments that reduce those risks. The possibility of choosing an asset for hedging climate change risk, however, considers many aspects. It is essential to consider several factors when making investments that hedge against climate change threats. These factors include the sector's resilience, investment structure changes, and company disclosure and transparency (Ansoff, 1957). For instance, when an asset is highly exposed to climate transition uncertainty, industries with high $CO_2$ emissions will be negatively impacted. This leads investors, however, toward investing in assets with less exposure to climate transition risk, such as ESG equities. Also, a rise in ESG reporting instruments has led multiple investors to assess their investment on the basis of sustainable assets. This is highly evidence with the increasing suggestions about ESG equities financial risk mitigation (Engle et al., 2020; Singh, 2020; Heeb et al., 2022; Liu et al., 2023; Cepni et al., 2023, and others).

*1.2.1.6 Evidence on Hedging Climate Change Risks*

Over the years, various hedging practices and approaches have been proposed to minimize the impact of climate change risks. Since the impacts of physical and transition climate change risks are partly related, proposed hedging approaches are not exclusive to either physical or transition risks. Cepni, Demirer and Rognone (2022) proposed hedging climate change risks using green assets and precious metals. This hedging practice is derived from the observation that green assets are less affected by climate change risks. By relocating assets into the green investment, firms are likely to avoid the strenuous climate change transition policies such as dirty penalizing, and possibly benefit from green support such as reduced credit risk and higher valuations. Similarly, hedging using popular precious metals introduces financial stability amidst climate change risks, therefore cushioning firms from losses. According to Cepni et al. (2022), hedging with green assets is more effective than hedging with precious metals. The former not only provides financial stability but also introduces a mechanism to manage climate change exposures in long-term investment portfolios.

The hedging practice described above operates by introducing security to hold off future climate risks. According to Engle et al. (2020), this approach is incomprehensive whenever future climate change risks cannot be predicted. Instead, Engle et al. (2020) suggested a hedging practice that utilizes mimicking portfolios to establish climate change hedging measures. The success of this practice heavily relies on the accuracy with which the mimicking portfolio is created. The first step in creating the mimicking portfolio is to establish a time series for previous long-run climate risks from which an appropriate hedge target can be determined (Engle et al., 2020). Data for this step is acquired through observations from credible news sources. Future climate risks can be predicted from this data through extrapolation. The second step involves creating an investment portfolio based on predicted climate change risks;

physical and transition (Engle et al., 2020). This portfolio should place assets strategically to respond accurately to climate risks without losses. The portfolio should be updated often to ensure relevance to new risks information.

The third approach to hedging climate change risk is by manipulating climate and weather derivatives through pricing. An example of such an approach is the copula-based pricing technique suggested by Bressan and Romagnoli (2021), which utilizes a deterministic pricing of production factors during climate change to mitigate risks. This hedging practice is most applicable for physical climate change risks, whereby the prices of the factors of production affected by change are revised to maintain financial stability. This hedging practice is, however, detrimental if mispricing occurs, such that the impact of the physical risk is heightened rather than reduced, hence undermining financial stability (Bressan & Romagnoli, 2021). This literature indicates that climate change risks can be hedged to prevent asset losses or financial stability.

**1.3. Problem Statement**

This study aims to fill a significant gap in the green finance literature related to the relationship between climate change news sentiment and stock market performance. First, to the best of the author's knowledge, this is the first study that tries to construct a climate change news sentiment index for financial investors in the GCC countries. Second, this study will contribute to this literature by filling the gap related to investigating the impact of climate change news sentiment indices on the stock market performance in oil-exporting countries and by focusing on the case of the GCC countries as a region and individual country analysis for the two cases of UAE and Qatar. To be precise, we will explore the impact of the newly proposed sentiment indices on both general and ESG equities returns.

### 1.4. Research Questions

Research questions aimed at answering in this study include:

1. Are there any impacts of climate change news on the stock markets in Qatar and the UAE?
2. Have investors' behavior changed because of climate change news?
3. Can ESG equities be weighted higher or lower in an uncertain climate to enhance the return on a portfolio?

### 1.5. Research Objective

The study aims to achieve the following objectives:

1. Analyzing the impact of climate change news on Qatar and UAE stock markets returns and volatility.
2. Determining whether climate change news impact investors behavior
3. Explore whether increasing/decreasing the weights of ESG equities can enhance the return on a given portfolio.

### 1.6. Scope of the Study

The purpose of this study is to investigate the impact of climate change news on stock markets of the GCC, specifically those in Qatar and the UAE. The analysis uses a total of 8,314 and 27,193 daily news headlines for Qatar and UAE, respectively, for the period June 2016 to June 2023.

The purpose of this study is to gain insight into the impact of climate change news on the GCC stock market. Moreover, the analysis will determine whether climate proxies are useful for predicting stock market returns. For news data gathered along with other explanatory variables, we will use descriptive statistics, data analysis, and VAR's special diagnosis in order to accomplish the objective of this thesis.

Additionally, the study will test the robustness of the analysis by excluding a significant portion of the news collected pertaining to natural disasters. It also assesses the robustness of the result using two lexicons for sentiment analysis.

### 1.7. Contribution

This study aims to fill a significant gap in the green finance literature related to the relationship between climate change news sentiment and stock market performance. First, to the best of author’s knowledge, this is the first study that tries to construct a climate change news sentiment index for investors in the GCC countries. Second, this study will contribute to the literature by filling the gap related to investigating the impact of climate change news sentiment indices on the stock market performance in oil exporting countries and by focusing on the case of the GCC countries as a region and individual country analysis for the two cases of UAE and Qatar. To be precise, we will explore the impact of the proposed climate change news sentiment indices on the returns and volatility for both general and ESG equities.

### 1.8. Thesis Structure

The first section of the thesis provides a brief introduction to the paper's subject matter and some background information. Section 2 synthesizes papers related to the topic. A discussion of empirical methodologies related to the research questions is presented in Section 3, including deep machine learning methods, sentiment analysis methods, and empirical model. Section 4 provides a comprehensive descriptive analysis of the data. Section 5 presents the study's findings and validation. A summary of the thesis, limitations, and recommendations for future research are then presented in Section 6.

# 2. LITERATURE REVIEW

## 2.1. Theoretical Framework and Concepts in Literature

This thesis examines how investors perceive news information and behave on the stock market, which is why noise traders' and news release theories are most relevant to this study. Thus, to better understand how climate change impacts the stock market, it is helpful to review some financial theories.

### *2.1.1. Investor Behavior and Stock Market Performance*

Behavioral finance literature suggests that investors' sentiment can cause prices to diverge from fundamentals, resulting in sustained mispricing (De Long et al., 1990; Pontiff, 1996; Shleifer and Vishny, 1997). In some cases, investors' sentiment can be attributed to market imbalances caused by the phenomenon of 'noise traders'. Traders deemed 'noise traders' tend to be unskilled, uninformed, or novice retail investors who follow trends, are emotional, and lack discipline. Professional or well-informed traders may suffer from irrational decisions or mistakes by noise traders, causing price volatility (De Long et al., 1990). According to the efficient market hypothesis, arbitrage intervention will assist in balancing the markets and correcting their imbalances (Fama, 1970). However, due to the presence of noise traders, rational traders may have to terminate the position at a loss. This is because when rational traders engage in arbitrage and the prices remain unbalanced for some time, clients may be unhappy, resulting in losses for the trader. Therefore, the trader's ability to engage in arbitrage is limited. Thus, noise traders create a restriction on rational traders, which is the limit to arbitrage (Shleifer and Vishny, 1997).

Baker and Wurgler (2007) stated that, unlike decades ago, today's concern is not whether investor sentiment affects stock prices but rather how to measure and quantify it. There would be considerable complexity and concern involved in studying the impact of noise traders on the stock market in the context of climate change. The importance of recognizing that these traders possess neither perfect information nor rational decision-making processes is irrefutable, yet their actions can still have a profound impact on the financial markets and, consequently, the allocation of resources for climate change threats mitigation. Therefore, the following theory is probably helpful in demonstrating how the news can be used as a measure for investors' sentiment.

*2.1.2. News Releases and Stock Market Performance*

Increasing evidence in the finance literature suggests that news can trigger rapid and often dramatic shifts in asset prices (Golsten Milgrom, 1985; Kyle, 1985; Graham et al., 2006). Indeed, news releases may present a competitive advantage to market makers, increasing information asymmetry (Kim and Verrecchia, 1994). As such, some components in the news may influence the bid-ask spread decomposition, thereby affecting stock market prices (Copeland and Galai 1983; Golsten Milgrom 1985; Stoll 1989, Christie & Schultz, 1994). In other words, when market makers have superior information that is not yet interpreted by the public, the quoted prices of the spread by market makers set a higher gap between ask and bid prices, indicating a high level of information asymmetry caused by the unanticipated components of news. In contrast, the bid-ask spread reduces when public information is released, reducing information asymmetry[1].

[1] Investors who are not completely rational and react irrationally to news may be responsible for the shift in stock market prices following news releases. However, after a couple of days, they begin to behave normally again. A price reversal may also result from sophisticated investors exploiting the relatively low prices (Lee et al., 1991).

Thus, we proposed a new proxy for investor sentiment about climate change. The interaction between environmental awareness, financial markets, and sustainability on a global scale can be fascinating when we understand how climate news influences the stock market. Stock prices can be significantly affected by news related to climate change. This includes extreme weather conditions, regulatory policy changes, or corporate environmental initiatives. Climate-related news is a significant driver of market sentiment since investors consider environmental, social, and governance (ESG) determinants in their investment decisions. For instance, news about renewable energy technology or a commitment to carbon neutrality is presumed to positively impact shares of companies poised to benefit from the transition to a more sustainable economy. Conversely, news such as natural disasters or tighter emissions regulations, may adversely impact industries that rely on fossil fuels or do not have adequate climate change mitigation strategies. Participants who take advantage of interpreting climate change news will continue to profoundly impact stock markets, influencing investment flows and changing the global economic landscape.

### 2.2. Empirical Analysis from Literature

Financial theories are valuable channels for studying climate change's impact on stock market performance. Theoretical research, however, emphasizes the overall assumptions, which are criticized for oversimplifying reality. Thus, empirical research is crucial in providing clarity to real-life datasets and specialized research fields. The effects of climate change on stock markets can be better understood by combining theoretical insights with empirical evidence. Therefore, to better understand how climate change impacts the stock market, it is helpful to review some empirical results of previous studies. Several research studies have been conducted on this topic, resulting in various conclusions. The results vary according to the country of investigation, industry by which a company is operating, class of equity, or the climate change indicator examined. Our study is consistent with the stream of empirical literature focusing on (i) the sensitivity of the stock market to climate change. It also emphasizes the stream of empirical literature studying (ii) climate change and ethical considerations and (iii) climate change and investor sentiment.

#### *2.2.1. Sensitivity of Stock Markets to Climate Change*

In recent literature, it has become prevalent to highlight the impact of climate change on the stock market as it relates to weather proxies. Research on climate impacts on the stock market includes analyzing temperature, wind, rain, cloudiness, and other weather proxies (Floros, 2008; Shu and Hung, 2009; Symeonidis et al., 2010; Hong et al., 2019; Huynh et al., 2020; Gregory; 2021; Rao et al., 2021).

Floros (2008) investigates the relationship between stock market returns and temperature. Among the European countries studied, only Austria, Belgium, and France were found to have a negative correlation between temperature and stock market returns. However, a positive correlation exists between temperature and stock market returns in Greece and the United Kingdom, but it is not statistically significant. In the meantime, Shu and Hung (2009) studied the nexus between the daily European stock market returns and the wind speed. Wind is shown to have a greater effect on stock returns than sunlight, indicating that wind might exert a stronger influence on mood than sunlight and thus serve as a better predictor of mood than sunshine for the stock market returns.

Symeonidis et al. (2010) investigated the empirical association between stock market volatility and climate proxies. It has been shown that cloudiness and the length of nighttime have inverse relationships with historical, implied, and realized volatility measures. It appears that the strength of the association varies according to the location of the exchange in relation to the equator on Earth[2]. However, it is concluded that weather deviations from seasonal norms and dummies representing extreme weather conditions cannot provide additional explanatory power in the datasets of this study.

Balvers et al. (2017), examined the impact of temperature shocks on equity costs. The study reveals a greater vulnerability to temperature shocks among firms exposed to climate risk high adjustment costs. The result of this study applies to 18 out of 30 industries traded within the United States. Transport, construction, mining, steel work, and other industries are all negatively affected by temperature shocks; therefore, they are vulnerable to climate risk (Balvers et al., 2017).

Hong et al. (2019) assessed whether drought risks are effectively discounted in food stock prices. Droughts caused by rising global temperatures are predicted to negatively impact the agricultural and food processing sectors. The authors, however, found that the stock markets of 31 countries have under-reacted to the risks associated with climate change driven by the trend toward droughts indicator[3]. However, another study by Huynh et al. (2020) tests the relationship between drought and expected rate of return given the state-level drought intensity in the United States. A positive correlation was found between drought intensity, financial costs of drought, drought

[2] Among the 26 exchange cities investigated are New York, Istanbul, Paris, London, Madrid, and others.

[3] China, Japan, the United States, France, the United Kingdom, and others are included in the 31 countries examined. The authors confirm that drought trends in the countries investigated are significantly dispersed, with a more significant left tail for the study's dataset. The findings suggest that there are more countries with statistically significant negative trends in assessing drought risk than countries with positive or improving trends, which makes those countries less vulnerable to the impact of drought risk.

duration, and the cost of equity capital. Drought also has a particularly strong impact on equity capital costs in states experiencing drought recently. This indicates the market understands drought's impact and prices it into equity capital costs more strongly.

Ramelli et al. (2021) investigated the impact of the first Global Climate Strike on European stock prices[4]. It was found that the high carbon-intensive firms' stock prices were negatively affected by the Global Climate Strike. During the climate strike, stock prices are penalized for the declines in carbon intensity. In other words, climate activism caused equity prices to suffer a carbon intensity penalty during the Global Climate Strike. At the same time, a study conducted by Bolton and Kacperczyk (2021) investigated whether carbon emissions affect cross-sectional returns on US stocks. There has been a significant and positive effect of carbon emissions on stock returns, as demonstrated by the authors. The returns of stocks of firms with higher total CO2 emissions are typically higher despite controlling for factors such as size, book-to-market, and other factors that influence return. Additionally, the authors suggest a direct link between the mitigation of climate change and the reduction of emissions of carbon dioxide. According to these findings, investors would demand compensation for their exposure to carbon emission risks in some industries such as oil and gas, automobile, and utilities[5].

Gregory (2021) demonstrates that global temperature pricing influences equity

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[4] This study refers to the first Global Climate Strike on March 15, 2019. A coordinated wave of student climate protests, under the slogan "Fridays for Future," mobilized over 1.3 million people in over 2000 cities worldwide, receiving massive media coverage given the data released on their website: https://fridaysforfuture.org/

[5] Those industries are undergoing divestment effect since they are on emission intensity screens from scope 1. This is, however, not evident with firms in industries that are on emission intensity screens from scope 2 to 3.

capital costs. In an era of multinational corporations, there is evidence that global temperature shocks are important for stock returns, not just regional temperature shocks. This results in a positive risk premium for both global and regional shocks. In addition, the author states that the study's findings indicate that positive exposure to temperature shocks is primarily associated with industries that increase carbon emissions[6]. The temperature shocks, however, were not priced before July 1990. As a result, equity prices are not only affected by productivity shocks caused by temperature shocks before that period. Using another climate indicator, Rao et al. (2021) have been investigating the impact of rainfall on the performance of firms whose operations are highly dependent on rain. The study reveals that firms sensitive to rainfall suffer a market-based value decline in the immediate aftermath of rainfall departures compared to other groups of firms[7].

Villa-Loaiza et al. (2023) examined the correlation between energy prices and the financial markets considering ENSO phenomena[8]. The study employs wavelet analysis to observe energy and financial variables' dynamic interdependencies. While ENSO phases do not necessarily affect stock indices, the authors assert that the El-Nino and La-Nina phases of ENSO can directly affect energy prices[9]. Thus, The Colombian

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[6] Those industries that utilize greater amounts of carbon are primarily exposed to positive temperature shocks with a positive risk premium. This result is in line with Bolton and Kacperczyk (2021).
[7] Study results were derived from investigating 5,639 non-financial companies listed on the Bombay Stock Exchange Ltd. (BSE) or the National Stock Exchange of India Ltd. (NSE). The results of this study indicate that rain-sensitive firms tend to increase their investments after experiencing excessive rainfall. Conversely, rain-sensitive firms significantly lessen their investments following deficit rainfall conditions.
[8] As explained by the authors, ENSO phenomena are caused by periodic fluctuations in air pressure and the temperature of the sea surface. Air pressure is measured by the Southern Oscillation Index (SOI), while sea surface temperature is measured by the Sea Surface Temperature Index (SST).
[9] According to the authors, El-Nino refers to an increase in the ocean surface's temperature or a sea surface temperature higher than average. However, La-Nina refers to an ocean surface cooling or with a below-average sea surface temperature.

energy and stock markets likely suffered from a contagion caused by the ENSO phenomenon that affected the global climate.

*2.2.2. Climate Change and Ethical Considerations*

There are other scholars that attempt to empirically explain the different responses of the equity classes to climate change. A study by Ramelli, Wagner, et al. (2021) revealed that corporate environmental responsibility significantly impacts a firm’s value when climate-related policies are changed, supporting the theory that climate change significantly impacts financial markets. In 2016, it appeared that climate regulation and control would slow under the Trump presidency but then return to its previous pace. Some investigations have supported this assertion. According to the authors, analysts' short-term earnings forecast revisions have positively correlated with carbon-intensity firms since the 2016 election but not with ESG firms[10]. Meanwhile, the value of climate-responsible firms rose following the U.S. election in 2020 as investors anticipated Biden's ambitious climate agenda.

