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Natural Gas Market Volatility in Turbulent Times:

Assessing the Impact of the 2022 Russian-Ukrainian War and the 2014 Invasion on the USA, EU, and Asia's markets

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ABSTRACT

In this thesis, I investigate the impact of the 2022 full-scale Russian-Ukrainian war on the natural gas market and compare it to the initial Russian invasion in 2014. This research aims to demonstrate the magnitude of such an effect across various regions, including the USA, the EU, and Asia. I employed two methods to conduct this study: an Event Study approach and the ARIMA model. The Event Study uses cumulative abnormal returns to explore the market responses to the geopolitical conflict. ARIMA allows to compare the baseline (expected market prices without military conflict) to the actual prices during that period. The empirical results show significant price fluctuations for the full-scale war while indicating an insignificant response to the initial Russian invasion. Such findings confirm the significant influence of the geopolitical conflict on the global market, thus highlighting the need for better crisis management policies and energy source diversification.

Keywords: natural gas markets, geopolitical conflicts, Russian-Ukrainian war, event study, price volatility.

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CHAPTER 1 Introduction

On February 24th, 2022, the Russian government officially commended a full-scale war against Ukraine, which has sent shockwaves all around the world. This military conflict had a massive impact on world economies and financial markets. Since then, the majority of European countries and the USA have stated their support for the territorial integrity of Ukraine and imposed economic sanctions on Russia's key industries. However, this political stance raised a few essential issues and uncertainties, including the diversification of energy sources. The war has sparked concerns about energy security, particularly the natural gas supply. *Natural gas* is an important fossil fuel source, accounting for a significant portion of the European energy mix. For example, in 2021, Russia's piped gas (which is directly piped to the households by gas mains) supplied to Europe amounted to 155 billion cubic meters – around 39% of all extra-EU gas imports (*Share of Russian gas in the EU 2021*, 2023). Such firm reliance on the supply from the aggressor state has highlighted Europe's vulnerability to geopolitical tensions and disruptions. Russia is the most significant natural gas exporter (*Russia - Countries & Regions*, 2024). Hence, any complications in the supply will significantly influence the prices and availability of this resource worldwide. Thus, as the war is still active, it can disrupt the global stage and international dynamics.

After the beginning of the war, many researchers were keen to explore the impact of such military actions on various aspects of the world's economies and markets. One of those papers was written by Yousaf et al. – "The reaction of G20+ stock markets to the Russia–Ukraine conflict ''black-swan'' event: Evidence from event study approach". The article discusses the financial impact of the Russian-Ukrainian military conflict on global stock markets. It highlights how significant this investigation of such geopolitical events may be for studying the impact on the financial markets and investors' behaviour. The study underscores the importance of the empirical evidence for the hedging strategies, portfolio rebalancing decisions and policymaking/regulations during the military conflicts. The researchers employed an event study to analyse the impact of the war on the stock exchanges of multiple countries. They defined the event as the beginning of the military action on the 24th of February 2022, and the event window was 11 days (-5 to +5 days). The methodology relies on abnormal returns (AR) and cumulative abnormal returns (CAR). To calculate the AR, the writers compared the actual returns with the expected returns resulting from the OLS model. Similarly, CAR was derived by aggregating indexes over the event window. Additionally, aggregate AR and CAR were introduced to measure the typical reaction of the stock to the conflict. As a result, significant negative abnormal returns were observed across most markets, especially in Russia (-31.601%). Furthermore, some countries such as Hungary, Poland, Russia, and Slovakia showed an adverse reaction before and after the event, while other countries were affected post-event. Most recent research articles focus on the effect of the full-scale attack, which started in 2022.

A paper by M. Izzeldin et al. 2023 discusses the impact of the Russian-Ukrainian war on the global financial markets. It compares the responses to military conflicts to past unexpected events such as the COVID-19 pandemic and the 2008 worldwide financial crisis. It pays attention to the stock markets and representative commodities, such as oil and natural gas. Another article by Y. Cheng et al. 2023 investigated the effect of the EU and the USA sanctions on Russia's economy, particularly the energy trade aspect. They have included the sanctions starting from 2014- the initial military actions against the Donetsk and Lugansk region – part of Eastern Ukraine.

Even though the article written by Yousaf et al., 2022, gives a solid perspective on how the stock market of G20+ countries has reacted to the beginning of the Russian-Ukrainian war, it has several limitations. Firstly, the research only focuses on the stock market and does not investigate the effects on other critical economic sectors, such as commodities (natural gas in particular). Secondly, it only looks at the short-term effects on the market and does not give perspective on the long-term outcomes or implications of such disruption. Furthermore, it is important to note that the initial conflict between Russia and Ukraine began in 2014 with the annexation of the Crimea peninsula. However, recent studies, including Yousaf et al. l, 2022, which study the war closely and its implications on worldwide relations/dynamics, tend to overlook the critical impacts of the 2014 military attack. Such an oversight may give an incomplete understanding of the situation and its long-term effects on important aspects, including political and economic matters. An exciting concept that combines all the research mentioned above is comparing the financial responses for the 2022 full-scale attack on Ukraine with the 2014 limited territory invasion on the commodity market. Therefore, the research question of the thesis is:

How did the natural gas markets of the USA, EU, and Asia react to the 2022 Russian-Ukrainian full-scale war compared to the initial invasion in 2014?

I employed two methods to tackle the research question: Event Study and the Autoregressive Integrated Moving Average (ARIMA) model. An Event Study Analysis was used to analyze the time-series data and to evaluate the impact of shocks or unforeseen events on financial or economic variables, in our case – the natural gas market. This method is based on calculating the AR (abnormal returns) and CAR (cumulative abnormal returns) to compare the actual returns with the expected (forecasted) ones. The ARIMA analysis is divided into two p arts: baseline analysis and the model with the post-attack/war dummy. The baseline model allows to investigate the natural patterns (dynamics) of the natural gas market. The other model (with the dummy variable) allows to examine the influence of the military conflict on the development of the chosen commodity market and to compare it with the benchmark (no post-attack/war variable). In the end, the findings of the two methods will be linked to show a comprehensive view of the impact of the Russian-Ukrainian war on natural gas prices.

For this research, I used the monthly historical data on the natural gas price for three regions: the USA, the EU, and Asia, including the event windows before and after military attacks. The event windows chosen for this research are five months before and after the attack. The first timeline – "Initial Attack", includes the period of September 2013 to July 2014, while the second period – "Full-scale War", investigates September 2021 to July 2022. The resulting coefficients and their significance levels were analyzed to conclude the effect of the Russia-Ukrainian war on global gas prices. The primary data for the natural gas prices (measured in *U.S. Dollars per Million Metric British Thermal Unit*) will be taken from the U.S. Energy Information Administration (for the USA) and Federal Reserve Bank of St. Louis (for the EU and Asia regions). The analysis includes control variables to reduce the bias of the model: region (includes USA, Europe and Asia), crude oil prices (measured *in U.S. Dollars per Barrel of Oil*), temperatures (measured in *degrees of Celsius*), inflation rates and the share prices (measured in *U.S. Dollars per Share*). The overall data includes 66 observations, with 22 observations per region.

There are numerous expectations about how the gas market will react to the Russian-Ukrainian conflict in 2022. Firstly, I hypothesize that the military conflict in 2022 will significantly increase the market price of natural gas and the energy export dynamics. Similarly to Yousaf et al. 2022, I expect a more profound effect on the price volatility and supply shortages for the countries that heavily rely on Russia's gas imports. Furthermore, I anticipate that the countless policy interventions, export controls and sanctions might also bring instability and influence the behaviour of the pricing mechanisms. In contrast to the first hypothesis, I anticipate that there will be no significant change in gas prices worldwide for the attack window 2014, even though the first sanctions were imposed soon after the initial attack. Therefore, I hypothesize that the full-scale war in 2022 will have a more significant and pronounced effect on natural gas prices than the primary military conflict in 2014. Lastly, I would like the final part of my research to show the current progression of the situation and its impact on the natural gas market in 2024.

Based on the empirical results regarding the reaction of the natural gas market to the Russian-Ukrainian conflict in 2022, several significant conclusions have been drawn. Firstly, examining the cumulative abnormal returns of the gas market indicates a slightly significant increase in returns for the chosen commodity following the military conflict in 2022. Moreover, the analysis shows a significant impact of crude oil prices on natural gas in ARIMA models during both event periods, further highlighting the interdependence of both commodity markets. Lastly, despite the imposition of initial sanctions shortly after the initial attack, there was no significant change in gas prices worldwide during the initial attack window in 2014. Thus, the study's findings underscore that the full-scale war in 2022 had a more substantial and pronounced effect on natural gas prices compared to the primary military conflict in 2014.

The remainder of this paper follows this structure. Chapter 2 reviews the existing literature and highlights essential theoretical frameworks and economic theories used in this research. Chapter 3 explains the data, the sources it was collected from, and its transformations. Chapter 4 discusses the methods used for the quantitative analysis. Chapter 5 displays the results obtained from employing the methodology mentioned in the previous section and diagnostic tests for the dataset. Chapter 6 links the empirical results with the literature and discusses the main hypotheses. The fundamental limitations of the research are explained in Chapter 7. Lastly, Chapter 8 concludes this research paper and provides practical remarks and recommendations for further study.

CHAPTER 2 Theoretical Framework

The main objective of this thesis is to explore the relationship between the Russian-Ukrainian war (the regressor) and the natural gas market volatility (the outcome) in several regions: the USA, the EU and Asia. In this chapter, the main factors of the research will be closely explained and investigated using information acquired from various academic articles. This step is done to give a better understanding of each one of them separately and their dynamics. Previous academic articles have thoroughly investigated such variables, their causes and implications, and the economic models/laws they follow. By collecting and reviewing all the appropriate literature, we can understand the nature of the events, identify the limitations and gaps in the open-access data and get a solid background for building the upcoming empirical analysis in future chapters. Throughout this part, I will identify the methodologies and economic frameworks used in first and seminal studies and incorporate the useful ones in the further steps of my research.

2.1 Russian-Ukrainian War Timeline

I want to start this section with the definition of war and explain this phenomenon. The Cambridge Dictionary claims that it is “an armed fighting between two or more countries” . However, a book called “A Study of War” by Quincy and Louise Leonard Wright (1983) argues that the meaning of this word is different for every person. For some, it is a kind of plague that should be erased from the face of the earth, and for others, it is a useful tool to control the public narrative. Throughout history, many civilizations have risen, expanded and lost their power and territories due to wars, with the first dated in approximately 2700 BC in Mesopotamia (*War in Ancient Times - World History Encyclopedia*, 2024). Unfortunately, even with the rise of technologies and open-access media, some are still trying to control history using brute and inhumane methods.

Ever since the establishment of the Russian Federation in 1991 (following the collapse of the Soviet Union), the country has taken part in approximately 14 military conflicts, 7 of which were initiated by the Russian government. One of the largest wars on the European continent since World War II is the Russian-Ukrainian war, where Russia is recognized as the aggressor state. This event has had many implications on international politics and global economic aspects. Before looking at the aftermath, I must establish a clear timeline for this conflict. It is widely believed that only the full-scale war of 2022 matters; however, the tensions between both countries have risen long before that. The book “Propaganda and Ideology in the Russian-Ukrainian War” by Jon Roozenbeek (2024) clearly outlines the causes and premises of the war. The author highlights the importance of the military propaganda campaign and how it tried to influence the outcome of this war. This book gives an overview of the timeline of all the tensions between the Russian and Ukrainian governments that have led up to this moment in history. It all began with Russia rejecting Ukraine’s intent to implement more Westerncentric governance models and joining NATO in 2008 (Korostelina, 2010). Fast forward to the "Revolution of Dignity", where thousands gathered on the Independence Square (Kyiv, Ukraine) in November 2013. Ukrainians protested their government rejecting political association and free trade agreements with the European Union in favour of building even closer ties with Russia. Many people have opposed such a decision, claiming that such a relationship will only increase the levels of corruption and the government's abuse of power. This revolution ended on February 22nd, 2014, with the impeachment of President Viktor Yanukovych, who fled the country the same day. After 4-month-long protests, which brought many casualties, the Ukrainian citizens had finally hoped that the removal of the corrupted government would bring stability to their country. As soon as the pro-Western government was elected in Ukraine, the Russian military, via the command of Vladimir Putin, swiftly invaded Crimea (a peninsula in the south of the country) and took over the military bases and multiple administration buildings. Despite the international judgement, Russia formally annexed Crimea on March 18th, 2014, ignoring any legal disputes (Roozenbeek, 2024). Soon after, the eastern region of Lugansk was seized as well and became the battlefield for the next ten years. In the period of 2014-2016, the Ukrainian army was actively trying to get those territories back. This was called ATO – Anti-Terrorist Operation. Unfortunately, this operation did not end in success, as many lives were lost. For the following years, both armies remained stationed in the Lugansk region but for different purposes. The Ukrainian army tried to control the border and protect the rest of the country from an unfortunate fate, while the Russian army was still planning on seizing the whole country. Those violent military attacks were limited only to the eastern part of Ukraine until February 24th, 2022. Every Ukrainian will remember waking up at 4 am to the sounds of bombs being launched into their houses. President Putin has motivated such brute attack by stating that his goal is to "denazify" Ukraine and to free the country from the European narratives. The Russians have called this event a Special Military Operation and refuse to call it war. To this day, the Russian government and their president keep violating the Geneva Convention laws and terrorizing innocent citizens across Ukraine.

