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The repercussions of Russia-Ukraine conflict on the global supply chain: A correlation and estimation analysis of electricity, crude oil and natural gas prices

Leonidas P. Tsetouras

Supervisor: Nikolaos Thomaidis

Patras, Greece, June 2024

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Leonidas P. Tsetouras

Supervising Committee

Supervisor:

Nikolaos Thomaidis

Professor, Department of Financial and Management Engineering, University of the Aegean

Co-Supervisor:

Michael Geranios

Adjunct Professor of Aegean University

Ioannis Giannikos

Professor, Department of Business Administration, University of Patras

Patras, Greece, June 2024

This dissertation is dedicated to my family

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Abstract

This dissertation tries to investigate the implications of the military conflict between the Russian Federation and Ukraine on the global supply chain and in addition to interpret the recent volatility of the electricity, crude oil and natural gas prices. Moreover, it is examined whether major energy sources prices like crude oil price and natural gas price are indeed interrelated to electricity prices and to what extent their fluctuations affect the global supply chain network.

Keywords

Global supply chain, Time series analysis, Energy prices estimation

Οι επιπτώσεις της σύγκρουσης Ρωσίας-Ουκρανίας στην παγκόσμια εφοδιαστική αλυσίδα: Μια ανάλυση συσχέτισης και εκτίμησης των τιμών του ηλεκτρικού ρεύματος, του αργού πετρελαίου και του φυσικού αερίου

Λεωνίδας Π. Τσέτουρας

Περίληψη

Η παρούσα διατριβή προσπαθεί να διερευνήσει τις επιπτώσεις της στρατιωτικής σύρραξης ανάμεσα στη Ρωσική Ομοσπονδία και την Ουκρανία στην παγκόσμια εφοδιαστική αλυσίδα και επιπρόσθετα να ερμηνεύσει την πρόσφατη μεταβλητότητα των τιμών του ηλεκτρικού ρεύματος, του αργού πετρελαίου και του φυσικού αερίου. Επίσης, εξετάζεται κατά πόσον οι τιμές μείζονων ενεργειακών πόρων όπως οι τιμή του αργού πετρελαίου και η τιμή του φυσικού αερίου αλληλοεπιδρούν μεταξύ τους και με την τιμή του ηλεκτρικού ρεύματος και σε ποιο βαθμό οι μεταβολές τους επηρεάζουν την παγκόσμια εφοδιαστική αλυσίδα.

Λέξεις – Κλειδιά

Παγκόσμια εφοδιαστική αλυσίδα, Ανάλυση χρονολογικών σειρών, Εκτίμηση ενεργειακών τιμών

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List of Abbreviations & Acronyms

GSPI: Global Supply Chain Pressure Index

US: United States

EU: European Union

VAR: Vector Autoregressive

SMA: Simple Moving Average

EWMA: Exponentially Weighted Moving Average

DF: Degrees of Freedom

ERP: Electricity Retail Price

NGP: Natural Gas Price

1. THE GLOBAL SUPPLY CHAIN

1.1 Introduction

1.1.1 Background of the study

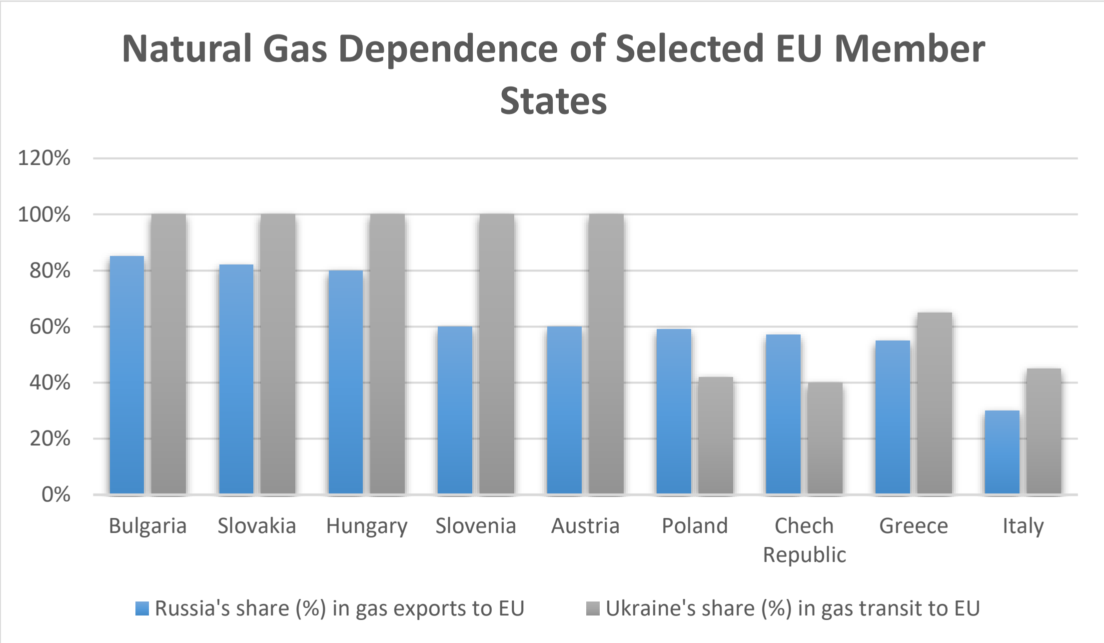
Several events of the geopolitical history have resulted in the change of dynamics within the global supply chain. One such most recent event is the Russia-Ukraine conflict, which has sent tremors throughout international trade, economics and energy policy. Comprehending the Russia-Ukraine conflict calls for further probing into the geopolitics that underpin contemporary world relations.

Russia and Ukraine have always had immense cultural, political and economic relations dating back from the past centuries. However, during the post-Soviet period there has been a lot of turbulence and tension as regards the relations between the two nations leading to the annexation of Crimea by the Russian Federation in 2014 and continued fights (Delcour, 2017). The conflict between Russia and Ukraine is not just a regional issue but its implications are far-reaching enough to attract major world powers and international organizations. The sanctions imposed on Russia by Western countries – specifically by the United States (US) of America and the European Union (EU) member-states – are also escalating complications within global trade frameworks (Tolkachev & Teplyakov, 2022).

