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The Impact of Investor Sentiment on Energy-Related Companies in Times of Crises

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Preface and acknowledgements

Writing this master thesis has been a though process, requiring hard work, dedication, and deep interest in the subject of investor sentiment. In the beginning I spent a lot of time thinking and developing the method, which did not generate a direct output for the thesis. This is a challenging time in which it seems like you are not making any progress, but in reality, it lays the foundation that makes writing the rest of the thesis a lot more pleasant. Now, a few months later and 77 pages further, I can look back with pride on the end result.

Throughout this process, I have been fortunate to work with my thesis supervisor, Dr. J. J. G. Lemmen, who provided valuable guidance and feedback. His insights, critiques, and suggestions have been instrumental in shaping this work.

I would also like to extend my sincere gratitude to my family and girlfriend for their unwavering support and belief in me, even during the most challenging moments of this journey. Their love, encouragement, and helpful advice have been my anchor during this process.

Abstract

The aftermath of the COVID-crisis had its impacts and caused a global energy crisis, which has been accelerated by the Russian invasion of Ukraine on the 24^{th} of February 2022. This paper studies the impact of investor sentiment on stock returns of Western energy-related companies during this ongoing energy crisis and examines the role of the invasion. A panel data approach is applied in which 426 companies and 69 weeks over September 2021 - December 2022 are included. Interaction effects between investor sentiment and oil, gas, and coal returns are examined to measure the impact on stock returns during these times in which commodity prices have risen sharply. To illustrate these interaction effects, graphs are used that display the impact of investor sentiment on stock returns, assuming the 25^{th} percentile, median, and 75^{th} percentile values in the sample distribution for oil, gas, and coal returns. The results provide evidence for a positive effect of investor sentiment on stock returns during the energy crisis, assuming the three energy returns between the 25^{th} percentile and the 75^{th} percentile values in the sample. In a short-term period of one week before and seven weeks after the invasion, a negative influence of investor sentiment is found, except when low values for gas returns are assumed. Sentiment has a different impact on stock returns during a short and chaotic period around the invasion compared to a longer energy crisis period, where sentiment adjusts to the circumstances.

Keywords: investor sentiment, energy crisis, Russian invasion of Ukraine, CAR

JEL Classification: G14, G01, H56, G12

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1. Introduction

Investor sentiment is a topic that has been widely studied by researchers. It is no longer a surprise that the way how individual investors react has its effects on stock markets, the challenge lies in how it should be measured (Baker & Wurgler, 2007). One way to measure investor sentiment is by using market variables such as trading volume, IPO returns, net fund flows or the put-call ratio. These variables can serve as indirect proxies (Finter et al., 2012). This paper applies Google Trends to find out the effect of investor sentiment (Bijl et al., 2016; Bank et al., 2011; Da et al., 2011; Jun et al., 2018; Preis et al., 2013). Google Trends is growing as a big data source among researchers in a wide range of areas (Jun et al., 2018). One advantage of this data source is that it can provide insights in the current interest of searchers and thus measure the effect of sentiment in a direct way.

On the 24th of February 2022, Russia officially launched the Ukrainian "Special Military Operation", which turned out to be the start of the Russian invasion of Ukraine. More than a year later, thousands of people have been killed by unnecessary purposes. Apart from these dramatic effects of the war, serious economic problems are arising worldwide. These problems are recognized by ECB President Christine Lagarde: "The Russia-Ukraine war will have a material impact on economic activity and inflation through higher energy and commodity prices, the disruption of international commerce and weaker confidence." (CNBC, 2022). The invasion has caused a global energy crisis with record highs for the price of natural gas, and oil prices hit their highest level since 2008 (IEA, n.d.). These records are partly the result of a negative energy supply shock after several countries imposed sanctions against Russia (BBC, 2022). However, vice chairman of S&P Global, Daniel Yergin, states that the current global energy crisis already started in late summer of 2021 (Yergin, 2022). In this period, most countries ceased COVID-19 lockdowns, resulting in high energy demands. These demands could not be met by supplies, which caused increasing energy prices. As a result, individual investors react by trading on stock markets. Therefore, this paper investigates to what extent investor sentiment has played a role on stock returns during the ongoing energy crisis. The main research question is as follows:

"What is the impact of investor sentiment on Western energy-related stock returns in 2021 - 2022 during the global energy crisis?"

Answering the research question through this research can lead to a broader knowledge on the role of investor sentiment during crises. This study is the first to link these subjects to the current energy crisis and the recent events that took place between Russia and Ukraine. In addition, this paper uses a direct measurement of investor sentiment by means of Google Trends. Not many studies focus solely on energy-related companies. By doing so, the most relevant effect can be examined as individual investors have become more interested in these companies due to the arisen energy crisis. Rationally, investor sentiment should not affect stock prices as it should be based merely on company valuation. It is already known that in practice this is not the case. Therefore, measuring how investors react on certain events can be very insightful. When a significant effect on stock prices is measured, changes in stock market regulation could be implemented.

This paper uses a panel data approach of 426 companies over 69 weeks from September 2021 to December 2022 to find out the effect of investor sentiment on stock returns. Weekly Cumulative Abnormal Returns (CARs) are calculated as a proxy for stock returns, a sentiment indicator that subtracts the average Google Search Volumes of positive search terms from the average of negative search terms is used to measure the market-wide investor sentiment. Interaction effects between this sentiment indicator and oil, gas, and coal returns mainly determine the central outcome of this research. To analyze these interaction effects as accurately as possible, figures are used that show the effect of investor sentiment on stock returns when assuming the 25th percentile, median, and 75th percentile[1] values in the sample distribution of oil, gas, and coal returns.

Although the current literature often points to a negative effect of sentiment on stock returns, this research finds contradictory results. Assuming oil, gas, and coal returns between the 25th percentile and the 75th percentile values in the sample distribution, a positive effect of investor sentiment on stock returns is found during the first period of the ongoing energy crisis (September 2021 - December 2022). Moreover, a negative effect is found during a shorter window of nine weeks around the Russian invasion of Ukraine (February 13, 2022 - April 16, 2022), except when low values of gas returns are assumed. In addition, the impact of investor

[1] The 25th percentile is the value at which 25% of the oil, gas, and coal returns in the sample lie below that value, and 75% above that value. The median is also known as the 50th percentile. At the 75th percentile, 75% of the returns in the sample lie below that value, and 25% above.

sentiment differs between regions and over time; the impact is bigger in the US than in the EU and bigger in the post-invasion period (February 20, 2022 - December 31, 2022) than before the invasion (September 5, 2021 - February 19, 2022). An increase in trading volumes in the post-invasion period is found. However, no significant results are found on the effect of investor sentiment on trading volumes.

The remainder of this thesis is divided into different chapters. In Chapter 2, an overview of the existing literature relative to investor sentiment, Google Trends data, and the outbreak of the Russia-Ukraine war is given and discussed. Subsequently, the hypotheses are formulated. Chapter 3 provides a description of the data process and discusses the descriptive statistics of the final dataset. Next, Chapter 4 describes the applied methodology of the paper. Chapter 5 contains the results of the conducted tests, on which is concluded in Chapter 6 in combination with the limitations and recommendations of this paper.

2. Literature Review

This chapter focuses on the existing literature that is relevant for the study. First, a detailed view into the theory of investor sentiment is given in Section 2.1. Most papers in this section use more classical ways of measuring sentiment. In this paper, the big data source Google Trends is used to measure the market wide sentiment. Literature relative to Google Trends will therefore be discussed in Section 2.2. Next, Section 2.3 provides some insights on the stock market reaction after the Russian invasion of Ukraine. For each section, a summary of the findings is given in a meta table. Finally, the hypotheses can be formulated based on the discussed literature in Section 2.4.

2.1 Investor sentiment

Investor sentiment is the central topic of this paper. It has been a topic of interest in the field of finance for many years. Therefore, it is important to discuss several papers that have contributed to the understanding of investor sentiment and its role in financial markets.

According to the Efficient Market Hypothesis, stocks should trade on their fair value, and it is impossible to generate alpha (Fama, 1970). Prices should quickly adjust to reflect new information and eliminate any mispricings. In practice, there have been several market bubbles, such as the Dotcom bubble, that show that stocks do not always trade on their fair value. These bubbles are predominantly caused by sentiment. Black (1986) explains investor sentiment using noise. Investors trade inefficiently on noise as if it is information. De Long et al. (1990) notice that sentiments from noise traders lead to deviations in stock prices from their fundamentals, even when there is no fundamental risk. Baker and Wurgler (2006) define investor sentiment as optimism or pessimism about stocks in general. They argue that during a bubble, there is a high tendency for investors to speculate on stock prices due to the subjectivity of their valuations. For investor sentiment to affect stock valuation, three assumptions have to be made, according to Brown and Cliff (2005). First, a subset of investors makes biased asset valuations. Second, these biases need to be persistent. Third, there are limits to arbitrage that hinder individual investors to exploit the asset mispricing. They find that periods of positive investor sentiment are associated with below-average returns in the following months, and vice versa. Schmeling (2007) agrees on this negative relationship between individual sentiment and future stock returns. He distinguishes between individual sentiment and institutional sentiment and finds that institutions are better at forecasting. Institutional sentiment takes expected individual sentiment into account, which leads to an expected mean-reversion in stock prices instead of trend continuation. Schmeling (2007) refers to high or low investor sentiment as periods of high overoptimism or overpessimism but does not draw the difference between positive sentiment and negative sentiment. Tetlock (2007) does make this distinction by examining the relationship between the media and stock market performance. His findings indicate that media pessimism tends to put downward pressure on market prices, followed by a reversal to fundamentals. Additionally, unusually high or low pessimism predicts increased trading volumes. Corredor et al. (2013) analyze investor sentiment in four key European stock markets and find that investor sentiment has an influence on stock returns, varying in intensity across markets. The results are sensitive to the choice of the sentiment proxy. Finter et al. (2012) zoom in on the German market by constructing a sentiment indicator based on several well-known sentiment proxies. Stocks that are difficult to arbitrage and hard to value are most sensitive to this indicator, but they cannot find much predictive power of sentiment for future stock returns. Many of these studies that investigate the relationship between stock returns or -volatility and investor sentiment tend to ignore using lagged returns in their models. Past returns can provide information for investors to trade. Wang et al. (2006) find that the forecasting power of sentiment indicators on stock volatility significantly shrinks when lagged returns are added to the model. Lagged returns are the variables that cause volatility. In fact, these returns Granger-cause sentiment proxies rather than the other way around.

Barber and Odean (2008) focus on investor attention and find that individual investors are attention-based buyers. Individual investors are net buyers of stocks that grab their attention as it is difficult to pick a stock from all the available options. Fang and Peress (2009) are inspired by the paper of Barber and Odean (2008) and perform a relatable research based on media attention. They find a negative impact of media attention on stock returns, even after controlling for multiple approved risk factors. However, this paper focuses on investor sentiment rather than investor attention. Investor sentiment refers to the emotional state of investors, which can be influenced by macroeconomic circumstances such as economic conditions and political events (Baker & Wurgler, 2006). Investor attention refers to the level of interest that investors have in a particular stock, and this can be determined by factors like media coverage and company performance (Barber & Odean, 2008). Because this paper aims to show the effect of the energy crisis and the Russian invasion, which are macroeconomic events that heavily influence investors' emotions, sentiment gives a better overall indication than attention.

Since this paper examines the role of investor sentiment for energy-related companies, it is important to add energy-related literature. Most literature measures investor sentiment in energy markets rather than in energy-related companies. Deeney et al. (2015) expand sentiment to energy markets and create a five-part sentiment index for oil based on that of Baker and Wurgler (2006) and demonstrate that sentiment partially influences oil prices during 2002-2013. Du et al. (2016) show that investor sentiment helps determining the fluctuation of oil prices, as well as those of gasoline, heating oil, and the stock prices of oil companies. Additionally, positive sentiment predicts subsequent high returns in oil prices, particularly over the long term, while negative sentiment is associated with subsequent low returns. They distinguish between nominal and real oil prices as inflation can heavily influence nominal prices. This distinction yields similar results. Apergis et al. (2018) investigate the other way around and test whether energy prices influence investor sentiment. Their findings suggest that there is a significant impact from both the crude oil and the natural gas price on investor sentiment. Mezghani et al. (2021) belong to the rare papers that discuss investor sentiment in the energy sector and focus on China, but they cannot find any significant effect of sentiment on returns. In Table 1, an overview of the discussed investor sentiment-related articles is shown.

Table 1: Overview of literature on investor sentiment

Author(s) (Publication year)	Time period	Region	Method	Results
Fama (1970)	1957-1962	US	Efficient Market Model	Extensive evidence that markets are efficient
De Long et al. (1990)	1990	US	Overlapping generations model of an asset market with two-period-lived agents	Noise traders create deviations in stock prices from fundamentals
Brown & Cliff (2005)	1963-2000	US	Survey data for sentiment, Fama and French portfolios for returns, linear regression	Sentiment affects asset valuation. Future returns are negatively related to sentiment
Baker & Wurgler (2006)	1962-2001	US	Sentiment index with six components, time series regression	Negative relationship between sentiment and returns for high-risk stocks
Wang et al. (2006)	1990-2001	US	Time series regression with lagged volatility	Sentiment is caused by returns and volatility rather than vice versa

Schmeling (2007)	2001-2006	EU, USA, Japan	Survey data for sentiment, time series regression, IV regression	Individual sentiment proxies for noise trader risk. Institutional sentiment proxies for smart money
Tetlock (2007)	1984-1999	US	Sentiment based on WSJ column, VAR and OLS regression	Media pessimism predicts downward pressure on prices followed by a reversion to fundamentals, unusually high/low pessimism predicts high trading volumes
Barber & Odean (2008)	1991-1996	US	Time series regression	Individual investors are attention-based buyers
Fang & Peress (2009)	1993-2002	US	Fama-MacBeth (1973) regression, OLS regression	Negative impact of media attention on stock returns
Finter et al. (2012)	1993-2006	Germany	Sentiment index with well-known sentiment proxies, time series regression	Not much predictive power of sentiment for future stock returns.
Corredor et al. (2013)	1990-2007	EU	Baker & Wurgler (2006) sentiment index, VAR regression	Sentiment has an influence on stock returns, varying in intensity across markets and sentiment indicator
Deeney et al. (2015)	2002-2013	World-wide	Oil sentiment index with 5 proxies, OLS regression	Sentiment influences WTI and Brent future prices
Du et al. (2016)	1986-2010	US	Baker & Wurgler (2006) sentiment index, OLS regression	Sentiment negatively explains the movements in oil prices.
Apergis et al. (2018)	1965-2015	US	Baker & Wurgler (2006) sentiment index, quantile regression	Crude oil and natural gas price impact investor sentiment.
Mezghani et al. (2021)	2012-2020	China	Sentiment through Google Trends, OLS regression	No significant effect of sentiment on energy-related firm returns

2.2 Google Trends

Google Trends is growing in popularity in contemporary research (Jun et al., 2018). In this paper, this search engine is used as a proxy for investor sentiment as well. As investors' interests are immediately visible through Google Trends, it can serve as a direct measure of sentiment.

Below, scientific papers on the use of Google Trends as a measure of investor sentiment are highlighted.

The lack of predictive power of sentiment indicators as proposed by authors such as Finter et al. (2012), can be solved by using Google Trends as a proxy for investor sentiment (Preis et al., 2013). Preis et al. (2013) use a set of 98 search terms regarding the current state of stock markets to construct a trading strategy. They find that Google search query volumes can be interpreted as a sign for stock market movements and suggest that these signs could have been used as profitable trading strategies during the period 2004 to 2011, retrospectively. However, this study has some biases that are recognized by Challet and Ayed (2013). They state that it is important to include a set of random keywords unrelated to finance to clearly point the effect of finance related keywords and find that a strategy based on these random keywords does not underperform a strategy based on finance related search terms. Other studies show that Google Search Volumes are a direct proxy for investor attention (Preis et al., 2010; Da et al., 2011; Bank et al., 2011) and they can influence the trading activity and stock liquidity in the German stock market (Bank et al., 2011). Increasing trading volumes occur when search volumes increase, and vice versa (Preis et al., 2010). Bordino et al. (2012) show a similar correlation using Yahoo! as search engine. Apart from that, high Google Search Volumes could lead to positive returns in the short term as well, followed by a price reversal after this period (Da et al., 2011; Bank et al., 2011). The price reversal in the long run corresponds with Bijl et al. (2016) who find that Google Search Volumes tend to have a negative impact on stock returns. The return-related findings from Bank et al. (2011), Da et al. (2011) and Bijl et al. (2016) are based on search terms related to investor attention rather than sentiment. All in all, Google Trends can serve as a direct proxy for investor sentiment. This can give additional insights in sentiment, apart from measuring sentiment with classic indirect proxies as described in Section 2.1. An overview of the abovementioned Google Trends-related articles can be found in Table 2.

Table 2: Overview of literature on Google Trends

Author(s) (Publication year)	**Time period**	**Region**	**Method**	**Results**
Preis et al. (2010)	2004-2010	US	Firm-specific search volumes, Time lag-dependent autocorrelation, pattern conformity analysis	Positive correlation between GSV and trading volumes

Bank et al. (2011)	2004-2010	Germany	Firm-specific search volumes, panel regression approach	Positive correlation between GSV and trading activity, GSV positively influences future returns in short run, price reversal for longer periods
Da et al. (2011)	2004-2008	US	Firm-specific search volumes, VAR regression, OLS regression	Higher SVI predicts higher stock prices in the short run, eventual price reversal in one year
Bordino et al. (2012)	2010-2011	US	Firm-specific search volumes, time-lagged cross-correlation	Trading volumes are correlated with search query volumes
Preis et al. (2013)	2004-2011	US	Finance related search volumes, constructed trading strategy	GSV can be interpreted as sign for stock market movements, could have been used as profitable trading strategy
Challet & Ayed (2013)	2004-2012	US	Keyword related search volumes, time series	Several biases in Preis et al. (2013), strategy on random keyworks does not underperform finance related strategy
Bijl et al. (2016)	2008-2013	US	Firm-specific standardized search volumes, VAR regression	GSV have a negative impact on stock returns
Jun et al. (2018)	2004-2017	World-wide	Analysis on 657 Google Trend related studies	Google Trends research has increased dramatically and can be used in a wide range of areas

2.3 Impact of the Russian invasion on global stock markets

The Russian invasion of Ukraine has been a big factor in the current energy crisis. Since the war is still going on and the invasion took place recently, little research on the effect of the war is available. A few papers are discussed below.

Stock markets have been hit hard by the occurring circumstances in Ukraine (Patel et al., 2022; Boungou & Yatié, 2022; Federle et al., 2022). According to Patel et al. (2022), the Russian invasion on the 24th of February 2022 had a strong negative impact on most stock markets, especially on the Russian market. The aggregate stock market analysis shows a significant negative influence in the short term on the event day and post event days. Boungou and Yatié (2022) agree on the negative influence of the war and document a large impact during the first two weeks after the invasion. The global reaction diminished in the weeks that followed. The authors also find that countries bordering Ukraine and Russia show the biggest effects, as well as UN member states that demanded Russia to stop the offensive in Ukraine. This implicates that geographical location could play a role in the stock market reaction. In fact, Federle et al. (2022) show that countries closer to Ukraine, react more negatively in a four-week window around the start of the war. Even within countries, firms located closer to Ukraine perform worse than more distant companies. They find a 1.1 percentage points increase in equity returns each 1,000 kilometers of extra distance. In Table 3, an overview of the discussed papers in this section is displayed.

Table 3: Overview of literature on the stock market reaction of the invasion

Author(s) (Publication year)	**Time period**	**Region**	**Method**	**Results**
Boungou & Yatié (2022)	Jan 22 – Mar 24, 2022	Worldwide	Panel data regression	Big negative effect of the war on global stock indices, countries bordering Ukraine and Russia, and UN member states show the biggest effects
Federle et al. (2022)	Feb 10- Mar 10, 2022	Worldwide	Geographic proximity analysis on the invasion, event study, OLS regression	1.1%-point increase in equity returns each 1,000 kilometers of extra distance from Ukraine
Patel et al. (2022)	Feb 17- Mar 3, 2022	Worldwide	Event study	Strong negative impact on most stock markets, significant negative influence in the short term

2.4 Hypotheses

Based on the discussed literature in this chapter, the hypotheses for this study can be formulated. Much energy-related literature on investor sentiment focuses on the energy market rather than on energy-related companies. Energy prices have risen due to the COVID-19 aftermath and the Russian invasion of Ukraine (Yergin, 2022). Apart from these macro-economic events, it is insightful to test whether investor sentiment has played a role in determining the energy prices in this period. Du et al. (2016) find that positive investor sentiment predicts high oil returns. Therefore, Hypothesis 1 is as follows:

H_1: Investor sentiment positively influences energy returns during the energy crisis (September 2021 - December 2022).

This means that when sentiment is positive, energy returns are expected to increase. September 2021 is used as the start of the energy crisis since Yergin (2022) mentioned late summer of 2021 as the starting period. To answer this hypothesis, the three most common energy sources are investigated. Therefore, Hypothesis 1 can be split into three sub-hypotheses:

H_{1A}: Investor sentiment positively influences oil returns during the energy crisis (September 2021 - December 2022).
H_{1B}: Investor sentiment positively influences gas returns during the energy crisis (September 2021 - December 2022).
H_{1C}: Investor sentiment positively influences coal returns during the energy crisis (September 2021 - December 2022).

Most important in answering the research question is testing whether investor sentiment has an impact on Western energy-related stock returns during the energy crisis and what sort of impact. Literature gives evidence for a positive impact of investor sentiment in the long run (Tetlock, 2007). However, this does not outweigh the papers that find a negative relationship (Schmeling, 2007; Brown & Cliff, 2005; Fang & Peress, 2009, Da et al., 2011; Bank et al., 2011; Bijl et al., 2016). Based on these findings, Hypothesis 2 can be formulated:

H_2: Investor sentiment negatively influences stock returns of Western energy-related companies during the energy crisis (September 2021 - December 2022).

Apart from stock returns, it is interesting to test whether investor sentiment has its impact on trading volumes during the energy crisis. It is likely that investors start trading in response to the rising energy prices and the fear of future energy shortages. Multiple papers find a positive correlation between investor sentiment and trading volumes (Tetlock, 2007; Preis et al., 2010; Bordino et al., 2012). Hence, Hypothesis 3 is as follows:

H_3: Investor sentiment positively influences trading volumes of Western energy-related companies during the energy crisis (September 2021 - December 2022).

The Russian invasion of Ukraine has had a major impact in the energy crisis. From that moment, it became clear that there would be a big shortage of energy if Russia ceased to be a supplier. Global stock markets have fallen sharply right after the invasion (Patel et al., 2022; Boungou

& Yatié, 2022; Federle et al., 2022). It will be investigated if investor sentiment has played a role in the short term around the Russian invasion of Ukraine on the 24th of February 2022. Google Search Volumes are positively correlated to stock returns in the short term (Da et al., 2011; Bank et al., 2011). This leads to Hypothesis 4:

H_4: Investor sentiment positively influences stock returns of Western energy-related companies in the short run around the invasion of Ukraine (February - April 2022).