Gong et al. (2022) explored how political uncertainty interacts with climate risk in affecting the stock market of international companies. The findings of their study are consistent with the literature that indicates that the U.S. presidential election is an indicator of global political uncertainty. Additionally, political uncertainty appears to affect the riskiness of firms that are highly exposed to climate change, which is in accordance with Ramelli, Wagner, et al.'s (2021) findings[11]. The study also suggests

[10] The authors also noted that the climate-responsible companies, especially those owned by long-term investors, also benefited. Investors of this type appear to have bet on what the author described as a 'boomerang' change in climate policy. During Trump's tenure, there were signs of a boomerang. Its arrival was marked by the 2020 election when Biden was elected. This was evidenced by 3,000 firms representing 98 percent of the United States equity market capitalization under investigation.

[11] In the study, the authors demonstrate that non-green firms are highly vulnerable to the risk associated

that the returns of international firms with high climate risk are generally low, return volatility is high, and return correlations are high. Accordingly, when political uncertainty is high, investors holding climate-risk firms are at greater risk and more likely to flee to quality[12].

Brown et al. (2022) studied the influence of climate policy on a company's new technology adoption for cutting costs. The authors argue that the imposition of emission taxes within U.S. firms increases the cost of continuing to use polluting technologies by polluting firms. As a result, the taxes encourage adopting and implementing cleaner production methods.

Bartram et al. (2022) examine the interactions between the U.S. climate policy and firm performance[13]. According to the authors, firms with financial constraints reallocate emissions from California to other states as a result of increased regulatory costs. There has been a significant reallocation of resources due to a shift in output rather than a change in carbon efficiency, with a disproportional amount of funds being reallocated to nearby or less regulated states. Thus, because of this reallocation, firms are not showing any evidence that they have reduced their total emissions[14].

Reboredo and Ugolini (2022) examined the degree to which climate transition

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with climate change.

[12] The authors suggest that investors may make green investments based on their expectations about global politics. For instance, a green fund manager may adjust exposure to climate risk following clients' risk preferences when U.S. presidential elections are approaching.

[13] The study examined 2,806 industrial plants owned by 511 publicly listed firms in the U.S. between 2010 and 2015.

[14] The authors also noted that although financially constrained firms reduce greenhouse gas emissions from plants in California by 33 percent relative to plants in other states, they significantly increase emissions from plants in other states by 29 percent more than those owned by firms without a presence in California. In contrast, there is no evidence that unconstrained firms financially adjust their emissions in response to the new regulation, either in California or other states. The difference in response between constrained and unconstrained firms is statistically significant across multiple financial constraint measures.

risk affected the financial performance and cross-section pricing of publicly traded European and U.S. firms. To assess climate risk, the Carbon Risk Score (CRS) was used to determine the degree of exposure and management of transition risk in the firm's supply chain, operations, and products. The study results reveal that firms with the lowest climate risk exposure perform better in terms of returns on assets (ROA), returns on equity (ROE), earnings before interest, tax, depreciation and amortization (EBITDA) and other measures compared to those with the highest climate risk exposure. There is also evidence that European firms exhibit greater sensitivity to transition risks, whereas U.S. firms only suffer a significant decline in profitability.

Lin and Wu (2023) claims that the internal managers' ability to conceal their information regarding climate risk can reduce the possibility of stock price crashes. According to the constructed climate risk disclosure indicator, some industries disclose higher levels of information[15]. Manufacturing, scientific research and technical services, mining, agriculture, forestry, animal husbandry, and fisheries constitute some of these industries. In contrast, disclosure levels are lower in transportation, retail trade, finance, real estate, culture, and education. Consequently, the study concludes that the greater attention and disclosure given to climate risk, the lesser the risk of future stock price crashes. In another study by Wu, G. S., & Wan, W. T. (2023), the authors explored how climate transition risks propagate across borders through the stock market. Specifically, the study indicates that a greater degree of climate transition risk is associated with a greater degree of bilateral co-movement of stock market returns. This relationship increases with greater similarity in economic conditions between the two

[15] The authors constructed the climate risk disclosure indicator by looking at the frequency with which climate-related words appear in the annual and quarterly reports of Chinese listed companies.

countries and import dependence between the two countries, which the authors interpret as evidence of cross-border climate transition risks. Although a country's performance in combating climate change can help reduce spillover risks, an effective mitigation may require both countries to perform well.

### *2.2.3. Climate Change and Investor Sentiment*

A growing body of literature seeks to explain investor behavior in light of climate change. An influential paper by Engle et al. (2020) has demonstrated that portfolios can be hedged against climate change news. Their paper provides a rigorous methodology for developing portfolios using relatively easy-to-trade equities to hedge against risks caused by climate news innovations[16]. The authors found evidence that larger firms are more exposed to climate change news than smaller firms since they perform worse when the number of articles about climate change in the Wall Street Journal increases[17]. Therefore, since investor sentiment is affected by news, the proposed portfolio construction methodology governs hedging opportunities during climate uncertainty.

Heeb et al. (2022), investigated how investors' willingness-to-pay (WTP) for sustainable investments changes over time. Study findings indicate investors are more likely to choose sustainable investments that have a positive social impact. Despite this, investors' WTP does not differ significantly between investments that save 0.5 tons and those that save five tons of carbon dioxide emissions.

[16] ESG factors were also considered in portfolio construction process.

[17] The author's climate news index is designed based on climate news coverage in the Wall Street Journal (WSJ) and data analytics vendor Crimson Hexagon. Crimson Hexagon covers over 1,000 outlets, including the Wall Street Journal (WSJ), the New York (NY) Times, Reuters, The Washington Post, Yahoo News, BBC, and CNN.

He and Zhang (2022) examine the effect that news-based climate policy uncertainty has on stock market performance. The study reveals that climate policy uncertainty shows a significant ability to predict the performance of the overall stock market and stock returns in multiple industries, especially the oil industry. Among other uncertainty indicators, Climate Policy Uncertainty (CPU) was the leading indicator of stock market return predictability. Meanwhile, a study by Chen et al. (2023) used the CPU to determine its predictive ability on the Chinese stock market. In this study, the CPU was shown to be capable of predicting the Chinese stock market returns. Thus, the authors suggested that weather shocks are present in the stock market and investors should pay greater attention to climate policies in this time of climate crisis.

Choi et al. (2020) empirically investigated how the public perceives and responds to the effects of global warming on the stock market. By using greenhouse gas emission levels as a proxy of climate, the authors categorize the stocks based on high and low sensitivities to climate. The authors argue that when investors reconsider their beliefs about global warming, they may buy stocks that have a lower climate sensitivity and sell stocks that have a higher climate sensitivity, which would result in the former outperforming the latter. Therefore, carbon-intensive reporting companies earn lower stock returns than other reporting companies when the local exchange city experiences abnormally warm temperatures in the month of investigation.

An examination of the interactions between the impacts of climate change on the economy has been carried out in the study by Barnett et al. (2020). In the context of social valuation, continuous-time decision theory and asset pricing tools were used to address multiple aspects of uncertainty. The study suggests the interacting uncertainty components coming from climate and economic modeling. Both uncertainties have a multiplicative effect, and when both are large, their combined impact is quite substantial. Therefore, when both sources of uncertainty are acknowledged, the social cost of carbon increases significantly.

Faccini et al. (2021) examined whether the market-wide risks associated with climate change are reflected in the price of U.S. stocks. According to the study, only the US climate policy factor is priced in the local market. In nearly all models used to estimate US climate alphas and betas, the spread portfolio formed on the US climate policy factor earns a statistically significant positive alpha. Neither natural disasters nor climate change nor the debate in international summits are priced as risks elicited by news.

Cepni et al. (2023) examined the transmission of shocks across conventional and ESG assets[18]. According to the study, any diversification strategy to mitigate climate risk in conventional equity portfolios must first assess the portfolio's risk exposure to climate uncertainty. This is done using physical or transitional risk climate factors. Consequently, the study suggests that the effectiveness of climate hedging strategies and the appropriate hedging instrument to be employed will be influenced by the nature of an investment portfolio's climate exposure. In conclusion, the authors confirm that environmental, social, and governance assets are less connected to conventional assets during periods of high climate uncertainty, suggesting that these assets can indeed provide diversification benefits for conventional investors.

Santi (2023) examined the impact of investor climate sentiment on the stock market. According to the author, the investor climate sentiment can be measured by

[18] According to the authors, the physical and transition climate risk data used as climate indicator are derived from Bua et al. (2021). The indices were created using textual analysis from Reuters News.

analyzing Stock Twits posts related to climate change. The study found that when social interaction is low, investor climate sentiment tends to be negative when there is more news about climate change and there is more concern about its environmental impact. A higher level of social interaction, however, results in the opposite effect. In addition, the EMC portfolio's returns are negatively impacted by an increase in climate sentiment[19]. Because of the relatively high environmental impact and the subjective valuation of such information, emission stocks are most impacted by investor's climate sentiment.

## 3. CONCEPTUAL FRAMEWORK AND RESEARCH METHODOLOGY

### 3.1. News Data Collection and Preprocessing Method

To scrape news headlines from Thomson Reuters, the Eikon Data API was used. This method implemented a live stream crawler that continuously stored news headlines according to a predefined news classification as they were posted in real-time. Compared to previous studies, the updated approach collects a wider range of news stories within a comprehensive timeline.

There is usually a great deal of noise in the raw data of daily news, reducing its reliability. Therefore, cleaning the news headlines before extracting sentiment scores is imperative. Through tokenization and normalization, natural language processing (NLP) improves the quality of raw text corpora. Each word in the headline is separated into tokens by tokenizing headline text. The text corpus is then normalized by converting it to lowercase, removing special characters, numbers, punctuation, and

[19] A long-short portfolio is computed by taking into account emissions minus clean (EMC). In the EMC portfolio, emission stocks are purchased equally or on a value-weighted basis and clean stocks are sold on an equal- or value-weighted basis.

whitespaces. The NLP has been widely used in finance literature when dealing with qualitative data that has a great deal of noise. Recently, Kraaijeveld and De Smedt (2020) uses NLP for tidying corpus of tweets used in predicting crypto currencies returns. Goutte (2021) uses NLP as a preprocessing method for cleaning Stock Twits data obtained for analyzing investors' beliefs and actions about future investment prospects. Bang et al. (2023) utilizes NLP in analyzing news data obtained for ESG equities in the stock market of Korea.

### 3.2. Climate News Sentiment Score

A further phase of tidying the news headlines text corpus is completed in which the qualitative information contained in the raw data is converted into a quantitative sentiment score. As a part of the sentiment analysis process, text data is analyzed using a lexicon or dictionary-based technique that has its own predefined collection of words each of which is assigned a score and may be used to establish the semantic orientation of a text. For instance, the lexicon contains words ranked according to their level of positivity or negativity. Most lexicons have three categories of scores: positive, neutral, and negative, but some have more. In typical applications, the presence of negative or positive words in a corpus of text is used to measure the emotional content of the corpus. One method of obtaining sentiment scores is through the Valence Aware Dictionary for Sentiment Reasoning (VADER) analyzer developed by Hutto and Gilbert (2014). It classifies sentiment based on sentence-level information. In addition to a lexicon, which includes a variety of words labeled from most negative to most positive, there are heuristic rules that consider a word's context. The context is captured through simple rules related to negation, punctuation, and capitalization, preceded by, or followed by the word "but" and the degree modifier "very", "extremely" or "slightly". The positive, negative, neutral scores obtained using VADER sentiment analysis on the sentence level is used to calculate the aggregate score. According to Hutto and Gilbert (2014), the aggregate valence score represented by the compound score is normalized between -1 and +1 through the following equation.

$$CS_t = \frac{SS_t}{\sqrt{{SS_t}^2 + \alpha}}$$

where the compound score ($CS_t$) computed by VADER on day t equals the sum of valence scores ($SS_t$), positive, negative, and neutral. Divided by the square root of the ($SS_t$) raised to power two plus alpha. As such, alpha takes a default value of 15 in VADER sentiment analysis.

Secondly, robustness of our sentiment scores were investigated through utilizing the Loughran and McDonald (2011) lexicon for sentiment analysis. In Loughran and McDonald (LM) sentiment analysis the meaning of a word can varies depending on its domain. It emphasizes words which can differ when used in common parlance from when used in economics or finance domains, so classify each word independently. Liability, for instance, is neutral in a financial setting but typically negative in everyday language. The composite sentiment score in LM will be calculated based on net positivity following Shapiro et al. (2022).

$$CS_t = Pos_t - Neg_t$$

where the composite score ($CS_t$) computed by LM on day t equals the difference between the collective positive word's sentiment ($Pos_t$) and negative words sentiment ($Neg_t$) in each news headline.

The Valence Aware Dictionary for Sentiment Reasoning (VADER) analyzer and Loughran & McDonald (LM) lexicons are widely used in economic and financial literature. The VADER and LM lexicons, for instance, were recently used by Kraaijeveld and De Smedt (2020) in analyzing Twitter sentiment in predicting crypto currencies returns. Also, both sentiments were utilized by Li et al. (2020), for analyzing the predictability of news sentiment on the stock market returns of Hong Kong. Both lexicons were also used by Shapiro et al. (2022), for quantifying the sentiment perceived by news.

### 3.3. The Climate Change News Cumulative Sentiment Scores

There has been research indicating that news can have a delayed impact on asset prices (Andreassen, 1990; McQueen et al., 1996; Klibanoff et al., 1998; Li et al., 2021). The reactions of some investors to news tend to be more immediate, whereas others need time to retrieve and process news and therefore manifest delayed reactions. Thus, following Li et al., (2021) method of constructing news sentiment, we can assume that the average daily news on a given day is affected by both recent and historical events. As such, recent news receives more weight than older news stories (Andreassen, 1990; Li et al., 2021). Therefore, a cumulative sentiment score is built following this methodology. A cumulative sentiment score is calculated by adding the sentiment value on day t to the sum of the sentiment value of six consecutive days prior, as shown in the equation below.

$$CumS_t = \sum_{d=1}^{6} e^{\frac{-d}{7}} CS_{t-d} + CS_t$$

where the cumulative sentiment score on day t is represented by $CumS_t$. The exponentially adjusted sentiment value of day t− d is denoted by $\sum_{d=1}^{6} e^{\frac{-d}{7}} CS_{t-d}$. As for $CS_t$, it specifies the compound (composite) sentiment value on day t.

Furthermore, dummy variable is used to separate positive sentiment from negative sentiment. A dummy variable is assigned to the cumulative sentiment score ($CumS_t$) in order to distinguish positive sentiment from negative sentiment. It is possible to obtain the positive (negative) sentiment series by multiplying the cumulative sentiment score series with an indicator function that takes a value of 1 if the cumulative sentiment is positive (negative) and 0 otherwise (Rognone et al., 2020).

### 3.4. Empirical model

To eliminate additional restrictive assumptions necessary to assign a behavioral interpretation to every parameter, the Vector Autoregressive model (VAR) makes explicit identification assumptions to isolate estimates of climate sentiment index behavior and its effects on the GCC stock market's returns. As Sims (1980) developed VARs, they were used for a range of purposes, including the nexus between the return on real estate property and the macroeconomic variables (Brooks and Tsolacos, 1999), examining how technology shocks affect the number of hours worked (Galí, 1999), and determining the relative impact of money on output (Sims & Zha, 2006). The use of the model in this study can give an insight into the stochastic changes in our variables given the climate change sentiment index movements throughout the sampling period.

The VAR model used will take the following general form given by, (Sims, 1980).

$$Ay_{it} = A\alpha_i + \sum_{n=1}^{p} \mathrm{T}\beta_i y_{it-n} + \varepsilon_{it}$$

where, $y_t$ is a (n×1) vector of endogenous variables. The list of endogenous variables to be used will include the returns and volatility of the GCC stock market for the case of Qatar and UAE, the positive and negative climate change sentiment index, return on Dow Jones Global Index (DJW), return on Brent Crude oil prices (BRENT), and CBOE

Volatility Index (VIX). $A\alpha_i$ is a (n×1) vector of the intercept that has a unique value in each endogenous variable equation. T$\beta_i$is the (n×nn×1) matrix attached to the explanatory variables (endogenous variables lags, $y_{it-n}$). $\varepsilon_{it}$ is a (n×1) vector of the residuals that has a unique value in each endogenous variable equation.