The scientific field of energy economics and energy systems management particularly intersects with geopolitical tensions and military conflicts. It should be mentioned that the Russian Federation is among the world's top producers of energy, more specifically natural gas and crude oil. In fact, the Russian national companies such as Rosneft in oil production sector and Gazprom in natural gas sector are large producers in these sectors respectively affecting the global energy markets (Falola & Genova, 2008). Hence Russia's role is quite significant in the global energy markets and therefore the global supply chain which is affected by the fluctuation of crude oil price and natural gas price, because they are widely used not only as fuels of transportation and heating but also as raw materials in the manufacturing sector. For example, some oil derivatives are used in the manufacturing of plastic products.

On the other side, Ukraine is also an important player in the transmission of the Russian natural gas into several European countries. This fact as is illustrated in the Figure 1 below.

Figure 1: Natural Gas Dependence of Selected EU Member Sates



Source: (Eurogas, 2015).

Consequently, any disruption in the transmission system of Russian natural gas from Ukraine to European Union countries can cause natural gas prices fluctuations. The countries which are most dependent on the Russian natural gas are the ones with high geographical proximity to Russia (Anderson, 2020).

This ongoing conflict has global effects on the international supply chain beyond the immediate region of the two nations. World logistics and supply chain activities are also affected by air travel disruption incidents due to the airspace closure (Simchi-Levi & Haren, 2022).

Similarly, combined with other logistical challenges, trade sanctions have brought a new risk to reconfiguring supply chains as companies review their strategies and operations (Krykavskyy et al., 2023).

In addition, the rippling effects of such events are strengthened by an intricate network that defines global energy supply chains. Energy markets tend to interrelate to each other in a complex network which forms mutual economic interdependencies (Cui, L. et al., 2023).

Understanding these interdependencies helps explain why some geopolitical tensions, including the Russia-Ukraine case, raise alarm among nations leaders and policy makers who fear of the fact that such tensions could set off cascading effects within the entire economic system of the world. As more countries are interconnecting with each other in trade and economics, all of them would need to account for or mitigate such conflicts' possible effects on international trade and economics. This study will seek to highlight these dynamics focusing more on the impacts that arise from the Russia-Ukraine conflict on the global supply chain and the volatility of electricity, crude oil and natural gas prices.

1.1.2 Research problem statement

The global supply chain is an intricately weaved mesh that continues to remain vulnerable towards geopolitical tensions and occurrences like the recent Russia-Ukraine conflict. While the implications of this conflict can be seen as reverberating across multiple domains such as political, economic and social, the global supply chain management is the domain which has shown acute sensitivity to the perturbations brought about this standoff (Simchi-Levi & Haren, 2022).

One of the sectors that has been heavily prone to the Russia-Ukraine conflict is the global energy sector. Russia plays a significant role in the global energy markets since it is one of the largest oil-producing countries and one of the largest suppliers of natural gas globally meaning that the ongoing conflict threatens to disrupt the supply of crude oil and natural gas to a great extent. Also, Ukraine serves as a transit country for most energy exports from the Russian Federation destined to European Union countries complicating even more this fragile status quo (Anderson, 2020).

The volatility has been translated into soaring global energy prices. Hence, there are several nations, corporations and consumers that are concerned about the future price stability in energy markets. The complex nature of the problem is deepened even further by the interrelation of electricity, crude oil and natural gas prices. Eventual fluctuations of commodities prices affect the supply chain on a global level (Cui, L. et al., 2023).

The logistics implications of the conflict are far reaching. The sanctions imposed on Russia and the various restrictions put on airspace as well as transport routes have not only impacted the fighting countries but also had a fallout in global logistics and supply chains. For instance, the cancellation and diversion of flights affect global cargo movements in the air logistics chains, therefore delivery delays and increased cost of transportation across the world have been noticed in several occasions during the ongoing conflict (Simchi-Levi & Haren, 2022). The same applies to the maritime logistics chains due to the increased price of oil since most of the vessels in the shipping industry use oil as main fuel for their engines.

The wider repercussions of the conflict on the global trade should also be considered. Other than energy and logistics, the potential reconfiguration of the global supply chains of various goods from agriculture to technology are facing major issues. Business strategies which were once built on stable relations they are now facing uncertainties and reconsider risk management and operation structure (Krykavskyy et al., 2023).

Having said that and with this multi-faceted problem at the focus of the study, there is a need to know the subsequent:

- The direct and future impacts of the Russia-Ukraine conflict on the global supply chain and particularly on the major energy prices.
- The cross-impact relationships between electricity, crude oil and natural gas prices as well as how geopolitical events affect their volatile dynamics.
- Mitigative strategies that businesses and governments can apply in order to possibly adapt to combat the situation in an alternative supply chain design following such a global supply chain disruption.

On the whole, this research endeavors to meet the current knowledge gap in terms of analyzing the impact of Russia-Ukraine conflict on global supply chain network and estimation any potential volatility in major energy commodity prices such as crude oil and natural gas prices.

1.1.3 Objectives of the study

The geopolitically driven energy sector fluctuations of the Russia-Ukraine conflict will stand a strong base for serious academic work. Most western countries are left to face with the consequences of this tussle in global energy markets and therefore an overall detailed analysis of the problem is deemed highly relevant. The current research intends to search for the details about the conflict and its spillover effects on globe's supply chain particularly regarding electricity, crude oil and natural gas prices.

This research aims to assess the multidimensional implications of the Russia-Ukraine conflict on the global supply chain network. Wars and conflicts echoed across borders shaping international trade, policies and economic strategies. Historically, these reverberations had relatively minor repercussions on the global economy due to less interconnected economies. However, this is not the case nowadays when most of the economies are highly interconnected (Thomson, H., 2022). Taking the cue from the current conundrum between Russia and Ukraine, this study discusses how geopolitical standoffs can disrupt established supply chains, alter major commodities price and make governments and companies to revisit their strategies.

A like objective is to understand the correlations between primary energy prices. The global energy market, which is often characterized by complex interdependencies, often sees ripples in one segment translating waves in another. For instance, if oil supplies are disrupted, it would trigger price volatility regarding electricity and natural gas markets. There can be no better way than identifying and measuring these price correlations for both policy makers and industry stakeholders so that they make well-informed decisions (Liadze, I. et al., 2022).

Furthermore, given the prevailing geopolitical environment, estimating the energy prices precisely seem to be a research endeavor of high importance. Thus, another aim of this study is the model construction for electricity, crude oil and natural gas price estimates. Effective estimates could avail governments and commercial organizations with the ability to foretell an impending crisis well in advance and then respond through anticipation rather than expostulation after it has already happened (Cui, L. et al., 2023).