The impact of the war on stock markets is bigger in countries that are closely located to Russia (Boungou & Yatié, 2022; Federle et al., 2022). Since this research takes all Western (i.e., Europe and US) energy-related companies into consideration, a difference of investor sentiment on European and US companies can be made in Hypothesis 5:

H_5: The impact of investor sentiment on stock returns of Western energy-related companies during the energy crisis (September 2021 - December 2022) is bigger in Europe than in the US.

As several news channels claim, the Russian invasion was the main cause of the current energy crisis (IEA, n.d.; Gaffen, 2022). Therefore, there will be tested if this event on the 24th of February 2022 was a turning point for the impact of investor sentiment on stock returns and the trading volumes of energy-related companies in Hypothesis 6 and Hypothesis 7:

H_6: Investor sentiment has a bigger impact on stock returns of Western energy-related companies after the start of the invasion than before the start of the invasion (from September 2021).

H_7: Trading volumes of Western energy-related companies are higher after the start of the invasion than before the start of the invasion (from September 2021).

3. Data

This study examines the effect of investor sentiment on the stock price regarding Western public energy-related companies during the current energy crisis and the Russian invasion of Ukraine. For this research, multiple sample period are used. The sample period for the energy crisis runs from September 5, 2021, to December 31, 2022. In addition, the impact of investor sentiment on stock returns is analyzed in a smaller period around the Russian invasion of Ukraine for Hypothesis 4. This period spans one week before and seven weeks after the invasion, covering a short-term window from February 13, 2022, to April 16, 2022. Moreover, the invasion is used as a turning point for the effect of investor sentiment on the stock returns and the difference in trading volumes for Hypotheses 6 and 7. The pre-invasion period includes Weeks 1-24 in the sample, spanning from September 5, 2021, to February 19, 2022. The post-invasion period includes the week in which the invasion took place (Week 25) and lasts until Week 69, covering the period from February 20, 2022, to December 31, 2022.

To find all energy-related companies, a data selection has to be constructed. First, all firms from the energy sector are put into the dataset. Apart from the energy sector, this research includes the utilities sector as well. In this sector, different sub-industries like electric-, gas-, water- and multi-utilities are active. Besides, the growing interest in renewable energy is covered within this sector. Including these sub-industries can give the research broader insights than by solely focusing on the energy sector. In Table 4, the Global Industry Classification Standard (GICS) of the sectors and sub-industries used for this study is shown.

This study contains Google Trends, Datastream and Investing.com data. These three components are merged into one dataset. The sample selection is mainly based on the data available from the Datastream database, since this database includes the most complete data for the research. Datastream distinguishes between industries in a slightly different way than the GICS classification. In total, companies from five different industries are included in the research:

1. Alternative energy
2. Electricity
3. Gas-, water-, and multi-utilities
4. Oil and gas producers
5. Oil equipment and services

The companies from these five industries will be referred to as energy-related companies. In addition, a geographical specification must be made for the sample. The aim of this study is to measure the effect of the energy crisis and the Russian invasion of Ukraine as precise as possible. Therefore, the countries most affected by these events are considered. Since Russia has exported 80% less natural gas to EU countries since the outbreak of the war (IEA, 2022), these EU countries are certainly included in the study. However, the United Kingdom – not part of the EU – has also banned Russian oil (James & Maclellan, 2022). Therefore, all European countries are included. In addition, the US cannot be forgotten with its strict and powerful sanctions against Russia (BBC, 2022). Thus, the dataset will contain companies from both European countries and the US. These will be referred to as Western companies. In Sections 3.1-3.3, the data collection is given for the dependent variable, the independent variable and the control variables. Section 3.4 provides the descriptive statistics of the final dataset.

Table 4: GICS of the Energy and Utilities Sector

Sector	Industry Group	Industry	Sub-Industry
Energy 10	**Energy** 1010	**Energy Equipment & Services** 101010	**Oil & Gas Drilling** 10101010
			Oil & Gas Equipment & Services 10101020
		Oil, Gas & Consumable Fuels 101020	**Integrated Oil & Gas** 10102010
			Oil & Gas Exploration & Production 10102020
			Oil & Gas Refining & Marketing 10102030
			Oil & Gas Storage & Transportation 10102040
			Coal & Consumable Fuels 10102050
Utilities 55	**Utilities** 5510	**Electric Utilities** 551010	**Electric Utilities** 55101010
		Gas Utilities 551020	**Gas Utilities** 55102010
		Multi-Utilities 551030	**Multi-Utilities** 55103010
		Water Utilities 551040	**Water Utilities** 55104010
		Independent Power & Renewable Electricity Producers 551050	**Independent Power Producers & Energy Traders** 55105010
			Renewable Electricity 55105020

Table 4 includes the Global Industry Classification Standard (GICS) for the sectors chosen for the research. These are divided in Columns (1)-(4) from sector to sub-industry. Source: S&P Global Market Intelligence, 2018.

3.1 Investor sentiment data

Investor sentiment is measured by means of Google Trends. Google Trends is a widely used data platform in research (Jun et al., 2018). With Google Search Volumes (GSV), the number of searches for certain keywords can be determined on a scale of 0 to 100 compared to the average interest in the same keyword. Google Trends only contains daily data for a period shorter than nine months. This has no negative influence, direct effects of Google Search Volumes on the stock returns are difficult to measure by daily data. Therefore, weekly data is used. Weeks last from Sunday to Saturday at Google Trends. The first week starts on Sunday September 5, 2021, the last week ends on Saturday December 31, 2022. This gives a total of 69 weeks from which Google Search Volumes are measured. For the research, positive and negative keywords are used to measure the sentiment as accurately as possible. The words can be related to the war, the current state of the economy, the COVID/energy crisis, or just normal words that can express a positive or negative feeling as suggested by Challet and Ayed (2013). In total, 94 different search terms are used, 47 positive and 47 negative words (see Appendix A). Afterwards, a sentiment index is created that represents the average of the Google Search Volumes of all positive sentiment related terms minus the average of all negative sentiment related terms. This leads to an indicator that varies over time within the range of [-100;100]. The bigger the indicator, the more positive investor sentiment is. The formula for the sentiment indicator is shown in Formula 1.

$$(1)\ GSV_t = Average\ GSV\ (positive)_t\ - Average\ GSV\ (negative)_t$$

3.2 Stock price data

Daily stock price data from September 5, 2021, to December 31, 2022, is taken from Datastream. Partly because the Google Search Volumes are taken on a weekly basis, returns are taken weekly as well. This is done by calculating weekly CARs after performing multiple steps. First, daily returns are calculated using daily stock prices obtained from Datastream (Formula 2).

$$(2)\ R_{i,t} = \frac{p_{i,t}}{p_{i,t-1}} - 1$$

These returns represent the actual returns. Companies with more than 40 missing returns in total or companies with more than four consecutive missing returns (weekends excluded) are dropped after this step. All steps in the data filtering process can be reviewed in Appendix B. Because the Russian market was closed for almost a month right after the Russian invasion, all Russian companies are dropped as well. After this, expected returns are calculated by applying the traditional CAPM model (Formula 3). This model consists of a risk-free rate (r_f), a company-specific beta (β_i) and a market risk premium ($r_m - r_f$). These components all depend on whether the company is based in the US or the EU. For US-companies, the 10-year T-bond is taken as a risk-free rate, and the S&P500 is used as benchmark. For the EU-companies, the risk-free rate is represented by the German 10-year bond and the STOXX600 is used as benchmark. These risk-free rates and benchmarks are obtained from Investing.com. The company-specific beta is calculated by using Formula 4. For the betas, an estimation window of [-250;-4] regarding the start of the Russian invasion of Ukraine on February 24, 2022, is used. The start of this window is -250 since this is approximately one trading year before the event. The end of the estimation window is -4, as on the 21st of February 2022, Vladimir Putin gave a speech on television in which he informed the country that he had ordered his troops to perform "peacekeeping duties" in southeast Ukraine after recognizing the Ukrainian territories as independent (The Guardian, 2022). This can indicate the start of trading behavior from individual investors. The end of -4 is one trading day before Putin's speech and cancels out this noise around the event. For the betas, the benchmarks are used depending on the country of origin as well.

$$(3)\ E[R_{i,t}] = r_f + \beta_i * (r_m - r_f)$$

$$(4)\ \beta_i = \frac{cov(r_i, r_m)}{var(r_m)}$$

After the expected returns are calculated, daily Abnormal Returns (ARs) can be measured by subtracting the expected returns from the actual returns (Formula 5).

$$(5)\ AR_{i,t} = R_{i,t} - E[R_{i,t}]$$

The weekly CARs are obtained after adding all ARs from a specific week (Formula 6). Since stock markets are closed on weekends, a standard week consists of 5 trading days. In some weeks other non-trading days occur (due to holidays, e.g.). In these cases, weekly CARs are calculated by adding of 3 or 4 ARs. By applying this method, each company has 69 weekly CARs.

$$(6) CAR\ [T_1, T_2] = \sum AR_{i,t}$$

To test whether the CARs are statistically different from zero, a two-sided one-sample t-test on the weekly CAR is performed (Formula 7). In this test, the null hypothesis is that the mean is equal to zero. The alternative hypothesis is that the mean is different from zero.

$$(7)\ t = \frac{(\bar{x} - \mu_0)\sqrt{n}}{s}$$

In Formula 7, $\bar{x}$ represents the mean of the sample. μ_0 is the expected mean, in this case 0. n is the number of observations and s represents the sample standard deviation. In Table 5, results of the t-test can be found. The critical value of the t-test is 3.4834, this in combination with 29,393 degrees of freedom leads to a P-value of .0005. This means that at a 1% significance level, the null hypothesis can be rejected, which indicates that the mean is different from zero.

Table 5: T-test for the CAR

Variable	#Obs	Mean	Std. Err.	Std. Dev	t-crit	df	P-value
CAR	29,394	0.2189%	0.0628%	.1077	3.4834***	29,393	.0005

Table 5 displays the performed one-sample t-test for the CAR and indicates whether the mean of the CAR differs from zero. #Obs = number of observations. Std. Err. = Standard Error. Std. Dev. = Standard Deviation. t-crit = t-critical value. df = Degrees of Freedom. ***, **, and * represent 1%, 5% and 10% significance, respectively.

3.3 Financial data

Multiple control variables are necessary when performing a regression analysis. The financial data for these control variables is retrieved from Datastream and Investing.com. This study focuses on energy-related companies, and stock prices of these firms are heavily influenced by the commodity price of the firm-specific underlying energy source such as crude oil or natural gas (Sadorsky, 1999; Ahmed & Sarkodie, 2021). Therefore, it is required to control for price fluctuations of these commodities, and this study uses the weekly oil, natural gas, and coal returns as proxy for the possible underlying commodities. The energy prices are obtained from Investing.com and these weekly returns are calculated by averaging the daily returns for each week. The Brent Futures, Dutch TTF Natural Gas Futures, and Rotterdam Coal Futures are used to proxy for the oil, gas, and coal price, respectively. Besides, there is controlled for two classic and commonly used sentiment indicators, the trading volumes of each stock and the weekly VIX volatility index. The weekly trading volumes are obtained from Datastream and are calculated by averaging the daily trading volumes within one week. Illiquid stocks (less than 10.000 daily trades on average) are removed from the sample. The weekly CBOE volatility index is retrieved from Investing.com, weekly values are calculated by averaging the daily volatilities. For some hypotheses, it is interesting to draw a difference between firms and not just over time. In these cases, company size, debt-to-equity ratio, trading volume, return on equity and firm industry are used as control variables as well. All of these controls are retrieved from Datastream and represent the most recent available numbers. Total assets are used as a proxy for company size. Because total assets can be large numbers and the dependent variable (CAR) is represented by a percentage, the obtained effect from the regressions will be small. Therefore, total assets are used on a logarithmic scale. For the trading volumes, this is the same case. The debt-to-equity (D/E) ratio is measured by dividing total long-term debt by common equity. Return on equity (RoE) is included to measure the firms' profitability. For the firm industry, a categorical variable is created that distinguishes in the five industries listed earlier in this section. Net revenues are not included but companies with a net revenue of zero are removed due to this sign of inactivity. In case companies originally have another currency than the dollar, the exchange rate on the 31st of December 2022 is used to convert the amounts to US-dollars. This leads to a total of 426 publicly listed companies included in the sample, 253 US companies and 173 EU companies. An overview of all companies per industry is shown in Appendix C. The number of firms per country and industry can be found in Table 6.

Table 6: Number of companies per country and industry

Industry/ Country	Alternative energy	Electricity	Gas, water & multi-utilities	Oil & gas producers	Oil equipment & services	Total
US	33	41	32	73	74	**253**
UK	3	4	7	16	9	**40**
Norway	7	3		7	9	**26**
Italy	1	9	4	2	2	**18**
Germany	7	5	3	1		**16**
Sweden	10	1		2		**13**
Spain	2	7	1	1	2	**13**
France	3	3	2	2	3	**13**
Poland	3	4				**7**
Netherlands	2				3	**5**
Austria		1	1	1	1	**4**

Denmark	2	1				**3**
Portugal		2		1		**3**
Cyprus					2	**2**
Turkey			1			**1**
Switzerland		1				**1**
Czech Republic		1				**1**
Luxemburg					1	**1**
Hungary				1		**1**
Romania				1		**1**
Finland		1				**1**
Greece			1			**1**
Belgium		1				**1**
Ireland	1					**1**
Israel	1					**1**
Total	**75**	**85**	**52**	**108**	**106**	**426**

Table 6 displays the number of companies per country and industry. In Column (1) the concerning countries are shown. Columns (2)-(6) represent the number of companies per country for each industry. Column (7) shows the total number of companies for each country. The bottom row displays the total number of companies for each industry.

3.4 Descriptive statistics

To get a good overview of with what type of data the regressions are performed, the descriptive statistics of all variables will be discussed in this section. For the CAR, trading volume (vol), and Google Search Volumes (GSV), a distinction is made between the period before the Russian invasion of Ukraine (pre-invasion) and the period after the invasion (post-invasion). The invasion on the 24th of February 2022, took place in Week 25 of the sample. Therefore, the pre-invasion period represents Weeks 1 through 24, and the post-invasion period Weeks 25 through 69. For the energy returns, VIX and other control variables, the overall descriptive statistics are given. For each variable, the mean, median, minimum, maximum, skewness, kurtosis, and the number of observations are highlighted. Table 7 shows the statistics of the weekly CARs, one of the two dependent variables for the research.

Table 7: Descriptive Statistics weekly CARs

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
CAR (pre-invasion)	0.19%	-0.50%	-67.32%	91.44%	1.19	12.75	**10,224**
CAR (post-invasion)	0.23%	-1.02%	-110.92%	454.15%	4.03	120.79	**19,170**
CAR (full)	0.22%	-0.78%	-110.92%	454.15%	3.84	124.56	**29,394**

Table 7 includes the descriptive statistics for the weekly CAR. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

In Table 7 several things stand out. First, the mean is positive for both periods. This indicates that energy-related companies overall outperformed the market during the energy crisis. Post-invasion, the mean is more positive than before the invasion (0.23% vs. 0.19%). Second, post-invasion, the CARs are more extreme, resulting in a bigger minimum and maximum. Third, the kurtosis post-invasion is 120.79, which is also an extreme number. This leads to a high kurtosis in the full sample as well. Skewness and kurtosis are important indicators for a data sample (Cain, Zhang & Yuan, 2017). Skewness describes to what extent the data distribution deviates from symmetry. Kurtosis measures if the data distribution deviates from normality in tails. When skewness and kurtosis are high, this can harm the validity of the research because in an OLS-regression, a normal distribution is assumed. The extreme kurtosis in the case of the CARs post-invasion can be diminished by deleting outliers or performing a winsorization. To distort the data as little as possible, winsorization is preferred in this study. The high kurtosis for the CARs is mainly caused by the extreme minima and maxima. Therefore, a winsorization of 0.5% is performed. This indicates that the highest and lowest 0.5% of CARs are replaced by the next highest and lowest CAR in the dataset. The adjusted descriptive statistics are displayed in Table 8.

Table 8: Descriptive Statistics weekly CARs after 0.5% winsorization

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
CAR (pre-invasion)	0.18%	-0.50%	-27.17%	38.10%	0.80	5.98	**10,224**
CAR (post-invasion)	0.17%	-1.02%	-27.17%	38.10%	0.68	4.18	**19,170**
CAR (full)	0.18%	-0.78%	-27.17%	38.10%	0.72	4.77	**29,394**

Table 8 includes the descriptive statistics for the weekly CAR after a 0.5% winsorization is performed. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

The kurtosis for the CAR is more acceptable after a small winsorization. Because the high maxima are reduced to a lower value, the mean of the post-invasion period is now lower than in the pre-invasion period. However, the difference is marginal. Remarkably, the kurtosis for the post-invasion period, which had the most extreme values, is now lower than the kurtosis for the pre-invasion period. The biggest deviation from a normal distribution now lies in pre-invasion period.

Table 9: Descriptive Statistics weekly trading volumes

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
Vol (pre-invasion)	13.14	13.21	7.41	18.32	-0.08	2.41	**10,224**
Vol (post-invasion)	13.29	13.35	7.14	18.50	-0.13	2.49	**19,170**
Vol (full)	13.24	13.30	7.14	18.50	-0.12	2.46	**29,394**

Table 9 includes the descriptive statistics for the weekly trading volumes on a logarithmic scale. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

Table 10: Descriptive Statistics weekly Google Search Volumes

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
Positive (pre-invasion)	61.04	59.44	53.09	71.55	0.68	2.71	**24**
Positive (post-invasion)	61.90	60.74	49.96	75.74	0.34	3.10	**45**
Positive (full)	61.60	60.60	49.96	75.74	0.46	3.07	**69**
Negative (pre-invasion)	50.26	49.69	41.17	56.81	-0.18	2.80	**24**
Negative (post-invasion)	52.01	51.47	43.34	67.70	0.87	3.60	**45**
Negative (full)	51.40	50.98	41.17	67.70	0.88	4.20	**69**
GSV (pre-invasion)	10.78	10.37	6.47	17.15	0.77	3.64	**24**
GSV (post-invasion)	9.88	10.11	4.79	14.62	-0.22	2.13	**45**
GSV (full)	10.19	10.36	4.79	17.15	0.02	2.84	**69**

Table 10 includes the descriptive statistics for the weekly Google Search Volumes. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations. Table 8 is divided into three parts; positive search terms, negative search terms, and the sentiment based on Formula 1.

In Tables 9 and 10, the descriptive statistics of the weekly trading volumes and Google Search Volumes are highlighted. As mentioned earlier, weekly trading volumes are taken on a logarithmic scale to obtain a more measurable effect on the CARs. For this reason, all trading volumes lie between a range of 7.14 to 18.50. Post-invasion, trading volumes are slightly higher than in the pre-invasion period (13.29 vs. 13.14). In Table 10, a division is shown between the weekly average of the positive and negative search, and the weekly Google Search Volumes (GSVs) based on Formula 1. The GSV is always positive, which states that the average of the positive terms is always higher than the average of the negative terms. The average GSV in the post-invasion period is lower than in the pre-invasion period, which could indicate that investor sentiment is more negative after the invasion. During the pre-invasion period, the GSVs are all in a range of 6.47 to 17.15. In the post-invasion period, this range is lower, namely between 4.79 and 14.62. This can be explained by the range of the negative search terms, which lies higher in the post-invasion period than in the pre-invasion period (43.34 - 67.70 vs. 41.17 - 56.81). The skewness and kurtosis for both the trading volumes and the GSVs are acceptable.

In the number of observations, a clear difference can be seen between the trading volumes and the GSVs. The trading volumes are both time- and company-specific (69 weeks x 426 companies), the GSVs are solely time-specific.

Table 11: Descriptive Statistics time-specific variables

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
Oil	0.09%	0.27%	-2.84%	3.88%	0.03	1.62	**69**
Gas	0.48%	0.27%	-11.62%	16.15%	0.46	3.59	**69**
Coal	0.24%	0.13%	-6.53%	19.50%	3.35	21.76	**69**
VIX	0.41%	-0.06%	-8.98%	11.61%	0.91	3.41	**69**

Table 11 includes the descriptive statistics for the time specific variables. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

In Table 11, the descriptive statistics of the variables that are time-specific are represented. All these time-specific variables are calculated by taking the weekly average of the daily returns. It is interesting to compare the three energy sources with each other. All three sources have a positive mean. This means that during the energy crisis all prices have increased on average. The oil price increase is the least substantial, with a daily return of 0.09% on average. The gas price increase is the largest, with a daily return of 0.48% on average. Furthermore, the oil price is most constant. The weekly average of the daily returns varies between a range of -2.84% and 3.88%. For gas and coal, these ranges are more extreme, a range between -11.62% and 16.15% for gas and a range between -6.53% and 19.50% for coal. The coal price has the biggest skewness and kurtosis, meaning that coal is most non-normal distributed. The VIX volatility also has a positive mean. This corresponds with the expectations that on average the market has become more volatile during the energy crisis. However, the median is negative, meaning that there are more weeks with a negative weekly average of daily VIX returns. The positive peaks are most likely larger than the negative peaks, which can be partly confirmed by the fact that the maximum is more extreme than the minimum (11.61% vs. -8.98%).

Table 12: Descriptive Statistics company-specific variables

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
Size	14.75	14.87	5.15	22.57	-0.35	3.23	**426**
D/E	1.62	0.62	-11.48	95.99	10.30	117.38	**426**
RoE	30.69	7.56	-601.49	6634.02	12.82	187.36	**409**

Table 12 includes the descriptive statistics for the company-specific variables. D/E = debt to equity ratio. RoE = return on equity. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

Finally, Table 12 summarizes the descriptive statistics of the company-specific variables. These variables are used for testing the short-term effect of the invasion in Hypotheses 4 and 5. These variables are constant and represent the most recent available numbers in Datastream. Size is measured by taking the Total Assets (TA) on a logarithmic scale as described earlier in this section. The D/E ratio is 1.62 on average. On average, the firms in the sample have more debt than equity. The minimum of -11.48 can be explained by the fact that some firms have more liabilities than assets and thus a negative equity. The skewness and kurtosis for both the D/E ratio and the Return on Equity (RoE) are extreme and require a winsorization, as do the CARs. The adjusted descriptive statistics after a 2.5% winsorization are shown in Table 13. The mean of the D/E ratio drops to 1.03, with a kurtosis of 8.93. RoE has a completely different mean after winsorization (-0.23 vs. 30.69) due to the adjustments of a few extreme high values such as the maximum of 6634.02, which now have a much lower value (121.51). The kurtosis is 9.01. The kurtosis of both variables has diminished significantly but is still not completely desirable. However, a more aggressive winsorization of for example 5% is not conducive to the accuracy of the data.

Table 13: Descriptive Statistics company-specific variables after 2.5% winsorization

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
D/E	1.03	0.62	-3.55	8.22	1.65	8.93	**426**
RoE	-0.23	7.56	-192.97	121.51	-1.57	9.01	**409**

Table 13 includes the descriptive statistics for the company-specific variables after a 2.5% winsorization. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

4. Method

The method for each of the stated hypotheses in Section 2.4 will be discussed in this section. For each hypothesis, the coefficient of interest and the tests that will be performed are highlighted. All regressions and tests are performed in Stata. Explanations of variables are presented in Chapter 3.