To start with specifying our VAR with restriction model, we first illustrate below the matrix equation for a Vector Autoregressive (VAR) Model with no restriction of our seven endogenous variables assuming one lag.

$$\begin{bmatrix} Return_{1t} \\ Volatlity.R_{2t} \\ RBRENT_{3t} \\ RDJW_{4t} \\ VIX_{5t} \\ Pos_{6t} \\ Neg_{7t} \end{bmatrix} = \begin{bmatrix} \alpha_{1t} \\ \alpha_{2t} \\ \alpha_{3t} \\ \alpha_{4t} \\ \alpha_{5t} \\ \alpha_{6t} \\ \alpha_{7t} \end{bmatrix} + \begin{bmatrix} \beta_{11t} & \beta_{12t} & \beta_{13t} & \beta_{14t} & \beta_{15t} & \beta_{16t} & \beta_{17t} \\ \beta_{21t} & \beta_{22t} & \beta_{23t} & \beta_{24t} & \beta_{25t} & \beta_{26t} & \beta_{27t} \\ \beta_{31t} & \beta_{32t} & \beta_{33t} & \beta_{34t} & \beta_{35t} & \beta_{36t} & \beta_{37t} \\ \beta_{41t} & \beta_{42t} & \beta_{43t} & \beta_{44t} & \beta_{45t} & \beta_{46t} & \beta_{47t} \\ \beta_{51t} & \beta_{52t} & \beta_{53t} & \beta_{54t} & \beta_{55t} & \beta_{56t} & \beta_{57t} \\ \beta_{61t} & \beta_{62t} & \beta_{63t} & \beta_{64t} & \beta_{65t} & \beta_{66t} & \beta_{67t} \\ \beta_{71t} & \beta_{72t} & \beta_{73t} & \beta_{74t} & \beta_{75t} & \beta_{76t} & \beta_{77t} \end{bmatrix} \times \begin{bmatrix} R_{eturn1t-1} \\ Volatlity.R_{2t-1} \\ RBRENT_{3t-1} \\ RDJW_{4t-1} \\ VIX_{5t-1} \\ Pos_{6t-1} \\ Neg_{7t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix}$$

To testify our hypothesis concerning the impact of climate change positive and negative news sentiments on the GCC stock market index returns and volatility, we have set a restriction to the positive and negative sentiments value in their own equations with return on DJW, return on Brent, and VIX equations to zero. The following equation matrix depicts the VAR model with the indicators used for this study.

$$\begin{bmatrix} Return_{1t} \\ Volatlity.R_{2t} \\ RBRENT_{3t} \\ RDJW_{4t} \\ VIX_{5t} \\ Pos_{6t} \\ Neg_{7t} \end{bmatrix} = \begin{bmatrix} \alpha_{1t} \\ \alpha_{2t} \\ \alpha_{3t} \\ \alpha_{4t} \\ \alpha_{5t} \\ \alpha_{6t} \\ \alpha_{7t} \end{bmatrix} + \begin{bmatrix} \beta_{11t} & \beta_{12t} & \beta_{13t} & \beta_{14t} & \beta_{15t} & \beta_{16t} & \beta_{17t} \\ \beta_{21t} & \beta_{22t} & \beta_{23t} & \beta_{24t} & \beta_{25t} & \beta_{26t} & \beta_{27t} \\ \beta_{31t} & \beta_{32t} & \beta_{33t} & \beta_{34t} & \beta_{35t} & 0 & 0 \\ \beta_{41t} & \beta_{42t} & \beta_{43t} & \beta_{44t} & \beta_{45t} & 0 & 0 \\ \beta_{51t} & \beta_{52t} & \beta_{53t} & \beta_{54t} & \beta_{55t} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} R_{eturn1t-1} \\ Volatlity.R_{2t-1} \\ RBRENT_{3t-1} \\ RDJW_{4t-1} \\ VIX_{5t-1} \\ Pos_{6t-1} \\ Neg_{7t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix}$$

Having estimated the VAR model with restriction, we performed an Impulse Response Function (IRF). An IRF is conducted to investigate the impact of a unit shock to the climate change news sentiments on the stock market performance of both ESG and general stock market indices (Sims, 1980; Koop et al., 1996).

The Impulse Response Function (IRF) for depicting the ESG or general stock market indices returns and volatility for Qatar and UAE response to a shock in climate change news positive or negative sentiments take the following general form given by, (Sims, 1980).

$$y_{it} = \sum_{j=0}^{\infty} \forall_{ij} \epsilon_{it-j}$$

Where the equation shows the endogenous variables responses ($y_{it}$) to shocks in the sentiment impulses ($\forall_{ij} \epsilon_{it-j}$).

## 4. DATA FACTS AND VISUALIZATION

### 4.1. Stock Market Data Description

Our daily indices' prices and characteristics are retrieved from DataStream. This study used five major indices, all of which were representative of Qatar (QA) and the United Arab Emirates (UAE), two countries in the Gulf Cooperation Council. The sample period of our study is unbalanced and extends from 1st June 2016 to 30th June 2023. The ESG equity indices of QA and UAE are MSCI QSE 20 ESG Index and S&P-Hawkamah ESG UAE Index, respectively. The two ESG indices have distinctive characteristics from the methodology of construction, goal, rebalancing, and others. The decomposition of the MSCI QSE 20 ESG index constitute of top 20 equities that are involved in Enviromental, Social, and Governance (ESG) reporting in Qatar. Figure 1 shows the decomposition of the index, which is constituted of 68.34% from financials, 10.70% from energy, 7.41% from industrials, 4.66% from communication services, 3.40% from materials, 2.37% from real estate, 2.07% from utilities, and 1.05% from consumer staples, respectively. Based on certain ESG metrics, the index seeks to increase exposure to companies that demonstrate strong ESG profiles and a positive trend toward improving them. The index rebalancing takes place periodically and quarterly. As for the S&P-Hawkamah ESG UAE Index, it consists of the best 20 stocks in the UAE based on ESG factors. Figure 2 shows the decomposition of the index which constitute of 30.90% from financials, 18.60% from real estate, 12.60% from industrials, 9.30% from communication services, 9.10% from energy, 6.90% from utilities, 5.20% from consumer staples, 3.90% from consumer discretionary, and 3.40% materials, respectively. The index rebalancing takes place annually every November. In addition, the general stock market index used for the purpose of the thesis for QA and UAE are Doha General Index (QSI), Dubai Financial Market General Index (DFMGI), and FTSE ADX General Index (FTFADGI), respectively.

Furthermore, we considered variables related to the global stock markets, including the Dow Jones global index, the CBOE volatility index, and Brent crude oil prices. Figures 3 and 4 shows the trajectory analysis for Qatar stock market data with global parameters in the form of raw data and log returns, respectively. Figures 5 and 6 show the trajectory analysis for UAE stock market data in the form of raw data and log returns, respectively. Tables 1 and 2 summarize the symbols of the indices used for this study with the description of the variable and the data available.

The log returns for the stock market data were calculated using the following formula. Tables 3 and 4 summarize the descriptive statistics for the return series for each index in each country, respectively.

$$R_t = 100 \times \left(\frac{P_t}{P_{t-1}}\right)$$

where the log return on day t is represented by $R_t$. The $P_t$ indicates the indices price.

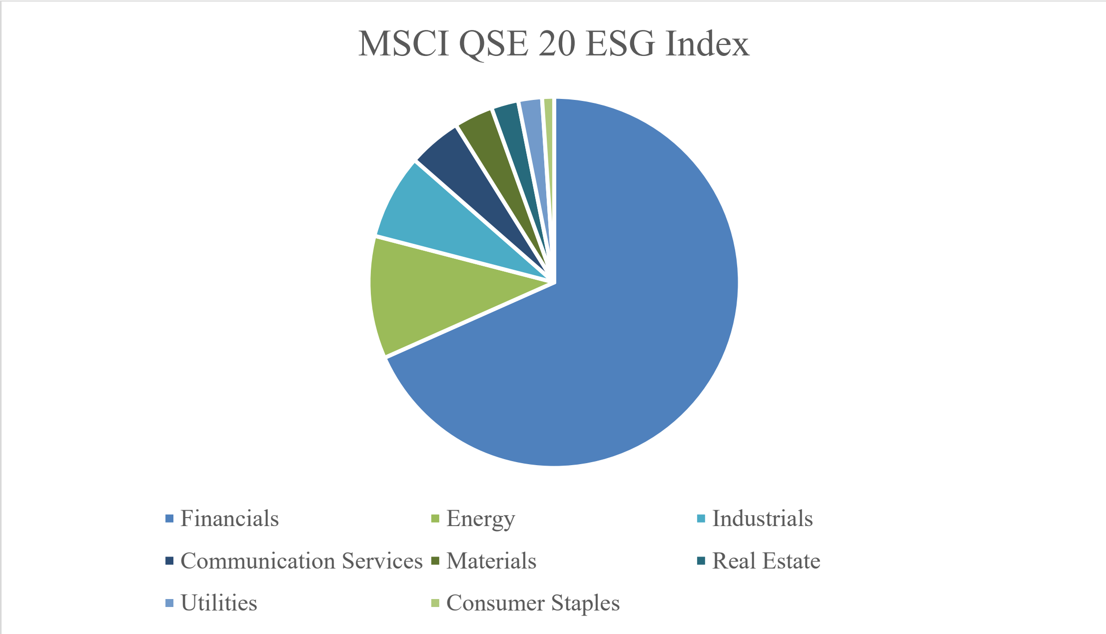



Figure 1. MSCI QSE 20 ESG Index Decomposition

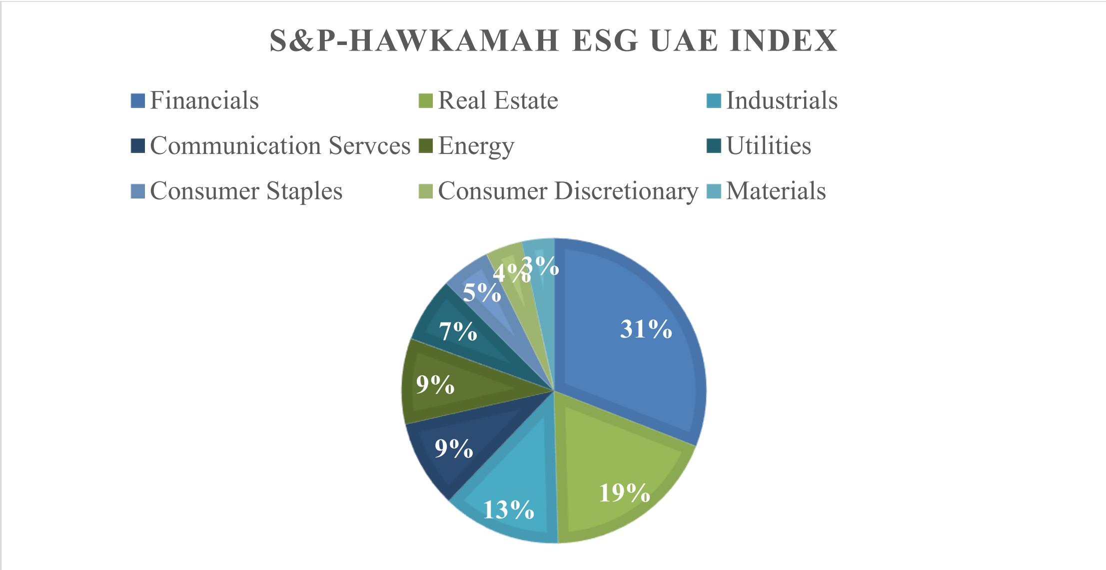



Figure 2. S&P-Hawkamah ESG UAE Index Decomposition

Table 1. Variables Description for Qatar

| Variable Symbol | Description | Data Sample (Daily) |
|---|---|---|
| **QSI** | Doha General Index | June 2016-June 2023 |
| **ESG** | MSCI QSE 20 ESG Index | June 2016-June 2023 |
| **DJW** | Dow Jones Global World Index (DJWD) | June 2016-June 2023 |
| **VIX** | CBOE Market Volatility Index | June 2016-June 2023 |
| **BRENT** | Brent Crude Oil Index | June 2016-June 2023 |

Table 2. Variables Description for United Arab Emirates

| Variable Symbol | Description | Data Sample |
|---|---|---|
| **ADX** | FTSE ADX General Index (FADGI) | June 2016-June 2023 |
| **DFM** | Dubai Financial Market General Index (DFMGI) | June 2016-June 2023 |
| **ESG** | S&P/Hawkamah ESG UAE Index (SPHMUEUP) | June 2016-June 2023 |
| **DJW** | Dow Jones Global World Index (DJWD) | June 2016-June 2023 |
| **VIX** | CBOE Market Volatility Index (VIX) | June 2016-June 2023 |
| **BRENT** | Brent Crude Oil Prices | June 2016-June 2023 |

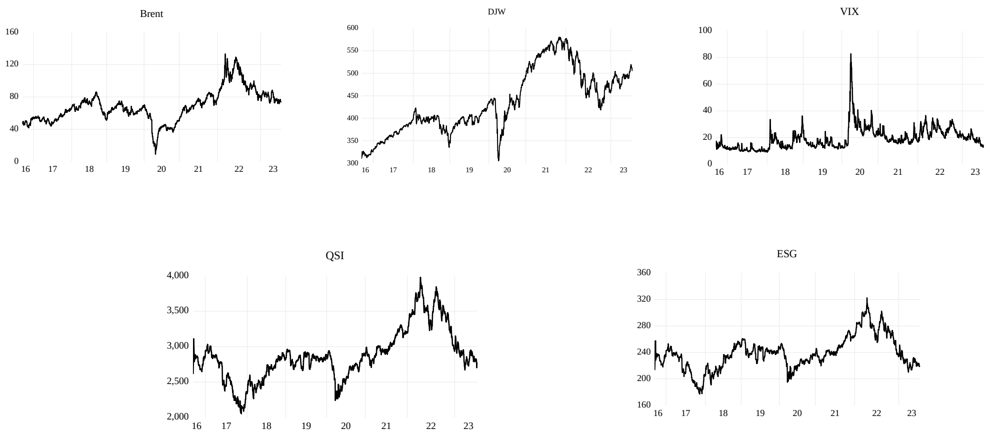
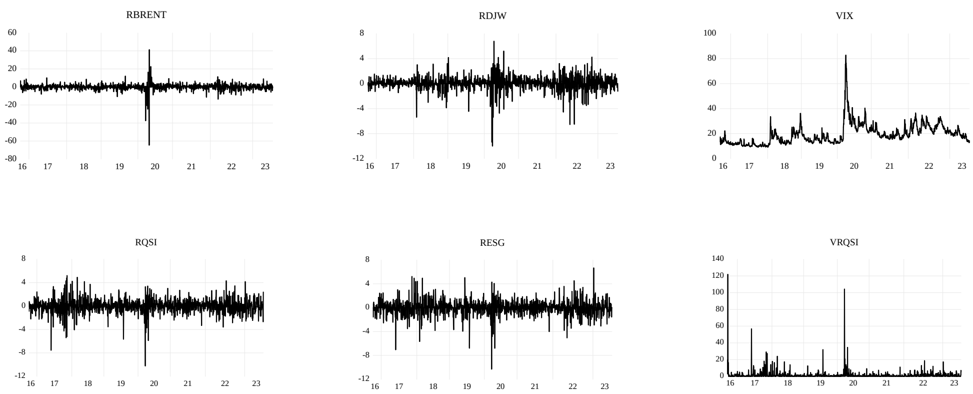



Figure 3. Stock Market Raw Data in Level for Qatar and Global Parameters

Note: Abbreviations: Brent Crude Oil Prices (BRENT), Dow Jones Global World Index Prices (DJW), CBOE Market Volatility Index (VIX), Doha General Index Prices (QSI), and MSCI QSE 20 ESG Index Prices (ESG)



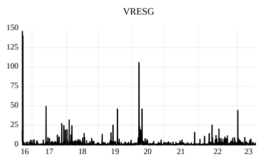



Figure 4. Stock Market Data with log returns for Qatar and Global Parameters

Note: Abbreviations: Log Return of Brent Crude Oil (RBRENT), Log Return of Dow Jones Global World Index (RDJW), CBOE Market Volatility Index (VIX), Log Return of Doha General Index (RQSI), Log Return of MSCI QSE 20 ESG Index (RESG), log Realized Volatility of Doha General Index (VRQSI), and log Realized Volatility of MSCI QSE 20 ESG Index (VRESG)


Figure 5. Stock Market Raw Data in Level for UAE

Note: Abbreviations: FTSE ADX General Index Prices (ADX), Dubai Financial Market General Index Prices (DFM), and S&P/Hawkamah ESG UAE Index Prices (ESG).

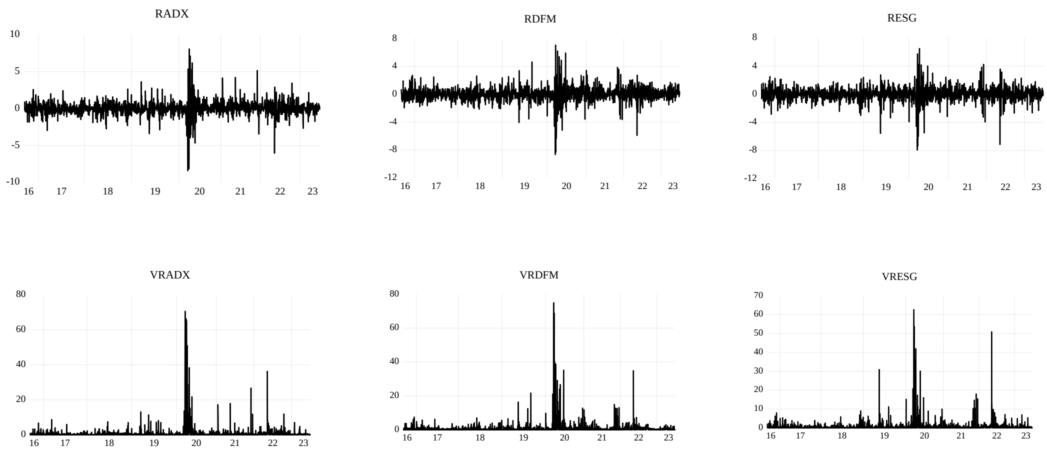



Figure 6. Stock Market Data with log returns for UAE

Note: Abbreviations: Log Return of FTSE ADX General Index (RADX), Log Return of Dubai Financial Market General Index (RDFM), Log Return of S&P/Hawkamah ESG UAE Index (RESG), log Realized

Volatility of FTSE ADX General Index (VRADX), log Realized Volatility of Dubai Financial Market General Index (VRDFM), and log Realized Volatility of S&P/Hawkamah ESG UAE Index (VRESG).

Table 3. Variable's Descriptive Statistics for Qatar

| | RQSI | RESG | VRQSI | VRESG | RDJW | RBRENT | VIX |
|---|---|---|---|---|---|---|---|
| **Mean** | -0.004 | -0.007 | 1.385 | 1.457 | 0.029 | 0.023 | 19.685 |
| **Maximum** | 5.189 | 6.645 | 104.197 | 105.544 | 6.767 | 41.202 | 82.690 |
| **Minimum** | -10.208 | -10.274 | 0.000 | 0.000 | -9.969 | -64.370 | 9.150 |
| **Standard Deviation** | 1.177 | 1.207 | 4.368 | 4.733 | 1.095 | 3.635 | 8.239 |
| **Skewness** | -0.717 | -0.654 | 12.818 | 11.423 | -1.424 | -4.012 | 2.403 |
| **Kurtosis** | 10.931 | 11.528 | 252.722 | 199.789 | 17.377 | 98.429 | 14.774 |
| **Observation** | 1456 Days | 1456 Days | 1456 Days | 1456 Days | 1456 Days | 1456 Days | 1456 Days |

The variables VRQSI and VRESG depict the volatility proxy of RQSI and RESG, respectively. The log realized volatility is the square of daily return (see Andersen & Bollerslev, 1998; Barndorff-Nielsen & Shephard, 2002).