Lastly, the statistical properties of the examined time series data will be invaluable in unravelling their inherent patterns such as stationarity and eventual trends. An essential analysis is needed to separate out effects propagated from external shocks such as geopolitical events and those that are attributable to internal market forces (Boungou , W.; Yatie, A., 2022).

1.1.3 Significance of the study

The research about the Russia-Ukraine conflict and its impact on global energy markets, including its corresponding supply chains is a must know subject especially in this integrated world where economies of nations are intertwined among themselves. There are several facets in this research: economic, geopolitical as well as environmental implications.

Economically, the global energy market represents one of the backbones of international trade as well as economic development. Energy, in whatever forms or sources propels industries, determine pricing for consumer goods affecting fiscal management as governments amend their budgets due to oil price differentials (Thomson, 2022). Hence, major disruptions or volatility in the energy markets because of geopolitical events like the Russia-Ukraine conflict may easily resonate across countries causing cascading effects on economies. This study provides insights through interdependencies and causal connections that exist among major energy commodities prices for stakeholders' better anticipations of potential imminent challenges towards economic stability (Liadze, Macchiarelli & Mortimer, 2022). Policymakers cannot afford not to know these dynamics since this is very important when drawing regulations, tariffs, and trade agreements so as economies can gain from sustained resilience.

Geopolitically speaking, the research highlights how nation-state conflicts could be influential in a globalized environment. The Russia-Ukraine confrontation is not an issue that stands single; it proves how regional disputes can take disproportionately large global scenarios (Boungou & Yatie, 2022). The findings of this research may shape diplomatic discourses, international agreements and also military strategies that nations might adopt to balance both national interest and general peace in the world.

The global environmental and food crisis aspects further boost the significance of this study. According to Carriquiry et al. (2022), food insufficiency and carbon emission issues may get worse with geopolitical tensions on the rise (Carriquiry, Dumortier, & Elobeid, 2022). In that regard, understanding probable environmental consequences by studying interruptions in the energy market due to the examined conflict is crucial. Countries which work towards sustainability and aim to tackle climate change may find this information useful.

In addition, this research could be taken as bridging a very specific gap in the literature when viewed from an academic perspective. Though several studies have been carried out on economic and environmental consequences of geopolitical conflicts, little work has been done by researchers to carry out a careful quantitative analysis of how such conflicts affect the energy supply chain per se (Carriquiry, Dumortier, & Elobeid, 2022). Therefore, this piece of work might trigger other academicians into similar areas while also providing related scientific fields students and scholars with insight for future reference.

Taking everything into account, the significance of this research flows from its potential to make a difference in a wide array of sectors and stakeholders, ranging from global leaders and policymakers to industry professionals and academia. In a world beset by complex interdependencies, unraveling the ripple effects of geopolitical events that impact important sectors like energy is not just academic; it's critical for the future we want to co-create.

1.1.4 Limitations of the study

The analysis of the implications of Russia-Ukraine conflict on world energy market and supply chain reveals a detailed perspective of an intricate geopolitical as well as economic mess. On the other hand, this research does have certain limitations like all academic ventures that cannot be ignored in order to develop a concrete idea about the findings derived through it.

The first inherent challenge of the study would be that it is based on secondary data. Based on such research design, relying on information given by organizations such as International Energy Agency, Eurostat and Federal Reserve Bank of St. Louis means this work is limited by those sources both in regard to its accuracy, comprehensiveness or timeliness as regards giving accurate research (Sanders, Lewis, & Thornhill, 2016).

Even though they are known for being reputable sources of such information, some inconsistencies may arise with respect to how the data are collected - timelines or definitions - hence influence reliability and consistency.

Secondly, the Russia-Ukraine conflict is dynamic and still ongoing, which means that there are variables that may not fully be captured within this time frame of study. As things change, new economic, geopolitical, and social consequences will come into play that might fall outside research purview at present. Sanctions could change as well as political alliances and global responses to the conflict itself in ways that would greatly impact the energy market but have yet to occur during the period of the study (Boungou & Yatie, 2022).

Moreover, the study is mostly grounded on moving average methods and vector autoregression models, that is quantitative methods of analysis. While these techniques offer great empirical understanding, they may exclude qualitative nuances such as sentiments among stakeholders, narratives in media or countless geopolitical tensions that impact global markets with less palpable but substantial dynamics (Creswell & Poth, 2018).

In addition, the focus on electricity, crude oil, as well as natural gas prices, despite the fact they are crucial for the global supply chain, it leaves behind other vital aspects of the energy market such as renewables or nuclear energy. Such forms of energy notably in consideration with new sustainability developments might have critical places within the world's energy scene and could therefore bring extra facets to the Russia-Ukraine conflict implications (Thomson, H., 2022).

Lastly, while the study points out causal relationships between some major energy commodities prices, it is also of high importance recognizing all other factors affecting global markets. Recession, technological breakthroughs, pandemics, or natural calamities can intersect with consequences of Russia-Ukraine conflict and generate layered impacts on the energy market which this study might not fully disaggregate (Rwatani, D. et al., 2022).

This research endeavors a full-scale analysis of the chosen subject matter, yet its limitations should be taken into account by readers, scholars, and policymakers while interpreting the ensued research findings. Geopolitics is complex in nature to an extent that serious academic investigations of such issues are inherently bound to have certain limits, but also commodities prices are prone to intense volatility triggered by major political or economic events. As a result, estimating energy prices accurately is not an easy task.

1.2 Literature Review

1.2.1 Global supply chain: An overview

The concept of global supply chains has been brought to the fore in contemporary business and economics with the coming of globalization and integration of economies. In its simplest sense, a supply chain is known as the string that connects various processes involved for providing an output commodity from production to distribution. But when realized on a world stage, it tends to get more complicated and challenging.

According to Christopher (2016), a global supply chain can be seen as being the network of businesses whose interconnectedness support the provision of packages comprising products and services required by end consumers in a large space known as the global market. The manner through which Christopher provides his views brings out an all-round perspective on how far and huge these chains are, stretching around continents and connecting numerous types of businesses-whether small or big (Christopher, 2016).

The advantages linked to global supply chains explain their rapid expansion. Some of the main reasons, according to Jacobs et al. (2011), include cost savings or efficiencies, access to new markets, as well as risk spreading or diversification by firms. For instance, through offshoring or outsourcing components where costs are lower in foreign countries, companies save much of their expenditure in manufacturing products. Besides reducing production costs, joining global supply chains has also been seen as a strategy that allows firms to tap innovation across many parts of the world thus enhancing their product lines (Jacobs, Chase, & Lummus, 2011).