H_1: Investor sentiment positively influences energy returns during the energy crisis (September 2021 - December 2022).
H_{1A}: Investor sentiment positively influences oil returns during the energy crisis (September 2021 - December 2022).
H_{1B}: Investor sentiment positively influences gas returns during the energy crisis (September 2021 - December 2022).
H_{1C}: Investor sentiment positively influences coal returns during the energy crisis (September 2021 - December 2022).

Hypothesis 1 is tested by means of OLS times series regressions. The regression equations for this hypothesis are shown in Formula 8. In this regression, return (R) is the dependent variable and refers to the weekly average of daily returns of oil, gas, and coal. This means that in total three regressions are made for Hypothesis 1. The different equations are present in Formula 8a-8c. Because this hypothesis is only time-variant, the optimal number of lags will be determined for all three energy sources, the sentiment indicator and for the volatility index. The VIX is included as control variable since this is a widely used traditional sentiment indicator. In Formula 8a-8c, α_0 represents the constant and the betas display coefficients for the different variables. Subscripts *L* and *t* represent the number of lags and the specific week, respectively. In the end, the error term at time t (ε_t) is added to the model. The coefficient of interest for this hypothesis is β_2 for sentiment. The expectation is that there is a positive effect of investor sentiment on each energy return. Therefore, a one-sided t-test is performed for $\beta_2 > 0$.

$$(8)\ R_{energy,t} = \alpha_0 + \sum_{L=1}^{L} \beta_1 R_{energy,t-L} + \sum_{L=0}^{L} \beta_2 Sentiment_{t-L} + \sum_{L=0}^{L} \beta_3 VIX_{t-L} + \varepsilon_t$$

$$(8a)\ R_{oil,t} = \alpha_0 + \sum_{L=1}^{L} \beta_1 R_{oil,t-L} + \sum_{L=0}^{L} \beta_2 Sentiment_{t-L} + \sum_{L=0}^{L} \beta_3 VIX_{t-L} + \varepsilon_t$$

$$(8b)\ R_{gas,t} = \alpha_0 + \sum_{L=1}^{L} \beta_1 R_{gas,t-L} + \sum_{L=0}^{L} \beta_2 Sentiment_{t-L} + \sum_{L=0}^{L} \beta_3 VIX_{t-L} + \varepsilon_t$$

$$(8c)\ R_{coal,t} = \alpha_0 + \sum_{L=1}^{L} \beta_1 R_{coal,t-L} + \sum_{L=0}^{L} \beta_2 Sentiment_{t-L} + \sum_{L=0}^{L} \beta_3 VIX_{t-L} + \varepsilon_t$$

H_2: Investor sentiment negatively influences stock returns of Western energy-related companies during the energy crisis (September 2021 - December 2022).

For Hypothesis 2, the panel data regression in Formula 9 is performed. In this case, the CAR represents the dependent variable. Weekly values of Google Search Volumes are regressed on weekly returns. Interaction terms are used as well between the sentiment index and the returns of the three energy-sources as described for Hypothesis 1. This means $R_{energy,t}$ can stand for either $R_{oil,t}$, $R_{gas,t}$, or $R_{coal,t}$. This regression includes the classic sentiment indicators VIX volatility (β_4) and the weekly trading volume (β_5) as well. Furthermore, a Hausman test will be performed to decide whether firm fixed effects (FE) or random effects (RE) are added in the regression, making use of the panel structure of the data. In case the random effects model is preferred, firm-specific variables will be added to the model as shown in Formula 9 ($\beta_6 - \beta_9$). Part of these firm-specific variables are firm size (β_6), debt-to-equity ratio (β_7), return on equity (β_8), and a dummy for firm industry (β_9). For each variable, the subscripts reflect on the specific time *t* and company *i* of a given observation. The error term ($\varepsilon_{i,t}$) is specific for each observation. The main variable of interest is a combination of $\beta_1$and β_2. β_1 shows the overall effect of investor sentiment on stock returns and β_2 shows the interaction effect between the sentiment indicator and all three energy returns. By adding the interaction term, it can be measured what part of stock price variation is due to sentiment and what part is due to the underlying energy sources. By assuming either an increase or decrease in energy price, conclusions can be made on the effect of investor sentiment. A negative impact of investor sentiment is expected. Therefore, a one-sided t-test is performed for $\beta_1 + \beta_2 * R_{energy,t} < 0$. Also in this case, $R_{energy,t}$ is represented by $R_{oil,t}$, $R_{gas,t}$ and $R_{coal,t}$. Conclusions on this hypothesis are highly sensitive to assumptions made on the energy sources.

$$(9)\ CAR_{i,t} = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Sentiment_t * R_{energy,t} + \beta_3 R_{energy,t} + \beta_4 VIX_t + \beta_5 Vol_{i,t} + \beta_6 Size_{i,t} + \beta_7 D/E_{i,t} + \beta_8 RoE_{i,t} + \beta_9 Ind_i + Firm\ FE/RE + \varepsilon_{i,t}$$

H_3: Investor sentiment positively influences trading volumes of Western energy-related companies during the energy crisis (September 2021 - December 2022).

Hypothesis 3 concerns the impact of investor sentiment on trading volumes. Therefore, the trading volume is used as dependent variable instead of control variable. Furthermore, all other variables are the same as for Hypothesis 2, fixed or random effects are included as well. The regression equation can be found in Formula 10. The same interaction effect between investor sentiment and all three energy returns is present in this hypothesis, which means the variable of interest is equal to Hypothesis 2 (combination of β_1 and β_2). In this case, a positive effect is expected between the variable of interest and the dependent variable, which is the weekly trading volume. This indicates a one-sided t-test for $\beta_1 + \beta_2 * R_{energy,t} > 0$.

$$(10)\ Vol_{i,t} = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Sentiment_t * R_{energy,t} + \beta_3 R_{energy,t} + \beta_4 VIX_t + \beta_5 Size_{i,t} + \beta_6 D/E_{i,t} + \beta_7 RoE_{i,t} + \beta_8 Ind_i + Firm\ FE/RE + \varepsilon_{i,t}$$

H_4: Investor sentiment positively influences stock returns of Western energy-related companies in the short run around the invasion of Ukraine (February - April 2022).

To test Hypothesis 4, the panel data regression in Formula 11 is performed in Stata. This regression equation is the same as Formula 9 that is used for testing Hypothesis 2. The difference lies in the timespan of the observations. For Hypothesis 4, a shorter time window is used to measure the effect of the outbreak of the war instead of the energy crisis. Therefore, a total of nine weeks of data is used in this case. On Week 25 of the sample, the invasion took place. For this short run approach, Weeks 24-32 are considered, one week before and seven weeks after the event took place (February 13, 2022 - April 16, 2022). Other studies found a positive relationship between Google Search Volumes and stock returns in the short run, followed by a price reversal in the long run (Da et al., 2011; Bank et al., 2011). This paper can conclude on both the short and long run by taking the effect during the energy crisis as long run and in the period around the Russian invasion of Ukraine as short run. Furthermore, the exact same CARs and other data are used for this regression. Only a new winsorization for the CAR is performed. Descriptive statistics of the CAR in this short run scenario around the invasion of Ukraine before and after winsorization can be found in Appendix D. The estimation window for these weekly CARs is [-250;-4], the same as for the overall sample for measuring the impact of the energy crisis. Apart from the dependent variable, the sentiment index, interaction terms, energy prices, and the classic sentiment indicators are put into the regression as well. In addition, the company-specific variables are included (company size, debt-to-equity ratio, return on equity and firm industry). Firm fixed or random effects are added as well. The variables of interest are β_1 and β_2, since for the short run CAR a positive effect of investor sentiment is expected, there is one-sided t-tested for $\beta_1 + \beta_2 * R_{energy,t} > 0$.

$$(11)\ CAR_{i,t} = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Sentiment_t * R_{energy,t} + \beta_3 R_{energy,t} + \beta_4 VIX_t + \beta_5 Vol_{i,t} + \beta_6 Size_{i,t} + \beta_7 D/E_{i,t} + \beta_8 RoE_{i,t} + \beta_9 Ind_i + Firm\ FE/RE + \varepsilon_{i,t}$$

H5: The impact of investor sentiment on stock returns of Western energy-related companies during the energy crisis (September 2021 - December 2022) is bigger in Europe than in the US.

Hypothesis 5 is similar to Hypothesis 2, except that Hypothesis 5 distinguishes between the EU and US. A similar regression is performed as for Hypothesis 2 (see Formula 12), except for the fact that now an interaction term is included with sentiment and a regional dummy ($\beta_2 Sentiment_t * D\_US_i$). The regional dummy has value 1 in case the company is from the US and value 0 in case the company is European. The variables of interest are β_1, β_2 and β_4. It is expected that the impact of investor sentiment is bigger in Europe than in the US, this indicates that for the US the returns should be less extreme. It is irrelevant whether the effect is positive or negative. This means there is one-sided t-tested for
$|\beta_1 + \beta_2 + \beta_4 * R_{energy,t}| < |\beta_1 + \beta_4 * R_{energy,t}|$.

$$(12)\ CAR_{i,t} = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Sentiment_t * D\_US_i + \beta_3 D\_US_i + \beta_4 Sentiment_t * R_{energy,t} + \beta_5 R_{energy,t} + \beta_6 VIX_t + \beta_7 Vol_{i,t} + \beta_8 Size_{i,t} + \beta_9 D/E_{i,t} + \beta_{10} RoE_{i,t} + \beta_{11} Ind_i + Firm\ FE/RE + \varepsilon_{i,t}$$

H6: Investor sentiment has a bigger impact on stock returns of Western energy-related companies after the start of the invasion than before the start of the invasion (from September 2021).

In Hypothesis 6, the difference in investor sentiment between the period before and after the start of the invasion is pointed out. The pre-invasion period includes Weeks 1-24 (September 5, 2021 - February 19, 2022), the post-invasion period lasts from Week 25 to Week 69 (February 20, 2022 - December 31, 2022). The difference in effect before and after the invasion

can be measured by adding an interaction term to the regression in Formula 9. This interaction term is between investor sentiment and a post-invasion dummy that has value 1 for all observations after the invasion and value 0 before the invasion. This approach is very similar to the one used for Hypothesis 5 (see Formula 13). The variables of interest are β_1, β_2 and β_4. Hypothesis 6 states that the effect of investor sentiment on stock returns is bigger after the invasion. Also in this case, whether the effect is either positive or negative cannot answer the hypothesis on itself. There is one-sided t-tested for
$|\beta_1 + \beta_2 + \beta_4 * R_{energy,t}| > |\beta_1 + \beta_4 * R_{energy,t}|$.

$$(13)\ CAR_{i,t} = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Sentiment_t * D\_Postinvasion_i + \beta_3 D\_Postinvasion_i \\ + \beta_4 Sentiment_t * R_{energy,t} + \beta_5 R_{energy,t} + \beta_6 VIX_t + \beta_7 Vol_{i,t} + \beta_8 Size_{i,t} \\ + \beta_9 D/E_{i,t} + \beta_{10} RoE_{i,t} + \beta_{11} Ind_i + Firm\ FE/RE + \varepsilon_{i,t}$$

H7: Trading volumes of Western energy-related companies are higher after the start of the invasion than before the start of the invasion (from September 2021).

For Hypothesis 7, the post-invasion dummy can be added to Formula 10 that is used to measure the effect of investor sentiment on the trading volume (Formula 14). The variable of interest is β_1. The expected effect is that trading volumes are higher when the postwar dummy has value 1. Therefore, a one-sided t-test for $\beta_1 > 0$ is performed.

$$(14)\ Vol_{i,t} = \alpha_0 + \beta_1 Postinvasion + \beta_2 Sentiment_t + \beta_3 Sentiment_t * R_{energy,t} \\ + \beta_4 R_{energy,t} + \beta_5 VIX_t + \beta_6 Size_{i,t} + \beta_7 D/E_{i,t} + \beta_8 RoE_{i,t} + \beta_9 Ind_i \\ + Firm\ FE/RE + \varepsilon_{i,t}$$

5. Results

After the data process and the methodology for each hypothesis have been considered, the regressions can be run in Stata. In this chapter, the results are analyzed. Sections 5.1-5.7 discuss the results for each hypothesis. In Section 5.8, robustness checks for the most important hypothesis are presented.

5.1 Effect of investor sentiment on energy returns

In this section Hypothesis 1 is tested, which states that investor sentiment had a positive influence on the energy returns during the energy crisis. First, an optimal lag determination is performed since Hypothesis 1 contains a time series regression. Second, the regression results are presented and interpreted with the optimal number of lags for each variable.

5.1.1 Optimal lag determination

To determine how many lags are needed for the energy returns, investor sentiment and the VIX volatility index, the optimal number of lags is determined for each variable. Most important for testing Hypothesis 1 is the number of lags for the investor sentiment variable. In Table 14, the statistics needed for the optimal lag determination for investor sentiment are shown. The lowest values for AIC, HQIC and SBIC are indicated by * and determine jointly which lag should be used in the research. For investor sentiment, the AIC and HQIC values are the lowest for lag 1, SBIC indicates that 0 lags should be used. Since two out of three indicators prefer 1 lag, this is the number that is used for testing Hypothesis 1. The same method is applied for the other variables, subsequently the number of optimal lags is 3 for oil, 0 for gas, 0 for coal, and 0 for the VIX volatility. In Appendix E, the optimal lag determination for the other variables can be found.

Table 14 Optimal lag determination for investor sentiment variable

Lag	LL	LR	p	AIC	HQIC	SBIC
0	-153.877			4.7654	4.7786	4.7989*
1	-151.844	4.0653*	.044	4.7337*	4.7601*	4.8006
2	-151.692	.3054	.581	4.7598	4.7993	4.8601
3	-151.155	1.0734	.300	4.7740	4.8268	4.9078
4	-150.156	1.9984	.157	4.7740	4.8400	4.9413

Table 14 displays the statistics for determining the optimal number of lags for investor sentiment. LL = log likelihood. LR = likelihood ratio. p = p-value. AIC = Akaike Information Criterion. HQIC = Hannan-

Quinn Information Criterion. SBIC = Schwarz-Bayesian Information Criterion. Column (1) shows the number of lags. Columns (2)-(7) show the descriptive statistics for a specific number of lags. * Indicates the most significant lag for the LR or the lowest value for AIC, HQIC or SBIC.

5.1.2 Regression results Hypotheses 1 and 1A-1C

In Table 15, the OLS regressions for the effect of investor sentiment on each of the three energy sources is shown. Each model contains one lag of investor sentiment, the oil model has three lags of the dependent variable as decided in the optimal lag determination. For all models, significance is low as can be interpreted from the T-statistics (2.47, 0.86, and 0.78). This could be due to a low number of observations (between 66-68). Only in the oil model any significant results occur. At a 5% significance level, the third lag of oil is .0028. This indicates that an increase of 1%-point in the weekly average of daily oil returns of week -3 increases the current weekly average of daily returns by 0.28%-points. The current investor sentiment does not have an impact on the current oil return. However, the first lag of investor sentiment has an effect of -.0012 at a 5% significance level. An increase of 1 in the first lag of the sentiment indicator results in a 0.12%-points decrease in the current weekly average of daily oil returns. In other words, the more positive sentiment gets, the lower oil returns from one week later will be. Following the hypothesis, the coefficients for sentiment and the first lag of sentiment should be bigger than zero. This is not the case and therefore, Hypothesis 1A cannot be accepted. This conflicts with Du et al. (2016), who find a positive effect of investor sentiment. This may be due to a difference in method, Du et al. (2016) use the Baker and Wurgler sentiment indicator and add different control variables such as the gasoline/heating oil spread, exchange rates and interest rates. The model used for Hypothesis 1 might suffer from Omitted Variable Bias (OVB), adding these control variables could help to measure more accurately the effect of investor sentiment on the oil price. For gas and coal, no significant results occur. Therefore, no conclusions can be made on accepting or rejecting Hypotheses 1B and 1C. All in all, Hypothesis 1 cannot be accepted.

Table 15 Effect of investor sentiment on energy returns

R_energy	Oil Coefficient	Oil Robust St. Error	Gas Coefficient	Gas Robust St. Error	Coal Coefficient	Coal Robust St. Error
L1.Oil	-.0008	.0012				
L2.Oil	-.0014	.0012				

L3.Oil	.0028**	.0012				
Sentiment	.0005	.0005	-.0007	.0021	-.0006	.0018
L1.Sentiment	-.0012**	.0006	-.0031	.0025	-.0021	.0024
VIX	-.0003	.0005	.0023	.0016	.0018	.0013
Constant	.0079	.0070	.0428	.0347	.0292	.0400
N	66		68		68	
F-Test	2.47		0.86		0.78	
R2	.2007		.0653		.0574	
R2_adj	.1194		.0215		.0132	

Table 15 shows the output of the time series regressions for the effect of investor sentiment on energy returns (R_energy). These can be the oil, gas and coal returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on oil and add three lags of oil to the model. Columns (4)-(5) and (6)-(7) show the effect of investor sentiment on gas and coal, respectively. The models for these energy sources do not contain any lags. N indicates the number of observations for the regression, the F-test displays the significance of the total model. R2 indicates what proportion of the variance in the energy returns can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.2 Effect of investor sentiment on weekly CARs during the energy crisis

In this section there will be determined whether random effects, fixed effects or pooled OLS is optimal for the data sample. Afterwards, Hypothesis 2 will be answered by interpreting the results in Table 18.

5.2.1 Hausman and Breusch-Pagan LM test

Hypothesis 2 addresses the most important effect for answering the research question and states a negative effect between investor sentiment and stock returns during the energy crisis. Before conclusions can be drawn regarding the regression in Formula 9, the most optimal way in using the panel structure of the data must be defined. There is decided whether a pooled OLS, a fixed effects or a random effects model is used. Therefore, a Hausman test is performed to see whether the fixed effects model or the random effects model is preferred. In this Hausman test, both the fixed effects and the random effects model for the regression in Formula 9 are run. Thereafter, the Hausman tests indicates what model should be used. The null hypothesis for the Hausman states that the random effects model is more suitable for the data than the fixed effects model, the alternative hypothesis states that the fixed effects is the preferred model. The results of the Hausman test can be found in Table 16.

Table 16: Hausman test for Hypothesis 2

Model	Test	Test-statistic
Base model (firm-specific variables excluded)	Chi Square	5.84
	P-value	0.7561
Extended model (firm-specific variables included)	Chi Square	0.09
	P-value	1.0000

Table 16 displays the performed Hausman test, with its chi square and P-value, and indicates whether a fixed effects or random effects model should be used.

From Table 16 can be concluded that the null hypothesis cannot be rejected, which means the random effects model is the preferred model. In this case, the firm-specific variables can be added to the model. If these variables are added to the fixed effects model, the variables will be dropped due to multicollinearity. Each value for the firm-specific value will be equal to the average value of each firm and therefore the fixed effect will not work. If the firm-specific variables are included to the model, the proof for using the random effects model is even bigger with a P-value of 1.0000. By caution, a Breusch-Pagan Lagrange Multiplier (LM) test is performed to verify whether a pooled OLS model should be used. The null hypothesis for the Breusch-Pagan LM test states that the pooled OLS model is appropriate, the alternative hypothesis states that the random effects model is appropriate. The results of the Breusch-Pagan LM test can be found in Table 17. For both the model with and without the firm-specific variables, the null hypothesis can be rejected. The random effects model is appropriate for the regression.

Table 17: Breusch-Pagan Lagrange Multiplier test for Hypothesis 2

Model	Test	Test-statistic
Equation 8 (firm-specific variables excluded)	Chi-bar Square	1.4e+05
	P-value	0.0000
Equation 8 (firm-specific variables included)	Chi-bar Square	91,380.41
	P-value	0.0000

Table 17 displays the performed Breusch-Pagan LM test, with its chi square and P-value, and indicates whether a pooled OLS or random effects model should be used.

5.2.2 Regression results Hypothesis 2

In Table 18, the regression results from the random effects model for Hypothesis 2 are shown. At first, the model without the firm-specific variables is regressed. In the remainder of this paper this model will be referred to as the base model. For all variables, a significant effect is shown, which leads to a high Wald test statistic of 553.42. The base model has an adjusted R2 of 6.20%. When the firm-specific variables are added to the base model, this is referred to as the extended model. In the extended model for Hypothesis 2, the adjusted R2 has increased to 16.16%, which indicates that the extended model has more explanatory power. Therefore, the extended model will be used for interpreting the results from Hypothesis 2. It is expected that there is a negative effect of investor sentiment on the weekly CAR. For investor sentiment itself, there is a positive effect of .0024 at a 1%-significance level. This indicates that an increase of 1 in the sentiment indicator leads - keeping all other variables equal - to an increase of 0.24%-points in the weekly CAR on average. However, the interaction effects between sentiment and the energy sources also play an important role in interpreting the results. Since these interaction effects are sensitive for assumptions made about the oil, gas, and coal return levels, interpreting the results from Table 18 is hard. Therefore, the effect of investor sentiment in this research is explained by figures in which the 25^{th} percentile, median, and 75^{th} percentile values of the oil, gas, and coal returns are assumed. When these assumed three levels of returns for a given energy source all indicate a similar impact of investor sentiment on stock returns, it can be concluded that all values between the 25^{th} percentile and the 75^{th} percentile of the sample distribution from that particular energy source reflect the same effect of investor sentiment. However, these figures do not provide information about the effect of investor sentiment when values lower than the 25^{th} percentile or higher than the 75^{th} percentile of the distribution for oil, gas, and coal returns are assumed. This means that the effect of investor sentiment on stock returns may differ for these values. In Appendix F, the interaction effects for investor sentiment and all three energy sources are shown in Figures 1-3. In Figures 1-3, the 25^{th} percentile, median, and 75^{th} percentile values in the sample distribution for the oil, gas, and coal returns are assumed to see the effect of investor sentiment at different energy return levels. Based on Figure 1 (Appendix F), an increase in investor sentiment will lead to a higher weekly CAR at all three assumed return levels of oil. Moreover, an increase in the weekly average of daily oil returns leads to a higher weekly CAR. The line for the 25^{th} percentile is steeper than the lines for the median and 75^{th} percentile. This indicates that investor sentiment has a bigger effect on stock returns when the weekly average of daily oil returns is low. This is supported by Table 18, in which a 1%-significant coefficient of -.0014 is found for the interaction effect with gas. Combined with the .0024 coefficient from sentiment, the positive effect of sentiment decreases for higher values of gas. From Figures 2 and 3 in Appendix F, it can also be concluded that there is a positive effect of investor sentiment on the weekly CAR, at the 25^{th} percentile, median, and 75^{th} percentile values for the gas and coal returns. The lines in Figures 2 and 3 become steeper when higher values of gas or lower values of coal are taken, respectively. This means that the effect of investor sentiment is bigger when returns are high for gas or low for coal. In Table 18, this effect can also be found in the sign of the interaction coefficients. Combined with the coefficient for sentiment (.0024), higher values of gas result in a bigger effect of investor sentiment due to the 1%-significant positive sign of the gas effect (.0002). For coal, the opposite effect is found due to the 1%-significant negative sign (-.0002). Since a negative effect between investor sentiment and stock returns is expected and all interaction effects show a positive effect between the 25th percentile and 75th percentile of all energy returns, Hypothesis 2 can be rejected. This research finds results similar to Tetlock (2007) but contradicts the majority of the discussed papers (Schmeling, 2007; Brown & Cliff, 2005; Fang & Peress, 2009, Da et al., 2011; Bank et al., 2011; Bijl et al., 2016). It should be noted that when assuming values that fall below the 25th percentile or above the 75th percentile, the conclusions may vary. Nevertheless, since these values can be considered more extreme, a deliberate choice is made not to include them in the primary conclusions. Furthermore, from Table 18 can be concluded that the classic sentiment indicators (VIX volatility and trading volume) both have a positive impact on stock returns at a 1% significance level. It can be added that size has a negative effect on the stock returns during the energy crisis on a 5% significance level. Moreover, all industry coefficients are negative. This implies that relative to the alternative energy industry, every industry underperforms during the crisis. The more polluting industries have been punished during the energy crisis.