Table 4. Variable's Descriptive Statistics for United Arab Emirates

| | RADX | RDFM | RESG | VRADX | VRDFM | VRESG |
|---|---|---|---|---|---|---|
| **Mean** | 0.041 | 0.004 | 0.009 | 0.920 | 1.000 | 0.960 |
| **Maximum** | 8.079 | 7.062 | 6.474 | 70.616 | 74.910 | 62.605 |
| **Minimum** | -8.403 | -8.655 | -7.912 | 0.000 | 0.000 | 0.000 |
| **Standard Deviation** | 0.959 | 1.000 | 0.980 | 4.201 | 4.047 | 3.573 |
| **Skewness** | -0.415 | -0.705 | -0.965 | 11.189 | 11.608 | 10.424 |
| **Kurtosis** | 21.957 | 17.384 | 14.900 | 151.099 | 170.785 | 137.055 |
| **Observation** | 1866 Days | 1866 Days | 1866 Days | 1866 Days | 1866 Days | 1866 Days |

The variables VRADX, VRDFM and VRESG depict the volatility proxy of RADX, RDFM and RESG, respectively. The log realized volatility is the square of daily return (see Andersen & Bollerslev, 1998; Barndorff-Nielsen & Shephard, 2002).

### 4.2. News Data Description

The news headline sample is taken from the Reuters News Monitor and consists of news published between June 2016 till June 2023. We restrict the analysis to climate-related headlines. It is interesting to note that Reuters has attached a news topic guide that categorizes the news headlines. We used three categories within this classification:

environment, climate change, and natural disasters news stories. Table 5 summarizes the news stories covered under each category. As part of our study, we aimed to configure climate news's impact on the GCC countries, given the region where the news has been published. Table 6 summarizes the statistics of news classification according to their region and type of publication from Thomson Reuters. Cleaning the corpus of news headlines before extracting sentiment scores is imperative. So, we report the preprocessing of a sample for news headlines before and after the cleaning process in Table 7. During our sampling period, disaster news headlines were massive, so we wanted to analyze the differences in each news classification depending on the region and whether disaster headlines were included. The robustness of the result would also be assessed in this way. Therefore, we classified our finalized news stories to be used in our analysis into the following sets:

#### *4.2.1. Global News Data with Disaster (GNDWD)*

This set contains news stories published worldwide, consisting of 9,411 sources about Qatar or UAE, provided the search criteria satisfy the topic guide for environment, climate change, and natural disasters news. This classification includes a total of 8,303 daily news headlines for Qatar from 02$^{nd}$ June 2016 through 30$^{th}$ June 2023. Meanwhile, it includes a total of 27,180 daily news headlines for UAE from 01$^{st}$ September 2016 through 30$^{th}$ June 2023. A word cloud visualization for this corpus of news for Qatar and the UAE is shown in Figures 7 and 8. The word cloud visualization summarizes the most repeated words from the cleaned corpus of news which should be indicative of our news topics elected for this purpose. In Qatar word cloud visualization, for instance, words such as climate change, Qatar sustainability, energy, green, water, food security, environment, and others are all represented by our news topics selected.

In the meantime, the UAE word visualization involves text such as climate change, renewable energy, sustainable development, flood victims, and others that are all represented by our news topics selected for this purpose.

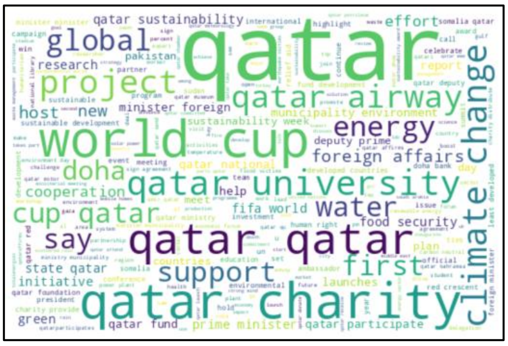



Figure 7. Word Cloud Visualization- Global News Data with Disaster for Qatar

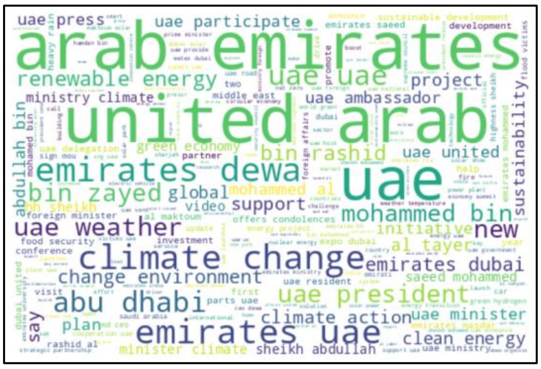



Figure 8. Word Cloud Visualization- Global News Data with Disaster for UAE

#### *4.2.2. Global News Data without Disaster (GNDWOD)*

This set contains news stories published worldwide, consisting of 9,411 global news sources about Qatar or UAE, provided the search criteria satisfy the topic guide for environment and climate change. This classification includes a total of 7,231 daily news headlines for Qatar from 23rd June 2016 through 30th June 2023. Meanwhile, it includes a total of 23,301 daily news headlines for UAE from 2nd October 2016 through 30th June 2023. A word cloud visualization for this corpus of news for Qatar and the UAE is shown in Figures 9 and 10. The word cloud visualization summarizes the most repeated words from the cleaned corpus of news which should be indicative of our news topics elected for this purpose.

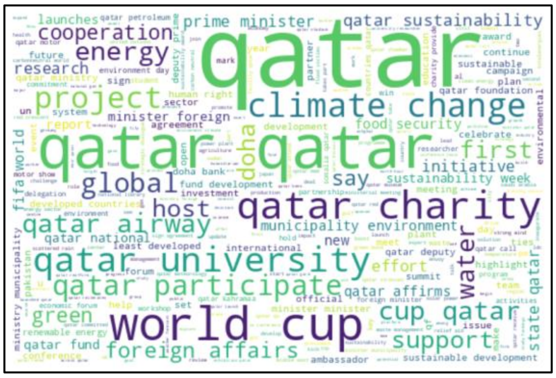



Figure 9. Word Cloud Visualization- Global News Data without Disaster for Qatar


Figure 10. Word Cloud Visualization- Global News Data without Disaster for UAE

#### *4.2.3. GCC News Data with Disaster (GCCNDWD)*

The set contains news stories about Qatar or UAE published in the GCC, with 148 sources, provided the search criteria are relevant to environmental, climate change, and natural disasters news topics. This classification includes a total of 3,863 daily news headlines for Qatar from 2nd October 2016 through 28th June 2023. Meanwhile, it includes a total of 11,077 daily news headlines for UAE from 1st October 2016 through 30th June 2023. A word cloud visualization for this corpus of news for Qatar and the UAE is shown in Figures 11 and 12. The word cloud visualization summarizes the most repeated words from the cleaned corpus of news which should be indicative of our news topics elected for this purpose.

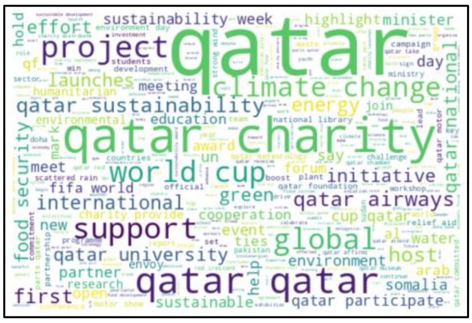



Figure 11. Word Cloud Visualization- GCC News Data with Disaster for Qatar


Figure 12. Word Cloud Visualization- GCC News Data with Disaster for UAE

#### *4.2.4. GCC News Data without Disaster (GCCNDWOD)*

The set contains news stories about Qatar or UAE published in the GCC, with 148 sources, provided the search criteria are relevant to environmental and climate change news topics. This classification includes a total of 3,503 daily news headlines for Qatar from 2nd October 2016 through 28th June 2023. Meanwhile, it includes a total of 8,613 daily news headlines for UAE from 3rd October 2016 through 30th June 2023. A word cloud visualization for this corpus of news for Qatar and the UAE is shown in Figures 13 and 14. The word cloud visualization summarizes the most repeated words from the cleaned corpus of news which should be indicative of our news topics elected for this purpose.

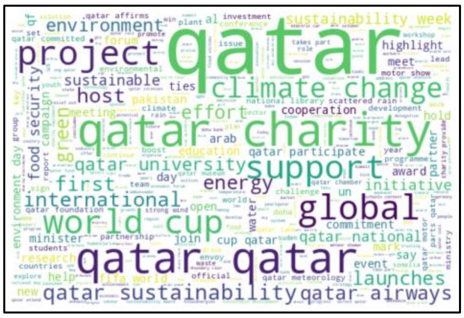



Figure 13. Word Cloud Visualization- GCC News Data without Disaster for Qatar

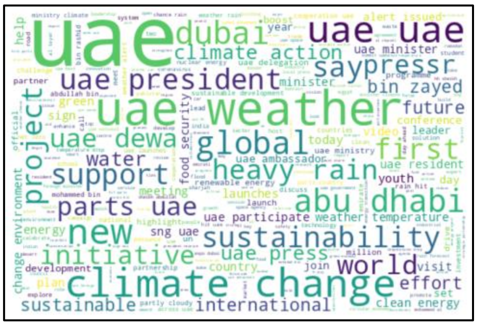



Figure 14. Word Cloud Visualization- GCC News Data without Disaster for UAE

#### *4.2.5. Local News Data with Disaster (LNDWD)*

In this set, you will find 10 and 70 local news sources in Qatar and the UAE, respectively. It assumes that the search criteria satisfy those listed in the topic guide for the environment, climate change, and natural disasters. This classification includes a total of 2,642 daily news headlines for Qatar from 2$^{nd}$ October 2016 through 28$^{th}$ June 2023. Meanwhile, it includes a total of 9,445 daily news headlines for UAE from 1$^{st}$ October 2016 through 30$^{th}$ June 2023. A word cloud visualization for this corpus of news for Qatar and the UAE is shown in Figures 15 and 16. The word cloud visualization summarizes the most repeated words from the cleaned corpus of news which should be indicative of our news topics elected for this purpose.


Figure 15. Word Cloud Visualization- Local News Data with Disaster for Qatar

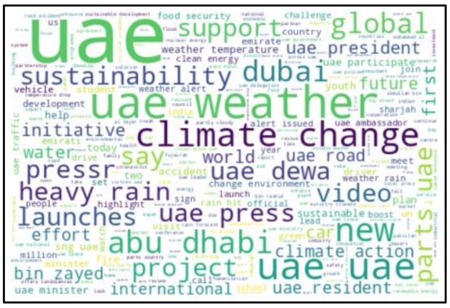



Figure 16. Word Cloud Visualization- Local News Data with Disaster for UAE

#### *4.2.6. Local News Data without Disaster (LNDWOD)*

In this set, you will find 10 and 70 local news sources in Qatar and the UAE, respectively. It assumes that the search criteria satisfy those listed in the topic guide for the environment and climate change. This classification includes a total of 2,297 daily news headlines for Qatar from 2$^{nd}$ October 2016 through 28$^{th}$ June 2023. Meanwhile, it includes a total of 7,949 daily news headlines for UAE from 3$^{rd}$ October 2016 through 30$^{th}$ June 2023. A word cloud visualization for this corpus of news for Qatar and the UAE is shown in Figures 17 and 18. The word cloud visualization summarizes the most repeated words from the cleaned corpus of news which should be indicative of our news topics elected for this purpose.

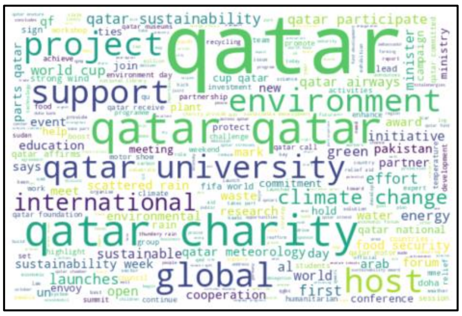



Figure 17. Word Cloud Visualization- Local News Data without Disaster for Qatar


Figure 18. Word Cloud Visualization- Local News Data without Disaster for UAE

Table 5. Classification of news by categories from Thomson Reuters

| No. | Categories | News Topic |
|---|---|---|
| 1 | **DISASTERS / ACCIDENTS [DIS]** | Air Accidents [CRSH] |
| | | Droughts [DFTS] |
| | | Floods [FLD] |
| | | Ground Accidents / Collisions [COLL] |
| | | Sea Accidents [DRWN] |
| | | Tsunami [TWAVE] |
| | | Wildfires / Forest Fires [WFIRE] |
| | | Wind / Hurricanes / Typhoons / Tornadoes [WND] |
| | | Earthquakes [QUAK] |
| | | Fires [INCEN] |
| 2 | **Climate Change [CLC]** | Circular Economy [CIRECO] |
| | | Climate Adaptation and Solutions [CLA] |
| | | Carbon Offsetting [CAROFF] |
| | | Carbon Pricing [CARPRI] |
| | | Climate Policy and Regulation [CLR] |
| | | Climate Finance [CLF] |
| | | Climate Politics [WRM] |
| 3 | **ENVIRONMENT [ENV]** | Carbon Neutrality [CNEUT] |
| | | Deforestation [DEFOR] |
| | | Pollution [AWLQ] |
| | | Greenhouse Gases [GHGS] |
| | | Green Technology [GRNTCH] |
| | | Nature / Wildlife [NATU] |
| | | Recycling [RECYCL] |

| | | |
|---|---|---|
| | | Waste Management [WASTE] |
| | | Weather [WEA] |
| | | Water [H2O] |

Table 6. Classification of news by Region and Type of Publication by Thomson Reuters

| News Classification by Region | News Wire | Global Press | Web News | Social Media | Total |
|---|---|---|---|---|---|
| ***Global News*** | 1,090 | 4,534 | 3,786 | 1 | 9,411 |
| ***GCC News*** | 16 | 91 | 40 | 1 | 148 |
| ***UAE Local News*** | 6 | 47 | 16 | 1 | 70 |
| ***Qatar Local News*** | 1 | 9 | 0 | 1 | 11 |

The global news wires include the Dow Jones News (DJN), Financial Times (FT), CNBC, London Stock Exchange Regulatory News (LSEND), The Guardian (THEGRD), Reuters News (RTRS), and others. While the global press constitutes of ABA Banking Journal (ABABAN), AANA Journal (AANJOU), Wall Street Journal (WSJ), Economist (ECONST), and others. The global web news constitutes of North Jersey (NORJER), Wales Online (WALONM). AT News (ATNITA), and others. Meanwhile, the GCC's news wires include Bahrain Bourse (BHB), Kuwait News Agency (KUNA), Saudi Press Agency (SAUPRE), NASDAQ Dubai (NDBX), and others. While the GCC's global press constitute of Bahraini Company News Bites (BAHBIT), Gulf Daily News (GULDAI), Kuwait Times (KUWTIM), and others. The GCC's web news includes Akhbar Al Khaleej (AKHALK), Al Watan News (ALWATB), Asharq Al-Awsat (ASHAWS), and others. In terms of UAE's news wires, it constitutes of Emirates News Agency (EMIRNA), Zawya (ZAWYA), and others. While the UAE's global press includes Arabian Post (ARAPOS), Dubai PR Network (DUBPRN), Gulf Business (GULBUS), and others. The UAE's web news constitutes of Emarat Al Youm (EMAALY), Oil and Gas Middle East (OILGAV), and others. As for Qatar's news wires it is only constitute of Qatar Exchange News Services (QE). While Qatar's global press includes Al Jazeera (ALJAZE), The Peninsula (PENQAT), Qatar Tribune (QATTRI), and others. According to the Thomson Reuters' news monitor, Twitter-published news is the only source of social media news available. It is categorized according to the region in which it is posted.

Table 7. News Headlines Sample of Cleaned Data through NLP for Qatar and UAE

| Positive News | | | | |
|---|---|---|---|---|
| **Date** | **Row News Data** | **Cleaned News Data** | **VADER** | **LM** |
| | | | $CS_t$ | $CS_t$ |
| **26-Jun-23** | SNG Qatar energy sector sees decade of accomplishments leveraging | sng qatar energy sector sees decade accomplishments | 0.7096 | 0.0830 |

| | | | | |
|---|---|---|---|---|
| | huge natural gas resources | leveraging huge natural gas resources | | |
| **28-May-23** | United Arab Emirates : DEWA?s Cleantech Youth Programme currently accepting applications from students and graduates of local universities | united arab emirates dewas cleantech youth programme currently accepting applications students graduates local universities | 0.6597 | 0.0000 |
| **09-May-23** | PRESSR: AIQ to showcase spearheading AI solutions for the energy sector at the UAE Climate Tech Forum | pressr aiq showcase spearheading ai solutions energy sector uae climate tech forum | 0.4215 | 0.0000 |
| **6-Dec-22** | Generosity™ and Qatar the 2022 World Cup Host Country Partner to Eliminate Plastic Waste with their Sustainability Initiative | generosity qatar world cup host country partner eliminates plastic waste sustainability initiative | 0.128 | 0.0000 |
| **29-Aug-20** | Green Qatar campaign at advanced stage | green qatar campaign advanced stage | 0.25 | 0.0000 |
| **02-Mar-18** | DCMMI successfully establishes the "United Arab Emirates Marine Environment Protection Association" UAEMEPA | dcmmi successfully establishes united arab emirates marine environment protection association uaemepa | 0.7184 | 0.0909 |
| **04-Dec-17** | United Arab Emirates : Farnek partners with myclimate, DCCE for carbon neutral cleaning programme | united arab emirates farnek partners myclimate dcce carbon neutral cleaning programme | 0.4215 | 0.0000 |
| **16-May-17** | United Arab Emirates : MBRSC showcases the first Sustainable Autonomous House for hot and humid climate | united arab emirates mbrsc showcases first sustainable autonomous house hot humid climate | 0.4215 | 0.0000 |

**Negative News**

| **Date** | **Row News Data** | **Cleaned News Data** | **VADER** | **LM** |
|---|---|---|---|---|
| | | | $CS_t$ | $CS_t$ |
| **8-Jun-23** | FIFAs claim of carbon neutral Qatar 2022 World Cup branded misleading by regulator | fifas claim of carbon neutral qatar 2022 world cup branded misleading by regulator | -0.4019 | -0.1000 |
| **7-Jun-23** | Fifa gets red card on greenwashing in Qatar World Cup claims | fifa gets red card on greenwashing in qatar world cup claims | -0.1027 | -0.1111 |
| **29-Jul-22** | UAE: Six expats found dead after floods, say authorities | uae six expats found dead floods say authorities | -0.6486 | 0.0000 |
| **28-Jun-22** | 6.0 magnitude earthquake strikes southern Iran, slightly felt in UAE | magnitude earthquake strikes southern iran slightly felt uae | -0.3612 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| **28-Jul-22** | UAE: Red alert for 'hazardous weather' issued, unstable conditions expected | uae red alert hazardous weather issued unstable conditions expected | -0.0772 | -0.2222 |
| **24-Oct-19** | UAE warns of tropical storm in Arabian Sea | uae warns tropical storm arabian sea | -0.1027 | -0.1667 |
| **21-Nov-17** | UN report on Qatar per capita carbon emission unfair | un report qatar per capita carbon emission unfair | -0.4767 | -0.1250 |

The $CS_t$ represents the compound (composite) score for each sentiment analysis method, including the Valence Aware Dictionary for Sentiment Reasoning (VADER) and Loughran-McDonald (LM) lexicons.