2.2 Impact of the Russian-Ukrainian War

After getting acquainted with the timeline of the conflict, we can look at the aftermath that it has caused. One of the most influential economists – John Keynes, stated in his book "The Economic Consequences of the Peace" (1919) that wars have a negative effect not only on the country that initiated the conflict but also on the world, causing high inflation and stagnation periods. On the other hand, the paper by Koubi (2005) discusses the impact of the wars on the economic development of the big countries during the period of 1960-1989. The author's main findings are that the different growth rates between countries can be traced to the experience of war and its nature. Koubi has argued that in some cases, the longer or the more brutal the war is, the higher the post-war economic growth rate is. This phenomenon can be caused because wars tend to occur more in poorer, less-developed countries; hence, after the ending of the war, giving a better opportunity to improve the economic state of the country. An essential part of this literature review is also to research how Ukraine and Russia's economies were affected by this shock. In the paper of Bluszcz & Valente (2019), we can investigate the internal costs of the Russian-Ukrainian war of 2014. The authors claim that this armed conflict led to a significant decline in the Ukrainian economy, especially the GDP levels, with a decrease of around 15% during 2013-2017. They have also noted that the Donbas' were affected the most in the whole country (Bluszcz & Valente, 2019). The paper of Dreger et al., 2016 describes the impact of the conflict on Russia's currency – rubel. The researchers claim that the impact of Western economic sanctions and the country's heavy reliance on international trade caused the rubel to lose 50% of its value against the US Dollar (Dreger et al., 2016).

2.3 Natural Gas Market Volatility

Natural gas is the second most consumed energy source in the world, after oil (*Global Primary Energy Consumption by Fuel 2022*, 2024). In 2022, the worldwide usage of this commodity was calculated to be around 4 trillion cubic meters (*Global Natural Gas Consumption 2022*, 2024). This amount at the standard atmospheric pressure can be used to fill in 1.6 Olympic-sized pools (volume of 1 pool = 2500 m^3 (*Competition Regulations*, 2024)). Natural gas is one of the cleanest fossil fuels (Liang et al., 2012), which has significantly helped with the transition from coal-powered electricity generation. Liang et al., 2012 have talked about how this fossil fuel is a great way to reduce the emissions of harmful pollutants. In their research, they included a study by the EPA (Environment Protection Agency), which has found that the increased consumption of natural gas is beneficial in decreasing greenhouse gases, particularly in the US. Other advantages include re-burning (the process of adding gas to the oil-fired boilers to reduce harmful emissions) and cointegration (the simultaneous generation of heat and electricity). Liang et al., 2012 have also listed the different users of this fossil fuel and how it is being enhanced via technological progress. The main uses include residential (mostly heating and cooking), commercial (space and water heating, cooling) and industrial (e.g. metal-refining or food-processing industries).

The other important aspect of natural gas is understanding its pricing mechanism. Cai & Wu, 2020 explained the gas-pricing mechanism in the major markets. They noted that in the 20th century, the price of gas was always dependent on oil prices. However, since then, both gas and crude oil markets have been in the process of decoupling, and currently, many economists argue whether this change is temporary or whether the two commodities will be permanently priced independently from each other. Cai & Wu have differentiated three primary markets: America, Europe and Asia, which vary from each other. The explanation for such differences is events that took place in those regions, namely the shale gas revolution in North America (2008), the Russian-Ukrainian war in Europe and the rising demand for energy in Asia. The research employs the rolling-window Granger test to investigate the interconnected relationship between natural gas and crude oil (for EU, USA and Japan in the period of 1992-2017). The empirical results have proven that the relationship between the prices of the two energy sources varies over time. Furthermore, the authors have proven that the change in oil prices causes fluctuation in the natural gas market in most sample periods. As for Europe, the findings show mixed connections between both markets. The US sample showed that the shale gas boom had a significant influence on the differentiation of gas from oil-pricing decisions. The paper ends on several policy-making implications as well as a proposal to employ an international uniform gas-trading system, where the index is calculated upon actual demand and supply of such commodity.

The ups and downs of natural gas prices reflect the broader trend of volatility observed in various commodities, where market conditions can change rapidly. A paper by Chen et al., 2023 describes the influence of financial stress on commodity price volatility by using the Markov-switching models. The authors prove that commodity volatility is better characterized by the three regimes (low-volatility, transitory and high-volatility) rather than two, as the previous papers showed. They also report that "a shock in financial stress has an adverse and highly significant effect on commodity price volatility". This study has demonstrated that financial stress has a 2.8 times larger effect on a high-volatile market rather than a low-volatility one. Furthermore, the shock on the prices of the commodities holds only for the energy, agriculture, and industrial metals indexes (precious metals indexes and sub-indexes remain stable). The research concludes with severe policy-making implications, where the authors recommend better financial monitoring of the commodity market.

This final research paper I want to touch upon, written by Liang et al. (2022), will discuss the prediction of natural gas volatility via employing an extended GARCH-MIDAS-ES model. With rising concern regarding the future outcomes of the Russian-Ukrainian war, it is crucial for policymakers to understand and forecast the changes in the natural gas market caused by sudden shocks. The authors focus on the influence of extreme weather as one of the most important and common factors that influence the energy commodity markets. Previous studies have usually confirmed the connection between the natural gas market and weather indicators, such as temperature and humidity. However, an econometric model regarding extreme weather is rare in the research field. The study used extended GARCH-MIDAS models (which will examine average and extreme weather on each own), which are great for inspecting the average effect of weather indicators on long-term volatility. As a result, Liang et al. have proven that the more extreme weather occurs, the more the natural gas market tends to fluctuate. The research paper ends by highlighting the importance of establishing weather-related policies to decrease energy risks at such environment-sensitive times (e.g. global warming and the greenhouse crisis).

2.4 Relationship between the Russian-Ukrainian war and a commodity market

This final section of the theoretical framework will investigate the impact of the Russian-Ukrainian war on various financial/commodity markets. The world has witnessed two significant "Black swan" events recently: the COVID-19 pandemic, which negatively affected global financial markets (due to strict restrictions, lockdowns and investor uncertainties) and the Russian-Ukrainian war. Compared to the pandemic, the military conflict is expected to leave a lasting stain on the worldwide economies and markets. A paper written by Yousaf et al. 2022, discussed the reaction of the G20+ stock markets to the full-scale Russian-Ukrainian war. The authors have conducted an event study approach to trace the abnormal returns before and after the beginning of the military attack. Several conclusions have been made after examining the results. The methodology of the research relies on the OLS regressions, with abnormal returns (AR) and cumulative abnormal returns (CAR). Firstly, the main result is that most of the stock markets had a significant adverse reaction to the announcement of the war, with Russia having the most significant negative impact on its market. Furthermore, this study has shown that some markets reacted negatively before and after the news of war broke out (e.g. Hungary, Russia, Poland, and Slovakia), while other markets were only impacted in the post-event days (e.g. Australia et al.). The paper summarized that the best regions to invest in are North America, Latin America, the Middle East, and Africa, which have been shown to be the least affected by the Russian-Ukrainian conflict.

2.5 Relationship between the Russian-Ukrainian war and foreign exchange rate

Another important variable that can be affected during a massive geopolitical conflict such as war is the exchange rate. Countries with unstable currencies can suffer from the effects of the war on exchange rates much more than others. A paper by Hossain et al. (2023) found that the military conflict had a vast negative impact on the foreign exchange markets. The authors have also investigated an additional factor that might influence the resilience of the exchange rate, which is the reliance of a specific country on Russian energy and the level of EPU. The results of the study demonstrate that the countries chosen in the sample (especially the neighbouring countries) demonstrated a significant plummet in their exchange rates towards the US dollar. (Hossain, Masum, Saadi, 2023). However, the authors have noted that further research (with a longer time series) regarding this topic is necessary as they have used a small event window of 15 days.

2.6 Russian-Ukrainian war on global energy market

At the same time, the article "Conflict vs sustainability of global energy, agricultural and metal markets: A lesson from Ukraine-Russia war" also makes a conclusion regarding global reliance on the countries (affected by the war in this case) when it comes to certain goods. The study demonstrates the effect of the war on the appearance of risks in energy, precious metals markets, and agricultural commodity markets. The last one takes special attention as it is directly connected to food safety on a global scale because Ukraine has been, for many years (and still is, despite the war), the leading exporter of sunflower seeds, corn, and wheat. These agricultural goods are used for both human consumption and animal feed. This way, disruption in the exporting country can affect the whole consumption chain and lead to significant shortages of dairy and meat products. The authors used a cross-quantilogram (CQ) approach and the rolling window multiple correlation method for the analysis. The CQ approach is generally used to explore the bi-directional predictability between two time series, and the rolling window looks at the dynamic correlation between the modelled time series. As for the results for the energy market, the authors claim that the military conflict has negatively influenced only crude and Brent oil, while the natural gas market profited during that time. The authors suggest the crucial importance of diversifying the risks by reducing the reliance on certain countries as leading exporters for trading. (Chrishti, Khalid, Sana, 2023).

Additionally, a paper written by Chen et al. (2023) investigates the impact of the Russian-Ukrainian war on the S&P GSCI natural gas index market volatility. They have looked at such event window: June 1st 2011–December 31st 2022, for the S&P GSCI Natural Gas, which is one of the most dominant markets in the world. For the methods, the authors have proposed a new technical statistic - Volatility Ratio and Volatility-of-Volatility approach to test the distributional nexus of volatility with the Russian–Ukraine war. The main finding from this analysis shows that there is a widely random situation for the natural gas index volatility in the post-war period. They have also concluded that the long-term returns of the gas prices do not follow a consistent trend.

An article called "*Assessing the Impact of the Russia–Ukraine War on Energy Prices: A Dynamic Cross-Correlation Analysis"* has also explored the aftermath of the military conflict on the energy market. Inacio Jr et al., 2023 used a Detrended cross-correlation analysis method (DCCA) to investigate the direct and indirect influences of the military conflict on the correlation of the natural gas price and crude oil. As a result, the relationship between both commodities remained stable event during the global shock, while the cross-correlation of crude oil with other refined product prices has weakened.

2.8 Hypothesis development

This literature review outlines the main components and econometric models needed to analyse the impact of the Russian-Ukrainian war on the natural gas market. Not only did it provide the necessary input on various methods to conduct quantitative research, but it also demonstrated some polar conclusions made about the impact of the geopolitical conflict on different financial markets. This section is crucial to link the results I obtained with some existing opinions and possibly contradict some of the paper's conclusions. After reviewing all the above academic literature, I have made several expectations regarding my research question. Firstly, based on a paper by Yousaf et al. 2022, I expect that the natural gas market will follow the same path as the stock market after the beginning of the Russian-Ukrainian war of 2022. Thus, the 1st hypothesis of this research is:

"The Russian-Ukrainian Full-scale war in 2022 led to a significant negative effect on the natural gas market for USA, Asia and Europe."

However, the Initial Attack of 2014 and its influence on the commodity markets are not well-represented in the existing literature. The absence of academic research on this topic may indicate that the event was not significant enough to examine. Hence, the lack of research on the event made me develop this 2nd hypothesis:

“There is no significant change in the gas prices for the Initial Attack in 2014, even though the first sanctions were imposed soon after the initial attack.”

Lastly, after reviewing papers by Cai & Wu (2020) and Inacio Jr et al. (2023), I also want to examine the importance of the crude oil prices on the energy market. The papers have previously mentioned that natural gas is often found in conjuction with crude, thus making them interrelated, when it come to the pricing mechanism. However, I want to investigate if this relationship holds even during the geopolitical conflicts. Hence, the 3rd hypothesis is:

“For both periods: “Initial Attack” and the “Full-scale war” the significant influence of the crude oil on the natural gas pricing mechanism will not change .”

CHAPTER 3 Data

In this chapter, I would like to outline the foundation of the elements necessary to conduct the following empirical research on the effects of geopolitical conflicts on the commodity market. This section will provide a better understanding of the data sources, the nature of the variables, and the statistical methods used to draw conclusions about the results of the leading research topic.