Table 18: Effect of investor sentiment on weekly CARs during the energy crisis

Weekly CAR	**Weekly CAR Base Coefficient**	**Weekly CAR Base Robust St. Error**	**Weekly CAR Extended Coefficient**	**Weekly CAR Extended Robust St. Error**
Sentiment	.0024***	.0002	.0024***	.0002
Sentiment * Oil	-.0015***	.0002	-.0014***	.0002
Sentiment * Gas	.0002***	.0001	.0002***	.0001
Sentiment * Coal	-.0002***	.0001	-.0002***	.0001
Oil	.0303***	.0022	.0292***	.0022
Gas	-.0016***	.0006	-.0018***	.0006
Coal	.0015**	.0006	.0017***	.0006
VIX	.0013***	.0001	.0013***	.0001
Vol	.0113***	.0015	.0111***	.0016
Size			-.0027**	.0012

D/E			.0005	.0017
RoE			-.0001	.0001
Industry				
Electricity			-.0665***	.0097
Gas, water & multi-utilities			-.0846***	.0087
Oil & gas producers			-.0259***	.0091
Oil equipment & services			-.0377***	.0084
Firm RE	YES		YES	
Constant	-.1749***	.0203	-.0924***	.0224
N	29,394		28,221	
# Firms	426		409	
# Weeks	69		69	
Wald Chi Square	553.42		681.05	
R2	.0623		.1621	
R2_adj	.0620		.1616	

Table 18 shows the results from the random effects regressions for the effect of investor sentiment on stock returns. Weekly CARs are used as dependent variable to proxy for stock returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly CARs for the base model which excludes the firm-specific variables. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the extended model is presented which adds the firm-specific variables to the base model. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly CAR can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.3 Effect of investor sentiment on weekly trading volumes during the energy crisis

Besides measuring the effect of investor sentiment on stock returns during the energy crisis, the effect on trading volumes is investigated as well. In this section Hypothesis 3 will be answered which states that investor sentiment has a positive influence on trading volumes of Western energy-related companies during the energy crisis. The results of the random effects panel regressions are shown in Table 19. In both the base model and the extended model, investor sentiment does not have a significant effect on the weekly trading volumes. Therefore, no conclusions on the sign of the investor sentiment coefficient itself can be made. However, some conclusions can still be made by means of the significant results for the interaction effects with the energy sources. Since the adjusted R2 is much higher for the extended model (41.79% vs 0.20%), the extended model is used for interpreting the results. The interaction effect is interpreted with figures in the same way as for Hypothesis 2. In Appendix G, Figures 4-6, the interaction effects for Hypothesis 3 are shown. When looking at oil and coal, a negative relationship between investor sentiment and weekly trading volumes is found when the 25th percentile, median, and 75th percentile values of the sample distribution for the oil and coal returns are assumed (Appendix G, Figures 4 and 6). Furthermore, higher values for oil and coal returns result in lower weekly trading volumes, which implies a negative effect for oil and coal returns on the weekly average of daily trading volumes. For oil, the impact of sentiment on the weekly volumes tends to diminish at higher levels of oil returns. This is not in line with the existing literature (Tetlock, 2007; Preis et al., 2010; Bordino et al., 2012). These papers all find a positive impact of investor sentiment on trading volumes. When looking at gas, more interesting conclusions can be made (Appendix G, Figure 5). An increase in gas returns leads to a different effect of sentiment on weekly trading volumes. For the 25th percentile value of gas returns, there is a positive relationship between sentiment and trading volumes. For the 75th percentile value of gas returns, this relationship turns negative. However, looking at Table 19, nothing can be said based on the combined effect of the interaction effects and sentiment itself due to the insignificance of the sentiment coefficient. In Figures 4-6 (Appendix G), this can be confirmed by looking at the confidence intervals. These are very big and relatively distant to the mean values, indicating insignificance. This means Hypothesis 3 is rejected due to insignificance between the 25th and 75th percentile values for all three energy returns. For more extreme values, below the 25th percentile or above the 75th percentile value of the energy returns, no conclusion can be drawn from Figures 4-6 (Appendix G). Furthermore, the VIX volatility has a negative impact at 1% significance. On average and keeping everything else equal, an increase in volatility leads to lower trading volumes. Besides, at 1% significance, an increase in company size leads to an increase in trading volumes and an increase in return on equity results in a decrease in trading volumes. A negative significant value for the electricity and gas, water & multi-utilities industry reflects that alternative energy stocks are traded more often than stocks from these two industries. In this model as well, it seems that alternative energy stocks are more popular. However, at 10% significance, the industry for oil & gas producers had higher trading volumes relative to alternative energy.

Table 19: Effect of investor sentiment on weekly trading volumes during the energy crisis

Weekly Vol	Weekly Vol Base Coefficient	Weekly Vol Base Robust St. Error	Weekly Vol Extended Coefficient	Weekly Vol Extended Robust St. Error
Sentiment	-.0016	.0014	-.0010	.0014
Sentiment * Oil	.0033***	.0013	.0030**	.0013
Sentiment * Gas	-.0083***	.0004	-.0084***	.0004
Sentiment * Coal	-.0007**	.0004	-.0005	.0004
Oil	-.0391**	.0118	-.0373***	.0119
Gas	.0837***	.0040	.0853***	.0041
Coal	-.0036	.0036	-.0054	.0036
VIX	-.0036***	.0010	-.0039***	.0010
Size			.5084***	.0317
D/E			-.0430	.0362
RoE			-.0029**	.0013
Industry				
Electricity			-.7243***	.2464
Gas, water & multi-utilities			-.7978***	.2519
Oil & gas producers			.4627*	.2448
Oil equipment & services			-.0488	.2348
Firm RE	YES		YES	
Constant	13.2474***	.0539	5.9071***	.4516
N	29,394		28,221	
# Firms	426		409	
# Weeks	69		69	
Wald Chi Square	861.35		1,169.96	
R2	.0023		.4182	
R2_adj	.0020		.4179	

Table 19 shows the results from the random effects regressions for the effect of investor sentiment on trading volumes. Weekly trading volumes are used as dependent variables. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly trading volumes for the base model which excludes the firm-specific variables. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the extended model is presented which adds the firm-specific variables to the base model. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly trading volumes can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.4 Effect of investor sentiment on weekly CARs in the short run around the invasion of Ukraine

In this section, Hypothesis 4 will be answered, in which investor sentiment is expected to positively influence stock returns in a short-term period of nine weeks around the invasion of Ukraine. For this Hypothesis, a shorter window of data is tested, namely one week before the invasion week and seven weeks after (February 13, 2022 - April 16, 2022). In Table 20, the regression results for Hypothesis 4 are shown. Interestingly, the sentiment coefficient is negative for both the base and the extended model, while this coefficient was positive for the model testing the impact during the energy crisis. The extended model yields a higher adjusted R2, therefore this model is used for interpreting the results. In Appendix H, Figures 7-9 illustrate the interaction effect between sentiment and the oil, gas and coal returns. The effect of investor sentiment is more sensitive to different levels of returns for all energy sources in this shorter window than in the window that is used for the energy crisis. For oil and coal returns (Appendix H, Figures 7 and 9), the effect of investor sentiment on the weekly CAR is negative at the 25th percentile, median, and 75th percentile values of oil and coal. For oil, the effect is bigger for low values (steeper line), this can be confirmed by the combined effect of sentiment (-.0084) and sentiment*oil (.0171) from Table 20. When oil returns increase, the effect of investor sentiment becomes less negative. For coal, this effect is opposite due to the negative interaction coefficient (-.0031). For gas (Appendix H, Figure 8), the results differ. The effect of investor sentiment on weekly CARs is positive when gas returns are low, this turns into a negative effect for values of gas returns around the median of the sample and higher. Hypothesis 4 can only be accepted when weekly averages of daily gas returns are low. This means that this paper largely contradicts the findings from Da et al. (2011) and Bank et al. (2011). However, these papers find a positive effect within the first two weeks after the event and this paper uses seven weeks after the event. Therefore, the results are not completely comparable. The effects of other control variables do not differ from Hypothesis 2: at a 1% significance level, a positive effect is found for the VIX volatility and for the trading volumes, for company size there is a negative effect. All industry coefficients are significant and negative, indicating an underperformance relative to stocks from the alternative energy sector.

Table 20: Effect of investor sentiment on weekly CARs in the short run around the invasion of Ukraine

Weekly CAR	Weekly CAR Base Coefficient	Weekly CAR Base Robust St. Error	Weekly CAR Extended Coefficient	Weekly CAR Extended Robust St. Error
Sentiment	-.0090***	.0020	-.0084***	.0020
Sentiment * Oil	.0177***	.0018	.0171***	.0019
Sentiment * Gas	-.0047***	.0004	-.0043 ***	.0004
Sentiment * Coal	-.0031***	.0003	-.0031***	.0003
Oil	-.1967***	.0209	-.1892***	.0215
Gas	.0344***	.0029	.0321***	.0030
Coal	.0300***	.0026	.0295***	.0026
VIX	.0214***	.0017	.0213***	.0017
Vol	.0161***	.0018	.0204***	.0021
Size			-.0091***	.0017
D/E			.0009	.0017
RoE			-.0001	.0001
Industry				
Electricity			-.0421***	.0094
Gas, water & multi-utilities			-.0626***	.0081
Oil & gas producers			-.0164*	.0089
Oil equipment & services			-.0244***	.0082
Firm RE	YES		YES	
Constant	-.1447***	.0316	-.0465	.0313
N	3,834		3,681	
# Firms	426		409	
# Weeks	9		9	
Wald Chi Square	592.42		730.02	
R2	.1669		.2511	
R2_adj	.1649		.2478	

Table 20 shows the results from the random effects regressions for the effect of investor sentiment on stock returns in the short run. Weekly CARs are used as dependent variable to proxy for stock returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly CARs for the base model which excludes the firm-specific variables. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the extended model is presented, where the firm-specific variables are added to the base model. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly CAR can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.5 Difference in investor sentiment effect on weekly CARs between EU and US

In this section, the difference in effect of investor sentiment on stock returns between European and US companies will be highlighted. To measure this difference, the interaction term between investor sentiment and the US dummy is added to the regression that is used for Hypothesis 2. It is expected that the effect of investor sentiment on the stock returns is bigger in Europe than in the US. In Table 21, the extended models for Hypothesis 2 and Hypothesis 5 are displayed. The R-squared rises from 16.16% to 16.28% when the new interaction effect is added to the regression, a minor increase which denotes that the explanatory power of the model is slightly better than the model used for Hypothesis 2. The coefficients are very similar between the models in Table 21. The coefficient for the US dummy is -.0236, which shows that returns are 2.36%-points lower for US-companies, assuming that investor sentiment is zero. This is contradictory to findings from Federle et al. (2022), who exhibit higher returns for companies that are more distant from the war. For Hypothesis 2, a positive impact of investor sentiment is found, even after looking into the interaction effects with the energy sources. The Sentiment * US interaction effect has a positive coefficient of .0018 at a 1% significance, which indicates an even more positive effect of investor sentiment in the US. Therefore, the impact of investor sentiment is bigger in the US than in the EU. The interaction effect is made more visible in Appendix I, Figure 10. The EU line lies above the US line, indicating an underperformance for US companies. Moreover, the line is steeper for the US, which specifies a bigger effect of investor sentiment here. This contradicts to the expectations for Hypothesis 5 and therefore this hypothesis can be rejected.

Table 21: Difference in investor sentiment effect on weekly CARs between EU and US

Weekly CAR	Weekly CAR Extended Coefficient	Weekly CAR Extended Robust St. Error	Weekly CAR Extended Coefficient	Weekly CAR Extended Robust St. Error
Sentiment	.0024***	.0002	.0013***	.0003
Sentiment * US			.0018***	.0004

Sentiment * Oil	-.0014***	.0002	-.0014***	.0002
Sentiment * Gas	.0002***	.0001	.0002***	.0001
Sentiment * Coal	-.0002***	.0001	-.0002***	.0001
US			-.0236***	.0064
Oil	.0292***	.0022	.0292***	.0022
Gas	-.0018***	.0006	-.0018***	.0006
Coal	.0017***	.0006	.0017***	.0006
VIX	.0013***	.0001	.0013***	.0001
Vol	.0111***	.0016	.0111***	.0016
Size	-.0027**	.0012	-.0028**	.0013
D/E	.0005	.0017	.0006	.0017
RoE	-.0001	.0001	-.0001	.0001
Industry				
Electricity	-.0665***	.0097	-.0656***	.0099
Gas, water & multi-utilities	-.0846***	.0087	-.0831***	.0094
Oil and gas producers	-.0259***	.0091	-.0243**	.0097
Oil equipment and services	-.0377***	.0084	-.0360***	.0091
Firm RE	YES		YES	
Constant	-.0924***	.0224	-.0779***	.0224
N	28,221		28,221	
# Firms	409		409	
# Weeks	69		69	
Wald Chi Square	681.05		754.48	
R2	.1621		.1633	
R2_adj	.1616		.1628	

Table 21 demonstrates the results from the random effects regressions for the effect of investor sentiment on stock returns. Weekly CARs are used as dependent variable to proxy for stock returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly CARs for the extended model that is used for answering Hypothesis 2. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the extended model for Hypothesis 5 is presented which adds the interaction effect between investor sentiment and the US dummy. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly CAR can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.6 Impact of the Russian invasion on weekly CARs during the energy crisis

The Russian invasion of Ukraine on the 24th of February 2022 was a big factor in the energy crisis (IEA, n.d.; Gaffen, 2022). For Hypothesis 6, a distinction is made between the pre-invasion period (September 5, 2021 - February 19, 2022) and the post-invasion period (February 20, 2022 - December 31, 2022). It is expected that investor sentiment has a bigger impact on stock returns after the start of the invasion than before the start. In Table 22, the interaction effect between investor sentiment and the post-invasion dummy is added to the extended model that is used for Hypothesis 2. At a 1% significance, the post-invasion coefficient is -.0130, indicating a lower weekly CAR in the post invasion period, assuming that investor sentiment is zero. In Appendix J, Figure 11, the interaction effect is displayed. The red line (post-invasion period) is positioned higher than the blue line (pre-invasion period) between the 25th and 75th percentile values of sentiment, this demonstrates higher weekly CARs in the post-invasion period. In Table 22, the interaction effect with the post-invasion dummy has a 1%-significant positive coefficient of .0016, which denotes that the effect of sentiment on the weekly CAR is higher on average in the post-invasion period. When this is combined with the fact that investor sentiment has a positive effect, even when the energy sources are taken into account, the impact is bigger in the post-invasion period than in the pre-invasion period. Moreover, in Figure 11 (Appendix J), the red line is steeper than the blue line, which indicates that the impact of investor sentiment is bigger in the post-invasion period. Therefore, Hypothesis 6 can be accepted.

Table 22: Impact of the invasion on weekly CARs during the energy crisis

Weekly CAR	**Weekly CAR Extended Coefficient**	**Weekly CAR Extended Robust St. Error**	**Weekly CAR Extended Coefficient**	**Weekly CAR Extended Robust St. Error**
Sentiment	.0024***	.0002	.0014***	.0003
Sentiment * Post-invasion			.0016***	.0003
Sentiment * Oil	-.0014***	.0002	-.0014***	.0002
Sentiment * Gas	.0002***	.0001	.0002***	.0001
Sentiment * Coal	-.0002***	.0001	-.0002***	.0001
Post-invasion			-.0130***	.0046
Oil	.0292***	.0022	.0294***	.0021
Gas	-.0018***	.0006	-.0016***	.0006
Coal	.0017***	.0006	.0017***	.0006

VIX	.0013***	.0001	.0013***	.0002
Vol	.0111***	.0016	.0108***	.0016
Size	-.0027**	.0012	-.0025**	.0012
D/E	.0005	.0017	.0005	.0017
RoE	-.0001	.0001	-.0001	.0001
Industry				
Electricity	-.0665***	.0097	-.0667***	.0097
Gas, water & multi-utilities	-.0846***	.0087	-.0848***	.0088
Oil and gas producers	-.0259***	.0091	-.0258***	.0091
Oil equipment and services	-.0377***	.0084	-.0377***	.0084
Firm RE	YES		YES	
Constant	-.0924***	.0224	-.0831***	.0223
N	28,221		28,221	
# Firms	409		409	
# Weeks	69		69	
Wald Chi Square	681.05		741.26	
R2	.1621		.1629	
R2_adj	.1616		.1624	

Table 22 demonstrates the results from the random effects regressions for the effect of investor sentiment on stock returns. Weekly CARs are used as dependent variable to proxy for stock returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly CARs for the extended model that is used for answering Hypothesis 2. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the extended model for Hypothesis 6 is presented which adds the interaction effect between investor sentiment and the post-invasion dummy. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly CAR can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.7 Impact of the Russian invasion on weekly trading volumes during the energy crisis

For Hypothesis 7, the expectation is that weekly trading volumes are higher after the start of the invasion (February 20, 2022 - December 31, 2022) than before the start of the invasion (September 5, 2021 - February 19, 2022). In order to measure this effect, the post-invasion dummy is added to the extended model that is used for Hypothesis 3 (see Table 23). The post-invasion coefficient is .1278 at a 1% significance level. This implies that in the post-invasion period, the natural logarithm of the weekly average of daily trading volumes is 0.1278 higher on average than in the pre-invasion period. Therefore, Hypothesis 7 can be accepted.

Table 23: Impact of the invasion on weekly trading volumes during the energy crisis

Weekly Vol	**Weekly Vol Extended Coefficient**	**Weekly Vol Extended Robust St. Error**	**Weekly Vol Extended Coefficient**	**Weekly Vol Extended Robust St. Error**
Sentiment	-.0010	.0014	.0011	.0013
Post-invasion			.1278***	.0230
Sentiment * Oil	.0030**	.0013	.0052***	.0012
Sentiment * Gas	-.0084***	.0004	-.0078***	.0004
Sentiment * Coal	-.0005	.0004	-.0005	.0004
Oil	-.0373***	.0119	-.0494***	.0118
Gas	.0853***	.0041	.0804***	.0042
Coal	-.0054	.0036	-.0057	.0036
VIX	-.0039***	.0010	-.0002	.0008
Size	.5084***	.0317	.5084***	.0317
D/E	-.0430	.0362	-.0430	.0362
RoE	-.0029**	.0013	-.0029**	.0013
Industry				
Electricity	-.7243***	.2464	-.7243***	.2464
Gas, water & multi-utilities	-.7978***	.2519	-.7978***	.2519
Oil and gas producers	.4627*	.2448	.4627*	.2448
Oil equipment and services	-.0488	.2348	-.0488	.2348
Firm RE	YES		YES	
Constant	5.9071***	.4516	5.799***	.4500
N	28,221		28,221	
# Firms	409		409	
# Weeks	69		69	
Wald Chi Square	1,169.96		1,189.71	
R2	.4182		.4192	
R2_adj	.4179		.4189	

Table 23 displays the results from the random effects regressions for the effect of investor sentiment on weekly trading volumes. Column (1) shows the variable or test statistic of interest. Columns (2)-(3)

show the results for the effect of investor sentiment on the weekly trading volumes for the extended model that is used for answering Hypothesis 3. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the extended model for Hypothesis 7 is presented which adds the post-invasion dummy. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly trading volume can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

5.8 Robustness checks

In this section, several robustness checks will be performed. With these checks, it can be concluded whether the results are sensitive to changes in some of the parameters that are used in the data process. Since this thesis counts seven hypotheses and there is no point in checking all hypotheses, the focus is on Hypothesis 2, since this is the main hypothesis of the paper. For this hypothesis, a 0.5% winsorization on the weekly CAR is performed in order to reduce the kurtosis. However, during the energy crisis, high variations in share prices are typical. Winsorizing the data gives a distorted picture of reality in this case. In Appendix K, Table 29, Columns 4 and 5, the robustness check for Hypothesis 2 without winsorizing for the weekly CAR can be found. Moreover, the control variables D/E (debt-to-equity ratio) and RoE (return on equity) are not winsorized in this robustness check. From Appendix K, Table 29 can be retrieved that the results from this robustness check are very similar to the results from Hypothesis 2. The overall significance of the model, the adjusted R2 and some control variables do vary a bit, but the interaction effects are very comparable and therefore the same conclusions on behalf of Hypothesis 2 can be made after this check.

Furthermore, the CARs are calculated by using different benchmarks based on if the company is based in the EU or the US. The STOXX600 is used for European companies, the S&P500 for the US. These two benchmarks have different constructions in determining market returns. This leads to a bias. An alternative would be using the MSCI Europe and the MSCI US index. These benchmarks stem from the same company and thus use identical constructions, which makes them better internationally comparable. In Appendix K, Table 29, Columns 6 and 7, the robustness check that uses the MSCI Europe and MSCI US index as benchmark is shown. The regression results are comparable to the results from Hypothesis 2 in Columns 2 and 3 of Table 29. A few coefficients differ a bit and the overall significance of the model and the adjusted R2 are even better than in the model used for Hypothesis 2. Most important, the coefficient for investor sentiment and the interaction effects are almost identical. The results for Hypothesis 2 are robust to using a different benchmark for calculating the CAR.

Moreover, the CAR is based on the CAPM model, which is sensitive to assumptions made for the risk-free rate, the company-specific beta and the benchmark. An alternative for this model Is the market-adjusted model, which only subtracts the return of the chosen benchmark from the actual return to retrieve the abnormal return (AR) (Formula 15). In this way, different weekly CARs will emerge. This method is less sensitive to assumptions and can influence the results.

$$(15)\ AR_{i,t} = R_{i,t} - R_{m,t}$$

In Appendix K, Table 30, Columns 4 and 5, the robustness check can be found for applying CARs based on the market-adjusted model. The regression results differ extremely. To start, there is no significant effect anymore for sentiment. The interaction effects are all 1%-significant, but the coefficients differ in sign and size relative to the results from Hypothesis 2 in Column 2 and 3. It seems that the effect of investor sentiment is positive when oil and gas returns increase (.0016 and .0008, respectively), and this effect is negative for increasing coal returns (-.0015). Purely based on the interaction effects and not on the insignificant sentiment coefficient, the same conclusions for the effect of investor sentiment on the weekly CAR as for Hypothesis 2 can be drawn at increasing levels of oil and gas returns. However, when looking at coal returns, it seems that opposite results occur.