### 4.3. News Data Sentiment Description

The news data sentiment specifies the sentiment scores of each news headline included in our data sample. The daily news sentiment obtained were then calculated by taking the average news sentiment in each day. The cumulative sentiment scores were then calculated using the equation provided in Section 3. The positive versus negative sentiment scores were then segregated using an indicator. Figures 19 and 20 illustrate the trajectory analysis of the average daily VADER compound sentiment scores versus the cumulative sentiment scores for climate change news with disaster about Qatar and UAE, respectively.

Meanwhile, as we conducted three different robustness checks, we illustrated the trajectory analysis for the data used for that purpose. Figures 21 and 22 illustrate the trajectory analysis of the average daily composite score obtained using LM lexicon for Qatar and UAE climate change news with disaster, respectively. Figures 23 and 24 illustrate the trajectory analysis for the climate change news VADER compound sentiment scores versus the cumulative sentiment scores for Qatar and UAE's climate news without disaster, respectively. As a third robustness check, we examine the causal relationship between GCC stock market data and climate change news sentiment.

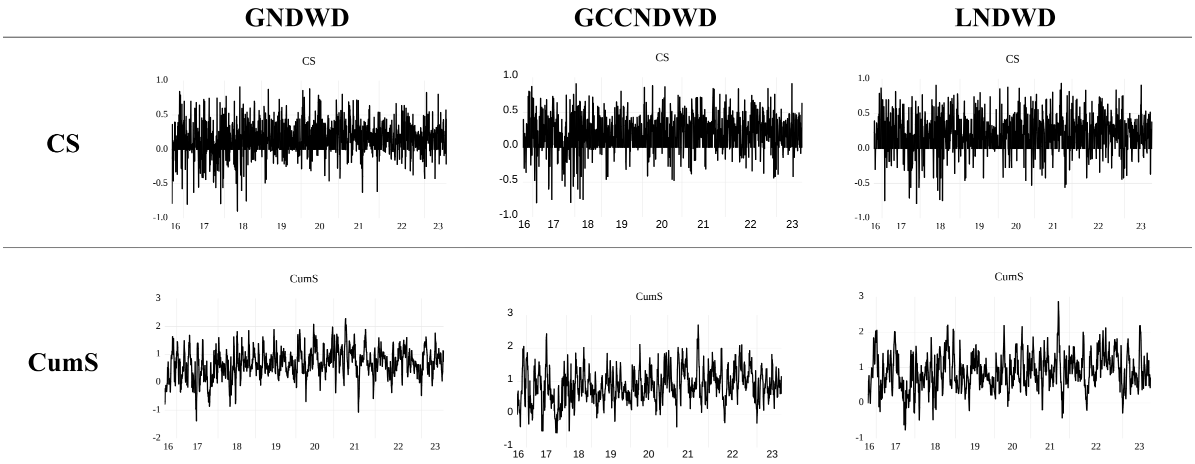



Figure 19. Trajectory Analysis of VADER’s Compound Score (CS) Versus Cumulative Sentiment (CumS) for GNDWD, GCCNDWD, LNDWD for Qatar

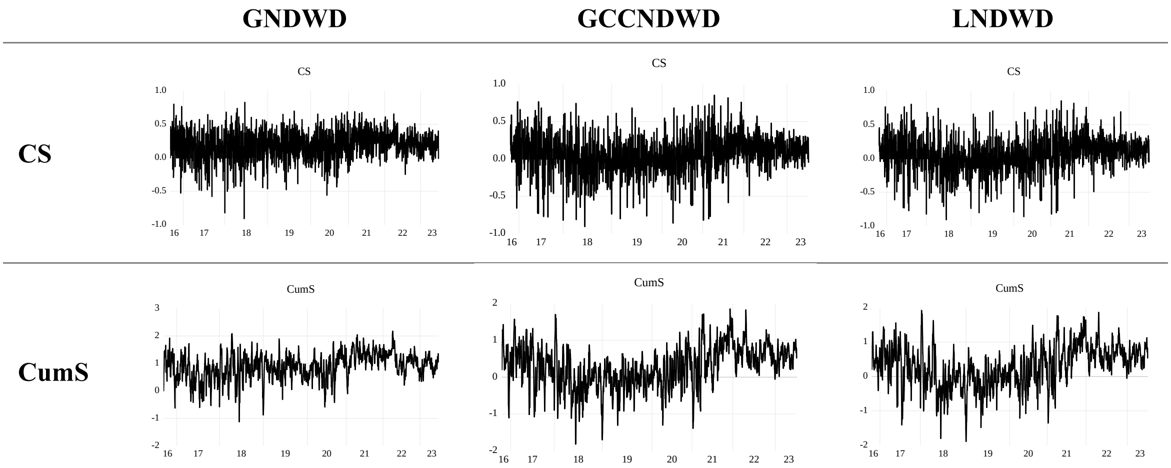
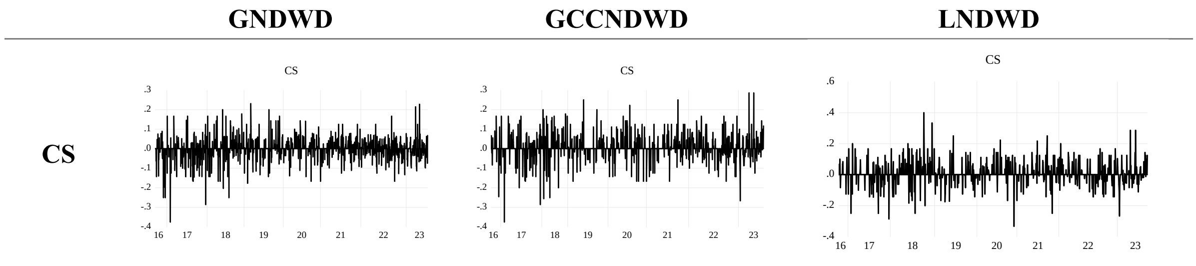
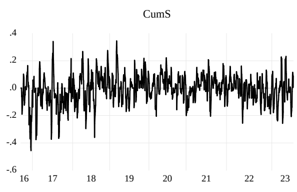
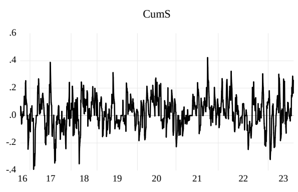



Figure 20. Trajectory Analysis of VADER’s Compound Score (CS) Versus Cumulative Sentiment (CumS) for GNDWD, GCCNDWD, LNDWD for United Arab Emirates



**CumS**



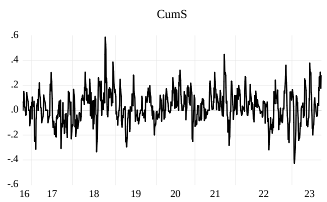
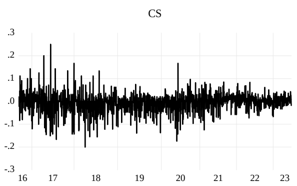
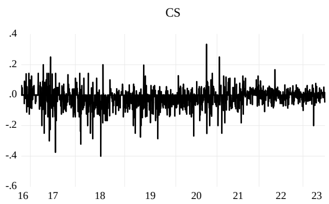



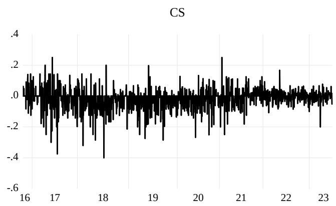

Figure 21. Trajectory Analysis of LM Composite Score (CS) Versus Cumulative Sentiment (CumS) for GNDWD, GCCNDWD, LNDWD for Qatar

| | GNDWD | GCCNDWD | LNDWD |
|---|---|---|---|

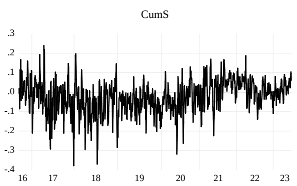
**CS**

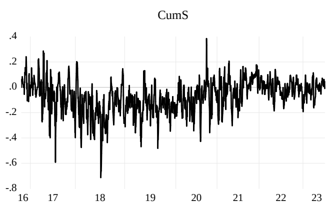



**CumS**



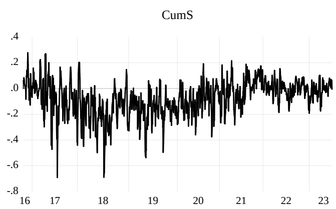
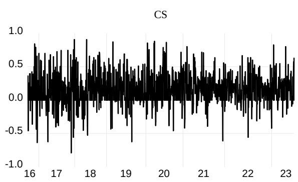
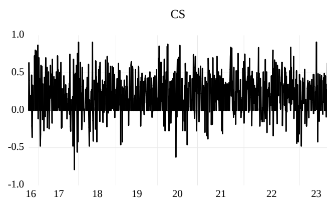



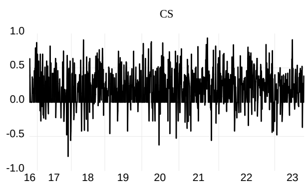

Figure 22. Trajectory Analysis of LM Composite Score (CS) Versus Cumulative Sentiment (CumS) for GNDWD, GCCNDWD, LNDWD for United Arab Emirates

| | GNDWOD | GCCNDWOD | LNDWOD |
|---|---|---|---|

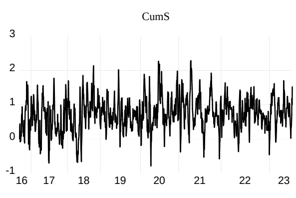
**CS**

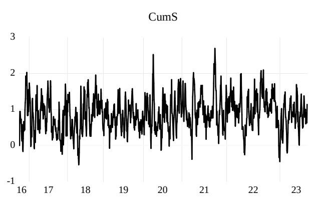



**CumS**



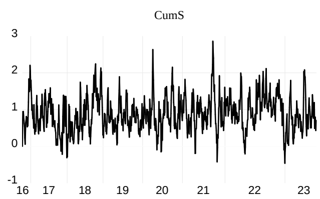




Figure 23. Trajectory Analysis of VADER's Compound Score (CS) Versus Cumulative Sentiment (CumS) for GNDWOD, GCCNDWOD, LNDWOD for Qatar

| | GNDWOD | GCCNDWOD | LNDWOD |
|---|---|---|---|

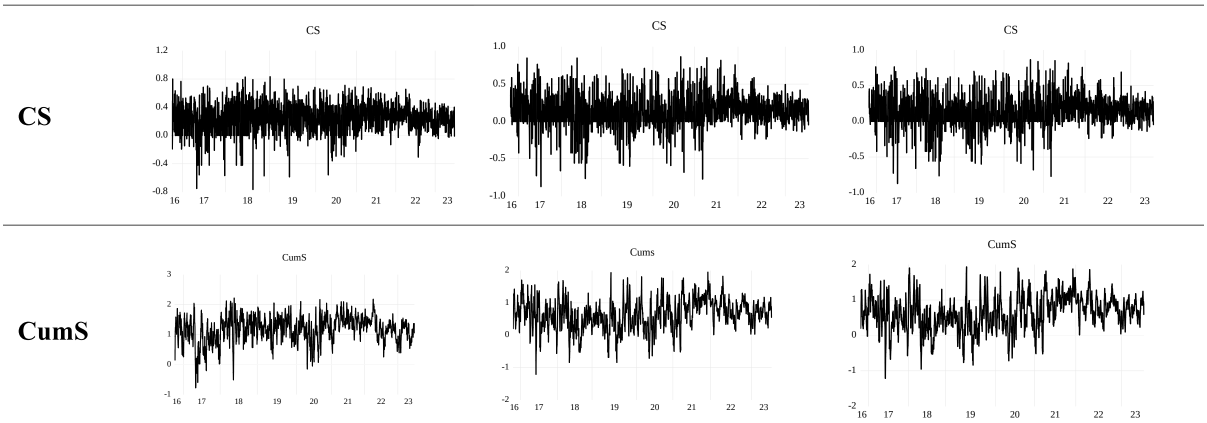



Figure 24. Trajectory Analysis of VADER's Compound Score (CS) Versus Cumulative Sentiment (CumS) for GNDWOD, GCCNDWOD, LNDWOD for United Arab Emirates

## 5. EMPIRICAL ANALYSIS

### 5.1. Preliminary Analysis

#### *5.1.1. Unit Root Test*

All variables must be stationary to conduct joint significance tests on the lags of variables included in the VAR's model. Among other characteristics, stationary variables show a constant mean, no trends, and no seasonal patterns. To evaluate stationary conditions, Fuller (1976) and Dickey and Fuller (1979) proposed the ADF test. If the test statistic is statistically significant, the ADF test rejects the null hypothesis that the series is non-stationary. Accordingly, the stock market data were subjected to the Augmented Dickey-Fuller (ADF) unit root test. Table 8 and 9 show that the null hypothesis of non-stationary is rejected, favoring the alternative hypothesis that all our stock market data are stationary.

Furthermore, a stationary pattern is evident in climate change news sentiment. Given six classifications of climate change news, Global, GCC, and local climate change news, with and without disaster. For the six climate change news classifications, positive and negative sentiments, we have utilized the ADF unit root test. This includes a total of 36 (VADER= 2 Countries × 6 Climate Change News Classification × 2 Sentiments "Positive and Negative", and LM= 2 Countries × 3 Climate Change News Classification × 2 Sentiments "Positive and Negative") ADF unit root test conducted. The result of the ADF unit root test conducted suggests that all positive and negative sentiments under each news classification were significant with 1, 5, and 10 percent significance level. It implies that the null hypothesis of non-stationary is rejected, favoring the alternative hypothesis that all our climate change news sentiments are stationary.

Table 8. Augmented Dickey-Fuller (ADF) , Unit Root Test for Srock Market Data for Qatar and Global Parameters

| | RQSI | RESG | VRQSI | VRESG | RDJW | RBRENT | VIX |
|---|---|---|---|---|---|---|---|
| **Automatic Lags Length** | 0 | 0 | 0 | 0 | 0 | 13 | 0 |
| **t-Statistic** | -39.171*** | -36.749*** | -32.346*** | -36.543*** | -37.276*** | -9.028*** | -4.578*** |
| **P-value** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.0001*** |

Note: the *, **, *** Depicts the significance with 10, 5, and 1 percent significance level using MacKinnon (1996) one sided p-values

Table 9. Augmented Dickey-Fuller (ADF), Unit Root Test for Srock Market Data for UAE

| | RADX | RDFM | RESG | VRADX | VRDFM | VRESG |
|---|---|---|---|---|---|---|
| **Automatic Lags Length** | 2 | 2 | 2 | 17 | 12 | 12 |
| **t-Statistic** | -23.813*** | -22.082*** | -22.449*** | -6.507*** | -7.623*** | -7.696*** |
| **P-value** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |

Note: the *, **, *** Depicts the significance with 10, 5, and 1 percent significance level using MacKinnon (1996) one sided p-values.

### *5.1.2. Unit Root Test with Structural Break*

If the series under investigation contains one or more structural breaks, the Augmented Dickey-Fuller-type of unit root test described previously will not be effective. Therefore, we followed the approach of Banerjee et al. (1992) for unit root testing with structural breaks. The approach testing for unit roots in the presence of structural breaks changes by selecting the break date endogenously. It suggests the use of ADF test with continuous, recursive, and iterative testing methods. Using the unit root test with structural break where the breakpoint selection is governed by the ADF test we obtain the results in Table 10 and 11. The results show that the null hypothesis of non-stationary with structural break is rejected, favoring the alternative hypothesis that all of our stock market data are stationary even when considering the unit root test with structural break.

Furthermore, a stationary pattern is evident in climate change news sentiment even with the structural break's unit root test. Given six classifications of climate change news, Global, GCC, and local climate change news, with and without disaster. For the six climate change news classifications, positive and negative sentiments, we have utilized the ADF unit root test with structural break. This includes a total of 36 (VADER= 2 Countries × 6 Climate Change News Classification × 2 Sentiments "Positive and Negative", and LM= 2 Countries × 3 Climate Change News Classification × 2 Sentiments "Positive and Negative") ADF unit root test conducted. The result of the ADF unit root test conducted suggests that all positive and negative sentiments under each news classification were significant with 1, 5, and 10 percent significance level. It implies that the null hypothesis of non-stationary with structural break is rejected, favoring the alternative hypothesis that all climate change news sentiments data are stationary even when considering the unit root test with structural break.