Apart from that, the magnitude and the complexity of supply chains globally also create problems. Ivanon et al. (2019) discussed how sensitive such chains are to various types of disruptions. These range from geopolitical events to natural disasters or catastrophes and technology breakdowns. The ongoing Russian-Ukraine conflict and the COVID-19 pandemic a couple of years ago were ideal examples of how interrelated systems worldwide could be threatened by great disturbances (Simchi-Levi & Haren, 2022).

Another issue that has generated a public debate relates to the ethical dimension of global supply chain. Carter and Rogers (2008) affirm that sustainability should be a core aspect of supply chain management. The dawn of 'fast fashion' followed by probes into factory conditions in developing countries is a proof of the ethics hurdles that globalization brings for most players in the chain (Carter & Rogers, 2008). Therefore, even though businesses can accrue greatly from such chains, their responsibilities cannot be ignored.

Global supply chains have become a core part of the current business world, essentially driving growth in an economy and improving trade on a global platform. As much as they come with various benefits such as offering low costs for businesses including new markets access avenues, challenges are eminent areas that need strategic attention and mitigation measures. With increasing global interconnectivity, there will be little room to escape comprehending and effectively managing these chains by entities across the globe.

1.2.2 The repercussions of the Russia-Ukraine conflict on the global supply chain

Rarely have there been such contemporary geopolitical events which send shock waves through global supply chains like the Russia-Ukraine conflict. Based on historical, political and territorial disputes, this escalation of tensions has not only sparked a regional fire but cast an all-reaching shadow over trade and business worldwide.

One understanding from this conflict on global supply chains is that Russia holds a significant position with regard to its role as the supplier to the world for various commodities. For instance, it qualifies among the largest suppliers of natural gas and oil globally where Europe is one of the leading consumers (Anderson, 2008). Any intermission or sanctions on Russian exports are direct influences on worldwide energy prices and subsequently affect industries reliant upon such kind of energy by changing their operating costs. As Anderson (2008) posits, Europe's dependence upon Russia for natural gas means both economic and strategic vulnerabilities since disruptions can render industries crippled resulting in energy crises within countries.

The conflict spilled out beyond the energy sector and impacted agriculture, a fact that is emphasized by Ukraine's nickname as the "breadbasket of Europe." The war has concerned food security given the vast amounts of wheat, corn, and sunflower oil exported out of Ukraine (Rawtani et al., 2022). In addition to these concerns are those towards potential ecological damage from the ongoing conflict- another factor to potentially strain agricultural output (Rwatani, D. et al., 2022).

The ripple effect of the conflict is not commodity-oriented only but instead reaches every corner and realm of global logistics. A maritime route such as the Black Sea, for instance, experienced decreased shipping activity because of the conflict which affects trade routes and thereby promoting delays and uncertainties (Simchi-Levi & Haren, 2022). This logistic challenge even worsens supply chains that are already on ice, more so in a current era where just-in-time systems have become a common practice with little slack time or manufacturing errors allowed.

From a more strategic perspective, the conflict reveals the inherent danger of over-concentration on certain regions or suppliers. It alludes to the necessity of diversification in supply chain management. Organizations and nations have to reflectively weigh and strike a compromise between efficiency and resilience so that they do not get excessively exposed to geopolitical risks from any particular region (Simchi-Levi & Haren, 2022).

Within these challenges is the silver lining - an opportunity for innovation and change. The disruptions brought into attention about by the Russia-Ukraine conflict may just be what businesses need in order to seriously consider other sources, more sustainable practices, as well as investments in technologies that can enable them to track and mitigate such geopolitical risks with greater diligence.

As a result, the Russia-Ukraine conflict presents a stark reminder of how easily global supply chains are affected by geopolitics. Immediate effects comprise energy, agriculture, and logistical disruptions; long-term impacts suggest a shift towards better strategizing supply chain management through diversification and sustainability.

In the recent past, globalization has integrated the global economy to have intertwined destinies where events taking place in one corner of the world can send shockwaves through the breadth and width of global fabric. Such is that nature of Russia-Ukraine conflict with its multidimensional consequences cutting across many other areas like economic, environmental, and sociopolitical aspects.

Economically, the war has posed deep-seated problems. Indeed, the EU's dependence on Russian natural gas exemplifies this vulnerability (Anderson, 2008). In fact, such reliance does not only affect energy prices but trickles down to impact consumer goods and services prices due to the spillover effect in the most-energy-intensive industrial sectors. These economic factors are compounded by disturbances in Ukrainian agricultural exports despite featuring amongst the world's key food exporters. Such economic disruptions trigger inflationary tendencies that erode living standards while intensifying disparities within nations and across countries (Thompson, 2022).

Environmentally, wars traditionally present a broad ecological footprint and that the Russia-Ukraine conflict is not an exception. Infrastructure damages, oil spills as well as more possible significant ecological disasters are acute threats. A notable aspect highlighted by Rawtani et al. (2022) refers to the direct environmental damages credited to the conflict in terms of air and water pollution due to bombings and destruction. Longer-term issues on environment also emerge such as nuclear concerns and degradation of farmlands which might have potential implications on food security as well as biodiversity losses.

Additionally, the business leaders and policy makers try to reorganize their strategy ramifications to reshape their organizations or their countries socio-politically. The human cost, in terms of refugees, death tolls and traumas are incalculable (Delcour, 2017). Furthermore, the war reconfigures nations' diplomatic alignments, trade partners if not defense and foreign policies with other countries. For instance, the EU has had its energy security threatened by a simple but potent existential question on the diversification of energy sources and dependencies (Anderson, 2008). Far beyond these immediate issues are global power dynamics which place the role of the conflict as an impetus for discussions towards collective security arrangements, alliances and international institutional deliberations relating to mediation processes.

Essentially, the Russia-Ukraine conflict is similar to other major global geopolitical occurrences: it is a magnifying lens exposing the fragility and interdependence of our world system. Although naturally fearsome in terms of implications for stability, the immediate concerns associated with today's pressing challenges also present countless opportunities. These challenges can be catalysts or triggers that propel nations and institutions alike into reformulating, redesigning, and strengthening their approaches so as to emerge stronger, more dynamic members of an improved global status quo.

According to Krykavskyy et al. (2023), since the beginning of the war the majority of supply chains have been disrupted. Even the supply chains of global companies, which seemingly have a wide arsenal of contingency plans, preferred security – are suspending or limiting their activities in the Ukrainian market. Instead, internal supply chains, having felt the consequences and extent of the destruction and their impact on all aspects of life, despite the risks, sought opportunities for recovery failure of supply chains – was logistics. Damage to infrastructure has led to limited logistics capacity, lack of drivers and vehicles available (Krykavskyy, Y. et al., 2023).