Finally, interpreting the interaction terms is very sensitive to the chosen levels of oil, gas, and coal returns. By using the figures to investigate the interaction effects, conclusions for Hypothesis 2 can only be made assuming that each energy return lies between the 25th and 75th percentile values in the sample distribution of the collected returns. This has its benefits; results are based on the most common values of returns in this way. Otherwise, conclusions are made on return values that can identify as outliers. However, it can still be interesting to have a look on these outliers. Therefore, in Appendix K, Figures 12-14, the minimum and maximum values for each energy return are added to Figures 1-3 that display the interaction effect at the 25th percentile, median, and 75th percentile values. In Figures 12 and 14 can be seen that for the maximum values of oil and coal, the effect of investor sentiment turns negative. In this case the negative coefficients that these interaction effects have in Table 18 from Section 5.2.2 (-.0014 and -.0002) overrule the overall positive effect of sentiment (.0024). On the other hand, at the minimum value for oil and coal, the impact of sentiment is the biggest (blue lines are the steepest). For gas, the opposite effect can be found in Figure 13. This is because for the interaction effect of sentiment and gas the coefficient is positive (.0002). In this case, taking the minimum value for gas causes a negative effect of sentiment on the weekly CAR, the maximum value makes the overall effect the biggest. This indicates that interpreting the results is sensitive to the assumed values of oil, gas and coal returns.

6. Conclusion

This chapter addresses the conclusion of the research. In Section 6.1, the results are summarized after which conclusions are drawn. Section 6.2 discusses the limitations of the study and provides some recommendations for follow-up research.

6.1 Conclusion

The aim of this paper was to determine the role of investor sentiment on stock returns during the energy crisis. Google Trends has been used as data source to measure the overall sentiment in the market, weekly CARs were used to represent stock returns. The Russian invasion of Ukraine is an important factor in the current energy crisis, which is why this event played a major role in the thesis. The rising energy prices have been a big cause of the energy crisis. Therefore, oil, gas, and coal returns were seriously taken into consideration for answering the research question:

"What is the impact of investor sentiment on Western energy-related stock returns in 2021 - 2022 during the global energy crisis?"

Seven different hypotheses were used to answer this question. In Table 24, an overview of all hypotheses is given, along with whether they are accepted or rejected. First, the relationship between investor sentiment and the three energy returns was highlighted. A negative effect of the first lag of investor sentiment on oil returns was found. No significant effect could be demonstrated for gas and coal.

Secondly, the most important panel data regression was performed on the effect of investor sentiment on weekly CARs during the energy crisis. A detailed look on the interaction effects between investor sentiment and each energy source (oil, gas, and coal) was used to investigate this effect. By assuming the 25th percentile, median, and 75th percentile values of the sample distribution for each energy source, a positive effect of investor sentiment on the weekly CAR was found in all cases. This indicates that the macro-economic sentiment measured by Google Trends has a positive impact on Western energy-related stock returns in 2021-2022 during the energy crisis. However, the results were partly sensitive to using the CAPM model. When the market-adjusted model was used as a robustness check, a negative effect of investor sentiment seemed to occur for higher values of coal returns. Moreover, the results were sensitive to the values of energy returns that were assumed. When values between the 25th and 75th percentile observation in the sample for oil, gas, and coal returns were assumed, a positive impact of investor sentiment was found. When the minimum and maximum values of oil, gas, and coal returns in the sample were assumed, investor sentiment had a negative effect on stock returns. It was also found that companies belonging to the alternative energy sector showed superior CARs in comparison to those from the other four sectors.

Thirdly, apart from measuring the impact of sentiment on stock returns, the effect of sentiment on trading volumes during the energy crisis was taken into consideration as well. It is insightful to see whether the overall sentiment has its influence on the trading behavior of investors. The same interaction effects between sentiment and the three energy sources were used to establish this effect. Against the expectations, a negative effect was found by assuming three different values for oil and coal returns. For gas, a more interesting effect occurred. At high levels of gas returns, the effect was negative as well. However, for low values of gas returns, this effect turned into a positive one. This underlines the importance of using the energy sources in interaction effects instead of as regular control variables, where no distinction could be made on different values of returns. However, it was not possible conclude on these effects due to insignificance. Apart from the effect of sentiment on trading volumes, the regression showed that stocks from the alternative energy sector were frequently traded. However, the oil and gas producers' sector was still the most popular, despite the increasing demand for a shift to sustainable energy sources.

Subsequently, the short-term effect of investor sentiment on the weekly CAR was investigated by declining the sample from 69 weeks to 9 weeks around the Russian invasion of Ukraine (February - April 2022). This was done because other papers found a difference in effects in the short term and long term (Da et al., 2011; Bank et al., 2011). By looking into the interaction effects between sentiment and the three energy sources, a negative effect of sentiment on the weekly CAR was found for the 25th percentile, median, and 75th percentile values of oil and coal returns. The same negative impact is found for the median and 75th percentile values of gas returns. However, this impact turns positive for low values of gas returns.

Then, it was investigated whether there was a regional effect for the effect of sentiment on the weekly CAR. By doing so, there can be seen whether sentiment plays a bigger role in determining stock prices for countries closer located to the war between Russia and Ukraine. A dummy was added that distinguishes in whether the company is from the US or the EU.

Hereafter, the interaction effect between sentiment and this dummy was examined. This showed, against expectations, a bigger impact of sentiment in the US.

Finally, the impact of the war was used to address differences in the effect of investor sentiment on both the weekly CAR and trading volume. A distinction was made between the period before and after the Russian invasion by creating a dummy with value 1 for weeks equal and above Week 25 of the sample (week of the Russian invasion). To test the impact of the war on the weekly CAR, an interaction term was used between sentiment and the post-invasion dummy. It showed that, in line with the expectations, the effect of sentiment is bigger in the post-invasion period than in the pre-invasion period. In addition, the post-war dummy was added to the regression for the effect on the weekly trading volumes and this showed a 1%-significant positive dummy coefficient, indicating an increase in trading volumes in the post-invasion period.

Altogether, several relationships are highlighted that help answering the research question. The main relationship that needed to be examined for this is between sentiment and stock returns during the energy crisis. From the results, it can be concluded that between the 25th and 75th percentile values of oil, gas, and coal, there is a positive effect of investor sentiment on stock returns. When investigating a shorter window of nine weeks (one week before and seven weeks after) around the Russian invasion of Ukraine, a negative relationship between investor sentiment and stock returns is found between the 25th and 75th percentile values of oil and coal returns. For low values of gas returns, a positive effect is retrieved. This indicates a different effect of investor sentiment during a short period which is very uncertain and chaotic (around the invasion) and in a longer period in which the effect of sentiment perhaps adjusts to the circumstances (energy crisis). Most results contradict the majority of the literature and therefore this study can have an important contribution in nuancing the effect of investor sentiment in both the short and long term. In any case it can be concluded that also in most recent times, investor sentiment has again had an impact on stock returns.

Table 24: Overview of all hypotheses

Hypothesis	Result
H_{1A}: Investor sentiment positively influences oil returns during the energy crisis (September 2021 - December 2022).	Rejected (negative effect)
H_{1B}: Investor sentiment positively influences gas returns during the energy crisis (September 2021 - December 2022).	Rejected (no significance)
H_{1C}: Investor sentiment positively influences coal returns during the energy crisis (September 2021 - December 2022).	Rejected (no significance)
H_2: Investor sentiment negatively influences stock returns of Western energy-related companies during the energy crisis (September 2021 - December 2022).	Rejected (positive effect)
H_3: Investor sentiment positively influences trading volumes of Western energy-related companies during the energy crisis (September 2021 - December 2022).	Rejected (no significance)
H_4: Investor sentiment positively influences stock returns of Western energy-related companies in the short run around the invasion of Ukraine (February - April 2022).	Rejected (negative effect), only accepted for low levels of gas returns
H_5: The impact of investor sentiment on stock returns of Western energy-related companies during the energy crisis (September 2021 - December 2022) is bigger in Europe than in the US.	Rejected (bigger effect in US)
H_6: Investor sentiment has a bigger impact on stock returns of Western energy-related companies after the start of the invasion than before the start of the invasion (from September 2021).	Accepted
H_7: Trading volumes of Western energy-related companies are higher after the start of the invasion than before the start of the invasion (from September 2021).	Accepted

Table 24 provides an overview of the hypotheses. In Column (1), the specific hypothesis is listed. Column (2) shows whether the hypotheses were accepted or rejected, in the latter case a minor reason for rejection is given as well.

6.2 Limitations and recommendations

In this section, the limitations of the research are discussed, in combination with some recommendations for future research. The results are largely contradictory to the hypotheses but still can add interesting conclusions to the existing literature. However, there are many factors that caused these results due to choices made in the data process. These choices may hinder the display of the real effects.

First, in Hypothesis 1, the number of observations is limited. Because only 69 weeks are considered and in the case of oil three lags are added to the model, the number of observations is between 66 and 68. To perform a proper regression, this number is too low. Therefore, it is comprehensible that the results were mainly insignificant. To conduct a study on the relationship between investor sentiment and energy prices, a higher number of weeks or daily data should be used. The weekly data is initially used because of the accessibility of Google Trends data. Though, this weekly approach is less accurate than using daily data to find a clearer impact on stock returns. In a follow-up study, daily data would be preferred.

In addition, the data structure of the thesis has its limitations. The weekly CAR and the trading volumes are the only two variables that are time and company specific. The most important independent variables, investor sentiment and the energy returns, are only time specific. On the other hand, control variables like firm size, debt-to-equity, and firm industry are only company specific. This causes a difficult dataset to work with. Consequently, the random effects model is preferred over the fixed effects model. An advantage of this is that the firm specific variables could be taken into consideration. However, the random effects model is a weaker model that uses z-statistics and the Wald chi square test instead of t-statistics and the F-test. Another downside of the random effects model is that there must be assumed that the error term ($\omega_{i,t}$) is uncorrelated with all explanatory variables. In other words, there is assumed that any unobserved omitted variables are uncorrelated with the included variables (Brooks, 2019, Chapter 11.6). Furthermore, the data structure makes it impossible to conduct an event study, which is the preferred way to test the effect of investor sentiment on stock returns in the short run around the Russian invasion in Hypothesis 4. In this case, the dependent variable (CAR) is only company specific, and the independent variable (sentiment) is only time specific. As a result, a window of 9 weeks around the invasion is taken for this hypothesis. This increases the noise around the event and makes it harder to estimate the pure effect of the invasion. This data structure issue can partly be solved by using a company specific sentiment indicator like the Google Search Volumes for certain company names instead of a market-wide sentiment indicator. In this case, the subject focuses on investor attention rather than investor sentiment. Additional research that investigates the role of investor attention could be a good addition to this study.

Moreover, in the data filtering process, several decisions are made that influence the final dataset. In Step 4 of the data filtering (Appendix B), stocks with an average daily trading volume lower than 10,000 are dropped due to illiquidity. These illiquid stocks are likely most sensitive to other factors like sentiment or the oil price. Dropping these values results in selection bias in the research.

Besides, this paper investigates the effect of investor sentiment for Western companies, i.e., European and US companies. In fact, a regional test is conducted which shows that the effect of investor sentiment is bigger in the US than in the EU. This test is performed because of the relative distance from the war but this approach ignores the fact that the EU and US are both on the same side and that is supporting Ukraine. The energy crisis and the Russia-Ukraine conflict are a global concern. However, several large countries tend to be less affected by it. For example, China has not chosen a clear side in the Russia-Ukraine conflict. In further research, it would be interesting to focus on a wider variety of countries/regions and see whether the impact of investor sentiment is smaller in "neutral" countries like China.

Finally, this thesis uses nominal energy returns. Du et al. (2016) correct for inflation and distinguish between nominal and real oil prices. In their study, results for both prices were comparable. Inflation can potentially play a large role in this study, whereby a clearer effect of investor sentiment can be reflected. Further research can take the inflation rate into account and investigate its impact on investor sentiment and stock returns.

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Appendix

Appendix A Google Search Terms

Table 25: Positive and negative Google search terms

Positive words				Negative words			
1	Buy	25	Opportunity	1	Inflation	25	Weak
2	Bull market	26	Energy	2	Unemployment	26	Negative
3	Invest	27	Dividend	3	Loss	27	Low
4	Booming	28	Revenue	4	Crisis	28	Tax
5	Return	29	Spend	5	War	29	Economic Downturn
6	Money	30	Economic Boom	6	Short sell	30	Breaking
7	Growth	31	Positive	7	Bubble	31	Broken
8	Hedge	32	High	8	Short selling	32	Closed
9	Bonds	33	Beneficial	9	Conflict	33	Closing
10	Derivatives	34	Benefit	10	Crash	34	Critical
11	Stocks	35	Effective	11	Bear market	35	Secrecy
12	Leverage	36	Great	12	Sell	36	Mispricing
13	Gains	37	Rewards	13	Debt	37	Threat
14	Cash	38	Excited	14	Credit	38	Worry
15	Nasdaq	39	Incredible	15	Save	39	Panic
16	S&P500	40	Ideal	16	Liability	40	Terror
17	STOXX600	41	Attract	17	Ukraine	41	Erode
18	Gain	42	Impressively	18	Russia	42	COVID-19
19	Success	43	Encouraging	19	Sanctions	43	Halve
20	Oil price	44	Impress	20	Oil shortage	44	Pessimistic
21	Oil	45	Double	21	Fine	45	Bad
22	Buy and Hold	46	Optimistic	22	Risk	46	Lockdown
23	Long	47	Good	23	Fail	47	Underperform
24	NYSE			24	Fall		

Table 25 provides the Google search terms that are used to measure for investor sentiment. Columns (1)-(2) show the positive words, Columns (4-5) the negative words.

Appendix B Data filtering process

The companies for the research are obtained after filtering the first data output in multiple steps. The starting output is retrieved from Datastream and concerns the daily stock prices and trading volumes of all stocks listed on any European or US market from the five industries described in Chapter 3: alternative energy; electricity; gas, water and multi-utilities; oil and gas producers; and oil equipment and services. In total, stock prices and trading volumes of 2,624 stocks are collected in the starting output. Afterwards, the following nine steps are performed in filtering the data:

Step 1: Several stocks do not display the company name but “ERROR” in the dataset for either the stock price or trading volume and do not contain any stock price or volume information. These stocks are filtered from the dataset.

Step 2: Stocks with more than 40 missing values for either the stock price or the trading volume are dropped.

Step 3: Some large companies have stocks listed on multiple stock markets. For example, Exxon Mobil, one of the largest oil producers, has its company listed on more than 10 different markets in the dataset. For these companies, all stocks are dropped except from the one on the market with the largest average daily trading volume.

Step 4: Stocks with an average daily trading volume lower than 10,000 are dropped because of illiquidity concerns.

Step 5: Daily returns are calculated with the stock price data. Several companies had periods of the same stock price on multiple consecutive days. For that reason, companies with more than 40 returns that are zero are dropped.

Step 6: For the same reason as described in Step 5, companies with more than 4 consecutive returns that are zero are dropped.

Step 7: For the remaining companies, other financial data is retrieved from Datastream as described in Section 3.3. Companies with missing values for all controls are dropped.

Step 8: Some companies have net sales of 0. These companies are filtered due to this sign of inactivity.

Step 9: In the starting data, companies listed on any EU or US market were taken into consideration. For the research, the country of domicile is the leading indicator. For example, a company can be listed on the Nasdaq, but the country of domicile is China. In these cases, the companies are dropped from the dataset.

Step 10: For the company beta that is needed to calculate expected returns, an estimation window of [-250;-4] for the event of the Russian invasion of Ukraine is used. Companies that were lacking stock price data for this estimation windows are filtered.

In Table 26, the number of stocks/companies per industry in each phase of the data filtering process is shown. Most companies are dropped in Step 2 due to a lack of information for stock prices or trading volumes in the period of interest.

Table 26: Number of stocks/companies in the data filtering process per industry

Step	Alternative energy	Elec-tricity	Gas, water & multi-utilities	Oil & gas producers	Oil equipment & services	Total	Difference
Start	504	577	302	809	432	**2,624**	-
1	467	517	248	736	400	**2,368**	**-256**
2	174	190	91	248	146	**849**	**-1,519**
3	130	164	70	199	138	**701**	**-148**
4	119	148	60	193	129	**649**	**-52**
5	93	105	55	125	114	**492**	**-157**
6	93	95	54	116	113	**471**	**-21**
7	93	91	53	115	113	**465**	**-6**
8	85	90	53	113	111	**452**	**-13**
9	82	88	53	108	108	**439**	**-13**
10	75	85	52	108	106	**426**	**-13**
Final	**75**	**85**	**52**	**108**	**106**	**426**	**-2,198**

Table 26 includes the number of stocks/companies in the data filtering process for each industry. Column (1) shows the phase in the filtering process. Columns (2)-(6) show the number of stocks/companies left in each industry after performing the filtering step in Column (1). Column (7) displays the total number of stocks/companies left in each phase. In Column (8) the total number of dropped stocks/companies is shown.

Appendix C Companies in the dataset per industry

Appendix C.1 Companies in the dataset from industry: Alternative energy

1. ADS-TEC ENERGY PLC
2. ADVENT TECHNOLOGIES HOLDINGS INC
3. AEMETIS INCORPORATED
4. AFC ENERGY PLC
5. AMERESCO, INCORPORATION
6. AMERICAN SUPERCONDUCTOR CORPORATION
7. ARCOSA INC
8. ARRAY TECHNOLOGIES INC
9. ASCENT SOLAR TECHNOLOGIES, INC
10. AZELIO AB
11. BEAM GLOBAL
12. BIOFRIGAS SWEDEN AB (PUBL)
13. CAPSTONE GREEN ENERGY CORP
14. CENTRUS ENERGY CORP
15. CERES POWER HOLDINGS LIMITED
16. CHARGEPOINT HOLDINGS INC
17. CLEAN INDUSTRY SOLUTIONS HOLDING EUROPE AB
18. CLIMEON AB (PUBL)
19. COLUMBUS ENERGY SA
20. COMPLEO CHARGING SOLUTIONS AG
21. CROPENERGIES AG
22. ECOARK HOLDINGS INC
23. ENERTIME SAS
24. ENPHASE ENERGY INC
25. ENVIVA INC
26. EOLUS VIND AB
27. EVERFUEL A/S
28. EVGO INC
29. FASTNED BV
30. FIRST SOLAR, INC.
31. FUELCELL ENERGY, INC.
32. GEVO, INC.
33. GLOBAL BIOENERGIES SA
34. GREEN PLAINS INC
35. HYDROGENPRO ASA
36. IDEAL POWER INC
37. INNOVATEC SPA
38. ISUN INC
39. ITM POWER PLC
40. MAGNORA ASA
41. MCPHY ENERGY SA
42. METACON AB (PUBL)
43. MIDSUMMER AB
44. ML SYSTEM SA
45. MONTAUK RENEWABLES INC
46. NEL ASA
47. NORDEX SE
48. OCEAN POWER TECHNOLOGIES
49. OCEAN SUN AS
50. OTOVO ASA
51. PINEAPPLE ENERGY INC
52. PLUG POWER INCORPORATED
53. REX AMERICAN RESOURCES CORPORATION
54. SCANDINAVIAN BIOGAS FUELS INTERNATIONAL AB
55. SCATEC ASA
56. SFC ENERGY AG
57. SHOALS TECHNOLOGIES GROUP INC
58. SIEMENS ENERGY AG
59. SIEMENS GAMESA RENEWABLE ENERGY SA
60. SIF HOLDING NV
61. SMA SOLAR TECHNOLOGY AG
62. SOLAREDGE TECHNOLOGIES INC
63. SOLTEC POWER HOLDINGS SA
64. SOLTECH ENERGY SWEDEN AB (PUBL)
65. SPI ENERGY CO LTD
66. STEM INC
67. SUNEX SA
68. SUNPOWER CORPORATION
69. SUNWORKS INC
70. SWEDISH STIRLING AB
71. TECO 2030 ASA
72. TPI COMPOSITES INC
73. VERBIO VEREINIGTE BIOENERGIE AG
74. VESTAS WIND SYSTEMS AS
75. VOLTA INC

Appendix C.2 Companies in the dataset from industry: Electricity

76. 2G ENERGY AG
77. 7C SOLARPARKEN AG
78. A2A SPA
79. ACEA SPA
80. AES CORP
81. AGATOS SPA
82. AKER HORIZONS ASA
83. ALERION CLEANPOWER SPA
84. ALGOWATT SPA
85. ALLETE, INC.
86. ALLIANT ENERGY CORPORATION
87. ALTUS POWER INC
88. AMERICAN ELECTRIC POWER COMPANY, INC.
89. ARISE AB
90. ATLANTICA SUSTAINABLE INFRASTRUCTURE PLC
91. AUDAX RENOVABLES SA
92. AVANGRID INC
93. BKW AG
94. BROOKFIELD RENEWABLE CORP
95. CEZ A.S.
96. CLEARWAY ENERGY INC
97. CLOUDBERRY CLEAN ENERGY ASA
98. CMS ENERGY CORPORATION
99. COMAL SPA
100. CONSOLIDATED EDISON, INC.
101. DOMINION ENERGY INC
102. DRAX GROUP PLC
103. DTE ENERGY COMPANY
104. EDISON INTERNATIONAL
105. EDP - ENERGIAS DE PORTUGAL S.A.
106. EDP RENOVAVEIS
107. ELIA GROUP SA
108. ELMERA GROUP ASA
109. ENCAVIS AG
110. ENDESA SA
111. ENEA SA
112. ENEL SPA
113. ENERGIEKONTOR AG
114. ENTERGY CORPORATION
115. ERG SPA
116. EVERGY INC
117. EVERSOURCE ENERGY
118. EXELON CORPORATION
119. FIRSTENERGY CORPORATION
120. FORTUM OYJ
121. GRENERGY RENOVABLES SL
122. HAWAIIAN ELECTRIC INDUSTRIES INCORPORATION
123. IBERDROLA S.A.
124. IDACORP, INC.
125. LA FRANCAISE DE L ENERGIE SA
126. MGE ENERGY, INC.
127. NEOEN SA
128. NEXTERA ENERGY INC
129. NEXTERA ENERGY PARTNERS LP
130. NORTHWESTERN CORPORATION
131. NRG ENERGY, INC.
132. OERSTED A/S
133. OGE ENERGY CORPORATION
134. ORMAT TECHNOLOGIES, INC.
135. PG&E CORPORATION
136. PGE POLSKA GRUPA ENERGETYCZNA SA
137. PINNACLE WEST CAPITAL CORPORATION
138. PNE AG
139. PNM RESOURCES, INC.
140. PORTLAND GENERAL ELECTRIC COMPANY
141. PPL CORP
142. PUBLIC SERVICE ENTERPRISE GROUP INC.
143. RED ELECTRICA CORPORACION SA
144. REN - REDES ENERGETICAS NACIONAIS, SGPS, S.A.
145. RENEW ENERGY GLOBAL PLC
146. SOLARIA ENERGIA Y MEDIO AMBIENTE, S.A.
147. SOUTHERN CO
148. SSE PLC
149. SUNNOVA ENERGY INTERNATIONAL INC
150. SUNRUN INC
151. TAURON POLSKA ENERGIA SA
152. TERNA RETE ELETTRICA NAZIONALE SPA
153. UNITIL CORPORATION
154. VERBUND AG
155. VIA RENEWABLES INC
156. VISTRA CORP
157. VIVOPOWER INTERNATIONAL PLC
158. VOLTALIA
159. XCEL ENERGY INC.
160. ZE PAK SA