3.1 Sample description

In this section, I will describe the composition of primary data. As mentioned in the main research question, I will look at the changes in natural gas prices over specific periods in three central regions: the USA, the EU and Asia. There are two main event periods: September 2013 – July 2014 (with the 20th of February 2014 marking the initial military attack) and September 2021 – July 2022 (the 24th of February 2022 – the beginning of the full-scale war), making it 11 observations per period. Compared to the previous study by Yousaf et al., 2022, the event windows incorporated in this study will use monthly data instead of daily data. Such a decision was made due to the lack of daily data on natural gas prices as well as other control variables. Furthermore, each month of the event window will be separately assigned to each of the three regions (e.g., September 2013 will be repeated three times, once for each location), making 66 observations in total. Lastly, for convenience reasons, the dataset was divided into two parts of 33 observations each: one for the initial attack period and the other for the full-scale war of 2022.

3.2 Variables description

This section will define the key variables used in this study, the source from which it was collected and the main units of the measurement.

The *region* is a categorical variable that is used to classify observations according to the geographical location they represent. In this study, only three regions are investigated: the USA, the EU, and Asia. The chosen regions represent the largest share of the consumption and international trade of natural gas. The analysis of the effect on these regions will allow us to explore the potential difference in the response to the military conflict. The USA is one of the biggest consumers and manufacturers of natural gas (*EIA, 2021)*. Its prices often serve as a benchmark for the worldwide markets (*e.g. Henry Hub*). European Union is one of the leading importers of such commodities, with the biggest supplies coming from Russia. Countries such as Germany, France and Italy have the highest levels of natural gas consumption on the continent (*EU Imports of Energy Products - Latest Developments*, 2024). However, due to the heavy reliance on Russian trade, the EU has become susceptible to gas market failures. Asia has many countries with fast-growing economies and growing urbanization, such as China, Japan, South Korea, etc., which are simultaneously one of the biggest gas consumers of that region. Those countries have close trade ties with Russia, which also protects them from disruption in the natural gas sector.

Hence, the choice of these locations will serve as a good representation of important participants in the natural gas market.

The *panel_id_numeric* is a long, consistent variable that combines a year, month, and region (e.g., **201309Asia** – stands for observations for September 2013 in Asia). It was created by merging *region and date_monthly*. This variable serves as a unique identifier for each panel in the following dataset, with the purpose of distinguishing the same date for the USA, EU and Asia. It allows us to get well-structured data for the further analysis of the data across multiple entities over time.

The *naturalgasprice* is a continuous numerical variable that describes the average monthly prices of natural gas. The imperial measurement unit of this variable is US Dollars per Million Metric British Thermal Unit. In this research, this is the dependent variable, and it is used to show how volatile the market is under geopolitical shocks. The prices for the USA region were taken from the Henry Hub database – "an important market clearing pricing concept, based on the actual supply and demand of natural gas as a stand-alone commodity" (*What Is Henry Hub?*, 2024). The data for the other two regions was taken from the Federal Reserve Bank of St. Louis, which is known to provide quite extensive and high-quality collection of economic data (*Federal Reserve Economic Data | FRED | St. Louis Fed*, 2024).

3.3 Control variables

To better understand the relationship between our variables of interest, I will also add control variables to reduce bias and other possible effects. Three requirements must be met for a control variable to be considered good to use. Firstly, it must be correlated with our independent variable of interest, and secondly, it must also influence our dependent variable (or at least be correlated with variables that achieve both). Finally, it also cannot be influenced by our independent variable of interest. In this study, I will be using 4 controls: crude oil prices, inflation rates, temperature and share prices.

The *crudeoilpric*e is a continuous numerical variable that represents a monthly average crude oil price. This is a good control variable as natural gas and crude oil are usually interconnected when it comes to the energy supply (natural gas is often a byproduct from the extraction process of the oil) (*How Crude Oil Affects Natural Gas Prices*, 2024). Hence, any sort of fluctuations in the crude oil market will lead to a reaction from the gas side. Furthermore, this commodity is often used as a proxy for the economic health of the country. The data for the prices was derived from the three main benchmarks in the oil prices. For the USA region, we will look at the West Texas Intermediate (WIT) for EU – Brent Crude and for Asia – Dubai Crude. Such a choice of benchmarks allows us to accurately reflect the oil market dynamics and specific trade regulations on the assigned regions.

The *shareprice* is a continuous numerical variable which describes the monthly average stock price of a selected market index. This control was chosen to reflect the economic and the financial states of the chosen regions. The data source of this variable for every location in the research is OECD. Such share price is calculated from the common share prices of the companies traded on both domestic and international markets (*Prices* - *Share Prices* - *OECD Data*, 2024). The average share price for the Asia was derived by taking the mean of the following countries observations: China, India, Japan, Russia, South Korea and Indonesia (Appendix A, Table A.2). The measurement unit of this variable US Dollars per 1 share.

The *temperature* is a continuous numerical variable, which stands for the monthly average temperature for the 3 regions, shown in degrees of Celsius. It shows how seasonal changes induce the demand for the natural gas and sequentially its prices. The average temperature was derived from National Centres for Environmental Information (NCEI).

The *inflationrate* is a continuous numerical variable, which reflects the monthly inflation per region. It is a good macroeconomic variable to control for the various economic fluctuations in the countries. It is correlated with the natural gas prices as energy is a part of the consumer price index (CPI). The data for the EU and USA was taken from Trading Economics – a frequently updated database with a broad range of various economic indicators (*Euro Area Inflation Rate*, 2024). As for the Asia, I have used the inflation.eu source, which gives country-specific data based on Eurostat and other official statistical agencies. The average inflation rate for Asia was derived by taking the mean of the following countries inflation rates: China, India, Japan, Russia, South Korea and Indonesia (Appendix A, Table A.1). These countries were picked as they greatly represent the various economic conditions, diverse financial structures. Such a method allows us to compare the Asian regions fairly to those of the US and the EU.

3.4 Descriptive Statistics

Table 1. Descriptive statistics for the "Initial Attack" period (2013-2014)

Variables	Observations	Mean	Std. dev.	Min	Max
naturalgasprice	33	10.849	5.421	3.620	17.960
crudeoilprice	33	104.683	4.600	92.720	111.800
shareprice	33	90.796	5.369	81.600	102.900
temperature	33	11.552	7.936	-0.900	26.700
Inflationrate	33	0.009	0.006	-0.000	0.021
region:					
USA	11				
EU	11				
Asia	11				

Note. The table shows descriptive statistics for 33 observations. The descriptive statistics include mean, standard deviation, minimum and maximum value for each variable. I only kept 3 decimals for each coefficient. *Region* - categorical variable, representing three regions: USA, EU, and Asia, with 11 observations each. The *naturalgasprice* and *crudeoilprice* are in dollars per million British thermal units (MMBtu) and dollars per barrel respectively. *Inflationrate* are represented as decimals.

Table 2. Descriptive statistics for the "Full-scale War" period (2021-2022)

Variables	Observations	Mean	Std. dev.	Min	Max
naturalgasprice	33	23.139	13.785	3.760	51.140
crudeoilprice	33	93.655	16.008	65.850	122.710
shareprice	33	145.141	18.431	109.600	176.380
temperature	33	11.933	7.558	-0.600	27.000
inflationrate	33	0.048	0.034	0.002	0.091
region:					
USA	11				
EU	11				
Asia	11				

Note. The table shows descriptive statistics for 33 observations. The descriptive statistics include mean, standard deviation, minimum and maximum value for each variable. I only kept 3 decimals for each coefficient. *Region* – categorical variable, representing three regions: USA, EU, and Asia, with 11 observations each. The *naturalgasprice* and *crudeoilprice* are in dollars per million British thermal units (MMBtu) and dollars per barrel respectively. *Inflationrate* variables are represented as decimals.

CHAPTER 4 Methodology

This chapter is dedicated to the explanation of the chosen statistical model and describing the steps I have taken to achieve my results. In this research, I decided to opt for the STATA software as this tool allows us to conduct a wide range of statistical analyses while maintaining a well-managed and clean dataset. This study is based on two main analyses: the Autoregressive Integrated Moving Average (ARIMA) model and the Event Study. Lastly, this section is finished with multiple diagnostics tests to ensure that my data set meets all the assumptions of the linear regression. The main goal of this method is to assess the impact of the event (shocks) on the variable of interest. It allows us to get a better picture of the situation before and after the primary event and to identify any sorts of trends or volatility associated with the shock.

As I mentioned previously, I have divided the obtained data into two separate sets – each for its own period to enhance the data management and to ensure the quality of the study. The same tests and STATA commands will be used for both datasets. Before conducting the analysis, I need to prepare the data by destringing numerical variables and adjusting the *inflationrate* variable from a percentage to a decimal. The next step was to get description statistics for natural gas prices, crude oil prices, inflation rates, temperature, and share prices. By using *the tsset* command, I set up the time series, and then I created the variables to represent the Russian-Ukrainian timeline.

Table 3. Time periods for "Initial Attack"

Pre_attack	September 2013 - January 2014
Attack	February 2014
Post_attack	March 2014 - July 2014

Table 4. Time periods for "Full-scale War"

Pre_war	September 2021 - January 2022
War_beginning	February 2022
Post_war_beginning	March 2022 - July 2022

After defining the periods, I split the data by region and plotted the natural gas prices over time for the USA, EU and Asia to visualize the trends and patterns. Furthermore, an augmented Dickey-Fuller test for stationarity (see Appendix B) was performed to spot the presence of unit root, which would mean that the data is non-stationary (mean and variance do not change with time). This test does not directly correspond to the linearity assumption, but it is still an important parameter for the quality of the analysis.

I began the analysis section with the ARIMA model, which is used to predict future outcomes based on past values (*Autoregressive Integrated Moving Average (ARIMA) Prediction Model*, 2024). This method aligns with my research, as natural gas prices are influenced by historical prices as well as patterns over time. Moreover, this model helps to address the possible non-stationarity in the data. The model is made of three main components: autoregressive terms (AR), moving average terms (MA) and the "integrated" parts. AR demonstrates the hanging variable that regresses on its own lagged values. MA investigates how each value depends on its previous observations' errors, and the "integrated" (I) part refers to differencing the "raw" observations (*Autoregressive Integrated Moving Average (ARIMA) Prediction Model*, 2024). This model is specified by three parameters: "p" - the lag order, "d"- the degree of differencing and "q" - the order of the moving average. Each period includes 2 ARIMAs: the baseline model (to see the normal dynamics of the natural gas market) and the model with a post-attack/war dummy (to show the influence of such event on the commodity market). **Equation 1** and **Equation 2** demonstrate the regression equation for the above-mentioned ARIMAs for the "Initial attack" and for "Full-scale War"

To determine the specification of ARIMAs, I created the ACF and PACF plots (see Appendix C). Furthermore, to pick the best-fitted models, I used a tuning approach, where I first plugged in different combinations of the ARIMA parameters p, d and q. Then, I examined the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values of all the obtained models. After this step, I kept only the combination of ARIMAs with the lowest values of the criteria (lower values indicate a better fit). Lastly, I conducted the Ljung-Box Q test to check the white noise (errors are random, with no patterns) in the residuals.

Equation 1. Baseline ARIMA (2,1,1) equation for the "Initial Attack" and "Full-scale War" periods:

$$
\begin{aligned}
naturalgasprice_t &= \beta_0 + \beta_1 crudeoilprice_t + \beta_2 temperature_t + \beta_3 shareprice_t \\
&+ \beta_4 inflationrate_t + \beta_5 USA\_dummy_t + \beta_6 Europe\_dummy_t \\
&+ \phi_1 naturalgasprice_{t-1} + \phi_2 naturalgasprice_{t-2} + \theta_1 \epsilon_{t-1} + \epsilon_t
\end{aligned}
$$

Note. Dependent variable – *naturalgasprice* at time t. *USA_dummy* – a dummy variable indicating observations from the USA; *Europe_dummy* – a dummy variable indicating observations for the EU; $\phi_1 naturalgasprice_{t-1}$ first lag of the natural gas price; $\phi_2 naturalgasprice_{t-2}$ – second lag of the natural gas price; $\theta_1 \epsilon_{t-1}$ the moving average term; ϵ_t - error term; β_0 - intercept term; $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ – coefficients for the independent variables; ϕ_1, ϕ_2 – coefficients for the autoregressive terms and θ_1- coefficient for the moving average term.