The geopolitical conflict between Russia and Ukraine is likely to result in a new round of allocation of energy resources on a global scale, thus reflecting the complex interactions and interdependence between geopolitics, the geo-economy, and energy resources (Cui, L. et al., 2023).

1.2.3 Energy prices and their interrelation: previous findings

Geopolitical events and the prices of energy, particularly natural gas and oil, are bound by a dynamic nexus that explains why they have received considerable attention from academia throughout time. Energy markets' complex dynamics which lean on supply as well as demand shocks have historically emulated worldwide geopolitical tensions to ensure their central position within the world economy.

Oil prices have traditionally represented a meter of the world economy due to oil influence pervading nearly every sector (Hamilton, 1983). A notable finding is that severe price fluctuation often accompanies significant events in international relations. The most famous example was the tripling of prices when OPEC declared an oil embargo in 1973 which caused global recession and initiated discussions on energy conservation as well as sources for it to start with (Yergin, 1992).

The European continent that displays huge dependence on Russian natural gas provides a special case study in energy geopolitics. Anderson (2008) had discussed its effects through elaboration, warning how any disruption of supply or strategic manipulation can have severe economic and political repercussions for the European Union as well. This assessment is shared by Thompson (2022), who has written about how the Russia-Ukraine conflict has made anxieties levels to shot up in most European capitals while prices swung wildly due to fears of disruptions in supplies.

Besides geopolitical events, there are also other economic indicators that significantly affect energy prices. As Kilian (2009) explained, oil price hikes should not be generalized since some of them can be due to emerging strong demand all over the globe while others are an effect of supply shortages because of geopolitical tensions (Kilian, 2009).

In addition, the environmental imperative has been slowly shaping energy markets. The global shift to cleaner energy supplies as espoused by the Paris Agreement which has brought with it another set of dynamics resulting in an increasing adoption of renewable energy sources by the developed countries.

Traditionally, energy prices have been intertwined with geopolitical issues, economic well-being, and more recently environmental concerns. Understanding these complex linkages is more critical in light of the current international events so that robust policies pertaining to energy and economics could be derived.

2. METHODOLOGY

This dissertation applies quantitative research methods using secondary data from the International Energy Agency and historical stored data from the Economic Research Division of the Federal Reserve Bank of St. Louis and the Federal Reserve Bank of New York to meet the probed research objectives. In order to do so it uses simple moving average and weighted moving average estimation models as well as vector autoregressive models to estimate the interrelation between the scrutinized energy prices. More specifically, the research study focuses on the global supply chain pressure index to quantify the repercussions of the military conflict on the global supply chain network and examines whether there is a correlation between the average city price of electricity per kilowatt-hour in US dollars, the global price of natural gas in US dollars per million metric British thermal unit and the price of Europe's brent crude oil in US dollars per barrel and to what extent these prices can be estimated. It should be noted that the afore mentioned time series taken are not seasonally adjusted.

2.1 Time Series Analysis

According to Thomaidis (2022), a time series is a data set of observations ordered by time

$$\{y_t; t = 1, \ldots, T\}$$

which show the development of a random variable during the course of time. The difference between time series data and cross-sectional data is that the latter include observations related to a specific unit (Thomaidis, 2022). In essence, the time series analysis accentuates the dependence among observations at various points in time with the temporal order being the distinguishing feature of time series analysis. Also, the correlation between the current and the past values of the probed variables are studied in time series analysis models, that is the relationships of variables over time.

Several economic time series alter dynamically at irregular intervals being consistent with economic models which state the existence of floors and ceilings, buffer stocks and regime data changes. Time series analytics models have many applications in economics and business administration such as dynamic econometric modelling and estimation of economic variables.

According to Thomaidis (2022), the properties of a time series are the following:

i. Deterministic trends
ii. Periodicity and seasonality
iii. Stationarity

As regards deterministic trends, a time series Y_t follows a deterministic trend if it meets the below decomposition:

$$Y_t = \gamma_t + Z_t$$

Where γ_t is a deterministic function of time and Z_t is another zero-mean stationary time series. It is worth mentioning that deterministic trends are either descending or ascending and linear or non-linear.

In regards to periodicity and seasonality, a time series behaves periodically or cyclically if it has similar values in recurring time periods. The deterministic part γ_t is a periodic function of time here. Therefore, there is a constant τ, which is the period, for each sample period such that $\gamma(t) = \gamma(t - \tau) = \gamma\ (t + \tau)$. Periodicity is a special case of a trend and seasonality is a special case of periodicity where the period τ is equal to a year. That means that periodicity and seasonality differ.

On stationarity, a stationary time series is the one which is stable over a specific period of time. It should be noted that the property of stationarity could also be referred to the cardinal metrics of probability distribution like the mean, the variance and the autocovariance. That is, a time series could be respectively stationary in mean, variance or covariance. In the weak sense of the term, a time series Y_t is stationary if:

- $E(\mathrm{Y_t}) \equiv \mu$ (constant mean)
- $\mathrm{Var}\ (\mathrm{Y_t}) \equiv \mathrm{E}\ [(\mathrm{Y_t} - \mu^2] \equiv \sigma^2$ (constant variance)
- $\mathrm{Cov}\ (\mathrm{Y_t}, \mathrm{Y_{t+h}}) \equiv \mathrm{E}[(\mathrm{Y_t} - \mu)\ (\mathrm{Y_{t+h}} - \mu)] \equiv \gamma_\mathrm{h}$ (autocovariance is a function of the time lag h).

2.2 Descriptive Statistics

Descriptive statistics are used for the summarization of the sample data. According to Fraser (2016), depending on the type of the data, descriptive statistics give information about the central tendency, the dispersion, the symmetry and the graphics of the data as described in the below table.

Table 1: Descriptive statistics for quantitative and categorical variables

	Quantitative	**Categorical**
Central tendency	Mean Median	Mode Proportion
Dispersion	Range Standard deviation	
Symmetry	Skewness	
Graphics	Histogram Cumulative distribution	Pie chart Column chart

Source: (Fraser, 2016).

In case the data are continuous with bell shape distribution, descriptive statistics can provide information about the mean, the median, the mode and the range of the data.

Measures of central tendency

The **median** M_e of a set of observations is the middle element of the ordered data set.

If the number of elements n is odd: the $\frac{n+1}{2}$-th element.