Appendix C.3 Companies in the dataset from industry: Gas, water and multi-utilities

161 AMEREN CORPORATION
162 AMERICAN STATES WATER COMPANY
163 AMERICAN WATER WORKS CO INCORPORATED
164 ARTESIAN RESOURCES CORPORATION
165 ASCOPIAVE SPA
166 ATHENS WATER SUPPLY AND SEWERAGE COMPANY
167 ATMOS ENERGY CORPORATION
168 AVISTA CORPORATION
169 AYGAZ A.S.
170 BLACK HILLS CORPORATION
171 BROOKFIELD INFRASTRUCTURE CORP
172 BROOKFIELD INFRASTRUCTURE PARTNERS L.P.
173 CADIZ INCORPORATED
174 CALIFORNIA WATER SERVICE GROUP
175 CENTERPOINT ENERGY, INC.
176 CENTRICA PLC
177 CHESAPEAKE UTILITIES CORPORATION
178 CONSOLIDATED WATER CO. LTD.
179 DUKE ENERGY CORPORATION
180 E ON SE
181 ENGIE SA
182 ESSENTIAL UTILITIES INC
183 EVN AKTIENGESELLSCHAFT
184 EVOQUA WATER TECHNOLOGIES CORP
185 GENIE ENERGY LIMITED
186 GLOBAL WATER RESOURCES INC
187 HERA SPA
188 IREN SPA
189 ITALGAS SPA
190 MIDDLESEX WATER COMPANY
191 NATIONAL FUEL GAS COMPANY
192 NATIONAL GRID PLC
193 NATURGY ENERGY GROUP SA
194 NEW JERSEY RESOURCES CORPORATION
195 NISOURCE INC.
196 NORTHWEST NATURAL HOLDING CO
197 ONE GAS INC
198 PENNON GROUP PLC
199 PURE CYCLE CORPORATION
200 RWE AG
201 SEMPRA ENERGY
202 SEVERN TRENT PLC
203 SJW CORP.
204 SOUTHWEST GAS CORPORATION
205 SPIRE INC
206 STAR GROUP LP
207 UGI CORPORATION
208 UNIPER SE
209 UNITED UTILITIES GROUP PLC
210 VEOLIA ENVIRONNEMENT SA
211 WEC ENERGY GROUP INC
212 YORK WATER CO

Appendix C.4 Companies in the dataset from industry: Oil and gas producers

213 AKER BP ASA
214 AMPLIFY ENERGY CORP
215 ANTERO RESOURCES CORP
216 APA CORP (US)
217 BATTALION OIL CORP
218 BERRY CORPORATION (BRY)
219 BLACK STONE MINERALS LP
220 BP PLC
221 BW ENERGY LTD
222 CALIFORNIA RESOURCES CORP
223 CALLON PETROLEUM COMPANY
224 CAMBER ENERGY INC
225 CAPRICORN ENERGY PLCX
226 CHEVRON CORPORATION
227 CHORD ENERGY CORP
228 CIVITAS RESOURCES INC
229 CNX RESOURCES CORP
230 COMSTOCK RESOURCES INC
231 CONOCOPHILLIPS
232 COTERRA ENERGY INC
233 CROSS TIMBERS ROYALTY TRUST
234 DENBURY INC
235 DEUTSCHE ROHSTOFF AG
236 DEVON ENERGY CORPORATION
237 DIAMONDBACK ENERGY INC
238 DIVERSIFIED ENERGY COMPANY PLC
239 DNO ASA
240 DORCHESTER MINERALS LP
241 EARTHSTONE ENERGY INC
242 ECA MARCELLUS TRUST I
243 ENERGEAN PLC
244 ENI - ENTE NAZIONALE IDROCARBURI
245 ENQUEST PLC
246 EOG RESOURCES INC
247 EQT CORPORATION
248 EQUINOR ASA
249 ETABLISSEMENTS MAUREL ET PROM SA
250 EVOLUTION PETROLEUM CORPORATION
251 EXXON MOBIL CORP
252 GALP ENERGIA SGPS, S.A.
253 GAS PLUS SPA
254 GENEL ENERGY PLC
255 HARBOUR ENERGY PLC
256 HIGHPEAK ENERGY INC
257 HOUSTON AMERICAN ENERGY CORP.
258 HURRICANE ENERGY PLC
259 IGAS ENERGY PLC
260 INTEROIL EXPLORATION & PRODUCTION
261 KIMBELL ROYALTY PARTNERS LP
262 KISTOS PLC
263 KOSMOS ENERGY LIMITED
264 MAGNOLIA OIL & GAS CORP
265 MAHA ENERGY AB
266 MARATHON OIL CORPORATION
267 MARINE PETROLEUM TRUST
268 MATADOR RESOURCES COMPANY
269 MESA ROYALTY TRUST
270 MEXCO ENERGY CORPORATION
271 MOL MAGYAR OLAJES GAZIPARI NYRT
272 MURPHY OIL CORPORATION
273 MV OIL TRUST
274 NEW CONCEPT ENERGY, INC
275 NEW FORTRESS ENERGY INC
276 NORTH EUROPEAN OIL ROYALTY TRUST
277 NORTHERN OIL & GAS INC
278 NORWEGIAN ENERGY COMPANY ASA
279 OCCIDENTAL PETROLEUM CORPORATION
280 OKEA ASA
281 OMV AKTIENGESELLSCHAFT
282 PANORO ENERGY ASA
283 PARKMEAD GROUP PLC
284 PDC ENERGY INCORPORATED
285 PERMIAN BASIN ROYALTY TRUST
286 PERMIAN RESOURCES CORP
287 PERMIANVILLE ROYALTY TRUST
288 PERMROCK ROYALTY TRUST
289 PHX MINERALS INC
290 PIONEER NATURAL RESOURCES COMPANY
291 RANGE RESOURCES CORPORATION
292 RANGER OIL CORP
293 REPSOL SA
294 RILEY EXPLORATION PERMIAN INC
295 RING ENERGY INCORPORATION
296 ROCKHOPPER EXPLORATION PLC
297 SABINE ROYALTY TRUST
298 SAN JUAN BASIN ROYALTY TRUST
299 SANDRIDGE ENERGY, INC.
300 SERICA ENERGY PLC
301 SHELL PLC
302 SHELL PLC
303 SILVERBOW RESOURCES INC
304 SITIO ROYALTIES CORP
305 SM ENERGY CO
306 SOCIETATEA NATIONALA DE GAZE NATURALE ROMGAZ
307 SOUTHWESTERN ENERGY COMPANY
308 TALOS ENERGY INC
309 TELLURIAN INC
310 TETHYS OIL AB
311 TEXAS PACIFIC LAND CORP
312 TOTALENERGIES SE
313 TULLOW OIL PLC
314 U.S. ENERGY CORP.
315 UNIT CORP
316 VAALCO ENERGY, INC.
317 VIPER ENERGY PARTNERS LP
318 VITAL ENERGY INC
319 VOC ENERGY TRUST
320 W&T OFFSHORE, INC.

Appendix C.5 Companies in the dataset from industry: Oil equipment and services

321	AKASTOR ASA
322	AKER SOLUTIONS ASA
323	ANTERO MIDSTREAM CORP
324	ARCHROCK INC
325	BAKER HUGHES CO
326	BORR DRILLING LTD
327	BRISTOW GROUP INC
328	BW OFFSHORE LIMITED
329	CACTUS INC
330	CGG SA
331	CHAMPIONX CORP
332	CHENIERE ENERGY PARTNERS L P
333	CHENIERE ENERGY, INC.
334	CIVEO CORP
335	CORE LABORATORIES NV
336	CRESTWOOD EQUITY PARTNERS LP
337	DCP MIDSTREAM LP
338	DELEK LOGISTICS PARTNERS LP
339	DMC GLOBAL INC
340	DOLFINES SA
341	DRIL-QUIP INC
342	ENAGAS SA
343	ENERGY TRANSFER LP
344	ENLINK MIDSTREAM LLC
345	ENSERVCO CORPORATION
346	ENTERPRISE PRODUCTS PARTNERS LP
347	EQUITRANS MIDSTREAM CORP
348	EVOLVE TRANSITION INFRASTRUCTURE LP
349	EXPRO GROUP HOLDINGS NV
350	FLOTEK INDUSTRIES INCORPORATION
351	FORUM ENERGY TECHNOLOGIES INC
352	GENESIS ENERGY, L.P.
353	GEOSPACE TECHNOLOGIES CORPORATION
354	GOLAR LNG LIMITED
355	GREEN PLAINS PARTNERS LP
356	GULF ISLAND FABRICATION INC
357	HALLIBURTON COMPANY
358	HAVILA SHIPPING ASA
359	HELIX ENERGY SOLUTIONS GROUP, INC.
360	HELMERICH & PAYNE, INC.
361	HESS MIDSTREAM LP
362	HOLLY ENERGY PARTNERS, L.P.
363	HUNTING PLC
364	INDEPENDENCE CONTRACT DRILLING INC
365	JOHN WOOD GROUP PLC
366	KINDER MORGAN INCORPORATED
367	KINETIK HOLDINGS INC
368	KLX ENERGY SERVICES HOLDINGS INC
369	LIBERTY ENERGY INC
370	MAGELLAN MIDSTREAM PARTNERS, L.P.
371	MAMMOTH ENERGY SERVICES INC
372	MARTIN MIDSTREAM PARTNERS LP
373	MATRIX SERVICE COMPANY
374	MIND TECHNOLOGY INC
375	MPLX LP
376	MRC GLOBAL INCORPORATED
377	NABORS INDUSTRIES LIMITED
378	NATIONAL ENERGY SERVICES REUNITED CORP
379	NATURAL GAS SERVICES GROUP, INC.
380	NEWPARK RESOURCES, INC.
381	NEXTIER OILFIELD SOLUTIONS INC
382	NINE ENERGY SERVICE INC
383	NORTHERN OCEAN LTD
384	NOV INC
385	NOW INC
386	NUSTAR ENERGY L P
387	OCEANEERING INTERNATIONAL, INC.
388	OIL STATES INTERNATIONAL, INC.
389	ONEOK INC
390	PATTERSON-UTI ENERGY, INC.
391	PETROLIA E&P HOLDINGS PLC
392	PGS ASA
393	PLAINS ALL AMERICAN PIPELINE, L.P.
394	PLAINS GP HOLDINGS LP
395	PROPETRO HOLDING CORP
396	RANGER ENERGY SERVICES INC
397	REACH SUBSEA ASA
398	RPC, INC.
399	SAIPEM SPA
400	SBM OFFSHORE NV
401	SCHLUMBERGER NV
402	SCHOELLER-BLECKMANN OILFIELD EQUIP. AG
403	SEABIRD EXPLORATION PLC
404	SEAWAY 7 ASA
405	SELECT ENERGY SERVICES INC
406	SIEM OFFSHORE INC
407	SMART SAND INC
408	SNAM SPA
409	SOLARIS OILFIELD INFRASTRUCTURE INC
410	SOLSTAD OFFSHORE ASA
411	SUBSEA 7 S.A.
412	SUMMIT MIDSTREAM PARTNERS LP
413	SUPERIOR DRILLING PRODUCTS INC
414	TARGA RESOURCES CORP
415	TECHNIP ENERGIES NV
416	TECHNIPFMC PLC
417	TECNICAS REUNIDAS S.A.
418	TENARIS S.A.
419	TETRA TECHNOLOGIES INC
420	TGS ASA
421	TIDEWATER INC.
422	USA COMPRESSION PARTNERS LP
423	USD PARTNERS LP
424	WEATHERFORD INTERNATIONAL PLC
425	WESTERN MIDSTREAM PARTNERS LP
426	WILLIAMS COMPANIES INC

Appendix D Descriptive statistics of CARs in the short run around the invasion of Ukraine

Table 27: Descriptive Statistics of CARs in the short run around the invasion of Ukraine before and after winsorization of 0.5%

Variable	Mean	Median	Min	Max	Skewness	Kurtosis	#
CAR	2.15%	0.52%	-61.52%	454.15%	10.77	332.31	**3,834**
CAR (winsorized)	2.00%	0.52%	-25.18%	49.88%	1.09	5.80	**3,834**

Table 27 includes the descriptive statistics for the short-term CARs around the invasion of Ukraine before and after winsorization of 0.5%. Column (1) shows the variable of interest. Columns (2)-(7) show the descriptive statistics for the variable, Column (8) displays the number of observations.

Appendix E Optimal lag determination

Table 28: Optimal lag determination for all variables concerning Hypothesis 1

Lag	LL	LR	p	AIC	HQIC	SBIC
Sentiment						
0	-153.877			4.7654	4.7786	4.7989*
1	**-151.844**	**4.0653***	**.044**	**4.7337***	**4.7601***	**4.8006**
2	-151.692	.3054	.581	4.7598	4.7993	4.8601
3	-151.155	1.0734	.300	4.7740	4.8268	4.9078
4	-150.156	1.9984	.157	4.7740	4.8400	4.9413
Oil						
0	197.486			-6.0457	-6.0325	-6.0123 *
1	198.129	1.2856	.257	-6.0347	-6.0083	-5.9678
2	199.100	1.9427	.163	-6.0338	-5.9942	-5.9334
3	**201.863**	**5.5258***	**.019**	**-6.0881***	**-6.0353***	**-5.9543**
4	201.881	.0356	.850	-6.0579	-5.9919	-5.8906
Gas						
0	**117.041**			**-3.5705***	**-3.5573***	**-3.5370***
1	117.083	.08479	.771	-3.5410	-3.5146	-3.4741
2	118.383	2.6001	.107	-3.5503	-3.5107	-3.4499
3	118.416	.0658	.798	-3.5205	-3.4677	-3.3867
4	118.708	.5839	.445	-3.4987	-3.4327	-3.3315
Coal						
0	**133.936**			**-4.0903***	**-4.0771***	**-4.0569***
1	134.091	.3113	.577	-4.0644	-4.0380	-3.9975
2	134.506	.8284	.363	-4.0463	-4.0067	-3.9460
3	134.525	.0408	.840	-4.0162	-3.9634	-3.8824
4	134.620	.1881	.665	-3.9883	-3.9223	-3.8211
VIX						
0	**133.848**			**-4.0876**	**-4.0744***	**-4.0542***
1	133.926	.1554	.693	-4.0593	-4.0329	-3.9923
2	135.665	3.4789	.062	-4.0820	-4.0424	-3.9816
3	136.128	.9251	.336	-4.0655	-4.0127	-3.9317
4	138.899	5.5422*	.019	-4.1200*	-4.0540	-3.9527

Table 28 displays the statistics for determining the optimal number of lags for investor sentiment. LL = log likelihood. LR = likelihood ratio. p = p-value. AIC = Akaike Information Criterion. HQIC = Hannan-Quinn Information Criterion. SBIC = Schwarz-Bayesian Information Criterion. Column (1) shows the number of lags. Columns (2)-(7) show the descriptive statistics for a specific number of lags. * Indicates the most significant lag for the LR or the lowest value for AIC, HQIC or SBIC. Rows in **bold** indicate the final chosen number of lags.

Appendix F Interaction effects for Hypothesis 2

Figure 1: H2: Interaction effect investor sentiment and oil return on weekly CARs

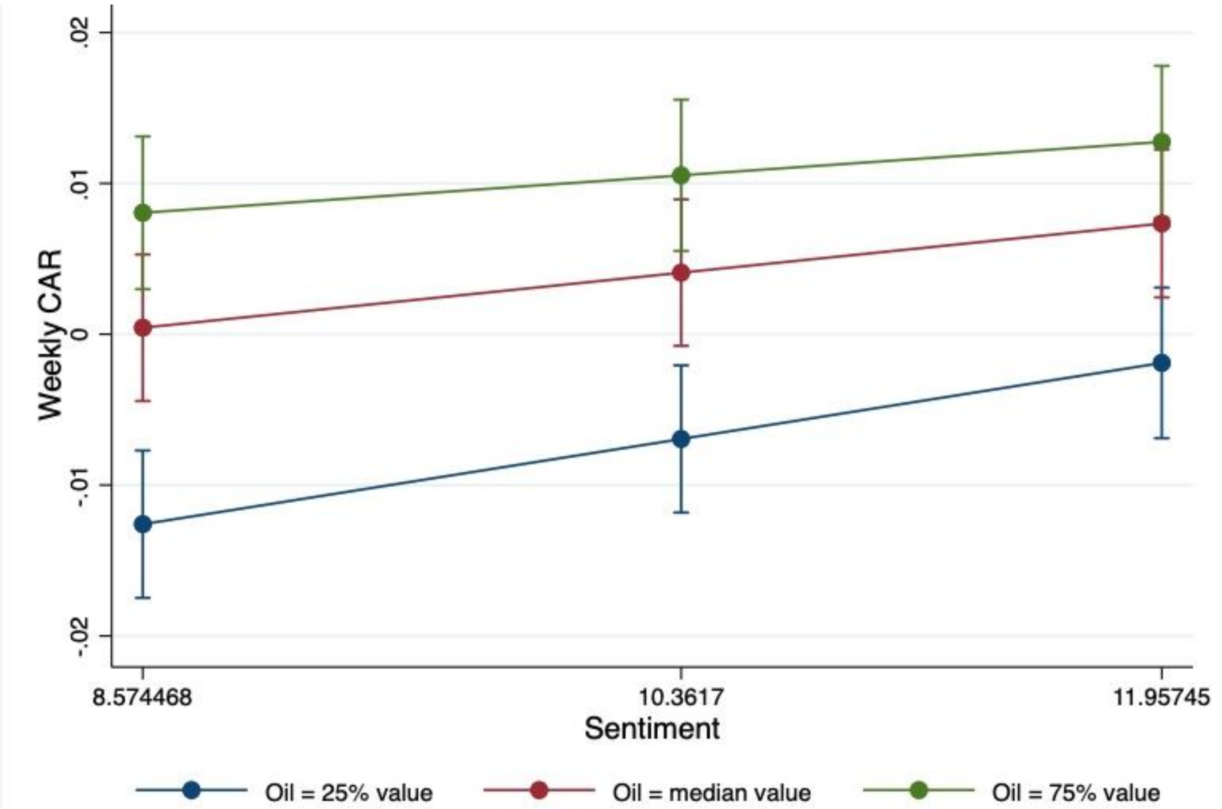


Figure 2: H2: Interaction effect investor sentiment and gas return on weekly CARs

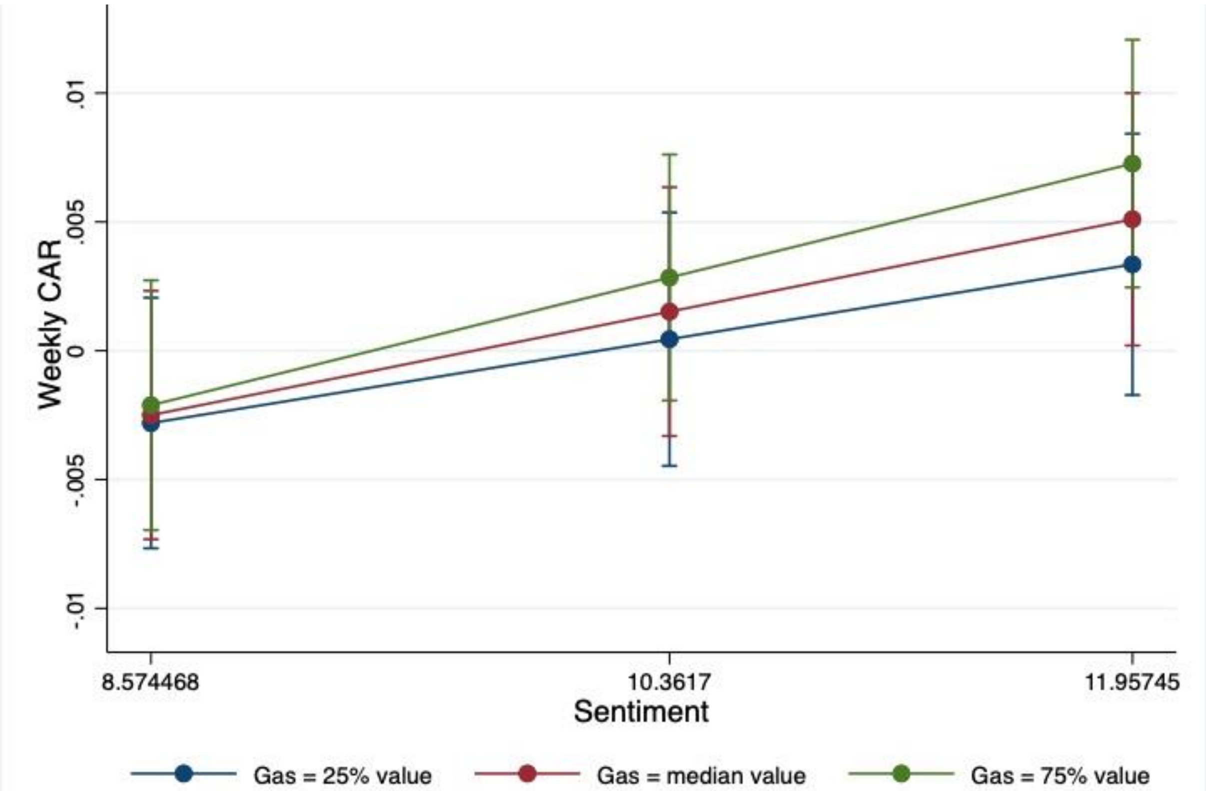
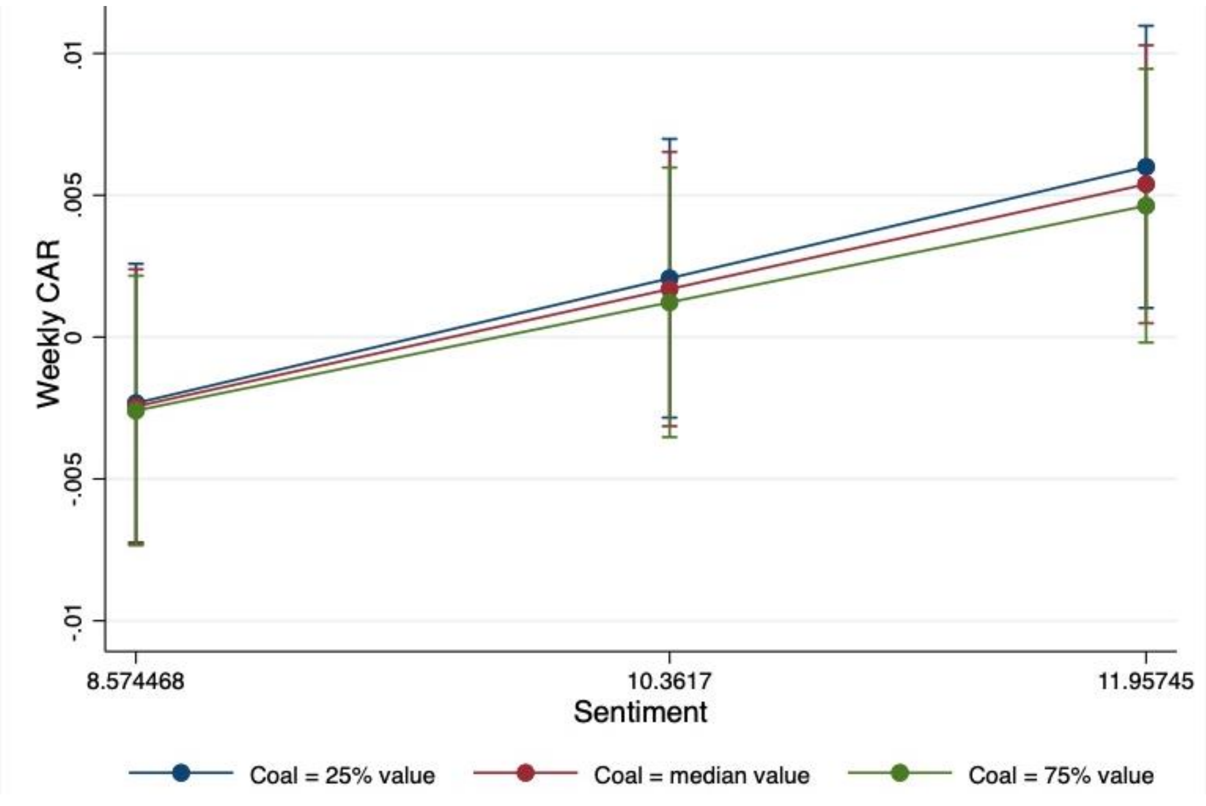


Figure 3: H2: Interaction effect investor sentiment and coal return on weekly CARs



Figures 1-3 show the effect of investor sentiment on weekly CARs during the energy crisis when the 25th percentile, median, and 75th percentile values in the sample distribution of oil, gas, and coal returns are assumed, respectively. The x-axis displays the level of investor sentiment, between the 25th percentile value (8.57) and the 75th percentile value (11.96). The y-axis shows the corresponding values for the weekly CAR. The lines in blue, red, and green represent the effect of investor sentiment on weekly CARs when the 25th percentile, median, and 75th percentile values are taken for the oil, gas, and coal return, respectively. The dots represent the average results, a 95%-confidence interval is included.