Equation 2. Post-attack/war_beginning ARIMA (2,1,1) equation for the "Initial Attack" and "Full-scale War" periods:

$$
\begin{aligned}
naturalgasprice_t & \\
&= \beta_0 + \beta_1 crudeoilprice_t + \beta_2 temperature_t + \beta_3 shareprice_t \\
&+ \beta_4 inflationrate_t + \beta_5 USA\_dummy_t + \beta_6 Europe\_dummy_t \\
&+ \beta_7 post\_attack(\_war\_beginning)_t + \phi_1 naturalgasprice_{t-1} \\
&+ \phi_2 naturalgasprice_{t-2} + \theta_1 \epsilon_{t-1} + \epsilon_t
\end{aligned}
$$

Note. Dependent variable – *naturalgasprice* at time t. *USA_dummy* – a dummy variable indicating observations from the USA; *Europe_dummy* – a dummy variable indicating observations for the EU; $post\_attack(\_war\_beginning)_t$ is a dummy variable indicating the period after the initial attack (for 2014) or the beginning of the full-scale war (for 2022); $\phi_1 naturalgasprice_{t-1}$ first lag of the natural gas price; $\phi_2 naturalgasprice_{t-2}$ – second lag of the natural gas price.;$\theta_1 \epsilon_{t-1}$ the moving average term; ϵ_t - error term; β_0 - intercept term; $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$ – coefficients for the independent variables; ϕ_1, ϕ_2 – coefficients for the autoregressive terms and θ_1- coefficient for the moving average term.

The next part of my research involves an Event Study model. This method is widely used to examine the influence of a certain event on the financial performance of a particular security (*Event Study: Definition, Methods, Uses in Investing and Economics*, n.d.). Some examples of the financial events used to research include mergers and acquisitions, earnings announcements, IPOs or any kinds of stock events. The market model is commonly used for this methodology. It is based on investigating the abnormal returns on the market and comparing them to the normal returns. Similarly to Yousaf et al. 2022 I have calculated the Expected Returns of the natural gas prices during chosen event window:

Equation 3 Expected Returns (ER) formula

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t}$$

Note. α_i is the intercept term for region i; β_i represents the slope of the coefficient for region i; $R_{m,t}$ stands for the return of the index at time t.

Next step is to compute the Abnormal Returns (AR) for each region by using this formula:

Equation 4. Abnormal Returns (AR) formula

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

Note. $R_{i,t}$ is the actual (observed) return of the commodity for region i at time t.

After computing the necessary measurements, I can calculate the Cumulative Abnormal Return (CAR) form time t_1 to t_2 for region i, which is used to investigate the overall effect of the shock on a financial market.

Equation 5. Cumulative Abnormal Returns (CAR) formula

$$CAR_i = \sum_{t=1}^{t_2} AR_{i,t}$$

However, before drawing conclusions, the t-test was conducted to test whether CAR is significantly different from zero (testing if the event had influenced the security). To account for the regional differences in CAR, I used ANOVA. This test helped to identify the magnitude of the localized effect on the natural gas market. These steps are identical for both periods – Initial Attack and Full-scale war.

The statistical part will be wrapped up by conducting the diagnostics checks. This is a crucial step to ensure that all the results obtained from this data are reliable and valid. The Durbin-Watson test for serial correlation will be used to spot the autocorrelation in the residuals. These diagnostics are good for investigating the connection between our dependent variable and the residuals. The White test for heteroskedasticity is used to assess the homoskedasticity, in other words constant variance, linearity assumption. The Variance Inflation Factor (VIF) test checks for the multicollinearity (a significant intercorrelation) among the independent variables with other predictors in our models. The Shapiro-Wilk test is employed to test the normality of the residuals. The Granger Causality Test is made to see if the past observations can forecast the other variables' current value.

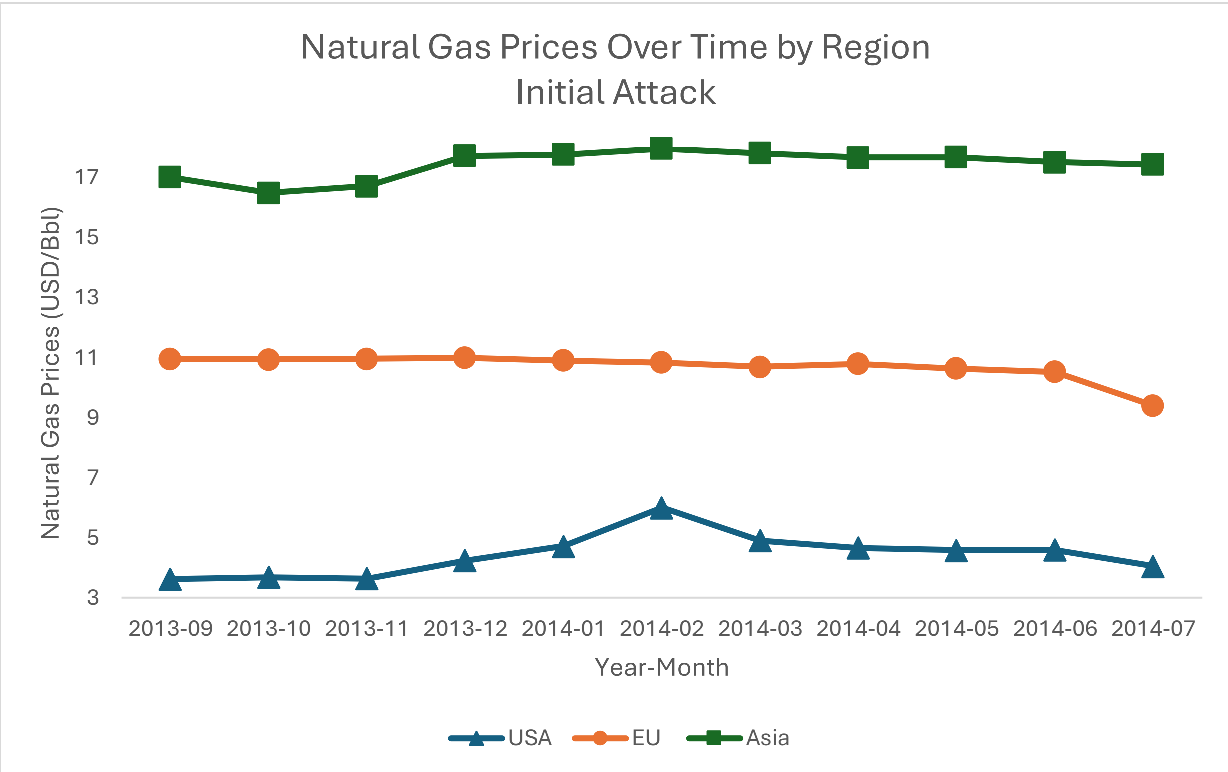
CHAPTER 5 Results

This section is dedicated to the presentation of the main findings of multiple regressions analyses on the impact of the military conflict on the natural gas market. The additional check and tests are also discussed in this section.

5.1 Main Findings

5.1.1 Visualization of the data

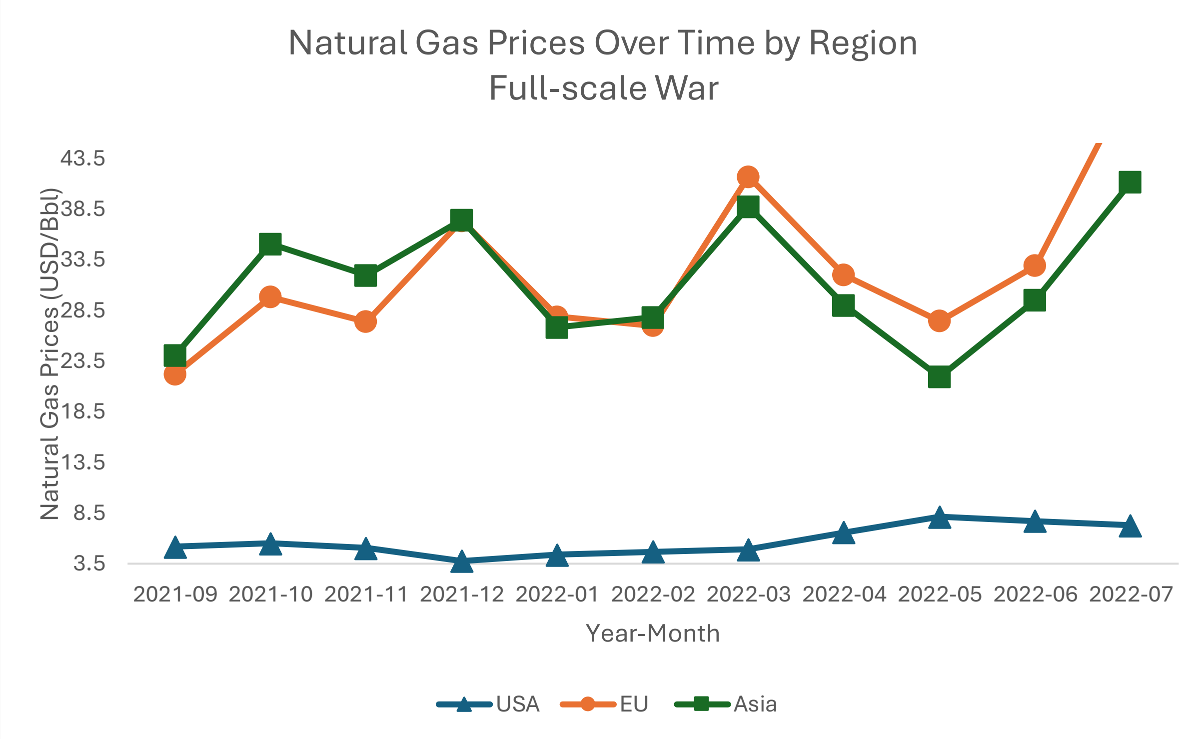
Figure 1.



Note. Y-axis – natural gas prices in USD per barrel (Bbl.); X-axis – the event window from September 2013 to July 2014; Blue triangles line represents natural gas prices for the USA; Orange circles line represents natural gas prices for the European region; Green squared line indicates natural gas prices for Asia. The main event happened in February 2013.

After investigating Figure 1, I can summarize the regional differences in the natural gas prices over the 11 months. From the graph, I can state that the only country which reacted to the military conflict of the 20th of February 2014 is the USA. The change in the price of the following commodity was 1.29 U.S. Dollars per Million Metric British Thermal Units. However, the next month (2014-03) after the initial attack, the price went to normal for that country – 4.9 U.S. Dollars per Million Metric British Thermal Unit, which goes in line with the second hypothesis of this thesis (there will be no significant change in the gas prices all around the world for the attack window of 2014). As for the other 2 locations, there were no significant changes in the gas market during or after the initiation of the military attack.

Figure 2.



Note. Y-axis – natural gas prices in USD per barrel (Bbl.); X-axis – the event window from September 2021 to July 2022; Blue triangles line represents natural gas prices for the USA; Orange circles line represents natural gas prices for the European region; Green squared line indicates natural gas prices for Asia. The main event happened in February 2022.

Contrary to Figure 2, I can state that the natural gas prices for the EU and Asia regions were volatile for the whole event window compared to the USA prices, which were stable. The significant spike in the commodity market for the EU and Asia gives evidence for the first hypothesis of the thesis (the military conflict in 2022 will lead to a significant increase in the market price of natural gas and the energy export dynamics). The further fall and rise in prices can be explained by establishing and implementing harsher sanctions against Russian gas exports.

5.1.2 Stationarity of the data

Before starting the regression analysis, it is important to check for the stationarity of the data. After determining the number of lags in Information Criteria – AIC & BIC (see Appendix C), I can conclude the appropriate parameters for each variable. The lags were employed to help us investigate the delayed effects or possible autocorrelation of the data. For the "Initial Attack" data, only *naturalgasprice* variable had a lag of 3, while other variables had a lag of 4 (see Appendix B, Table B.1). As for "Full-scale war", every variable had a lag of 4 (see Appendix B, Table B.3).

After performing the Augmented Dickey-Fuller test for the "Initial Attack", two variables appeared to be non-stationary. Naturalgasprice had a test statistic of -1.283, which was bigger than all the critical values at 1%, 5% and 10%. Furthermore, the p-value (0.6369) is way greater than the other significance levels. This result means that I fail to reject the null hypothesis (that the data had a unit-root), or that the time-series is non-stationary. Similarly, for the *inflationrate,* I cannot reject the H0 (the test statistic (-1.956)) was less negative than the other critical values (see Appendix B, Table B.2). To battle the problem of the unit-root, there are several methods, but the differencing was chosen in the research. This technique calculates the differences between the consecutive observations. New variables, based on that method, were created: *diff_naturalgasprices* and*diff_inflatiorate.*
Similarly, the "Full-scale War" all the variables have experienced non-stationarity, apart from the shareprice (see Appendix B, Table B.4). The new variables have been created by using the differencing method: *diff_naturalgasprices,diff_inflatiorate, diff_crude, diff_temp.*

5.1.3 The ARIMA model

Before discussing the findings of the ARIMA models, I would like to note that the variables used in the following statistical analysis are not differentiated. One of the biggest advantages of the ARIMA is that it works for non-stationary data (which, unfortunately, is present in this research). The parameter *d* ("integrated" part) handles the differencing of the variables. Thus, to avoid over- or under-differencing, I opted for the "original" data and set the d parameter to 1 for both periods. Also, to account for the impact of different regions, I created dummy variables for the USA, Europe, and Asia: *USA_dummy, Europe_dummy, and Asia_dummy*.