If the number of elements n is even: the mean of the $\frac{n}{2} - th$ and the $(\frac{n}{2} + 1) - th$ element.

The **mode** $\boldsymbol{M_0}$ of a sample is the observation with the highest frequency.

The **arithmetic mean,** $\bar{x}$, of observations $x_1, x_2, \ldots, x_n$ of a sample with n observations is $\bar{x} = \frac{1}{n}(x_1 + x_2 + \cdots + x_n) = \frac{1}{n}\sum_{i=1}^{n} x_i$.

In case the arithmetic mean is calculated for the entire population with N elements, the formula of the **population mean** is $\mu = \frac{1}{N} \sum_{i=1}^{N} x_i$.

Measures of dispersion or variation

The **range** R of a data set of observations is the value of the largest minus the smallest observation:

$$R = x_{max} - x_{min}$$

The **sample variance** s^2 of a set of observations $x_1, \dots, x_n$ is

$$s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$$

The **population variance** $\boldsymbol{\sigma^2}$ for the entire population with N elements, is calculated as follows:

$$\sigma^2 = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N}$$

The **sample standard deviation** is the square root of the sample variance and it is calculated as follows:

$$s = \sqrt{s^2}$$

The **population standard deviation** is the square root of the population variance and it is calculated as follows:

$$\sigma^2 = \sqrt{\sigma^2}$$

Essentially, the measures of dispersion measure the variation around a central value, since data with the same mean might still differ concerning variation, whilst the measures of central tendency provide indicators about the size of a data set describing the central tendency of the data (Goos & Meintrup, 2015).

2.3 Vector Autoregressive Models

There are cases in which economic theory is not able to interpret the dynamic behavior that determines the complex relationships between the examined variables. Also, the endogenous variables may appear on both sides of the equation. This kind of problem has led to the creation of vector autoregressive (VAR) models which are considered to be the proper tool in estimating systems with correlative time series and the analysis of the dynamic impact of random disturbances on the variables system (Sims, 1980).

Vector autoregressive models are dynamic multivariate models which have been introduced by Sims (1980). These models arise mainly as a response to the incredible identifying assumptions embedded in traditional large-scale econometric models of Cowels Commission. The traditional approach uses predetermined or exogenous variables, coupled with many strong exclusion restrictions, to identify each structural equation. They explicitly recognize that all economic variables are interdependent and thus they should be treated endogenously. The notion of VAR modelling begins with a multivariate time series model that has minimal restrictions and gradually introduces identifying information with emphasis always placed on the model's fit to the data.

The methodology of VAR models focuses on identifying structural shocks as a way to specify the contemporaneous relationships among economic variables. With most dynamic relationships being unrestricted, the intent of such an identifying strategy is to construct models that have both economic interpretability and superior fit to data. Dynamic responses to a particular shock, called impulse responses, are often used as economic interpretations to the model. As a matter of fact, they are able to summarize properties of all systematic components of the system and have become a major tool in modelling economic analysis.

Due to their estimation an forecasting ability, VAR models have given researchers a useful tool to assess the feasibility or the plausibility of real-time policy projections of other economic models (Sims, 1980).

The term "autoregressive" refers to the appearance of the lags of the dependent variables on the right side of the equation. Regarding the term "vector", it refers to the fact that the system contains at least 2 variables (Sims, 1980).

If we have the following AR (p) model:

$$Y_t = a_0 + a_1 Y_{t-1} + a_2 Y_{t-2} + \cdots + a_p Y_{t-p} + e_t.$$

We assume that the variable Y is a vector of column k of variables $Y_{k,t}$, expressed as a function of its own time lags and is called autoregressive vector. The ensuing system of class k is constituted by the time lags of the dependent variables of the vector Y.

Thus, a VAR system for $p = 2$ lags and $k = 2$ endogenous variables (where k is the vector of the endogenous variable) are written in the subsequent form:

$$Y_{1t} = a_1 + a_{11} + Y_{1,t-1} + a_{12}Y_{2,t-2} + e_{1t}$$

$$Y_{2t} = a_2 + a_{21}Y_{1,t-1} + a_{22}Y_{2,t-2} + e_{2t}$$

According to Zha (1999) the most popular usage of the VAR models is for estimating the implications of structural shocks such as technology and policy shocks and that structural shocks should be independent of one another. The notion of VAR modelling starts with minimal restrictions on dynamic time series models, explores regularities ignored by simple models and gradually incorporates identifying information emphasized on the model's fit to data (Zha, 1999).

It should be underlined here that for the implementation of an autoregressive model the condition of stationarity must be in existence. In that case, the VAR model can be estimated with the Ordinary Least Squares (OLS) method in each equation (Mann & Wald, 1948).

The basic assumptions for the vector autoregressive models are the subsequent:

i) VAR models refer to time series which have been exempted from trend and other factors connected with frequency. In other words, the used time series have to be stationary.

ii) The time series e_{1t}, e_{2t} are white noise.

iii) The error terms are not cross-correlated at various lag orders. Therefore $E\left(e_{1t}, e_{2,t-j}\right) = 0 \; for \; j = 0,1,\ldots,n$.

The diagnostic control of the VAR models includes the following stages:

- Autocorrelation test of the residuals. It is done either with Portmanteau test or with Lagrange Multiplier test.

- Heteroskedasticity test of the residuals. This is conducted with autoregressive conditional heteroskedasticity test.
- Test of normality of the residuals. It is done with Jacque-Berra test.
- Test of the parameters structural stability which is done with Cumulative sum test.
- For the selection of the optimal class of the model, that is the maximum number of time lags, Likelihood Ration test or Lütkepohl method is deployed.
- The selection of the best model, that is the optimal number of time lags. Usually, the information criteria used are Akaike Information Criterion and Schwarz Criterion. The model with the smallest number of criteria is selected as the best.

2.4 Moving Average Methods

The moving average methods calculate the average of a small number of the immediate values of the estimated or forecasted time series rather than the entire time series (Christou, 2012). This dissertation applies the Simple Moving Average (SMA) and Exponential Weighted Moving Average (EWMA) methods for the estimation of the probed time series.

According to Thomaidis (2022), the SMA and EWMA models are calculated as follows:

The SMA (q) model:

$$\hat{Y}_{t+1} = E\ (Y_{t+1}|I_t) = (1/q)\sum_{j=1}^{q} Y_{t-j+1}$$

Where I_t stands for the information gathered by the predictor up to period t, $E(Y_{t+1}|I_t)$ is the expectation of Y_{t+1} given the information set I_t and q stands for the parameter which represents the length of the rolling window of the observations.