Appendix G Interaction effects for Hypothesis 3

Figure 4: H3: Interaction effect investor sentiment and oil return on weekly volumes

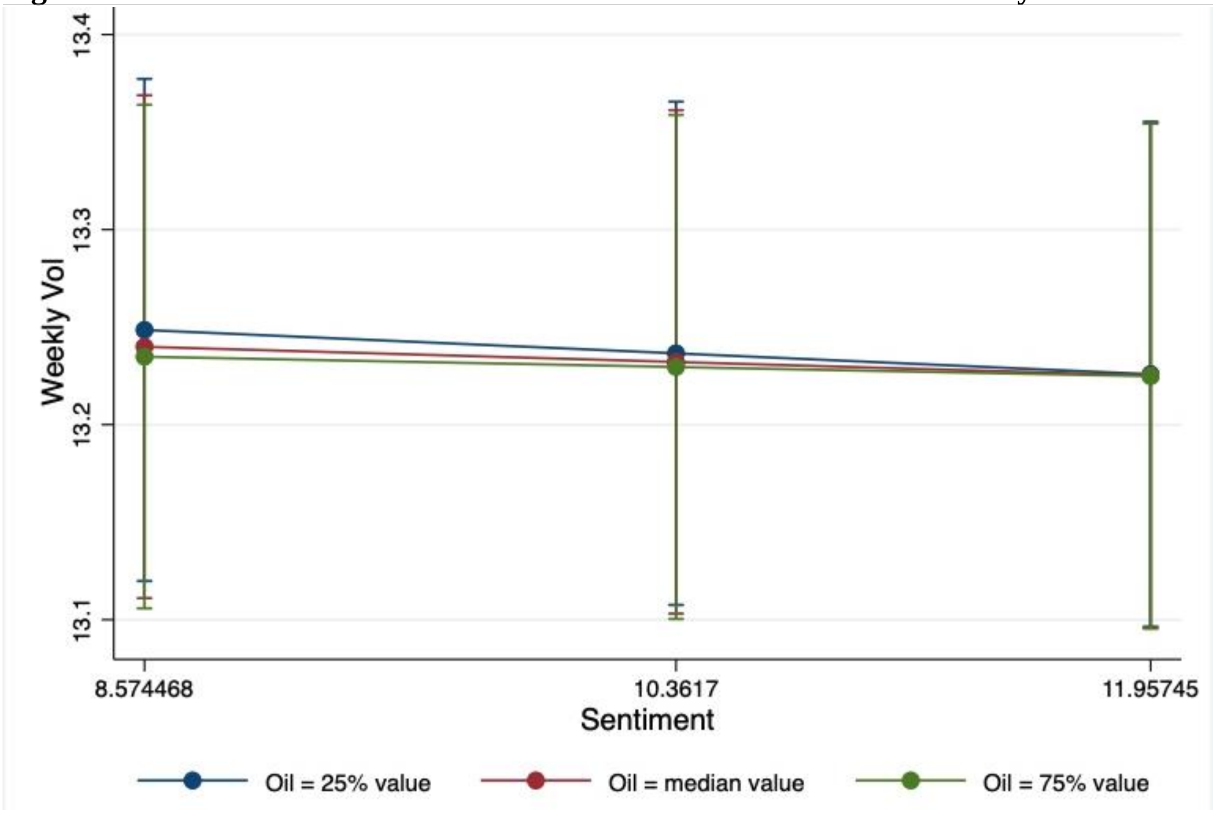


Figure 5: H3: Interaction effect investor sentiment and gas return on weekly volumes

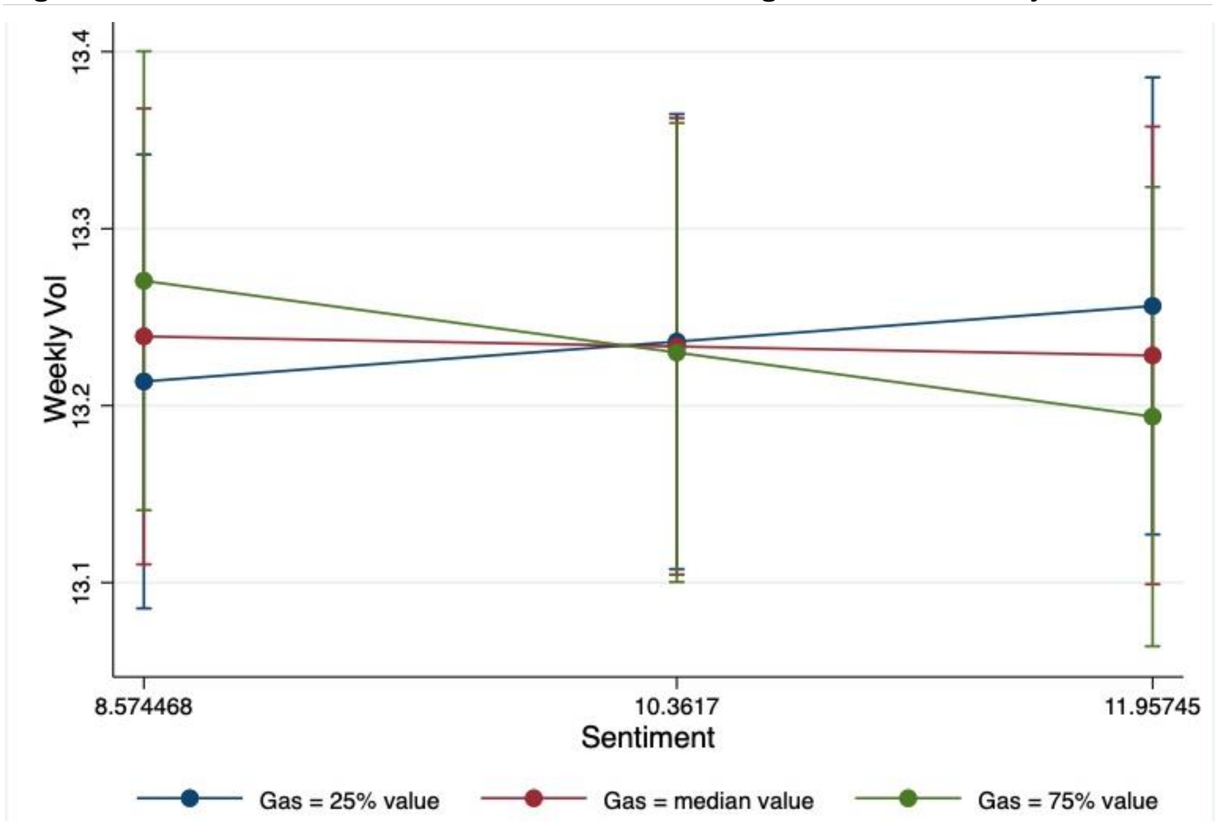
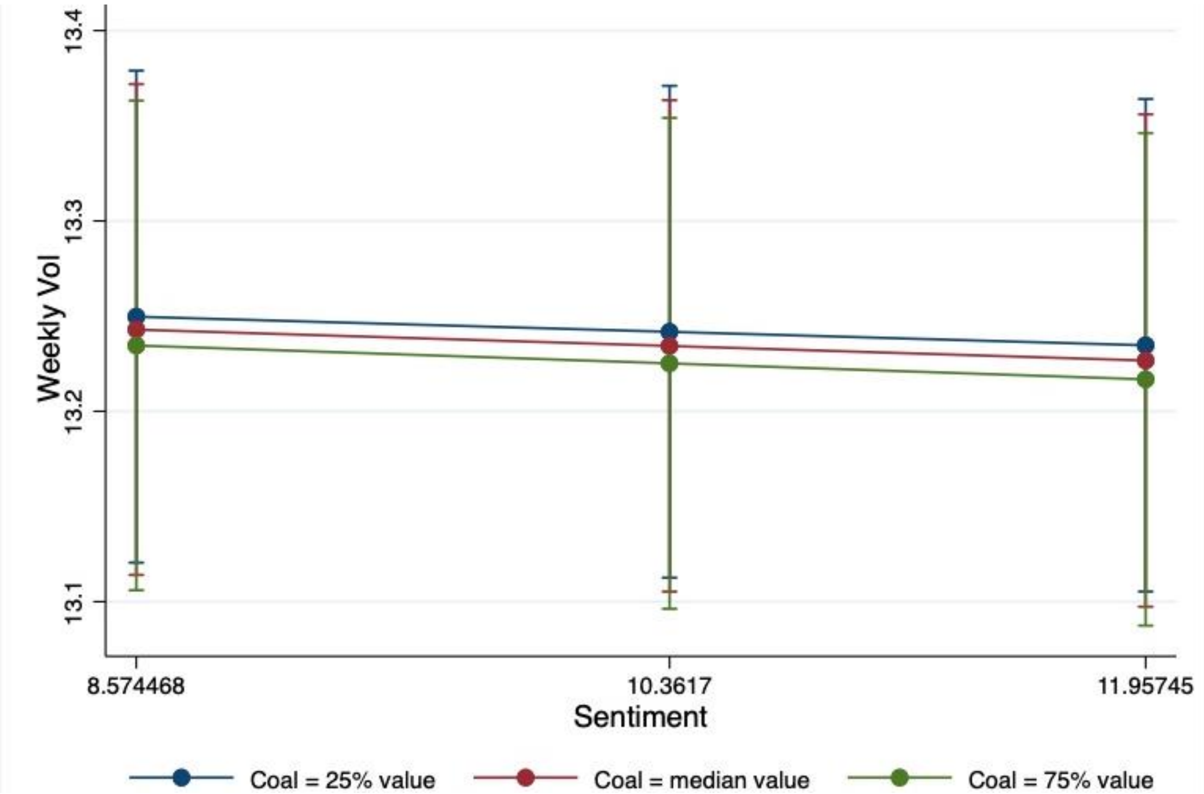


Figure 6: H3: Interaction effect investor sentiment and coal return on weekly volumes



Figures 4-6 show the effect of investor sentiment on the natural logarithm of weekly trading volumes during the energy crisis when the 25th percentile, median, and 75th percentile values in the sample distribution of oil, gas, and coal returns are assumed, respectively. The x-axis displays the level of investor sentiment, between the 25th percentile value (8.57) and the 75th percentile value (11.96). The y-axis shows the corresponding values for the weekly trading volume. The lines in blue, red, and green represent the effect of investor sentiment on weekly volumes when the 25th percentile, median, and 75th percentile values are taken for the oil, gas, and coal return, respectively. The dots represent the average results, a 95%-confidence interval is included.

Appendix H Interaction effects for Hypothesis 4

Figure 7: H4: Interaction effect investor sentiment and oil return on weekly CARs

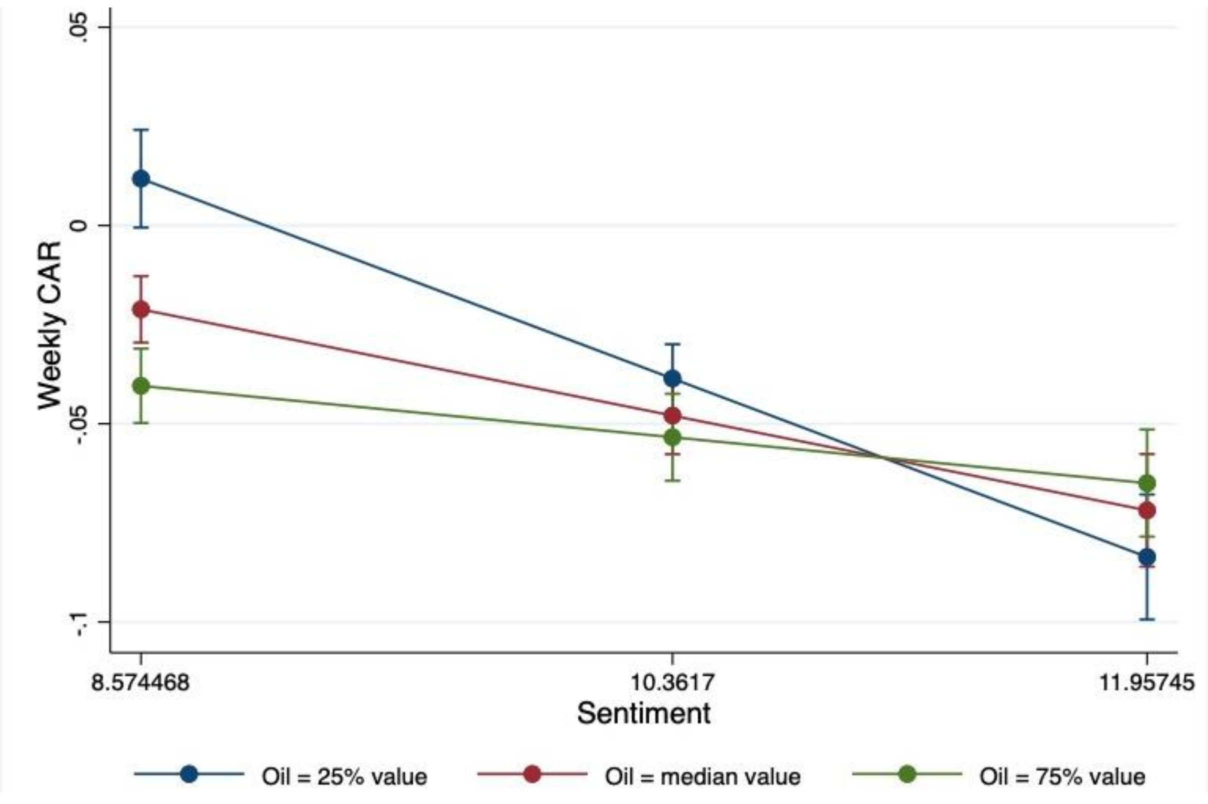


Figure 8: H4: Interaction effect investor sentiment and gas return on weekly CARs

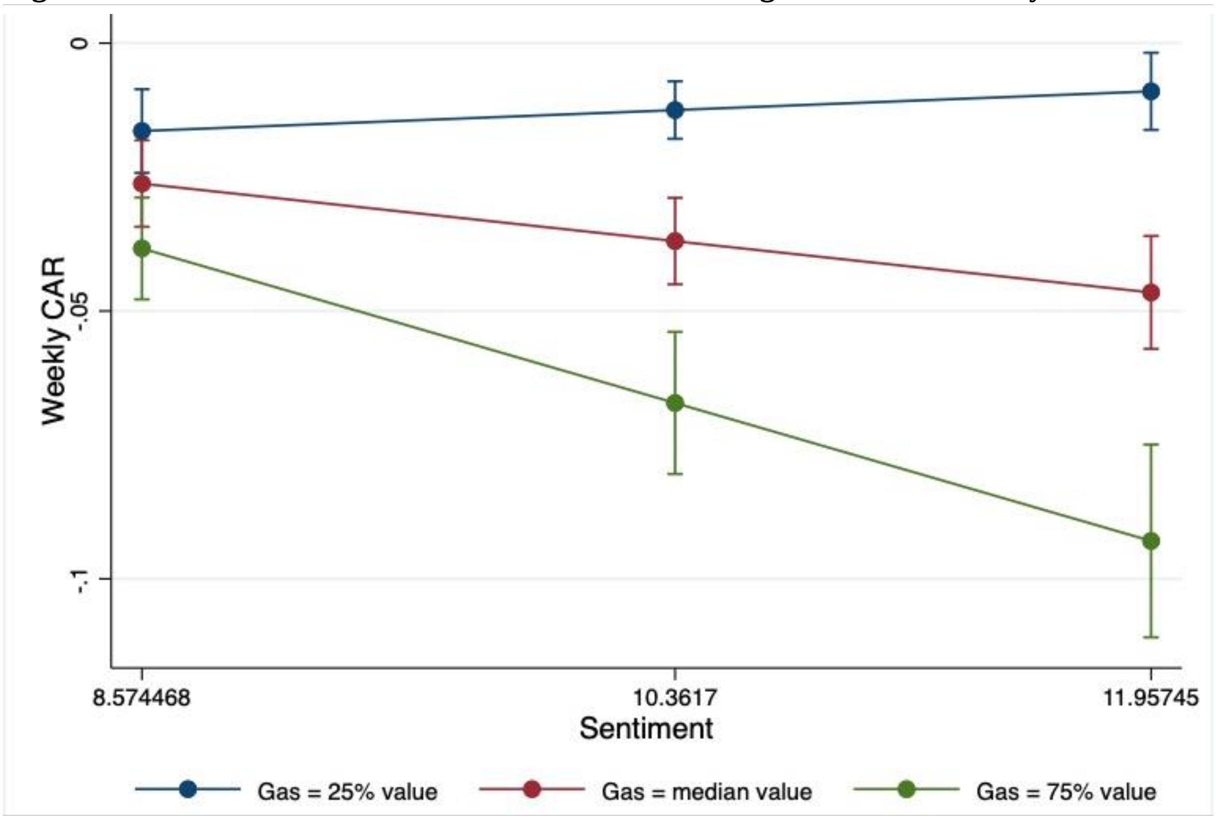
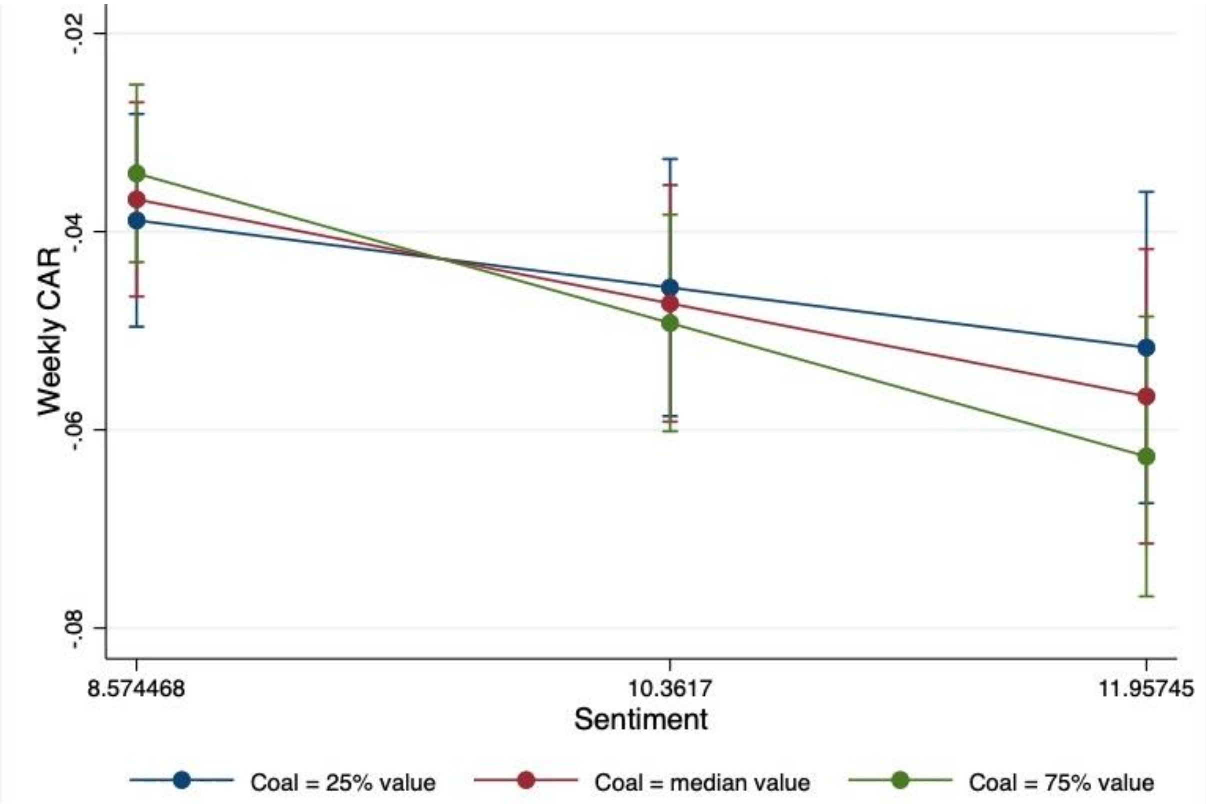


Figure 9: H4: Interaction effect investor sentiment and coal return on weekly CARs



Figures 7-9 show the effect of investor sentiment on weekly CARs in the short run around the Russian invasion of Ukraine when the 25th percentile, median, and 75th percentile values in the sample distribution of oil, gas, and coal returns are assumed, respectively. The x-axis displays the level of investor sentiment, between the 25th percentile value (8.57) and the 75th percentile value (11.96). The y-axis shows the corresponding values for the weekly CAR. The lines in blue, red, and green represent the effect of investor sentiment on weekly CARs when the 25th percentile, median, and 75th percentile values are taken for the oil, gas, and coal return, respectively. The dots represent the average results, a 95%-confidence interval is included.