Based on the ACF and PACF plots for the "Initial Attack" (see Appendix C, Figure C.1 and Figure C.2), we can set the rest of the parameters for the model specification. Both the ACF and PACF plots show significant spikes at lag 2 and 3, meaning that we can have few combinations of the p and q parameters. After plugging in all the possible variations and checking the AIC and BIC, I chose ARIMA (2, 1, 2), as it had the lowest values for the above-mentioned criteria (see Appendix C Table C.1). The last step is to check whether the residuals follow the white noise. The Portmanteau Q statistic is 10.061 (with a p-value of 0.758), indicating that the residuals have no autocorrelation at a 5% significance level. These tests were conducted for the baseline model. To ensure that the second (post-attack dummy) model is valid and well-fitted, I have applied the same methods to the updated regression. The AIC and BIC are 41.979 and 59.568, respectively, and the Portmanteau Q statistic is 19.259 (p-value 0.155), meaning that the upgraded model is well-fit.

The same methodology was used for the “Full-scale War” ARIMA in Figure C.3 and Figure C.4 (see Appendix C) show that PACF has a significant spike at lags 1, 2, and 3 and ACF at lags 2 and 3. This means that I must investigate the BIC and AIC of each possible combination. ARIMA (2, 1, 2) had the lowest values – BIC of 210.444 and AIC of 192.8551 among all the models. The next step, examining the residuals, showed the Portmanteau Q statistic of 7.903 (p-value 0.894). This means that the Baseline model is well-fitted and accurate. The second model, which looks into the effect of full-scale war on the market, has a BIC of 213.659, an AIC of 194.605 and a Portmanteau Q statistic of 8.314 (p-value 0.872). Those values indicate that this model can also be used to investigate the research topic.

Table 5. Results of ARIMA Models for Natural Gas Price During “Initial Attack” and “Full-scale War” Periods

	ARIMA (2, 1, 2)		ARIMA (2, 1, 2)	
naturalgasprice	Baseline 1	After “Initial Attack”	Baseline 2	After “Full-scale War”
post_attack/ war_beginning		-0.744		1.661
		(2.433)		(5.856)
crudeoilprice	0.124***	0.080*	0.331**	0.325**
	(0.029)	(0.044)	(0.131)	(0.133)
inflationrate	32.521	78. 641***	173.777***	169.627***
	(26.532)	(23.860)	(42.207)	(48.632)
temperature	-0.059***	-0.022	0.132	0.115
	(0.007)	(0.040)	(0.188)	(0.186)
shareprice	-0.074	-0.076	0.195	0.195
	(0.075)	(0.074)	(0.147)	(0.148)
USA_dummy	-12.334***	-12.982***	-34.286***	-33.948***
	(0.606)	(0.603)	(3.979)	(4.534)
Europe_dummy	-7.537***	-7.414***	-1.970	-1.701
	(0.320)	(0.235)	(6.750)	(7.003)
Constant	0.042*	0.043	0.020	-0.038
	(0.023)	(0.111)	(1.130)	(1.162)
Observations	32	32	32	32
Log likelihood	-5.150	-8.989	-84.428	-84.302
Wald chi^2	4287.820	1.04e+08	20476.230	21305.480

Note. The table presents results for the ARIMA (2,1,2) models applied to natural gas prices during two distinct periods: “Initial Attack” and “Full-scale War”; "Baseline 1" and "Baseline 2" refer to the models without the event dummy variable, representing the periods before the "Initial Attack" and "Full-scale War," respectively; *post_attack/war_beginning* are dummy variables representing the post-attack or war beginning period; “*” p<0.1, “**” p<0.05, “***”p < 0.01 indicate the significance levels of the coefficients; Log likelihood – a measurement of model fit, with higher (less negative) values indicating better fit; Wald chi^2 – a test statistic for the significance of a model.

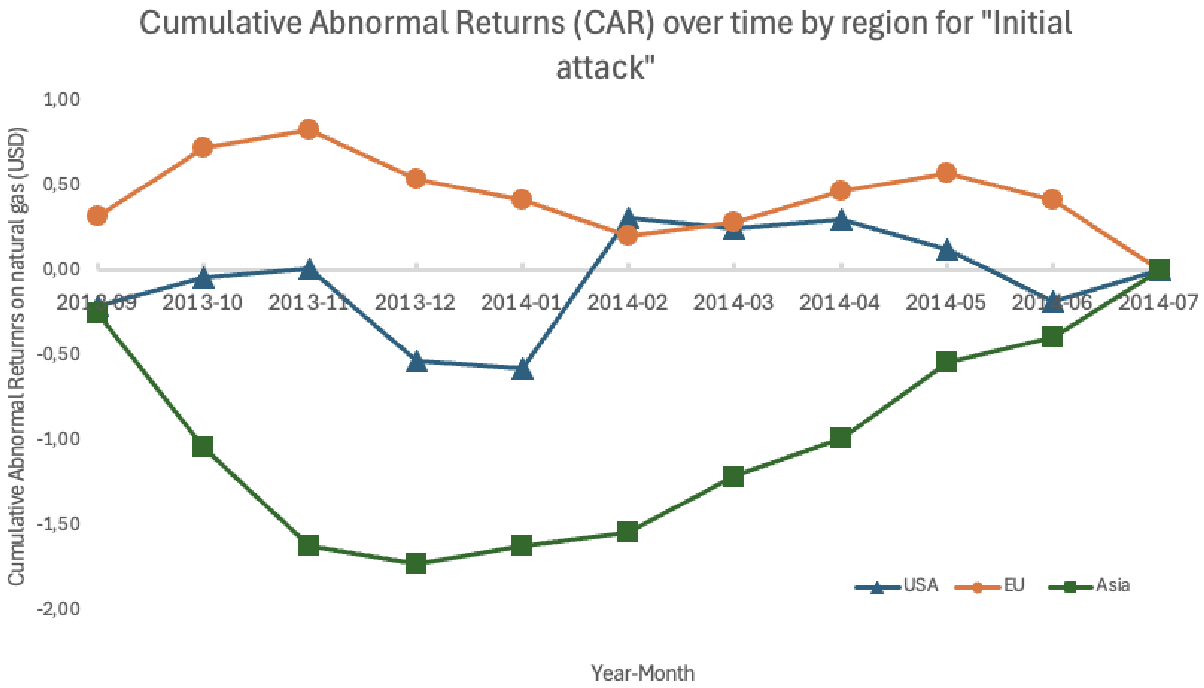
After examining the table, several conclusions can be drawn. The key variables in these ARIMA models - *post_attack* and *post_war_beginning- indicated* a non-significant impact on the natural gas market. That finding suggests that there was no significant change in the dynamics of the commodity prices caused by those two events. However, some control variables have proven to be significant predictors of gas prices. The *crudeoilprices* demonstrated a significant positive effect on the dependent variable in all four models. This finding proves that crude oil prices are interconnected with natural gas ones, similar to what (Cai & Wu, 2020)) demonstrated in their paper. Thus, this significant result allows me to accept the 3rd hypothesis. The *inflationrate* became significant after the “Initial attack” and remained that way for the Baseline 2 and “Full-scale war”. This macroeconomic indicator has the biggest significant impact among all the controls. The *temperature* variable is seen to have a negative significant influence on the price only for the Baseline 1 model but not for the rest. The *shareprice* is an insignificant indicator in all the models. After controlling for the regional differences, it is shown that the USA has a consistently significant negative impact on natural gas prices. Europe has a significant negative effect only for the “Initial Attack” period.

In conclusion, the empirical results obtained from the ARIMA models give clarity about whether to reject or accept the hypotheses of this study. The findings support the 2nd hypothesis, which states that the “Initial Attack” had no significant impact on the natural gas market for all the regions. That means I accept 2nd hypothesis. However, as ARIMA showed that there was also no effect of the “Full-scale War” on the market, I must reject 1st hypothesis.

5.1.3 Event study

This sub-section describes the empirical results obtained from an Event Study model using abnormal returns. The graph of the cumulative abnormal returns (CAR) for each period and respective diagnostics tests are included for each period.

Figure 3.

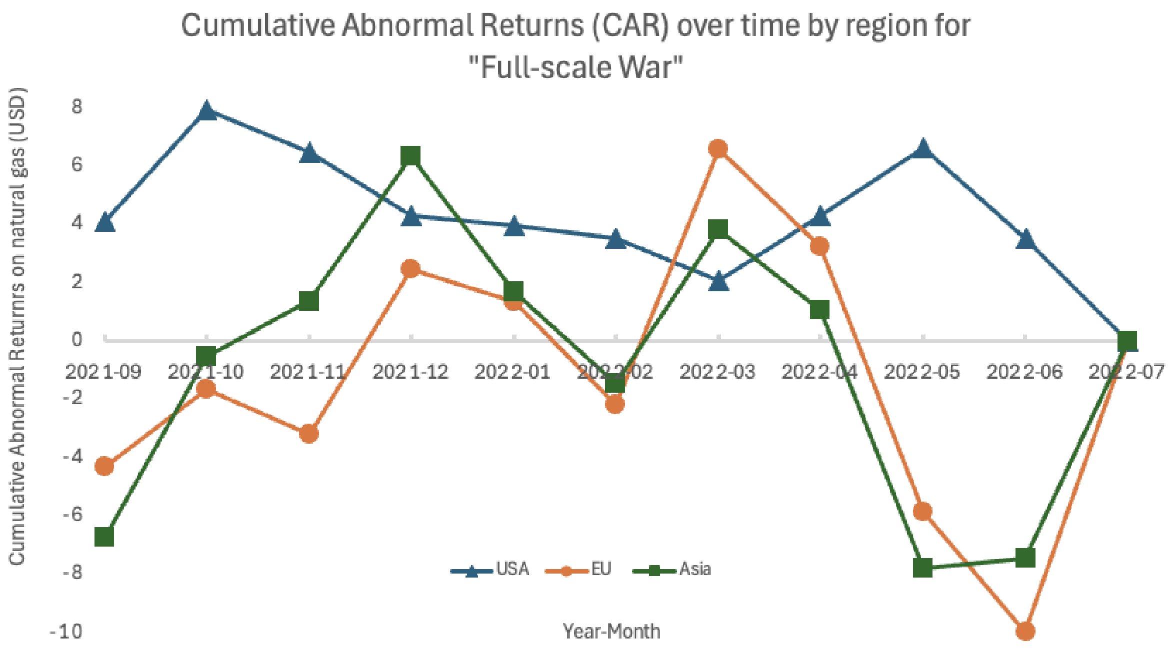


Note. Y-axis – cumulative abnormal returns on natural gas prices in USD; X-axis – time window from September 2013 to July 2014 – "Initial Attack"; Blue triangles line represents CAR for the USA; Orange circles line represents CAR for the European region; Green squared line indicates CAR for Asia. The main event happened in February 2013.

The graph above, visually represents the dynamic of the cumulative abnormal returns (CAR) over the event widow for the "Initial Attack". Asia showed a significant drop in CAR towards the end of 2013, but the market has recovered around June-July 2014. The US and Europe had smaller fluctuations compared to Asian region. The CAR for the American region starts of slightly below zero, but significantly drops around December 2013 – January 2014. However, next month (February 2014) it bounces back to a return of 0.31 and stays stable over the rest of the period. Europe presented the highest CAR among the regions (CAR = 0.83) in November of 2013. Compared to the US and Asia, Europe had not experienced any negative cumulative returns of the natural gas market. Overall, USA and Europe had stable CAR values though the whole event window.
The results for the t-test showed a negative average CAR of – 0.202 for all regions. The t-statistic of -1.603 (p-value = 0.119) state that the mean cumulative return is not significant from zero at a 5% significance level.
Findings from ANOVA test show that around 69% of the variance in returns are explained by the regional differences (R^2 = 0.688). Moreover, the f-statistic is 33.09 (p-value = 0,000) proves the returns of the gas market depend on the regions.

The t-test and the Figure 3 support 2nd hypothesis, stating that there had been no global significant impact on the natural gas market during an event window. Furthermore, ANOVA shows that even though the "Initial attack" had no effect on the prices, the regional disparities are present in the market.

Figure 4.



Note. Y-axis – cumulative abnormal returns on natural gas prices in USD; X-axis – time window from September 2021 to July 2022 – "Full-scale War"; Blue triangles line represents CAR for the USA; Orange circles line represents CAR for the European region; Green squared line indicates CAR for Asia. The main event happened in February 2022.