It should be underlined here that the lower the q, the better the incorporation of the changes in the course of the time series is, therefore the more the noise is included in the SMA estimates or forecasts (Thomaidis, 2022).

Respectively, the higher the q, the higher the estimating or forecasting strength of the EWMA model but lowly adaptive to trend changes (Thomaidis, 2022).

The EWMA model:

$$\hat{Y}_{t+1} = \hat{Y}_{t+1}(q, a_1, a_2, \ldots, a_q) = \sum_{j=1}^{q} a_j \, Y_{t-j+1}$$

Where $\hat{Y}_t$ is the moving average at time t, a is the degree of mixing parameter value between 0 and 1, q is the value of signal q at time q.

It is worth mentioning that EWMA models are deemed pretty effective as regards the short-term forecasts of the time series dynamics because they decrease the required parameters to be fine-tuned to a great extent (Thomaidis, 2022).

Overall, according to Holt (2004), the main differences between the above cited methods are summarized in the below table:

Table 2: Comparison of SMA and EWMA methods

SMA	**EWMA**
Same weight to all observations	More weight to recent immediate past observations
Lower adaptivity to abrupt alterations	Higher adaptivity to abrupt alterations
Low sensitivity to noise	High sensitivity to noise

Source: (Holt, 2004)

2.5 Measures of Estimation Accuracy

The evaluation of the estimation accuracy of the used estimation models has been conducted with the calculation of the below widely used statistical measures of estimation accuracy error (Wrinkler & Makridakis, 1983). These statistical criteria have the subsequent formulas:

Mean Squared Error: $MSE = \frac{1}{N} \sum_{t=1}^{N} e_t^2$

Root Mean Squared Error: $RMSE = \sqrt{\frac{\sum_{t=1}^{N} e_t^2}{N}}$

Mean Absolute Error: $MAE = \frac{1}{N} \sum_{t=1}^{N} |e_t|$

Mean Absolute Percentage Error: $MAPE = \frac{1}{N} \sum_{t=1}^{N} \left|\frac{A_t - F_t}{A_t}\right|$

Where N is the number of observations of the time series, e_t is the error term which is the difference between the actual and the estimated value, A_t is the actual value and F_t is the estimated or forecasted value.

It should be underlined here that the above cited statistical measures are not taken into account by investors and the users of the estimates of the trend. The investors are more concerned about the estimate of the direction of the trend and less about the minimalization of the statistical errors. Nevertheless, the above statistical criteria are used widely with regards to the comparison of the estimation models.

In this research study, the above-mentioned statistical measures of estimation accuracy are used to evaluate the estimation capacity of the used models for the probed time series.

3. EMPIRICAL STUDY

The empirical research and the presentation of the findings are performed using Excel and the econometrics program EViews. The historical data used in the research are monthly time series dating from January 2010 to September 2023 and their statistical properties are presented. Additionally, they are tested for stationarity, seasonality, trend and any pattern they might have. First, the GSPI index is presented historically to illustrate how the conflict influenced the global supply chain network and then the selected energy prices are estimated with the deployed estimation models. The variables are calculated at first differences so that any trends are eliminated because the data are non-stationary at levels. Then, some diagnostics tests are conducted on what it concerns the residuals of the deployed vector autoregressive model. Finally, the estimates are made for one month ahead utilizing the simple moving average and exponentially weighted moving average models as well as the standard vector autoregressive model with model specification the prices of electricity, brent crude oil and the natural gas as endogenous variables of the system.

3.1 Unit Root Tests and Descriptive Statistics

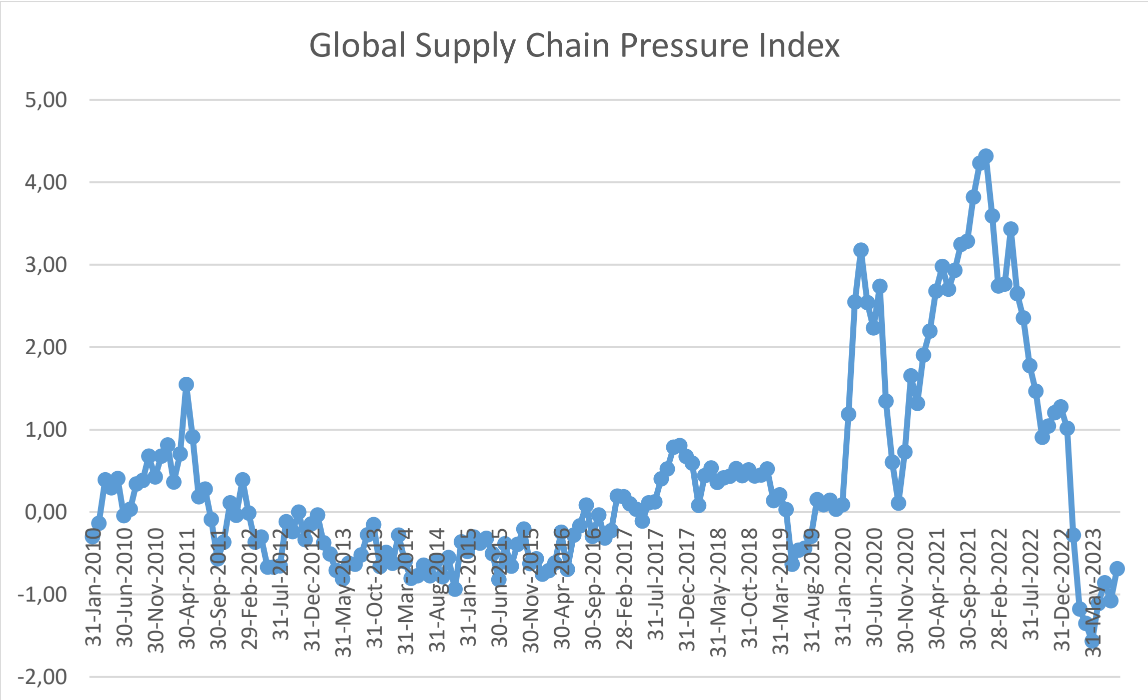
This section of the dissertation is about the statistical properties of the examined time series such as stationarity and linear trend. Moreover, the descriptive statistics of the time series are presented so that any variations are measured and any eventual outliers are detected. In order to do so, figures and tables are used providing an illustration of any patterns and trends with respect to the data.