Appendix I Interaction effects for Hypothesis 5

Figure 10: H5: Interaction effect investor sentiment and US dummy on weekly CARs

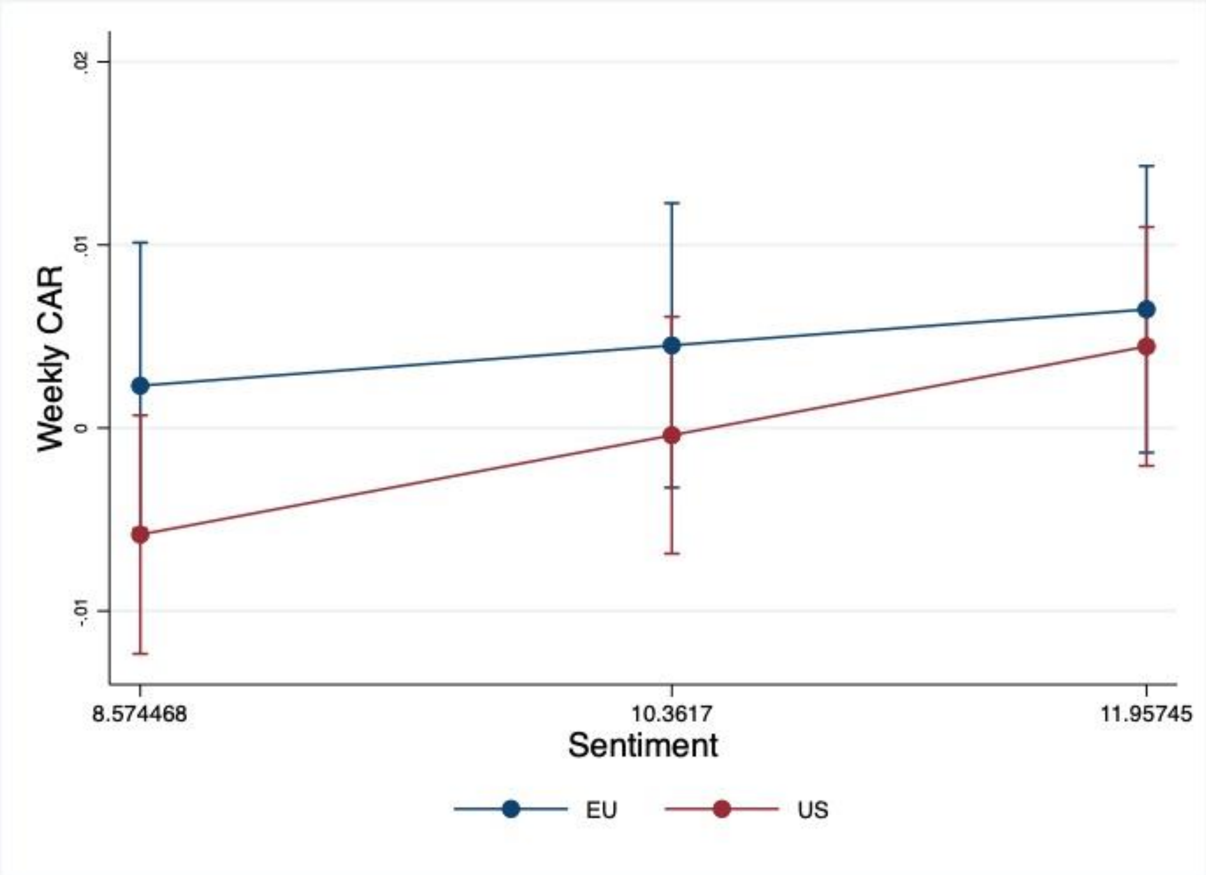


Figure 10 shows the interaction effect between investor sentiment and US dummy during the energy crisis. The x-axis displays the level of investor sentiment, between the 25th percentile value (8.57) and the 75th percentile value (11.96). The y-axis shows the corresponding values for the weekly CAR. The blue line represents the effect of investor sentiment on the weekly CAR in the EU, the red line represents the US effect. The dots represent the average results, a 95%-confidence interval is included.

Appendix J Interaction effects for Hypothesis 6

Figure 11: H6: Interaction effect investor sentiment and post-invasion dummy on weekly CARs

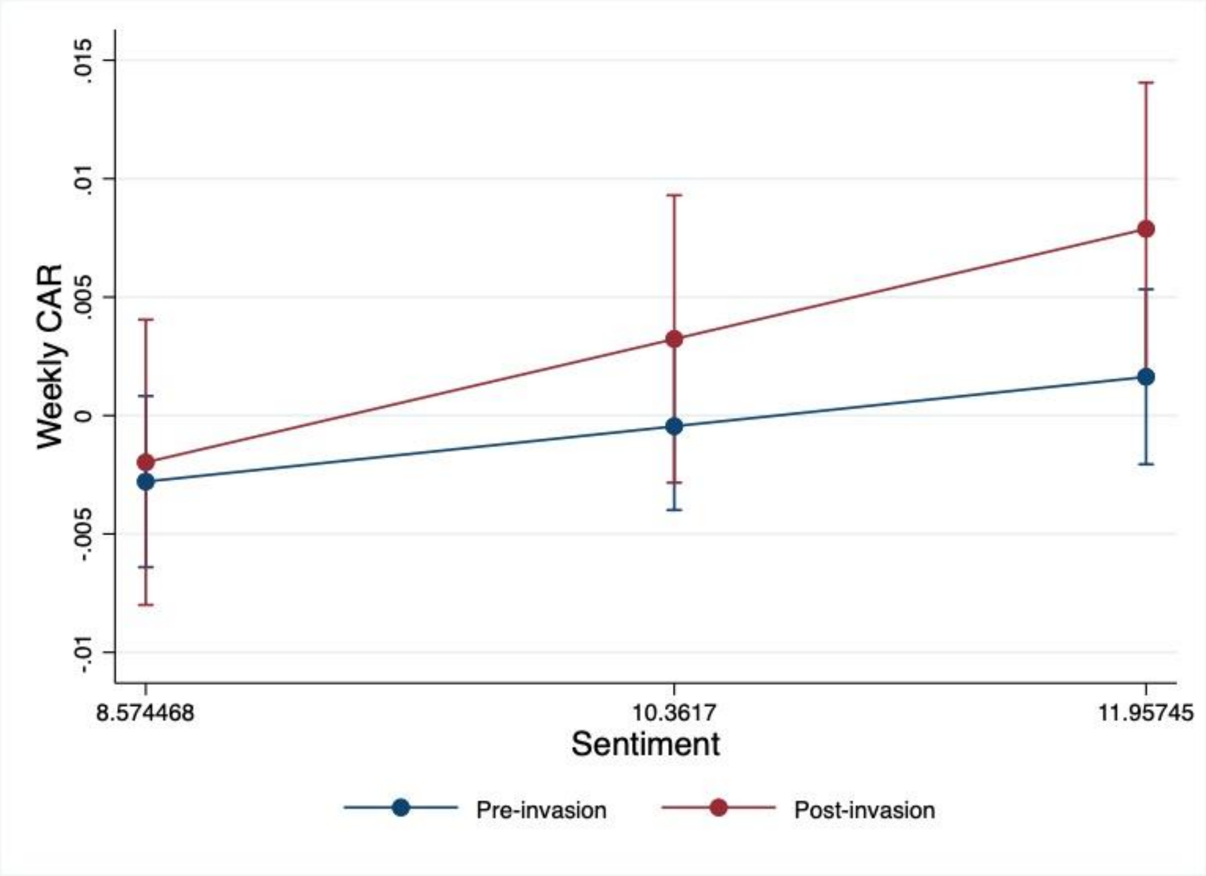


Figure 11 shows the interaction effect between investor sentiment and post-invasion dummy during the energy crisis. The x-axis displays the level of investor sentiment, between the 25th percentile-value (8.57) and the 75th percentile value (11.96). The y-axis shows the corresponding values for the weekly CAR. The blue line represents the effect of investor sentiment on the weekly CAR before the Russian invasion of Ukraine took place, the red line represents the post-invasion effect. The dots represent the average results, a 95%-confidence interval is included.

Appendix K Robustness checks Hypothesis 2

Table 29: Robustness check for winsorization and benchmarks in Hypothesis 2

Weekly CAR	**Weekly CAR Coeff.**	**Weekly CAR R. St. Error**	**Weekly CAR Coeff.**	**Weekly CAR R. St. Error**	**Weekly CAR Coeff.**	**Weekly CAR R. St. Error**
Sentiment	.0024***	.0002	.0024***	.0002	.0024***	.0002
Sentiment * Oil	-.0014***	.0002	-.0015***	.0002	-.0014***	.0002
Sentiment * Gas	.0002***	.0001	.0002***	.0001	.0004***	.0001
Sentiment * Coal	-.0002***	.0001	-.0002***	.0001	-.0003***	.0001
Oil	.0292***	.0022	.0304***	.0028	.0293***	.0022
Gas	-.0018***	.0006	-.0020***	.0007	-.0029***	.0006
Coal	.0017***	.0006	.0017**	.0007	.0029**	.0006
VIX	.0013***	.0001	.0013***	.0001	.0015***	.0001
Vol	.0111***	.0016	.0161***	.0031	.0115***	.0016
Size	-.0027**	.0012	-.0059***	.0018	-.0031**	.0013
D/E	.0005	.0017	-.0000	.0003	.0001	.0017
RoE	-.0001	.0001	-.0000***	.0000	-.0001*	.0001
Industry						
Electricity	-.0665***	.0097	-.0625***	.0099	-.0714***	.0106
Gas, water & multi-utilities	-.0846***	.0087	-.0810***	.0089	-.0907***	.0096
Oil and gas producers	-.0259***	.0091	-.0287***	.0088	-.0328***	.0099
Oil equipment and services	-.0377***	.0084	-.0366***	.0083	-.0453***	.0091
Firm RE	YES		YES		YES	
Constant	-.0924***	.0224	-.1113***	.0295	-.0914***	.0235
N	28,221		28,221		28,221	
# Firms	409		409		409	
# Weeks	69		69		69	
Wald Chi Square	681.05		677.90		828.40	
R2	.1621		.1407		.1723	
R2_adj	.1616		.1402		.1718	

Table 29 shows the results from the random effects regressions for the effect of investor sentiment on stock returns. Weekly CARs are used as dependent variable to proxy for stock returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly CARs for the extended model that is used for answering Hypothesis 2, which uses winsorized values of the weekly CAR. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the robustness check is presented which removed the winsorization of the weekly CAR, D/E and RoE. In Columns (6)-(7), the robustness check that uses CARs based on the MSCI Europe and MSCI US benchmark is shown. Coeff. = Coefficient. R. = Robust. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly CAR can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 30: Robustness check for CAPM model in Hypothesis 2

Weekly CAR	**Weekly CAR Coefficient**	**Weekly CAR Robust St. Error**	**Weekly CAR Coefficient**	**Weekly CAR Robust St. Error**
Sentiment	.0024***	.0002	-.0005	.0003
Sentiment * Oil	-.0014***	.0002	.0016***	.0002
Sentiment * Gas	.0002***	.0001	.0008***	.0001
Sentiment * Coal	-.0002***	.0001	-.0015***	.0001
Oil	.0292***	.0022	-.0182***	.0025
Gas	-.0018***	.0006	-.0083***	.0008
Coal	.0017***	.0006	.0130***	.0008
VIX	.0013***	.0001	.0071***	.0002
Vol	.0111***	.0016	.0004	.0004
Size	-.0027**	.0012	.0003	.0004
D/E	.0005	.0017	-.0001	.0004
RoE	-.0001	.0001	.0001***	.0000
Industry				
Electricity	-.0665***	.0097	.0043*	.0024
Gas, water & multi-utilities	-.0846***	.0087	.0061**	.0028
Oil and gas producers	-.0259***	.0091	.0212***	.0024
Oil equipment and services	-.0377***	.0084	.0123***	.0023
Firm RE	YES		YES	
Constant	-.0924***	.0224	-.0142***	.0051
N	28,221		28,221	
# Firms	409		409	

# Weeks	69	69
Wald Chi Square	681.05	1,900.13
R2	.1621	.0568
R2_adj	.1616	.0563

Table 30 displays the results from the random effects regressions for the effect of investor sentiment on stock returns. Weekly CARs are used as dependent variable to proxy for stock returns. Column (1) shows the variable or test statistic of interest. Columns (2)-(3) show the results for the effect of investor sentiment on the weekly CARs for the extended model that is used for answering Hypothesis 2, which uses the CAPM model to calculate the CARs. Here, Sentiment * Oil/Gas/Coal displays the interaction effect between investor sentiment and the three energy sources. In Columns (4)-(5), the robustness check with the market adjusted model instead of the CAPM is shown. D/E = debt to equity ratio. RoE = return on equity. Firm RE = Firm Random Effects. N indicates the number of observations for the regression, the Wald Chi Square statistic displays the significance of the total model. R2 indicates what proportion of the variance in the weekly CAR can be explained by the model. The R2_adj is the adjusted version of the R2 for the number of variables used. ***, **, and * represent 1%, 5% and 10% significance, respectively.

Figure 12: Robustness check for interaction effect of sentiment and oil on weekly CARs

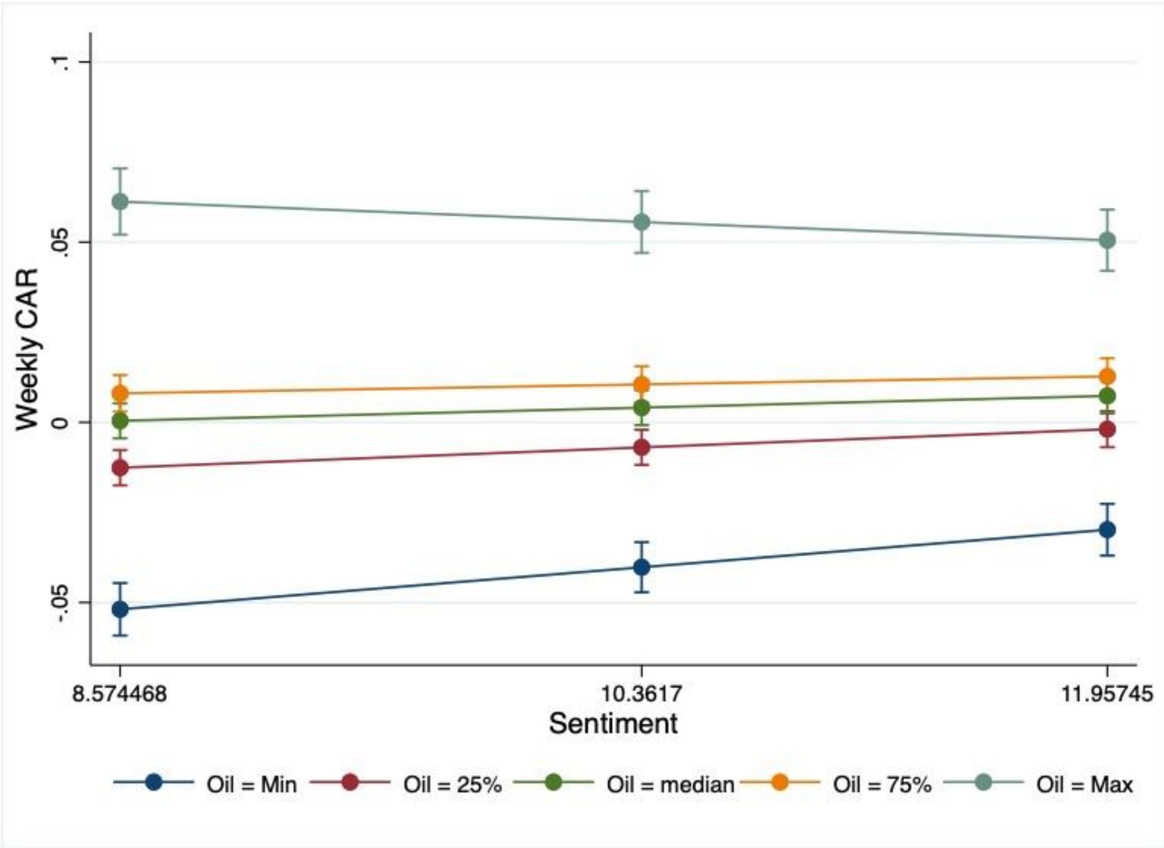


Figure 13: Robustness check for interaction effect of sentiment and gas on weekly CARs

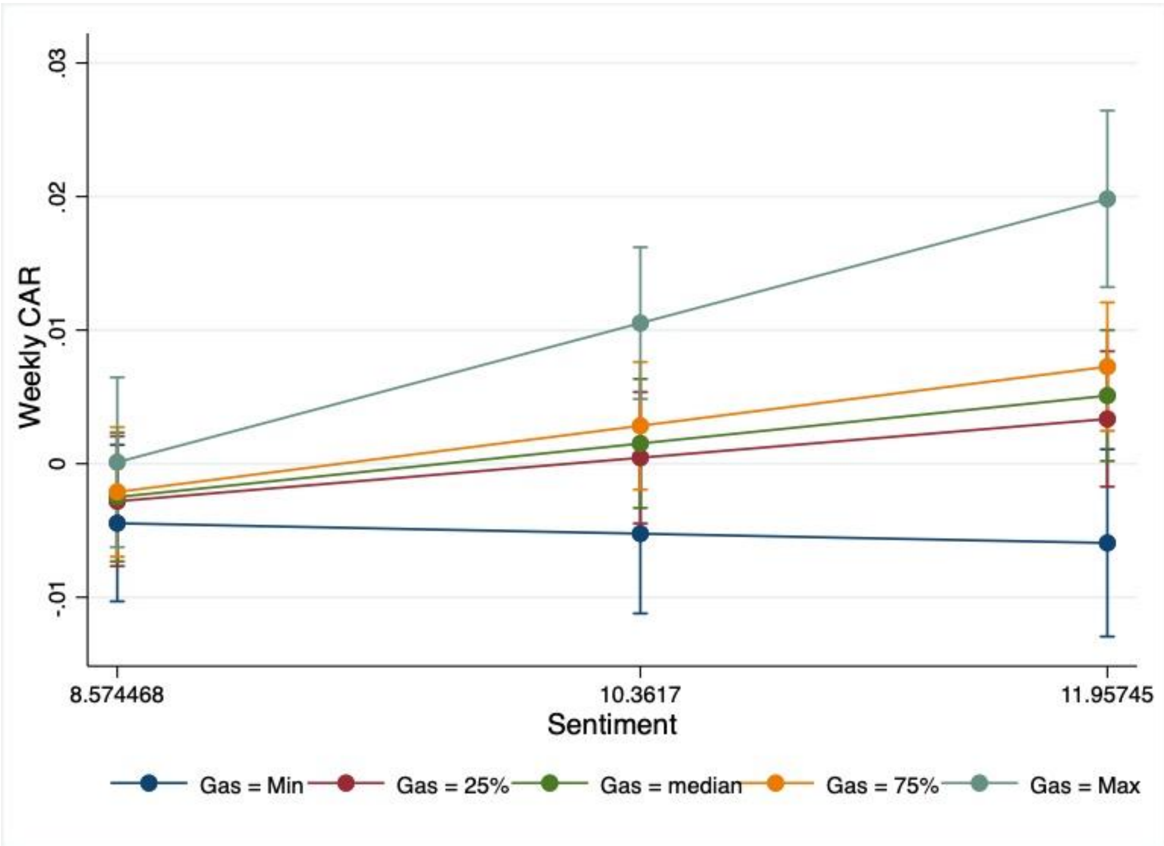
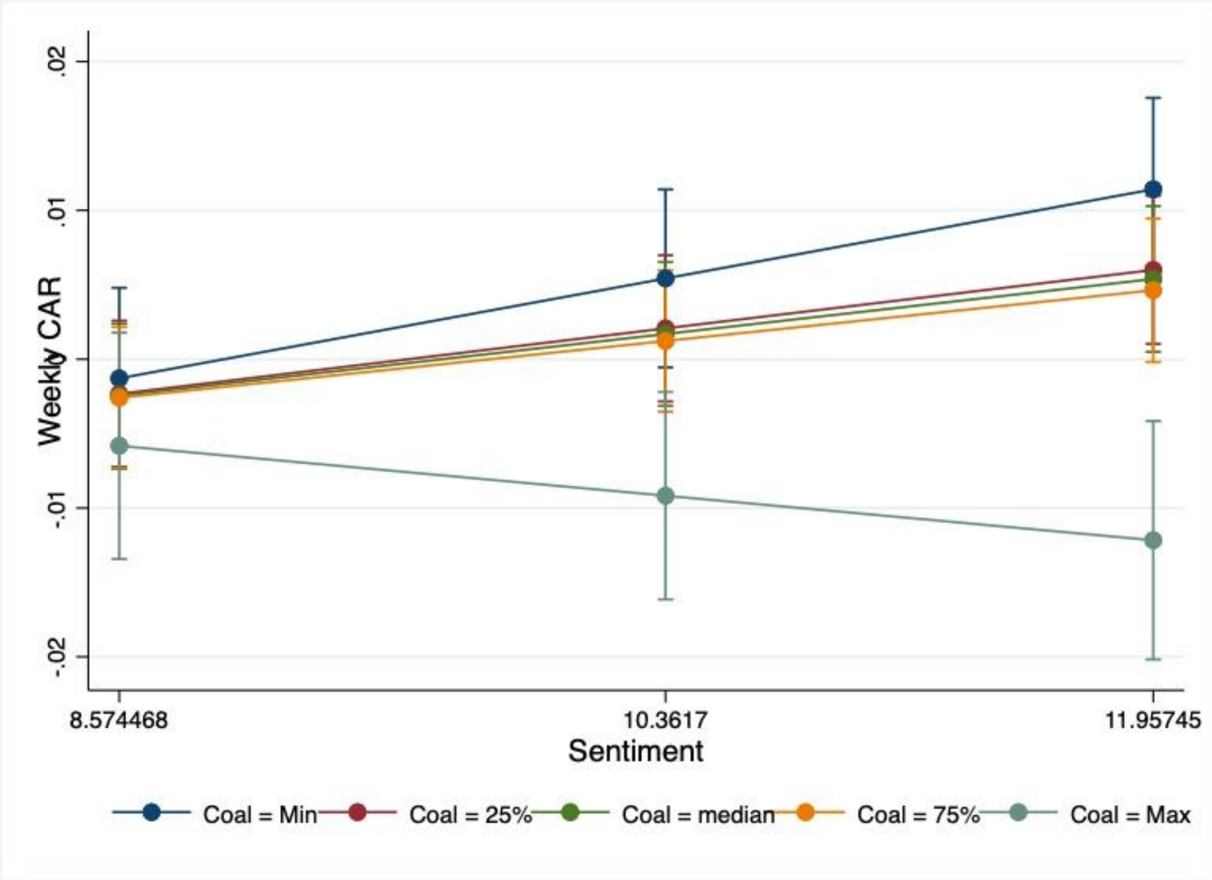


Figure 14: Robustness check for interaction effect of sentiment and coal on weekly CARs



Figures 12-14 show the robustness check for the effect of investor sentiment on weekly CARs during the energy crisis when the minimum, 25th percentile, median, and 75th percentile, and maximum values in the sample distribution of oil, gas, and coal returns are assumed, respectively. The x-axis displays the level of investor sentiment, between the 25th percentile value (8.57) and the 75th percentile value (11.96). The y-axis shows the corresponding values for the weekly CAR. The lines in blue, red, green, orange and grey represent the effect of investor sentiment on weekly CARs when the minimum, 25th percentile, median, 75th percentile, and maximum values are taken for the oil, gas, and coal return, respectively. The dots represent the average results, a 95%-confidence interval is included.