The graphic analysis of the cumulative abnormal returns during "Full-scale war" event window shows much more volatility on the market compared to the "Initial attack". These fluctuations tend to be more profound for USA and Europe. The US appears to have the most stable trend, with nonnegative cumulative returns through the whole period. Europe has followed the same patter as the American region until the February 2022. After the beginning of the full-scale war, the returns on the European market had a significant rise, reaching a peak of 6,56, however, starting from March 2022, the returns had a significant drop. Asian market followed an almost identical trajectory as Europe, but with smaller returns. The graph shows an ambiguous effect of the "Full-scale war" on the market, with the Asian and European market displaying a decrease of the returns after the beginning of the military conflict. Meanwhile, USA had an upward trend following the Russian-Ukrainian war.

The ANOVA reveals that the impact from the war varied significantly in each region (the f-statistic of 6.50 is significant at the 1% level). Thus, proving that including the regional differences is useful in order to correctly investigate the impact of a shock on a commodity market.

The p-value for the one-tailed test is 0.096, indicating that CAR is marginally significant. This result states that full-scale war caused a slight significant positive return on a global market. Hence, I accept the 1st hypothesis.

5.2 Diagnostic Tests

The results of the 4 main diagnostic tests indicate that the econometric models, built on the collected data for "Initial Attack" and "Full-scale war" periods, are well-fitted. The datasets do not show any autocorrelation, heteroskedasticity, multicollinearity or that the residuals do not follow normal distribution. The checking of all the OLS assumptions ensures that all the empirical results obtained from the models are valid and reliable.

Table 6. Durbin-Watson test for serial correlation

Period	Durbin- Watson d-statistic
"Initial Attack"	2.413
"Full-scale War"	2.135

Both periods show a test statistic in rage between 1.5 and 2.5, meaning that there is no significant autocorrelation in the residuals. There are no serial correlation issues in both datasets.

Table 7. White test for the heteroskedasticity

Period	Chi-square Test Statistic	Probability (p-value):
"Initial Attack"	19.810	0.136
"Full-scale War"	16.760	0.269

The findings from the White test show that both p-values are bigger than 0.05, which shows that the residuals have constant variance (no heteroskedasticity present).

Table 8. Variance Inflation Factor (VIF) test for multicollinearity

Variable	Variance Inflation Factor	
	"Initial Attack"	"Full-scale war"
shareprice	2.800	4.230
diff_inflatiorate	1.840	3.330
crudeoilprice/diff_crude	1.810	1.960
temperature/diff_temp	1.520	1.500
Mean VIF	1.990	2.760

As all the Variance Inflation Factors (VIF) are below 10, there is no multicollinearity in the data (all the independent variables have no correlation among each other).

Table 9. Shapiro-Wilk test for normality of the residuals

Period	Test Statistic W	Probability (p-value):
“Initial Attack”	0.951	0.162
“Full-scale War”	0.978	0.753

CHAPTER 6 Discussion

In this section, I will discuss the empirical results in depth and link them with the academic articles. Firstly, I want to touch upon the impact of the control variables, crude oil prices specifically. This explanatory variable proved to have a significant positive effect on the natural gas market across all the models. The influence of oil prices demonstrated no change even during the military conflict in both periods. This finding aligns with previous studies by Cai and Wu (2020), who have empirically proved the significant relationship between crude oil and a gas pricing mechanism. Thus, these results support my hypothesis that the influence of crude oil does not change even during geopolitical crises. However, contrary to Liang et al. (2020), the temperature showed a limited significance for the natural gas prices. The difference between the findings for my paper and the one mentioned above may be due to the frequency of dissimilar data.

The Event Study analysis demonstrated that cumulative abnormal returns (CAR) for the US and Europe remained stable, with the only exception for the Asian region, influencing a slight drop in returns. The respective ANOVA and t-test findings supported the hypothesis about the absence of any global influence of the "Initial Attack" on the natural gas market. Moreover, the graph obtained from this analysis supports the paper by Chen et al. (2023) regarding the fact that the cumulative returns do not seem to follow the same trend globally (in this case, Asia varies from the rest regions). However, similarly to Yousaf et al. (2022), the "Full-scale war" affected the natural gas prices. The CAR analysis highlighted the volatility of the commodity market, noting significant fluctuations globally.

An important point to discuss is the reason why the impact of the two military conflicts differed. One of the most significant determinants is the scale and severity of the armed attacks. The "Initial Attack" affected only a small part of Ukraine, thus not getting worldwide public attention and media coverage. Furthermore, Russian propaganda tried to downplay the severity of the conflict up until the full-scale war. The 2022 invasion had immediate worldwide attention by being a large-scale, visible and brutal war with many civilian casualties. Hence, the increased severity of the conflict highlighted market uncertainty and involved many economic implications, such as sanctions and trade restrictions. The initial EU sanctions were imposed in March of 2014, which included asset freezes and travel bans for Russians. Until the full-scale attack, the parliament had been adding more and more sanctions, which were useless. The first EU sanctions (targeted the natural gas market) were introduced immediately in February 2022. The main goals of implementing such penalties are to create incentives to change Russia's aggressive policies and to limit the aggressor's financial resources for waging war against Ukraine. Unfortunately, Russia managed to avoid or mitigate the impact of these sanctions due to the inadequacy of the restrictions and the evolution of alternative markets for raw materials and essential goods. Thus, the sanctions have partially achieved their goals by having the EU reduce its dependence on Russian natural gas exports and its overall influence on the worldwide energy market. On the other hand, Russia demonstrated a significantly greater resilience to these restrictions than anticipated by Ukraine's partners. In conclusion, the effectiveness of the sanctions remains a big discussion point in the economist community, while the impact of the sanctions on Russia's economy is becoming increasingly significant with each passing day, and the gaps in the sanction's mechanisms are gradually being addressed. This development inspires optimism regarding the ultimate goal of weakening Russia's economy and making the country incapable of sustaining military operations.

CHAPTER 7 Limitations

In this section, I will discuss the main limitations of this research and the data used. Including this section in the thesis is crucial for several reasons. The discussion of the limitations identifies possible gaps that should be considered for future studies. It also demonstrates that the author profoundly understands the research process and acknowledges that studies are flawed.

One of the most significant limitations of this study is its relatively small sample size and data granularity. This research uses 66 observations, with 33 observations per event period. Compared to Yousaf et al. (2022), I could not use daily data for natural gas prices or other explanatory variables. Most data about the commodity markets are compiled with quarterly frequency, so the monthly prices were the closest values to employ in this thesis. This limited sample size can restrict the statistical power of the analysis and lead to less reliable estimates. Monthly data usage instead of daily, especially in the context of prices and returns, may lead to a loss of detailed insights (significant price fluctuations may be averaged out). Furthermore, some immediate effects may be missed due to decreased granularity of the data.

Another limitation is the potential impact of leaving out other important control variables from the analysis due to data availability. The omission of variables such as GDP growth rates, industrial production index, and seasonal demand patterns, which were not all available with a monthly frequency or for each of the three chosen regions, may lead to the omitted variable bias. This bias can cause incorrect estimates of the influence of geopolitical risk on commodity markets.

To conclude, adding more control variables and changing the frequency from monthly to daily will enhance the robustness and validity of future research on the effect of geopolitical events on commodity markets.

CHAPTER 8 Conclusion

In this thesis, I have examined the influence of the full-scale Russian-Ukrainian war in 2022 on natural gas prices and compared it to the reaction of the same market during the initial invasion of Russia in 2014. The study of the aftermath of this geopolitical conflict is a critical discussion nowadays. Firstly, this war greatly influenced the worldwide financial and political dynamics, especially for Europe, which relied heavily on Russia's exports. As Russia is the biggest producer of natural gas, any changes in the supply dynamics directly affect the prices of this commodity. Furthermore, studying different scales of the same geopolitical conflict can be helpful in improving crisis management practices and providing a much more straightforward overview of the economic fallout from different-scale military attacks. Such research is crucial for determining efficient strategies and policies to adapt to the fast-changing markets affected by unforeseen crises. Therefore, the main research question of this study is: "*How did the natural gas markets of the USA, EU, and Asia react to the 2022 Russian-Ukrainian full-scale war compared to the initial invasion in 2014?*"

To answer the research question, I have used the ARIMA (Autoregressive Moving Average) model and the Event Study approach to examine two distinct periods: the "Initial Attack" in 2014 and the "Full-scale War" in 2022. The ARIMA model was employed using historical data and patterns to forecast the expected natural gas prices without including the war/attack variable and to compare them to the prices during the military attacks. The Event Study model was based on calculating the cumulative abnormal returns (CAR) to investigate the impact of the Russian-Ukrainian war on the market performance. The main finding of this thesis demonstrates huge fluctuations in the returns and the price shifts on the market for the full-scale war in comparison to the initial invasion in 2014. Such results conclude the presence of the impact of geopolitical conflicts on the commodity markets.

The following research reveals that large-scale geopolitical conflicts, like the Russian-Ukrainian war in 2022, have a significant instant effect on the global financial markets, compared to the impact of more minor armed attacks – such as the initial invasion in 2014. These results may help researchers in this field to trace the magnitude and the severity of the conflicts' nature, which can affect the market's reaction and the levels of volatility. Thus, by controlling for the scale of the geopolitical conflicts, the researchers can more precisely evaluate the aftermath of such events. The findings of this study have practical implications for investors and policymakers. After skimming through such academic papers, stakeholders can improve their crisis management strategies, and develop more energy security programmes. Furthermore, this research is a good base for developing more effective and precise forecasting models to evaluate other challenges caused by unexpected global crises. If these results taken into consideration while forecasting, it can positively affect the strategy of businesses and their preparation for crticial events and drops in the market.

REFERENCES

Al-Saadi, N. (2023). Russian-ukrainian war’s effects on the World Economy. *International Journal of Economics and Business Administration, XI*(Issue 1), 77–94. https://doi.org/10.35808/ijeba/799

Bluszcz, J., & Valente, M. (2019). The war in Europe: Economic costs of the Ukrainian conflict. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3392199

Cai, Y., & Wu, Y. (2021). Understanding gas pricing mechanisms: Implications for the Asian market. *Australasian Journal of Environmental Management*, *28*(4), 373–390. https://doi.org/10.1080/14486563.2021.1979111

Chen, J. (2017). *What is Henry Hub? definition, location, owner, and connections*. Investopedia. https://www.investopedia.com/terms/h/henry_hub.asp

Chen, L., Verousis, T., Wang, K., & Zhou, Z. (2023). Financial Stress and Commodity price volatility. *Energy Economics*, *125*, 106874. https://doi.org/10.1016/j.eneco.2023.106874

Chen, S., Bouteska, A., Sharif, T., & Abedin, M. Z. (2023). The Russia–ukraine war and energy market volatility: A novel application of the volatility ratio in the context of natural gas. *Resources Policy*, *85*, 103792. https://doi.org/10.1016/j.resourpol.2023.103792

Chen, Y., Jiang, J., Wang, L., & Wang, R. (2023). Impact assessment of energy sanctions in Geo-Conflict: Russian–ukrainian war. *Energy Reports*, *9*, 3082–3095. https://doi.org/10.1016/j.egyr.2023.01.124

Chishti, M. Z., Khalid, A. A., & Sana, M. (2023). Conflict vs sustainability of global energy, agricultural and Metal Markets: A Lesson from Ukraine-Russia War. *Resources Policy*, *84*, 103775. https://doi.org/10.1016/j.resourpol.2023.103775

Competition regulations. World Aquatics. (2023). https://www.worldaquatics.com/rules/competition-regulations

Crude oil prices: Brent - Europe. FRED. (2024). https://fred.stlouisfed.org/series/MCOILBRENTEU

Crude oilprice - chart - historical data - news. Crude Oil - Price - Chart - Historical Data - News. (2024). https://tradingeconomics.com/commodity/crude-oil

Dreger, C., Fidrmuc, J., Kholodilin, K. A., & Ulbricht, D. (2015). The ruble between the hammer and the anvil: Oil prices and economic sanctions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2668096

EU imports of energy products. Statistics Explained. (2023). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_imports_of_energy_products_-_latest_developments

EU Natural Gas TTFPRICE - chart - historical data - news. EU Natural Gas TTF - Price - Chart - Historical Data - News. (2022). https://tradingeconomics.com/commodity/eu-natural-gas

Euro Area Inflation Rate. Euro area inflation rate. (2022). https://tradingeconomics.com/euro-area/inflation-cpi

Euro Area Inflation Rate. Euro area inflation rate. (2022). https://tradingeconomics.com/euro-area/inflation-cpi

Federal Reserve Bank of St. Louis. (2024). *Welcome to fred, Federal Reserve Economic Data. your trusted source for economic data since 1991.* FRED. https://fred.stlouisfed.org/

Giziene, V., & Zalgiryte, L. (2015). The assessment of Natural Gas Pricing. *Procedia - Social and Behavioral Sciences, 213,* 111–116. https://doi.org/10.1016/j.sbspro.2015.11.412

Global price of dubai crude. FRED. (2024). https://fred.stlouisfed.org/series/POILDUBUSDM