Table 20. Augmented Dickey-Fuller (ADF), Unit Root Test with Structural Break for Srock Market Data for Qatar and Global Parameters

| | RQSI | RESG | VRQSI | VRESG | RDJW | RBRENT | VIX |
|---|---|---|---|---|---|---|---|
| **t-Statistic** | -40.608*** | -38.642*** | -37.652*** | -46.650*** | -38.276*** | -39.573*** | -6.701*** |
| **p-value** | <0.01*** | <0.01*** | <0.01*** | <0.01*** | <0.01*** | <0.01*** | <0.01*** |

Note: the *, **,*** Depicts the significance with 10, 5, and 1 percent significance level using Vogeldang (1993) asymptotic one sided p-values

Table 31. Augmented Dickey-Fuller (ADF), Unit Root Test with Structural Break for Srock Market Data for UAE

| | RADX | RDFM | RESG | VRADX | VRDFM | VRESG |
|---|---|---|---|---|---|---|
| **t-Statistic** | -40.118*** | -40.056*** | -40.592*** | -30.042*** | -29.627*** | -30.401*** |
| **p-value** | <0.01*** | <0.01*** | <0.01*** | <0.01*** | <0.01*** | <0.01*** |

Note: the *, **,*** Depicts the significance with 10, 5, and 1 percent significance level using Vogeldang (1993) asymptotic one sided p-values

### *5.1.3. VAR Lag Length Selection*

We perform information criteria test to determine the lags in our VAR model. The information criteria specify the optimal lag length to accommodate in the VAR model. In our analysis we compare the results of five widely used information criteria, given that the max lag length inserted is 10 lags. The information criterions for this purpose are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike Information Criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Considering the results were not entirely consistent, we selected the number of lags that was confirmed by at least two information criteria. The optimal lag lengths for each VAR model are shown in Tables 12 and 13.

Table 42. Lag Length Included in VAR Model Estimation for Qatar

| Sentiment Variables Based on Global Climate Change News with Disaster (GNDWD) | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on GCC Climate Change News with Disaster (GCCNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on Local Climate Change News with Disaster (LNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lag | FPE, AIC, SC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lag | FPE, AIC, SC |

The information criteria used for conducting the optimal lag length are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Where Pos and Neg are sentiment obtained using VADER lexicon.

Table 53. Lag Length Included in VAR Model Estimation for UAE

| Sentiment Variables Based on Global Climate Change News with Disaster (GNDWD) | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on GCC Climate Change News with Disaster (GCCNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, DJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, DJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |

| Sentiment Variables Based on Local Climate Change News with Disaster (LNDWD) | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |

The information criteria used for conducting the optimal lag length are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Where Pos and Neg are sentiment obtained using VADER lexicon.

## 5.2. Responses of GCC Countries Stock Markets to Climate Change News

### *5.2.1. Response of Qatar Stock Market to Climate Change News*

#### *5.2.1.1. Response of Doha General Index to Climate Change News*

According to the general stock market index (RQSI) impulse response function, the IRF shows in Figure 25 evident that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. The general stock market index (RQSI) responds positively to positive sentiment on the first to second day following global climate change news publication. The market, however, began to react negatively after the third day. In contrast, investors need more time to recognize the negative sentiment associated with global climate change news. The impact of negative global climate change news is thus erratic in the first five days following its publication and negatively affects RQSI thereafter. In addition, the results indicate that the general stock market index volatility for Qatar (VRQSI) has, on average, a negative to erratic response to both positive and negative global climate change news. Therefore, when global climate change news is published, the stock market volatility remains erratic for at least ten days after publication. A similar effect is observed on the RQSI and VRQSI when the news is published from GCC and local news sources. However, the investors perceive the negative GCC and local climate change news much faster than the global news publications.

According to this result about RQSI, investors in Qatar are optimistic when they observe positive news that should appeal to corporations with environmental responsibility. It must be noted, however, that the market response to positive global, GCC and local climate change news has deteriorated on average after the first two days of their publication, as non-ESG stocks have been responding negatively to these sorts of news. It also implies that Qatari investors take ten or more days to react to global, GCC, and local climate change news.

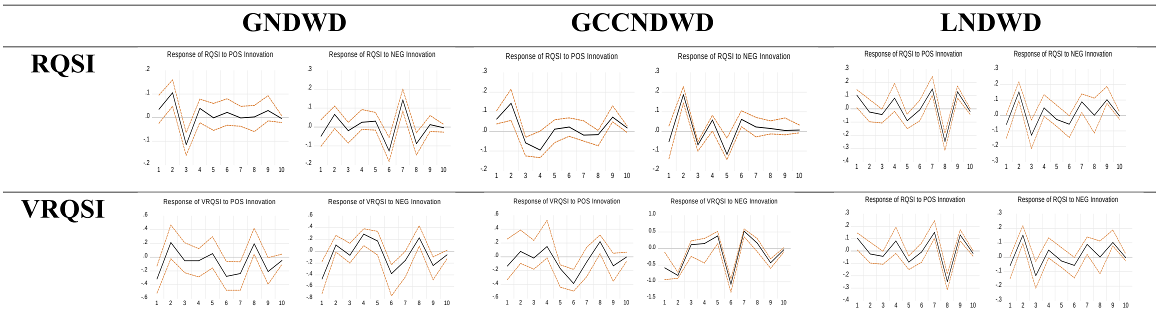



Figure 25. The Impulse Response Function (IRF) for Doha General Stock Market Index.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about Qatar, GCC Climate Change News with Disaster (GCCNDWD) about Qatar, and Local Climate Change News with Disaster (LNDWD) about Qatar. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*5.2.1.2. Response MSCI QSE 20 ESG to Climate Change News*

According to the response functions for Qatar’s ESG equity index, it is evident that (RESG) responds positively to positive and negative climate change news. Figure

26 suggests that during the positive and negative global, GCC and local news publications about climate change, the returns on ESG equities convey a favorable reaction. The performance of ESG equities during positive and negative climate change news sentiment is also coupled with an, on average, lower market volatility. As a result, ESG equities are less exposed to the uncertainty associated with positive and negative climate change news. According to the results, ESG equities react, on average, positively to positive and negative global, GCC, and local climate change news. Aside from this, Qatar's investors react to global, GCC, and local news about climate change for ten days or more following its announcement.

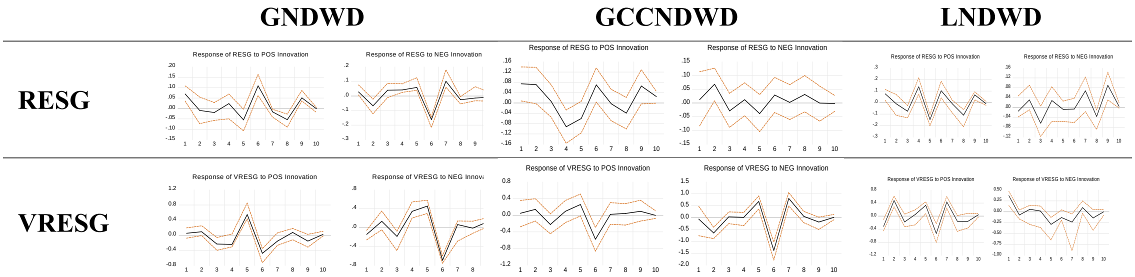



Figure 26. The Impulse Response Function (IRF) for MSCI QSE 20 ESG Index.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about Qatar, GCC Climate Change News with Disaster (GCCNDWD) about Qatar, and Local Climate Change News with Disaster (LNDWD) about Qatar. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*5.2.1.3. Discussion on Qatar Stock Market Response to Climate Change News*

The results of this study are consistent with the previous studies suggesting that climate change proxies impact the stock market performance (Floros, 2008; Shu and Hung, 2009; Symeonidis et al., 2010; Huynh et al., 2020; Gregory, 2021; He and Zhang, 2022). There are differences in how investors in Qatar perceive climate change news, however, the results suggest a positive social impact, supporting corporations with environmental responsibility (Heeb et al., 2022). Although climate change is claimed to play a significant role in causing prices to deviate from their fundamentals, the impact varies based on the type of equity being investigated (Rao et al., 2021). Overall, our results indicate that RESG performs better than RQSI during positive and negative climate change news. It is important to note that the implications of this result vary based on the type of news included in this investigation. For instance, the value of climate-responsible companies may increase, with news highlighting ambitious climate agendas, favoring the reduction of human involvement in climate change threats (Ramelli, Wagner, et al., 2021; Gong et al., 2022). This may result in investors buying stocks that have a lower climate sensitivity and selling stocks that have a higher climate sensitivity, which would result in the former outperforming the latter (Choi et al., 2020; Santi, 2023). In addition, a high level of climate risk disclosure factors, such as ESG factors, may also reduce the risk of future stock price crashes (Lin and Wu, 2023). Thus, the result of this study induces that both equities performance is subjected to the social cost of climate change uncertainty during positive and negative climate change news sentiments (Shu and Hung, 2009; Engle et al., 2020; Barnett et al., 2020; Cepni et al., 2023; Santi, 2023). ESG stocks have been shown to be less connected to conventional stocks during positive and negative climate change news sentiments. Consequently, the results suggest that Qatar's stock market prices reflect climate change news. Investors in Qatar therefore respond to this news differently and change their investment strategies accordingly. The study result contributes to the behavioral finance literature, where investing behavior might be affected by climate change news, resulting in price changes in the stock market.

#### *5.2.2. Response of UAE Stock Market to Climate Change News*

*5.2.2.1. Response of UAE General Stock Market Indices to Climate Change News*

According to the responses of Abu-Dhabi and Dubai general stock market indices it is evident that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. Figure 27 suggests that the Abu-Dhabi Stock Market Index (RADX) responds negatively to the positive global climate change news with increased market volatility. At the same time, the negative sentiment associated with global climate change news depicts, on average, negative influence on the RADX performance. The return on ADX respond negatively to this sort of news on day three and nine after the news publication with almost lower volatility. In addition, the return on ADX depicts, on average, a negative response to positive GCC and local climate change news with higher market volatility. Similarly, the return on ADX depicts, on average, a negative response to negative GCC and local climate change news with higher volatility. The result indicates that RADX responds negatively to the positive and negative global, GCC, and local climate change news. A second finding suggests that UAE investors react for up to ten days following the publication of global, GCC, and local climate change news. Furthermore, the return on Dubai Stock Market Index (RDFM) depicts, approximately, a negative response to the positive global climate change news sentiment with higher market volatility. At the same time, the negative sentiment associated with global climate change news depicts, on average, negative influence on the RDFM performance. The volatility response to both news sentiment, negative and positive, declines after the global climate change news publication. Meanwhile, positive climate change news from the GCC and local news sources were perceived as a positive influence on the return of DFM as well as a lowering the level of volatility. The negative GCC and local climate change news, however, depicts negative impact on the return on DFM with higher market volatility.

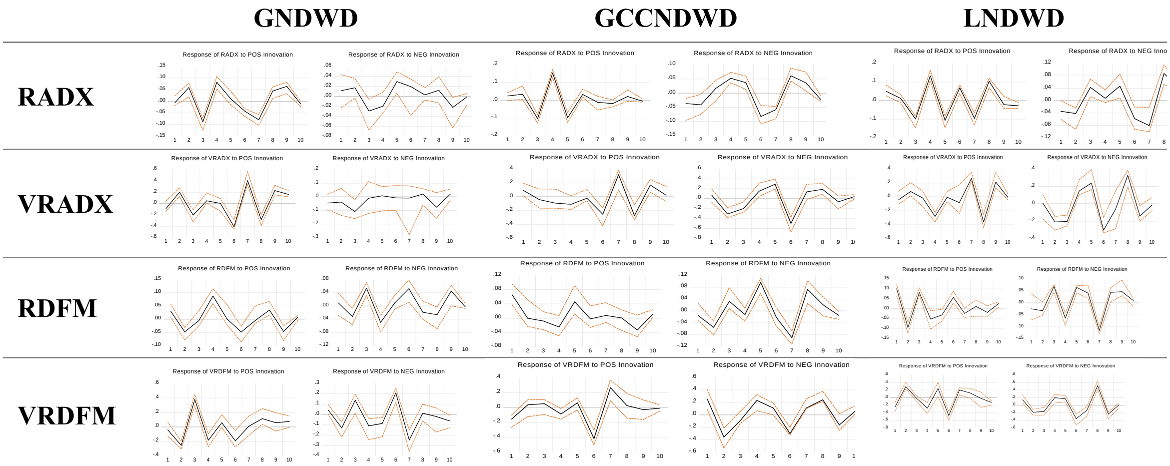



Figure 27. The Impulse Response Function (IRF) for FTSE ADX General and Dubai General Indices.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about UAE, GCC Climate Change News with Disaster (GCCNDWD) about UAE, and Local Climate Change News with Disaster (LNDWD) about UAE. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*5.2.2.2. Response of S&P-Hawkamah ESG UAE Index to Climate Change News*

The climate change news depicts a clear path of impact on the UAE's ESG equity index varying according to the news publication region and sentiment classification, positive and negative. Figure 28 suggests that the positive global, GCC, and local climate change news sentiment depicts, on average, positive influence on UAE's ESG equity index returns. The volatility for the return, however, declines after the publication of the same sort of news. The study suggests that when there is favorable news toward a better environmental outcome, environmental, social, and governance, ESG compliant stocks perform better, suggesting that investors migrate towards quality. A further analysis of RESG's response to negative global, GCC, and local news sentiment indicates that RESG consistently exhibits positive response. The average volatility of the returns during the negative global, GCC, and local climate change news publication declines. Accordingly, RESG exhibits positive response to both positive and negative global, GCC, and local climate change news sentiment. A second finding suggests that UAE investors react for up to ten days following global, GCC, and local climate change news.

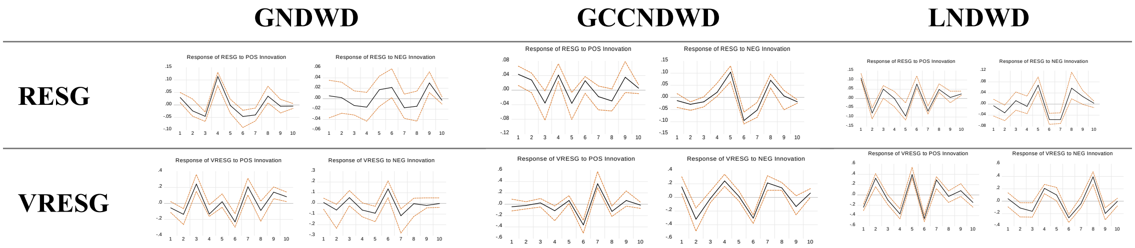



Figure 28. The Impulse Response Function (IRF) for S&P-Hawkamah ESG UAE Index.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about UAE, GCC Climate Change News with Disaster (GCCNDWD) about UAE, and Local Climate Change News with Disaster (LNDWD) about UAE. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*5.2.2.3. Discussion on UAE Stock Market Response to Climate Change News*

There appears to be a similar pattern of performance for the UAE stock market to that found in Qatar stock market. It is generally acknowledged that increasing the weight of ESG equities in the given portfolio can enhance the return on portfolio while declining volatility. During both positive and negative climate change news publication, RESG were found to respond positively, while RADX respond negatively to positive climate change news sentiments. RESG also provides a diversification benefit to investors in Dubai during a time of negative climate change news sentiment.

Despite this, given the positive response of RDFMs to positive GCC and local climate change sentiment, RESG can only be beneficial for Dubai investors when considering the positive global climate change news. This is contrary to Cepni et al. (2023), who state that ESG equities performance is less connected to conventional assets during climate uncertainty. The results also show that the stock markets in both GCC countries, Qatar and UAE, are sensitive to climate change news. Investors in Qatar and UAE, therefore, perceive this news differently and change their investment strategies accordingly. It has also been found that a greater bilateral co-movement of stock market returns between Qatar and UAE is associated with greater dependence in responding to the climate transition risks (Wu, G. S., & Wan, W. T., 2023). It implies that if economic conditions and import dependence between the two countries are highly evidenced, the cross-border climate transition risks between the two countries will likely be prominent. In other words, a country's performance in combating climate change threats can reduce spillover risks caused by climate change. However, effective mitigation may require both countries to perform well in combating climate change threats. In this respect, it was found that the responses of the two countries were, on average, similar.

# 6. ROBUSTNESS CHECK

## 6.1. Loughran-McDonald Lexicon (LM)

This study utilizes another approach for sentiment analysis to check for the result's robustness. The Loughran and McDonald (2011) have been utilized for that purpose. Thus, we have replicated the results for the model specification and Impulse Response Function (IRF) with the sentiment obtained using Loughran-Mcdonald (LM) lexicon.

### *6.1.1. VAR Lag Length Selection*

We perform information criteria test to determine the lags in our VAR model with the news sentiment obtained from Loughran-Mcdonald (LM). The information criteria specify the optimal lag lengths to accommodate in the VAR model. In our analysis we compare the results of five widely used information criteria, given that the max lag length inserted is 10 lags. The information criterions for this purpose are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike Information Criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Considering the results were not entirely consistent, we selected the number of lags that was confirmed by at least two information criteria. The optimal lag lengths for each VAR model are shown in Tables 14 and 15.

Table 64. Lag Length Included in VAR Model Estimation for Qatar

| **Sentiment Variables Based on Global Climate Change News with Disaster (GNDWD)** | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on GCC Climate Change News with Disaster (GCCNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on Local Climate Change News with Disaster (LNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 1 Lags | FPE, AIC, SC, HQ |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 1 Lags | FPE, SC, HQ |

The information criteria used for conducting the optimal lag length are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Where Pos and Neg are sentiment obtained using LM lexicon.