Global price of LNG, Asia. FRED. (2024). https://fred.stlouisfed.org/series/PNGASJPUSDM

Global price of LNG, Asia. FRED. (2024). https://fred.stlouisfed.org/series/PNGASJPUSDM

Global price of natural gas, EU. FRED. (2024). https://fred.stlouisfed.org/series/PNGASEUUSDM

Globex. (2021). Henry Hub Natural Gas Futures Quotes. https://www.cmegroup.com/trading/energy/natural-gas/natural-gas.html

Hayes, A. (2021). *Autoregressive integrated moving average (ARIMA) prediction model*. Investopedia. https://www.investopedia.com/terms/a/autoregressive-integrated-moving-average-arima.asp

Henry Hub Natural Gas Spot Price. Henry Hub Natural Gas Spot Price (dollars per million btu). (2022). https://www.eia.gov/dnav/ng/hist/rngwhhdm.htm

Hossain, A. T., Masum, A.-A., & Saadi, S. (2024). The impact of geopolitical risks on foreign exchange markets: Evidence from the Russia–ukraine war. *Finance Research Letters*, *59*, 104750. https://doi.org/10.1016/j.frl.2023.104750

Iea. (2022). *Russia - countries & regions*. IEA. https://www.iea.org/countries/russia

Inacio, C. M. C., Kristoufek, L., & David, S. A. (2023). Assessing the impact of the Russia–ukraine war on energy prices: A Dynamic cross-correlation analysis. *Physica A: Statistical Mechanics and Its Applications*, *626*, 129084. https://doi.org/10.1016/j.physa.2023.129084

Izzeldin, M., Muradoğlu, Y. G., Pappas, V., Petropoulou, A., & Sivaprasad, S. (2023). The impact of the Russian-ukrainian war on Global Financial Markets. *International Review of Financial Analysis, 87,* 102598. https://doi.org/10.1016/j.irfa.2023.102598

Korostelina, K. (2010). War of textbooks: History education in Russia and Ukraine. *Communist and Post-Communist Studies*, *43*(2), 129–137. https://doi.org/10.1016/j.postcomstud.2010.03.004

Koubi, V. (2005). War and economic performance. *Journal of Peace Research*, *42*(1), 67–82. https://doi.org/10.1177/0022343305049667

Liang, C., Xia, Z., Lai, X., & Wang, L. (2022). Natural gas volatility prediction: Fresh evidence from extreme weather and extended GARCH-Midas-ES model. *Energy Economics*, *116*, 106437. https://doi.org/10.1016/j.eneco.2022.106437

Liang, F.-Y., Ryvak, M., Sayeed, S., & Zhao, N. (2012). The role of natural gas as a primary fuel in the near future, including comparisons of acquisition, transmission and waste handling costs of as with competitive alternatives. *Chemistry Central Journal*, *6*(S1). https://doi.org/10.1186/1752-153x-6-s1-s4

Lioudis, N. (2023). *How crude oil affects natural gas prices*. Investopedia. https://www.investopedia.com/articles/economics/08/crude-and-gas-prices.asp

Mark, J. J. (2024). *Warfare*. World History Encyclopedia. https://www.worldhistory.org/warfare/

Media, T. (2022). *Historic inflation Russia - CPI inflation*. Historic inflation Russia – historic CPI inflation Russia. https://www.inflation.eu/en/inflation-rates/russia/historic-inflation/cpi-inflation-russia.aspx

Media, T. (2023). *Inflation China 2022*. Inflation China 2022 – CPI inflation China 2022. https://www.inflation.eu/en/inflation-rates/china/historic-inflation/cpi-inflation-china-2022.aspx

Media, T. (2023). *Inflation India 2022*. Inflation India 2022 – CPI inflation India 2022. https://www.inflation.eu/en/inflation-rates/india/historic-inflation/cpi-inflation-india-2022.aspx

Media, T. (2023). *Inflation Indonesia 2022*. Inflation Indonesia 2022 – CPI inflation Indonesia 2022. https://www.inflation.eu/en/inflation-rates/indonesia/historic-inflation/cpi-inflation-indonesia-2022.aspx

Media, T. (2023). *Inflation South Korea 2022*. Inflation South Korea 2022 – CPI inflation South Korea 2022. https://www.inflation.eu/en/inflation-rates/south-korea/historic-inflation/cpi-inflation-south-korea-2022.aspx

Media, T. (2014). *Inflation Japan 2013*. Inflation Japan 2013 – CPI inflation Japan 2013. https://www.inflation.eu/en/inflation-rates/japan/historic-inflation/cpi-inflation-japan-2013.aspx

MIT. (2011). The Future of Natural Gas. https://energy.mit.edu/wp-content/uploads/2011/06/MITEI-The-Future-of-Natural-Gas.pdf

National Centers for Environmental Information. National Centers for Environmental Information (NCEI). (n.d.). https://www.ncei.noaa.gov/

Natural gas prices in Europe. FRED Blog. (2012). https://fredblog.stlouisfed.org/2023/01/unnatural-gas-prices-in-europe/

Natural gas supply statistics. Statistics Explained. (2023). https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Natural_gas_supply_statistics

NCEI.Monitoring.Info@noaa.gov. (2019). *Climate at a glance*. Climate at a Glance | National Centers for Environmental Information (NCEI). https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/

NCEI.Monitoring.Info@noaa.gov. (2022). *Climate at a glance: Global time series*. Climate at a Glance | Global Time Series | National Centers for Environmental Information (NCEI). https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series

Oldenborgh, G. J. V., Haarsma, R., Vries, H. D., & Allen, M. R. (2015, May 1). *Cold extremes in North America vs. mild weather in Europe: The winter of 2013–14 in the context of a warming world*. AMETSOC. https://journals.ametsoc.org:443/view/journals/bams/96/5/bams-d-14-00036.1.xml

Prices - share prices - OECD data. The OECD. (2024). http://data.oecd.org/price/share-prices.htm

Roozenbeek, J. (2024). *Propaganda and ideology in the Russian-ukrainian war*. Cambridge University Press.

Statista Research Department, & 2, J. (2024). *Global primary energy consumption by fuel 2023*. Statista. https://www.statista.com/statistics/265619/primary-energy-consumption-worldwide-by-fuel/

Statista Research Department, & 28, N. (2023, November 28). *Share of Russian gas in the EU 2022*. Statista. https://www.statista.com/statistics/1021735/share-russian-gas-imports-eu/

U.S. Price of Natural Gas Delivered to Residential Consumers (Dollars per Thousand Cubic Feet). U.S. price of natural gas delivered to residential consumers (dollars per thousand cubic feet). (2022). https://www.eia.gov/dnav/ng/hist/n3010us3m.htm

United States Inflation Rate. United States inflation rate. (2022). https://tradingeconomics.com/united-states/inflation-cpi

Wang, Y., Li, H., & Altuntaş, M. (2022). Volatility in Natural Resources Commodity Prices: Evaluating volatility in oil and gas rents. *Resources Policy*, *77*, 102766. https://doi.org/10.1016/j.resourpol.2022.102766

Wright, Q., & Wright, L. L. (1983). *A study of war*. University of Chicago Press.

Yousaf, I., Patel, R., & Yarovaya, L. (2022). The reaction of G20+ stock markets to the Russia-Ukraine conflict 'black-swan' event: Evidence from event study approach. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4069555

APPENDIX A - The derivation of inflation rate and share prices for Asia

Table A.1. The derivation of the Average Monthly Inflation Rates for Asia

Average Monthly Inflation Rates (Asian Countries)						
Date	India	Japan	Indonesia	China	Russia	Korea
2013-09	0,42%	0,32%	-0,25%	0,80%	0,21%	0,19%
2013-10	1,26%	0,10%	0,18%	0,10%	0,57%	-0,31%
2013-11	0,83%	0,00%	0,16%	-0,10%	0,56%	-0,02%
2013-12	-1,65%	0,10%	0,45%	0,30%	0,51%	0,12%
2014-01	-0,84%	-0,10%	1,07%	1,00%	0,59%	0,54%
2014-02	0,42%	0,00%	0,26%	0,51%	0,70%	0,27%
2014-03	0,42%	0,21%	0,08%	-0,50%	1,02%	0,18%
2014-04	1,26%	2,09%	-0,02%	-0,41%	0,90%	0,06%
2014-05	0,83%	0,41%	0,16%	0,10%	0,90%	0,16%
2014-06	0,82%	-0,10%	0,43%	-0,10%	0,62%	-0,13%
2014-07	2,44%	0,10%	0,93%	0,00%	0,49%	0,15%
2021-09	0,24%	0,40%	-0,04%	0,00%	0,60%	0,41%
2021-10	1,30%	-0,20%	0,12%	0,70%	1,11%	0,17%
2021-11	0,64%	0,20%	0,37%	0,39%	0,96%	0,50%
2021-12	-0,24%	0,00%	0,57%	-0,30%	0,82%	0,16%
2022-01	-0,24%	0,20%	0,56%	0,49%	0,99%	0,78%
2022-02	-0,08%	0,40%	-0,02%	0,59%	1,17%	0,54%
2022-03	0,80%	0,40%	0,66%	0,00%	7,61%	0,65%
2022-04	1,32%	0,40%	0,95%	0,39%	N/A	0,69%
2022-05	1,02%	0,30%	0,40%	-0,19%	N/A	0,63%
2022-06	0,16%	0,00%	0,61%	0,00%	N/A	0,66%
2022-07	0,54%	0,49%	0,64%	0,49%	N/A	0,48%

Table A.2. The derivation of the Average Monthly Share Prices for Asia

Average Monthly Share Prices						
Date	India	Japan	Indonesia	China	Russia	Korea
2013-09	71,7	76,5	88,7	59.1	86	98,8
2013-10	74,8	76,6	91,7	59.1	89,4	100,8
2013-11	75,4	78,7	88,9	58.5	88,8	99,9
2013-12	76,7	81	86	58.5	87,7	98,9
2014-01	76,6	82,5	88,7	55.2	87,9	97
2014-02	75,1	77,4	92	56.3	87,6	96,3
2014-03	79,8	76,6	96,2	55.1	78,2	97,1
2014-04	82,5	75,5	99,3	56.1	79,5	99
2014-05	86,6	75,8	100,4	54.9	82,5	98,9
2014-06	92,2	80,3	99,8	55.3	88,3	99,2
2014-07	94,1	82,2	102,7	56.4	86	100,5
2021-09	214,8	133	124,6	98.1	239,2	156,2
2021-10	221	128,4	133,1	96.7	250,7	148,7
2021-11	217,3	130,5	135,1	95.7	242	147,4
2021-12	210,8	127,5	134,2	98.1	223,4	148,6
2022-01	217,5	126,2	135,5	95.5	212,9	142
2022-02	210,9	123,6	138,8	93.1	195,1	135,1
2022-03	206,4	121,6	141,7	88.9	147,4	134
2022-04	212,7	122,6	146,7	85.2	146,3	134,4
2022-05	199,4	121,3	141,1	83.5	141,4	130,8
2022-06	195,5	122,2	143,7	89.0	138,9	124
2022-07	199,9	123	137,9	89.4	127,7	117,5

APPENDIX B – STATA output for AIC and Stationarity tests

Figure B.1. Output for the AIC criterion of the *naturalgasprice, crudeoilprice, inflationrate, temperature and shareprice* variables for the Initial Attack period

varsoc naturalgasprice

ag-order selection criteria

Sample: 5 thru 33 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-89.5627				30.2003	6.2457	6.26047	6.29285
1	-85.963	7.1994	1	0.007	25.2482	6.06641	6.09595	6.16071
2	-42.1797	87.567	1	0.000	1.32142	3.11584	3.16014	3.25728
3	-17.6275	49.104*	1	0.000	.260655*	1.49155*	1.55062*	1.68014*
4	-16.9173	1.4205	1	0.233	.266372	1.51153	1.58537	1.74728

* optimal lag
Endogenous: naturalgasprice
Exogenous: _cons

varsoc crudeoilprice

ag-order selection criteria

Sample: 5 thru 33 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-85.1645				22.2988	5.94238	5.95715	5.98953
1	-84.1453	2.0385	1	0.153	22.2735	5.94105	5.97059	6.03535
2	-81.5269	5.2367	1	0.022	19.9316	5.82944	5.87374	5.97089
3	-71.8952	19.263	1	0.000	11.0017	5.23415	5.29322	5.42275
4	-66.9831	9.8242*	1	0.002	8.41451*	4.96436*	5.03819*	5.2001*

varsoc inflationrate

.ag-order selection criteria

Sample: 5 thru 33 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	107.059				.000039	-7.31443	-7.29966	-7.26728
1	109.303	4.4877	1	0.034	.000036	-7.40022	-7.37068	-7.30592
2	119.048	19.49	1	0.000	.00002	-8.00334	-7.95904	-7.86189
3	133.966	29.836*	1	0.000	7.5e-06	-8.96321	-8.90414	-8.77461*
4	135.641	3.3488	1	0.067	7.2e-06*	-9.00971*	-8.93588*	-8.77397

* optimal lag
Endogenous: inflationrate
Exogenous: _cons

varsoc temperature

.ag-order selection criteria

Sample: 5 thru 33 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-100.67				64.9645	7.01169	7.02646	7.05884
1	-85.3063	30.726	1	0.000	24.1302	6.02112	6.05065	6.11542
2	-83.2274	4.1577	1	0.041	22.4117	5.94672	5.99102	6.08816
3	-79.1473	8.1603	1	0.004	18.1412	5.73429	5.79336	5.92289
4	-52.8235	52.647*	1	0.000	3.16905*	3.98783*	4.06166*	4.22357*

. varsoc shareprice

.ag-order selection criteria

Sample: 5 thru 33 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-88.5859				28.233	6.17834	6.19311	6.22549
1	-88.4923	.18728	1	0.665	30.0598	6.24085	6.27038	6.33514
2	-88.3734	.23775	1	0.626	31.9599	6.30161	6.34591	6.44306
3	-48.5769	79.593*	1	0.000	2.20315	3.626	3.68506*	3.81459*
4	-47.4457	2.2625	1	0.133	2.18704*	3.61695*	3.69078	3.85269

* optimal lag
Endogenous: shareprice
Exogenous: _cons

Figure B.2. Output for the Augmented Dickey-Fuller test of the *naturalgasprice*, *diff_naturalgasprice*, *crudeoilprice*, *inflationrate*, *diff_inflatiorate*, *temperature and shareprice* for Initial Attack period

```
ugmented Dickey-Fuller test for unit root

ariable: naturalgasprice                    Number of obs  = 29
                                            Number of lags =  3

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)             -1.283     -3.723      -2.989       -2.625

acKinnon approximate p-value for Z(t) = 0.6369.
```

```
ickey-Fuller test for unit root             Number of obs  = 31
ariable: diff_naturalga~e                   Number of lags =  0

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)             -9.129     -3.709      -2.983       -2.623

acKinnon approximate p-value for Z(t) = 0.0000.
```

```
ariable: crudeoilprice                      Number of obs  = 28
                                            Number of lags =  4

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)             -2.984     -3.730      -2.992       -2.626

acKinnon approximate p-value for Z(t) = 0.0364.
```

```
ariable: inflationrate                      Number of obs  = 28
                                            Number of lags =  4

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)             -1.956     -3.730      -2.992       -2.626

acKinnon approximate p-value for Z(t) = 0.3064.
```

```
 dfuller diff_inflatiorate

ickey-Fuller test for unit root             Number of obs  = 31
ariable: diff_inflatior~e                   Number of lags =  0

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)             -8.477     -3.709      -2.983       -2.623

acKinnon approximate p-value for Z(t) = 0.0000.
```

```
 dfuller temperature, regress lags(4)

ugmented Dickey-Fuller test for unit root

ariable: temperature                        Number of obs  = 28
                                            Number of lags =  4

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)             -3.058     -3.730      -2.992       -2.626

acKinnon approximate p-value for Z(t) = 0.0299.
```

```
ariable: shareprice                         Number of obs  = 28
                                            Number of lags =  4

0: Random walk without drift, d = 0

                                     Dickey-Fuller
                   Test          ——— critical value ———
              statistic         1%          5%          10%
Z(t)              0.017     -3.730      -2.992       -2.626

acKinnon approximate p-value for Z(t) = 0.9599.
```

Figure B.3. Output for the AIC criterion of *the naturalgasprice*, *crudeoilprice*, *inflationrate*, *temperature and shareprice* for Full-cale War

. varsoc naturalgasprice

Lag-order selection criteria

Sample: 38 thru 66 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-117.497				207.34	8.17221	8.18698	8.21936
1	-115.792	3.4103	1	0.065	197.536	8.12358	8.15311	8.21787
2	-106.385	18.813	1	0.000	110.685	7.54382	7.58812	7.68527
3	-96.8074	19.156	1	0.000	61.3213	6.95223	7.0113	7.14083
4	-89.8557	13.903*	1	0.000	40.7465*	6.54177*	6.6156*	6.77751*

* optimal lag
Endogenous: naturalgasprice
Exogenous: _cons

. varsoc crudeoilprice

Lag-order selection criteria

Sample: 38 thru 66 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-120.166				249.24	8.35627	8.37103	8.40341
1	-101.289	37.755	1	0.000	72.6528	7.12335	7.15288	7.21765
2	-100.792	.99339	1	0.319	75.2583	7.15806	7.20236	7.29951
3	-98.9647	3.6544	1	0.056	71.1582	7.10101	7.16008	7.28961
4	-96.1207	5.688*	1	0.017	62.7679*	6.97384*	7.04767*	7.20958*

* optimal lag
Endogenous: crudeoilprice
Exogenous: _cons

. varsoc inflationrate

Lag-order selection criteria

Sample: 38 thru 66 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	57.7717				.001167	-3.91529	-3.90052	-3.86814
1	59.901	4.2587	1	0.039	.00108	-3.99317	-3.96364	-3.89888
2	67.5289	15.256	1	0.000	.000684	-4.45027	-4.40597	-4.30883
3	115.313	95.567	1	0.000	.000027	-7.67673	-7.61766	-7.48814
4	118.351	6.0772*	1	0.014	.000024*	-7.81732*	-7.74349*	-7.58158*

* optimal lag
Endogenous: inflationrate
Exogenous: _cons

. varsoc temperature

Lag-order selection criteria

Sample: 38 thru 66 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-99.0698				58.1783	6.90136	6.91613	6.94851
1	-87.6739	22.792	1	0.000	28.4102	6.1844	6.21394	6.2787
2	-85.2024	4.9429	1	0.026	25.682	6.08293	6.12722	6.22437
3	-80.2923	9.8202	1	0.002	19.6319	5.81326	5.87233	6.00186
4	-66.5221	27.54*	1	0.000	8.15115*	4.93256*	5.00639*	5.1683*

* optimal lag
Endogenous: temperature
Exogenous: _cons

. varsoc shareprice

Lag-order selection criteria

Sample: 38 thru 66 Number of obs = 29

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-123.811				320.472	8.60764	8.62241	8.65479
1	-123.454	.71395	1	0.398	335.068	8.65199	8.68152	8.74629
2	-123.131	.64526	1	0.422	351.276	8.69871	8.743	8.84015
3	-76.1625	93.937	1	0.000	14.7662	5.52845	5.58751	5.71704
4	-73.8008	4.7233*	1	0.030	13.4657*	5.43454*	5.50837*	5.67028*

* optimal lag
Endogenous: shareprice
Exogenous: _cons

Figure B.4. Output for the Augmented Dickey-Fuller test of *the naturalgasprice, diff_naturalgasprice, crudeoilprice, diff_crude, inflationrate, diff_inflatiorate, temperature, diff_temp and shareprice* for Full-scale War

```
Variable: naturalgasprice                          Number of obs  = 28
                                                   Number of lags =  4

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -1.776         -3.730       -2.992       -2.626
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.3925.
```

```
Dickey-Fuller test for unit root                   Number of obs  = 31
Variable: diff_naturalga~e                         Number of lags =  0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -8.305         -3.709       -2.983       -2.623
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Variable: crudeoilprice                            Number of obs  = 28
                                                   Number of lags =  4

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -1.029         -3.730       -2.992       -2.626
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.7424.
```

```
dfuller diff_crude

Dickey-Fuller test for unit root                   Number of obs  = 31
Variable: diff_crude                               Number of lags =  0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -6.518         -3.709       -2.983       -2.623
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Variable: inflationrate                            Number of obs  = 28
                                                   Number of lags =  4

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -1.351         -3.730       -2.992       -2.626
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.6055.
```

```
dfuller diff_inflatiorate

Dickey-Fuller test for unit root                   Number of obs  = 31
Variable: diff_inflatior~e                         Number of lags =  0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -9.473         -3.709       -2.983       -2.623
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Variable: temperature                              Number of obs  = 28
                                                   Number of lags =  4

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -0.620         -3.730       -2.992       -2.626
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.8664.
```

```
dfuller diff_temp

Dickey-Fuller test for unit root                   Number of obs  = 31
Variable: diff_temp                                Number of lags =  0

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)            -9.311         -3.709       -2.983       -2.623
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Variable: shareprice                               Number of obs  = 28
                                                   Number of lags =  4

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          ────── critical value ──────
              statistic            1%           5%          10%
─────────────────────────────────────────────────────────────────
 Z(t)             0.571         -3.730       -2.992       -2.626
─────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.9869.
```

APPENDIX C – ARIMA specifications

Figure C.1. ACF plot for the Initial Attack period

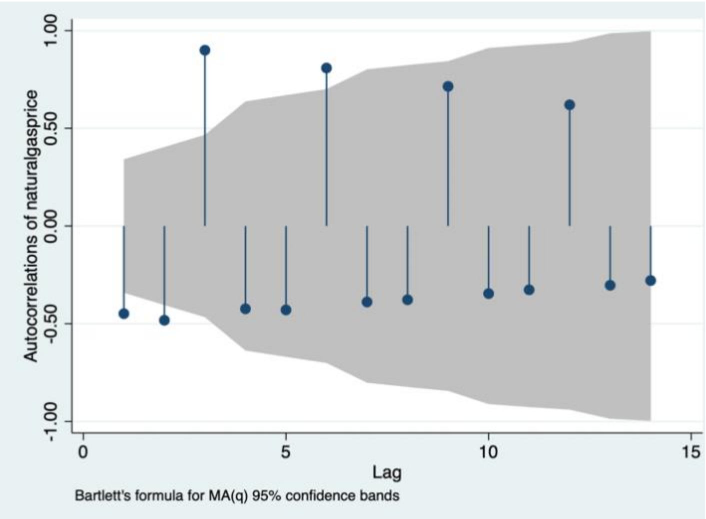


Figure C.2. PACF plot for the Initial Attack period

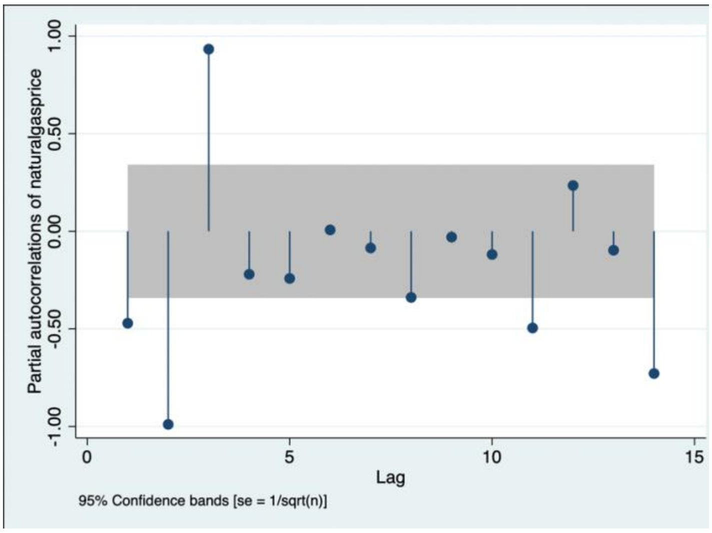


Table C.1. ARIMA model specifications for the "Initial Attack" and their respective AIC and BIC values

Model Specifications	AIC	BIC
2,1,1	33.845	49.968
2,1,2	32.299	48.422
2,1,3	N/A	N/A
3,1,3	34.599	55.120
3,1,2	35.753	54.808

Figure C.3. PACF plot for the Full-scale War period

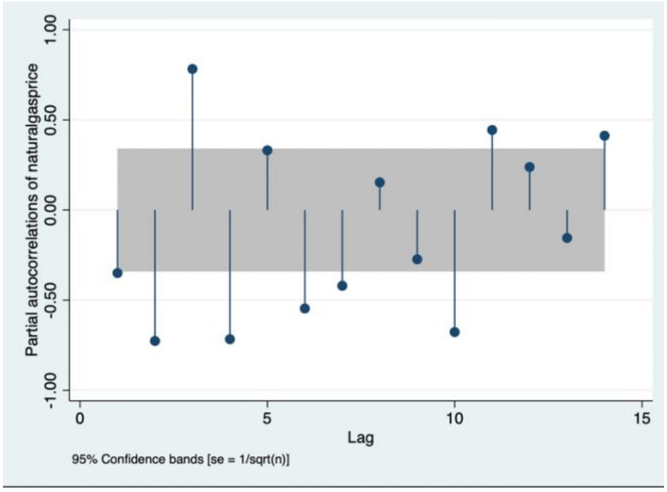


Figure C.4. ACF plot for the Full-scale War period