Table 75. Lag Length Included in VAR Model Estimation for UAE

| Sentiment Variables Based on Global Climate Change News with Disaster (GNDWD) | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on GCC Climate Change News with Disaster (GCCNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, DJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, DJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on Local Climate Change News with Disaster (LNDWD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC, HQ |
| RDFM, VRDFM, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC, HQ |

The information criteria used for conducting the optimal lag length are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Where Pos and Neg are sentiment obtained using LM lexicon.

### *6.1.2. Response of Qatar Stock Market to Climate Change News*

#### *6.1.2.1. Response of Doha General Index to Climate Change News*

According to the general stock market index (RQSI) impulse response function, the IRF shows evident that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. Since Loughran and McDonald (2011) interpret our climate change news in their economic and financial contexts, there appear to be slight differences in the results shown in Figure 29 compared to those interpreted previously using the VADER lexicon.

The Doha General Stock Market Index (RQSI) responds negatively to positive sentiment on the first to second day following global climate change news publication. The market, however, began to react positively after the second day. The impact on RQSI stays on average negative and dies away throughout the consequence days. Meanwhile, the impact of negative global climate change news is significantly erratic, while it appears that highest negative impact takes place at the eighth day after the global climate change news publication. The volatility of RQSI response to positive and negative climate change news seems to have an erratic impact on the stock market volatility. It indicates that the general stock market index volatility for Qatar (VRQSI) has, on average, a negative to erratic response to both positive and negative global climate change news. Therefore, when global climate change news is published, the stock market volatility remains erratic for at least ten days after its publication. A similar effect is observed on the RQSI and VRQSI when the news is published from the GCC. However, according to LM observed local climate change news sentiment, investors perceive the news much faster than the global and GCC news publications. RQSI has also responded negatively to positive local climate change news about Qatar on the first day. The second day, however, results in an immediate positive return with higher volatility.

According to this result about RQSI, the LM observed sentiments for the climate change news shows that investors in Qatar are pessimistic when they observe positive news. When this result is compared to the one obtained using VADER sentiments, it appears that LM shows superiority in terms of the first day impact of climate change news on the stock market. It implies that the market response to positive global, GCC and local climate change news has deteriorated due to non-ESG stocks responding negatively. The result, however, are different than that obtained using VADER lexicon in terms of the time horizon Qatari investors take to react to local climate change news. As it appears that the market reacts for one to two days to local climate change news, when utilizing LM lexicon. While using VADER, the result suggests that investors in Qatar take ten days or more to respond to local climate change news.

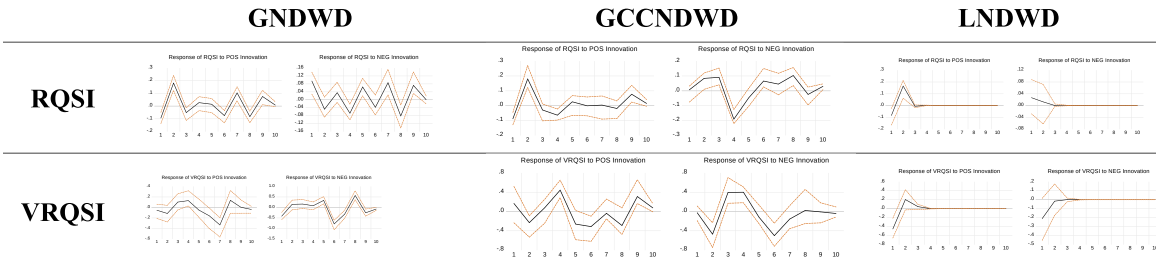



Figure 29. The Impulse Response Function (IRF) for Doha General Stock Market Index.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about Qatar, GCC Climate Change News with Disaster (GCCNDWD) about Qatar, and Local Climate Change News with Disaster (LNDWD) about Qatar. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through LM lexicon.

*6.1.2.2. Response MSCI QSE 20 ESG to Climate Change News*

According to the response functions for Qatar's ESG equity index, it is evident that (RESG) responds positively to positive and negative climate change news. Figure 30 shows that during the positive and negative global and GCC news publications about climate change, the returns on ESG convey a favorable reaction. The performance of ESG equities during positive and negative climate change news sentiment is also coupled with an, on average, lower market volatility. As a result, ESG equities are less exposed to the uncertainty associated with positive and negative climate change news. The results also confirm with the results we obtained when utilizing VADER lexicon.

However, the impact of positive local climate change news about Qatar on RESG depicts the same impact on RQSI and VRQSI when utilizing LM lexicon. In other words, the local climate change news sentiment obtained by LM cannot determine whether investors prefer ESG or non-ESG equities, since both classes of equities are responding similarly to the local climate change news. When this result is compared to the one obtained using VADER sentiments, LM results seems different than that obtained using VADER lexicon in terms of the time horizon Qatari investors take to react to local climate change news. As it appears that the market reacts for one to two days to climate change news, when utilizing LM lexicon. While using VADER, the result suggests that investors in Qatar take ten days or more to react to local climate change news.

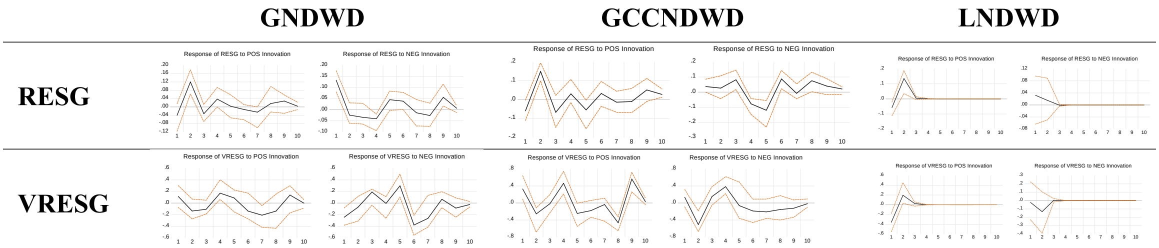



Figure 30. The Impulse Response Function (IRF) for MSCI QSE 20 ESG Index.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about Qatar, GCC Climate Change News with Disaster (GCCNDWD) about Qatar, and Local Climate Change News with Disaster (LNDWD) about Qatar. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through LM lexicon.

### *6.1.2.3. Discussion on Qatar Stock Market Response to Climate Change News (VADER Versus LM)*

The results of the study when utilizing LM lexicon, on average, depicts like that obtained when utilizing VADER lexicon. The results of RQSI and VRQSI when LM is used, however, appear to be slightly different than the results compared to those interpreted using the VADER. However, the results of RESG are consistent to that obtained in VADER.

In general, the LM and VADER lexicons could observe different results in terms of sentiments score. The differences are attributed to the technicalities, scope, and others. As we have already stated earlier, when utilizing the VADER sentiment, the news headlines are analyzed at the sentence level. Meanwhile, the LM sentiments are obtained at the word level. Therefore, the difference in translating qualitative information to quantitative sentiment scores will result in slight difference. The scope of LM is concerned much on quantifying the climate change news in their financial context, which can also be attributed to some difference. Whereas VADER lexicon is more general and quantifies a wide range of text with different scope (Hutto and Gilbert, 2014).

### *6.1.3. Response of UAE Stock Market to Climate Change News*

#### *6.1.3.1. Response of UAE General Stock Market Indices to Climate Change News*

According to the responses of Abu-Dhabi and Dubai general stock market index it is evident that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. Figure 31 shows that the Abu-Dhabi Stock Market Index (RADX) responds, approximately, negatively to the positive and negative global climate change news with erratic market volatility. Similarly, the return on ADX depicts, on average, a negative response to positive and negative GCC and local climate change news with erratic market volatility. Furthermore, the return on Dubai Stock Market Index (RDFM) depicts, approximately, negative response to the positive and negative global and local climate change news sentiment with higher market volatility. Meanwhile, positive GCC climate change news was perceived as a positive influence on the return of DFM and leading to erratic market volatility. The negative GCC climate change news, however, depicts negative impact on the return on DFM with higher market volatility.

When the result about ADX and DFM is compared to the one obtained using VADER lexicon, it appears that there are slight differences. The results for RADX and VRADX for the news sentiments obtained by LM are consistent with that obtained with the VADER lexicon. The results, however, are different than that obtained using VADER lexicon in terms of the response of RDFM to the positive local climate change news. As it appears that the RDFM react negatively to positive climate change news sentiments obtained using LM lexicon. While using VADER, the result suggests that the positive local climate change news sentiment impacts the return on DFM positively.

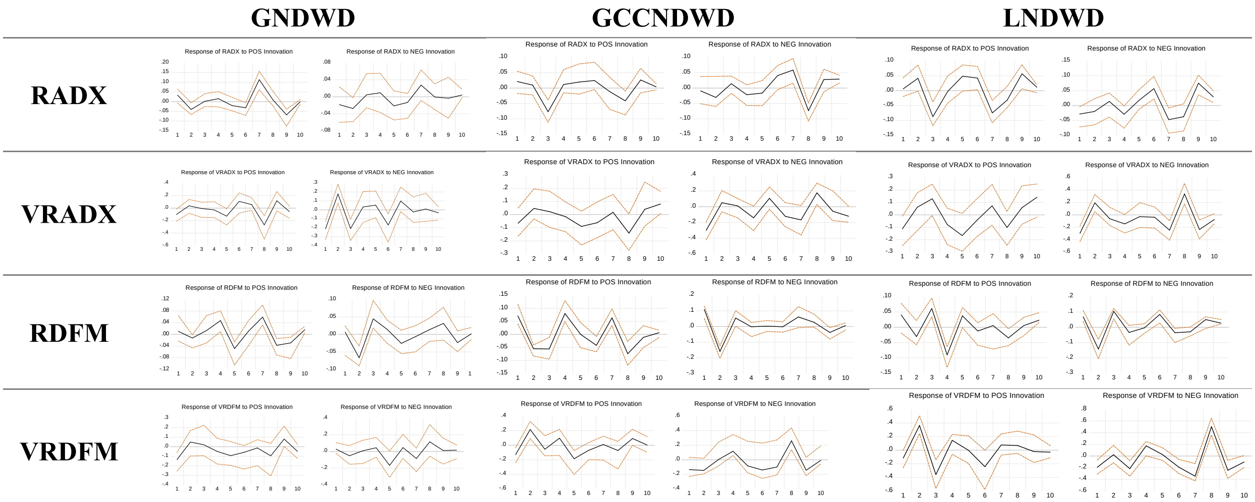



Figure 31. The Impulse Response Function (IRF) for FTSE ADX General and Dubai General Indices.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about UAE, GCC Climate Change News with Disaster (GCCNDWD) about UAE, and Local Climate Change News with Disaster (LNDWD) about UAE. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through LM lexicon.

### *6.1.3.2. Response of S&P-Hawkamah ESG UAE Index to Climate Change News*

The climate change news depicts a clear path of impact on the UAE's ESG index varying according to the news publication region and sentiment classification, positive and negative. Figure 32 shows that the positive global, GCC, and local climate change news sentiment depicts, on average, positive response by the return on ESG equity index. The volatility for the return, however, declines after the publication of the same sort of news. The results of RESG depict, on average, a similar pattern about the ESG equities, when obtaining the sentiments through the VADER lexicon.

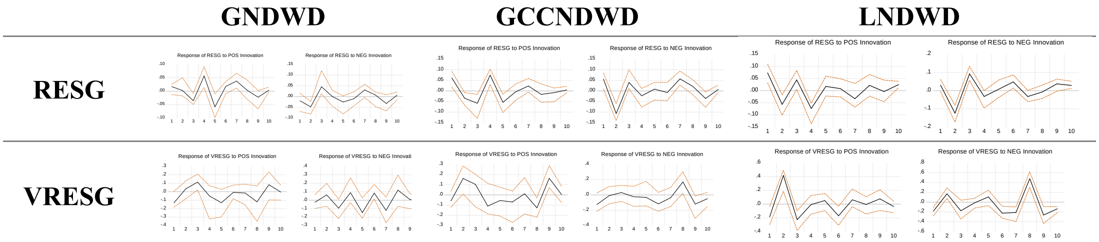



Figure 32. The Impulse Response Function (IRF) for S&P-Hawkamah ESG UAE Index.

Note: Abbreviations: Global Climate Change News with Disaster (GNDWD) about UAE, GCC Climate Change News with Disaster (GCCNDWD) about UAE, and Local Climate Change News with Disaster (LNDWD) about UAE. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through LM lexicon.

### *6.1.3.3. Discussion on UAE Stock Market Response to Climate Change News (VADER Versus LM)*

The results of the study when utilizing LM lexicon, on average, depict like that obtained when utilizing VADER lexicon. The results of RADX and VRADX when LM is used appear to be like the results interpreted using VADER. Similarly, the results of

RESG and VRESG when LM is used appear to be like the results interpreted using the VADER. However, the main difference between the LM and VADER result is when the RDFM responds negatively to positive local climate change news.

## 6.2. Excluding Natural Disaster News

This study utilizes another approach to check for the result's robustness. The news classification excludes the natural disaster news for that purpose. Thus, we have replicated the results for the model specification and Impulse Response Function (IRF) with the sentiment obtained using news classification excluding natural disaster news.

### *6.2.1. VAR Lag Length Selection*

We perform information criteria test to determine the lags in our VAR model. The information criteria specify the optimal lag lengths to accommodate in the VAR model. In our analysis we compare the results of five widely used information criteria, given that the max lag length inserted is 10 lags. The information criterions for this purpose are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike Information Criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Considering the results were not entirely consistent, we selected the number of lags that was confirmed by at least two information criteria. The optimal lag lengths for each VAR model are shown in Tables 16 and 17.

Table 86. Lag Length Included in VAR Model Estimation for Qatar

| **Sentiment Variables Based on Global Climate Change News without Disaster (GNDWOD)** | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on GCC Climate Change News without Disaster (GCCNDWOD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to** | **Information** |

| | Accommodate (Max=10 Lags) | Criteria |
|---|---|---|
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on Local Climate Change News without Disaster (LNDWOD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RQSI, VRQSI, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |

The information criteria used for conducting the optimal lag length are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Where Pos and Neg are sentiment obtained using VADER lexicon.

Table 97. Lag Length Included in VAR Model Estimation for UAE

| **Sentiment Variables Based on Global Climate Change News without Disaster (GNDWOD)** | | |
|---|---|---|
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on GCC Climate Change News without Disaster (GCCNDWOD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, DJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RDFM, VRDFM, RBRENT, DJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| **Sentiment Variables Based on Local Climate Change News without Disaster (LNDWOD)** | | |
| **VAR Model Variables Included** | **Optimal Lag Length to Accommodate (Max=10 Lags)** | **Information Criteria** |
| RADX, VRADX, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC, HQ |
| RDFM, VRDFM, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC |
| RESG, VRESG, RBRENT, RDJW, VIX, Pos, Neg | 8 Lags | LR, FPE, AIC, HQ |

The information criteria used for conducting the optimal lag length are the sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Where Pos and Neg are sentiment obtained using VADER lexicon.

### *6.2.2. Response of Qatar Stock Market to Climate Change News*

*6.2.2.1. Response of Doha General Index to Climate Change News*

According to the general stock market index (RQSI) impulse response functions, the IRF shows evident that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. Figure 33 suggests that the impact of climate change news sentiment obtained from VADER remains consistent even when disaster news is excluded. The Doha General Stock Market Index (RQSI) responds, on average, negatively to the positive global, GCC, and local climate change news sentiment with, on average, higher volatility. Meanwhile, when disaster climate change news was excluded, the impact of negative news sentiment becomes less prominent by the market. This is evident with all our climate change news classifications. As it results in, on average, negative return but it is not prominent.

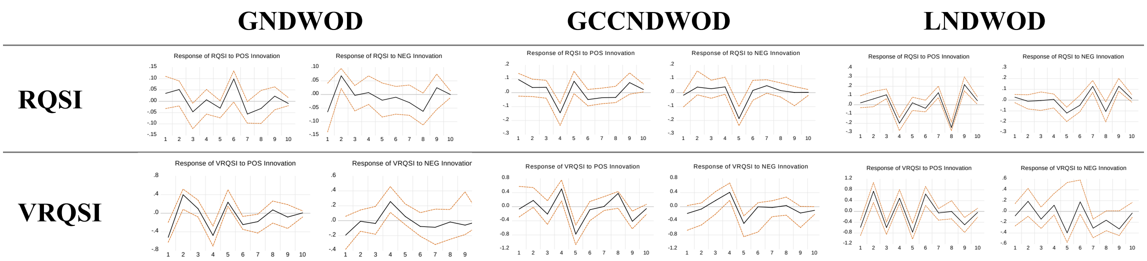



Figure 33. The Impulse Response Function (IRF) for Doha General Stock Market Index.

Note: Abbreviations: Global Climate Change News without Disaster (GNDWOD) about Qatar, GCC Climate Change News without Disaster (GCCNDWOD) about Qatar, and Local Climate Change News without Disaster (LNDWOD) about Qatar. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*6.2.2.2. Response MSCI QSE 20 ESG to Climate Change News*

According to the MSCI QSE 20 ESG stock market index (RESG) impulse response functions, the IRF shows evidence that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. Figure 34 suggests that the impact of climate change news sentiment remains consistent even when disaster news is excluded. The RESG responds, on average, positively to the positive global, GCC, and local climate change news sentiment with an on average lower volatility. Meanwhile, when disaster climate change news was excluded, the impact of negative news sentiment was still positive on RESG, but it became less prominent. This is evident with all our climate change news classifications.

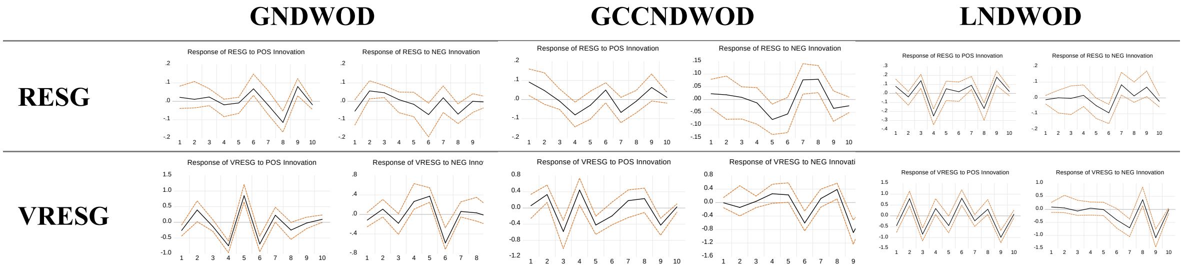



Figure 34. The Impulse Response Function (IRF) for MSCI QSE 20 ESG Index.

Note: Abbreviations: Global Climate Change News without Disaster (GNDWOD) about Qatar, GCC Climate Change News without Disaster (GCCNDWOD) about Qatar, and Local Climate Change News without Disaster (LNDWOD) about Qatar. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*6.2.2.3. Discussion on Qatar Stock Market IRF*

The results of the study when disaster news was excluded, on average, depicts like that obtained when utilizing the climate change news with disaster. However, the impact of the negative climate change news has become less prominent in both indices' impulse response functions. Due to this finding, we can suggest that our result is robust for the case of Qatar.

### *6.2.3. Response of UAE Stock Market to Climate Change News*

#### *6.2.3.1. Response of UAE General Stock Market Indices to Climate Change News*

According to the responses of Abu-Dhabi and Dubai general stock market index it is evident that investors perceive news differently based on the region of news publication and the news sentiment classification, positive and negative. Figure 35 suggests that the Abu-Dhabi Stock Market Index (RADX) responds, approximately, negatively to the positive and negative global, GCC, and local climate change news with higher market volatility. Furthermore, the return on Dubai Stock Market Index (RDFM) depicts, approximately, negative response to the positive and negative global, GCC, and local climate change news sentiment with higher market volatility. The results are consistent with the result obtained including disaster news. The main difference is that the impact of climate change news excluding disaster becomes more prominent for the return on DFM with all news classifications.

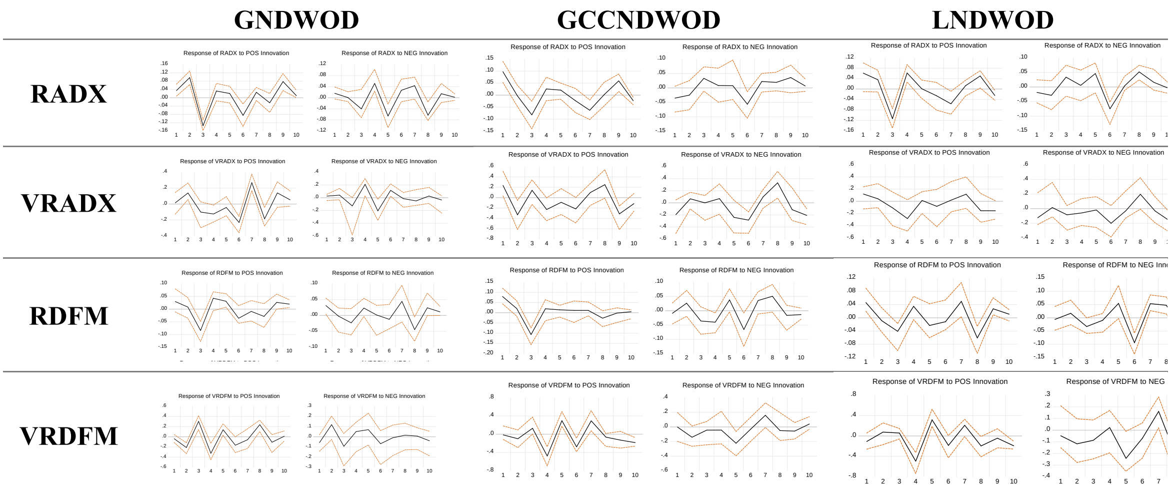


Figure 35. The Impulse Response Function (IRF) for FTSE ADX General and Dubai General Indices.

Note: Abbreviations: Global Climate Change News without Disaster (GNDWOD) about UAE, GCC Climate Change News without Disaster (GCCNDWOD) about UAE, and Local Climate Change News without Disaster (LNDWOD) about UAE. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

*6.2.3.2. Response of S&P-Hawkamah ESG UAE Index to Climate Change News without Disaster*

The climate change news depicts a clear path of impact on the UAE's ESG equity index varying according to the news publication region and sentiment classification, positive and negative. Figure 36 shows that the positive global, GCC, and local climate change news excluding disaster news sentiment depicts, on average, positive response of ESG's equities returns. The volatility for the return, however, declines after the publication of the same sort of news. Similarly, the negative global, GCC, and local climate change news excluding disaster news sentiment depicts, on average, positive response of ESG's equities returns with lower volatility. The results are consistent with that obtained using climate change news including natural disasters.

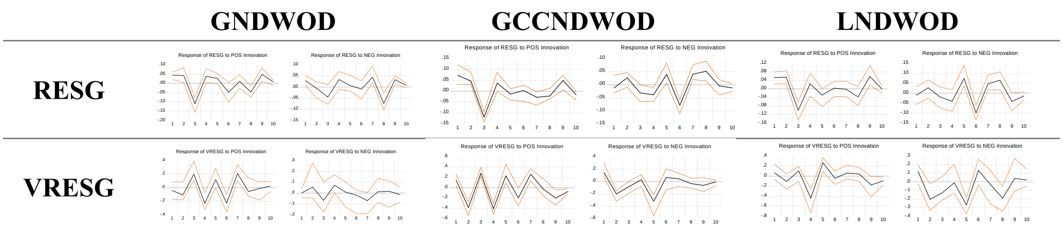



Figure 36. The Impulse Response Function (IRF) for S&P-Hawkamah ESG UAE Index.

Note: Abbreviations: Global Climate Change News without Disaster (GNDWOD) about UAE, GCC

Climate Change News without Disaster (GCCNDWOD) about UAE, and Local Climate Change News without Disaster (LNDWOD) about UAE. As such, the Positive and Negative sentiment for each classification is represented by POS and NEG, respectively. The IRF depicts significance with a 90 percent confidence interval. The climate change news sentiments were obtained through VADER lexicon.

#### *6.2.3.3. Discussion on UAE Stock Market IRF*

The results of the study when disaster news was excluded, on average, depicts like that obtained when utilizing the climate change news with disaster. Due to this finding, we can suggest that our results are robust for the case of UAE.

### 6.3. Granger Causality

To ensure the reliability and validity of our study results, a robustness test was conducted to validate the causal relationship between the investigated variables. For this purpose, we use the Granger causality test, invented by Nobel laureate Clive Granger, an economist who developed a method to analyze causal relationships between variables (Granger, 1969). The Granger causality test requires the tested variable series to be stationary. The stationarity condition of our stock market data along with the sentiment indices has already been verified in Section 5.1. However, because we conducted causality tests using VARs with restrictions, as such, the stock market variables have been restricted to zero in the sentiment's equations. Therefore, the study suggests that the effects of the stock market variables on climate change news sentiments are limited. This is backed by multiple facts. In the first place, previous studies have found causal links between sentiment proxies and stock market indicators (Zhang et al., 2018; Li, 2021). Sentiment proxies were found to cause indicators for stock markets but not vice versa. Secondly, the VAR was estimated before any restrictions were applied, and neither the return nor volatility coefficients of the positive and negative sentiments equations were statistically significant. Furthermore, the Granger causality diagnosis for the causal link from stock market returns and volatility to positive and negative sentiments accepts the null hypothesis that there is no Granger causality between the indicators. Hence, we conducted the Granger causality diagnosis, assuming a directed causality from positive and negative sentiments about climate change to stock market returns and volatility.

***6.3.1. Causality between Qatar Stock Market and Climate Change News***

According to the Granger causality results for Qatar, the study's results are robust. The Granger causality test is conducted to establish if climate change news sentiments, both positive and negative sentiments, do not granger cause RQSI, VRQSI, RESG, and VRESG, respectively. Table 18 summarizes the results of the Granger causality test. In this regard, the results have been divided into three panels. The first panel examines the null hypothesis that global climate change news sentiments do not granger causes RQSI, VRQSI, RESG, or VRESG. The second panel examines the null hypothesis that GCC climate change news sentiments do not granger causes RQSI, VRQSI, RESG, or VRESG. The third panel examines the null hypothesis that local climate change news sentiments do not granger causes RQSI, VRQSI, RESG, or VRESG. The results indicate that the sentiments associated with the GCC, and local climate change news are significant factors causing the RQSI, RESG, VRQSI, and VRESG. As for the results in the first panel, they are significant except for the global positive sentiment causing RESG. According to the results, lagged climate change news sentiments are approximately sufficient to cause movements in Qatar's stock markets return and volatility. Due to these findings, we can suggest that our results are robust for the case of Qatar

Table 108. Granger Causality Diagnosis for Qatar

| Sentiment Variables Based on Global Climate Change News with Disaster (GNDWD) | |
|---|---|
| **H0: Sentiment (Pos/ Neg) Does not Granger Cause (RQSI, VRQSI, RESG, VRESG)** | **P-Value** |
| Pos → RQSI | 0.081* |
| Pos → VRQSI | 0.014** |
| Pos → RESG | 0.105 |
| Pos → VRESG | 0.016** |
| Neg → RQSI | 0.072* |
| Neg → VRQSI | 0.000*** |
| Neg → RESG | 0.020** |
| Neg → VRESG | 0.000*** |
| **Sentiment Variables Based on GCC Climate Change News with Disaster (GCCNDWD)** | |
| **H0: Sentiment (Pos/ Neg) Does not Granger Cause (RQSI, VRQSI, RESG, VRESG)** | **P-Value** |
| Pos → RQSI | 0.084* |
| Pos → VRQSI | 0.059* |
| Pos → RESG | 0.018** |
| Pos → VRESG | 0.037** |
| Neg → RQSI | 0.006*** |
| Neg → VRQSI | 0.000*** |
| Neg → RESG | 0.062* |
| Neg → VRESG | 0.001*** |
| **Sentiment Variables Based on Local Climate Change News with Disaster (LNDWD)** | |
| **H0: Sentiment (Pos/ Neg) Does not Granger Cause (RQSI, VRQSI, RESG, VRESG)** | |
| Pos → RQSI | 0.097* |
| Pos → VRQSI | 0.032** |
| Pos → RESG | 0.082* |
| Pos → VRESG | 0.073* |
| Neg → RQSI | 0.041** |
| Neg → VRQSI | 0.004*** |
| Neg → RESG | 0.100* |
| Neg → VRESG | 0.000*** |

Note: the *, **, *** Depicts the significance with 10, 5, and 1 percent significance level using.

### *6.3.2. Causality between UAE Stock Market and Climate Change News*

According to the Granger causality results for UAE, the study's results are robust. The Granger causality test is conducted to establish if climate change news sentiments, both positive and negative sentiments, do not granger cause RADX, VRADX, RDFM, VRDFM, RESG, and VRESG, respectively. Table 18 summarizes the results of the Granger causality test. In this regard, the results have been divided into three panels. The first panel examines the null hypothesis that global climate change news sentiments do not granger causes RADX, VRADX, RDFM, VRDFM, RESG, and VRESG.  The second panel examines the null hypothesis that GCC climate change news sentiments do not granger causes RADX, VRADX, RDFM, VRDFM, RESG, and VRESG. The third panel examines the null hypothesis that local climate change news sentiments do not granger causes RADX, VRADX, RDFM, VRDFM, RESG, and VRESG. The results indicate that the sentiments associated with the global, GCC, and local climate change news are significant factors causing the movements in RADX, VRADX, RDFM, VRDFM, RESG, and VRESG. According to the results, lagged climate change news sentiments are approximately sufficient to cause movements in UAE's stock markets return and volatility. Due to these findings, we can suggest that our results are robust for the case of UAE.

Table 119. Granger Causality Diagnosis for UAE

| **Sentiment Variables Based on Global Climate Change News with Disaster (GNDWD)** | |
|---|---|
| **H0: Sentiment (Pos/ Neg) Granger Cause (RADX, VRADX, RDFM, VRDFM, RESG, VRESG)** | **P-Value** |
| Pos → RADX | 0.082* |
| Pos → VRADX | 0.097* |
| Pos → RDFM | 0.099* |
| Pos → VRDFM | 0.010* |
| Pos → RESG | 0.083* |
| Pos → VRESG | 0.077* |
| Neg → RADX | 0.068* |
| Neg → VRADX | 0.000*** |
| Neg → RDFM | 0.092* |
| Neg →VRDFM | 0.034** |
| Neg → RESG | 0.041** |

| | |
|---|---|
| Neg →VRESG | 0.007*** |
| **Sentiment Variables Based on GCC Climate Change News with Disaster (GCCNDWD)** | |
| **H0: Sentiment (Pos/ Neg) Granger Cause (RADX, VRADX, RDFM, VRDFM, RESG, VRESG)** | **P-Value** |
| Pos → RADX | 0.050** |
| Pos → VRADX | 0.090* |
| Pos → RDFM | 0.031** |
| Pos → VRDFM | 0.103* |
| Pos → RESG | 0.061* |
| Pos → VRESG | 0.085* |
| Neg → RADX | 0.075* |
| Neg → VRADX | 0.025** |
| Neg → RDFM | 0.061* |
| Neg →VRDFM | 0.009*** |
| Neg → RESG | 0.052* |
| Neg →VRESG | 0.025** |
| **Sentiment Variables Based on Local Climate Change News with Disaster (LNDWD)** | |
| **H0: Sentiment (Pos/ Neg) Granger Cause (RADX, VRADX, RDFM, VRDFM, RESG, VRESG)** | **P-Value** |
| Pos → RADX | 0.034** |
| Pos → VRADX | 0.046** |
| Pos → RDFM | 0.067* |
| Pos → VRDFM | 0.100* |
| Pos → RESG | 0.076* |
| Pos → VRESG | 0.078* |
| Neg → RADX | 0.013** |
| Neg → VRADX | 0.002*** |
| Neg → RDFM | 0.084* |
| Neg →VRDFM | 0.025** |
| Neg → RESG | 0.089* |
| Neg →VRESG | 0.042** |

Note: the *, **, *** Depicts the significance with 10, 5, and 1 percent significance level using MacKinnon (1996) one sided p-values

# 7. CONCLUSION AND THESIS IMPLICATIONS

## 7.1. Conclusion

This thesis examines several underlying insights concerning the impact of climate change news sentiment on selected GCC stock markets. We focus on exploring the different impacts climate change news has on Environmental, Social, and

Governance (ESG) equity index compared to the general stock market index. Particularly, the study results highlight the impact of climate change news on the stock markets of Qatar and UAE, two GCC countries. The study suggests analyzing the impact of climate change news as a proxy of investor sentiment with distinctive classification considering the news publication region. As per the publication region, the news classification exhibited the magnitude and path of climate change news's impact on the stock market.

Furthermore, the study indicates that climate change news sentiment positively impacts the return on ESG equity (RESG) in Qatar and the UAE. In the meantime, the sentiments associated with climate change news result in lower RESG volatility. The results also show that ESG equities are less connected to the general stock market index during climate uncertainty. This is due to the general stock market indices for both countries responding negatively to climate change news sentiments. In the meantime, stock market returns were subjected to increased market volatility. It has also been found that a greater bilateral co-movement of stock market returns between Qatar and UAE is associated with greater dependence in how both countries respond to climate change risks. This is further evidenced by the fact that both countries export oil and share the same economic characteristics.

Additionally, the study results indicate that investors' behavior in Qatar and the UAE is influenced by climate change news. According to the Impulse Response Functions (IRF) for the stock market indices, investors in both GCC countries react significantly for ten days or more following the publication of global, GCC, and local climate change news. Therefore, investors in Qatar and UAE perceive the news differently and change their investment strategies accordingly. As investors change their investment strategies in responding to climate change news sentiment, the overall impact obtained in this study suggests a positive social impact, supporting corporations with environmental responsibility.

### 7.2. Thesis Implication

This study provides significant implications for stimulating growth in the stock markets of the Gulf Cooperation Council. First, considering the considerable risk climate change poses to the two GCC stock markets, this study highlights the importance of addressing and overcoming the long-run physical and transitional risks of climate change on the societies of GCC countries. The social factor is a major factor that determines ESG equities. Society's role can be centered on multiple aspects in the context of reducing the impact of climate change. Whether it is their consumption behavior or investment behavior, the role of society in the evolution of companies cannot be overstated. This study suggests that GCC investors should raise concerns regarding climate-related risk disclosures in ESG and non-ESG equities. Reporting climate-related risks in the company's annual financial statements should be strictly followed. A detailed framework for the company's disclosure from the regulators is needed to increase climate change-related disclosure and prevent greenwashing effectively. The climate relevant disclosure would lead to lower market volatility and prices shifts as we have stated in the beginning of this thesis “It is essential to consider several factors when making investments that hedge against climate change threats. These factors include the sector's resilience, investment structure changes, and company disclosure and transparency.”

Furthermore, the findings of this study provide significant implications for investors, including potential opportunities for capital appreciation. Through constructing a set of climate change news sentiment indices with distinctive features, the study quantifies the impact of climate change for investment purposes. Climate change news sentiments can be used as an indicator for investors to measure their portfolio's sensitivity to climate change incidents. Investors highly concerned about climate change would hold a portfolio that weighs a higher allocation to equities compliant with ESG reporting and vice versa.

### 7.3. Study Limitations

Finally, there are some limitations to the study. It is important to note that the GCC region consists of six countries, including Saudi Arabia, Kuwait, Oman, Bahrain, the United Arab Emirates, and Qatar. We limit our study, however, to Qatar and UAE since both countries have ESG equity indices that can be used to measure the performance of ESG securities.

### 7.4. Future Research

The proxy for climate change proposed here can be used to guide further research in a variety of fields. As the concern of climate change threats is widely investigated in recent research, the implication of this study may pave the way toward studying the impact of climate change news on stock market industries, energy prices, and others.

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