The graphical representation of the time series data could be useful for researchers or investors interested in global supply chain and energy prices, since they present a detailed analysis of the overall development of these time series.

3.1.1 Global Supply Chain Pressure Index

The GSPI is depicted in the below figure with monthly observations taken from January 2010 until September 2023.

Figure 2: Global Supply Pressure Index



The GSPI quantifies the pressure of external shocks on the supply chain globally due to supply chain disruptions and supply restrains. It includes global transportation cost data and manufacturing indicators focusing on seven interlinked large economies which are the subsequent: the United States, the United Kingdom, the Eurozone area, Taiwan, China, South Korea and Japan.

Table 3: Global Supply Pressure Index descriptive statistics

Mean	0,372578
Standard Error	0,09339
Median	0,079215
Standard Deviation	1,199612
Sample Variance	1,43907
Kurtosis	1,40314
Skewness	1,384433
Range	5,88212
Minimum	-1,56515
Maximum	4,316971
Sum	61,47533
Count	165
Largest(1)	4,316971
Smallest(1)	-1,56515
Confidence Level(95,0%)	0,184401

Stationarity

Based on the results of the analysis, time series data that exhibit a constant mean and constant variance are classified as stationary data. However, the data being analyzed in this case indicate that the mean is not constant over time. The table also shows that the variance of the data has changed over the years. Non-stationary time series data can be more difficult to analyze, as the patterns and trends in the data may change over time, making it challenging to make accurate estimates.

The Phillips-Perron Test is used to test whether the time series is stationary.

Null Hypothesis: GSPI has a unit root

Exogenous: Constant

Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

The Phillips-Perron test statistic is -2.209770 and the p-value is 0.2037.

Test critical values:

At significance level a=1% level, the critical value is -3.471192.

At a=5% level, the critical value is -2.879380.

At a=10% level, the critical value is -2.576361.

Since p-value > a, the null hypothesis is accepted so it is deducted that the time series is non-stationary.

Linear Trend

According to data, it seems there is a long-term linear trend which is more intense after January 2020 when the military invasion of the Russian army into Ukrainian territory started. Also, the GPSI reaches its maximum value in December 2021, and then it plummets the following months. It should be noted that the index presents its minimum value in May 2023.

3.1.2 Electricity Retail Price

Figure 3: Electricity Retail Price per Kilowatt-Hour in US city average in US dollars

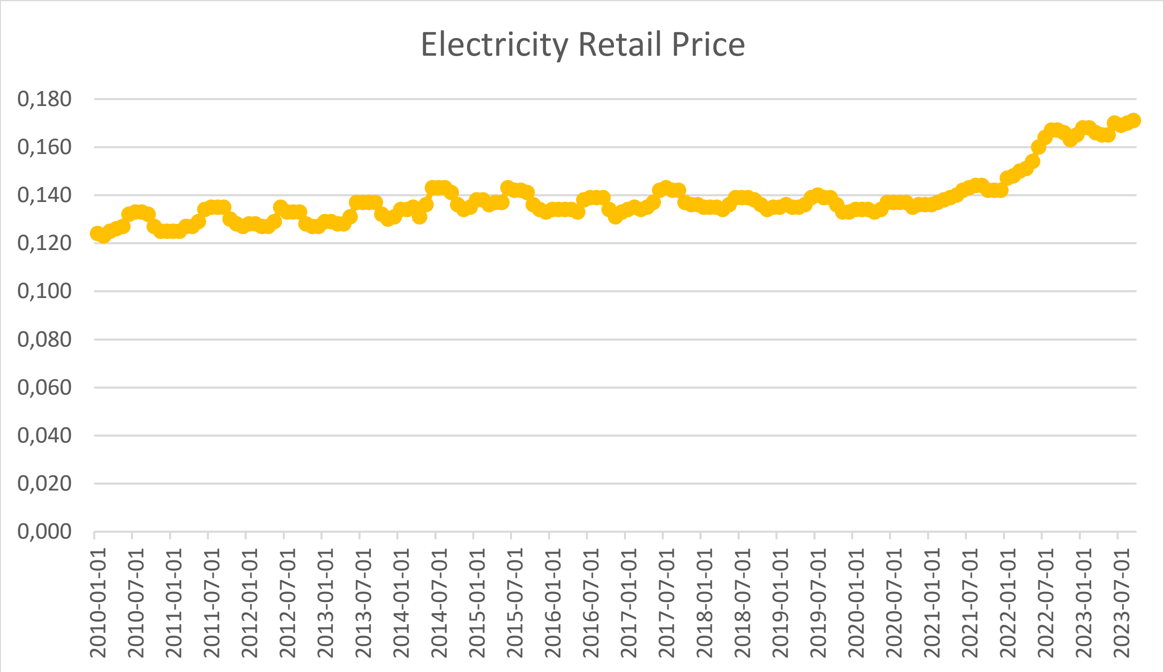


Table 4: Electricity Retail Price descriptive statistics

Mean	0,138212121
Standard Error	0,000835634
Median	0,136
Mode	0,134
Standard Deviation	0,010733915
Sample Variance	0,000115217
Kurtosis	2,424987254
Skewness	1,669707354
Range	0,048
Minimum	0,123
Maximum	0,171
Sum	22,805
Count	165
Largest(1)	0,171
Smallest(1)	0,123
Confidence Level(95,0%)	0,001649988

Stationarity

The historical development of the monthly electricity price from January 2010 until September 2023 indicates that the mean is not constant over time. However, during the biggest part of the sample this time series seems to have a constant mean. The descriptive statistics table also shows that the variance of the data has changed over the years. Therefore, it can be concluded that the data being analyzed are not stationary. Non stationary time series data can be more difficult to analyze, as the patterns and trends in the data may change over time, making it challenging to make accurate estimates.

The Phillips-Perron Test is used to test whether the time series is stationary.

Null Hypothesis: Electricity Price has a unit root

Exogenous: Constant

Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

The Phillips-Perron test statistic is 0.275269 and the p-value is 0.9764.

Test critical values:

At significance level a=1% level, the critical value is -3.470427.

At a=5% level, the critical value is -2.879045.

At a=10% level, the critical value is -2.576182.

Since p-value > a, the null hypothesis is accepted and therefore it is deducted that the time series is non-stationary.

Linear Trend

According to data, it seems there is a long-term linear trend which is more intense after January 2020 and it continues to be uptrend till September 2023 which is the last observation of the selected period of the sample.

3.1.3 Brent Crude Oil Price

Figure 4: Crude Oil Prices: Brent - Europe, Dollars per Barrel

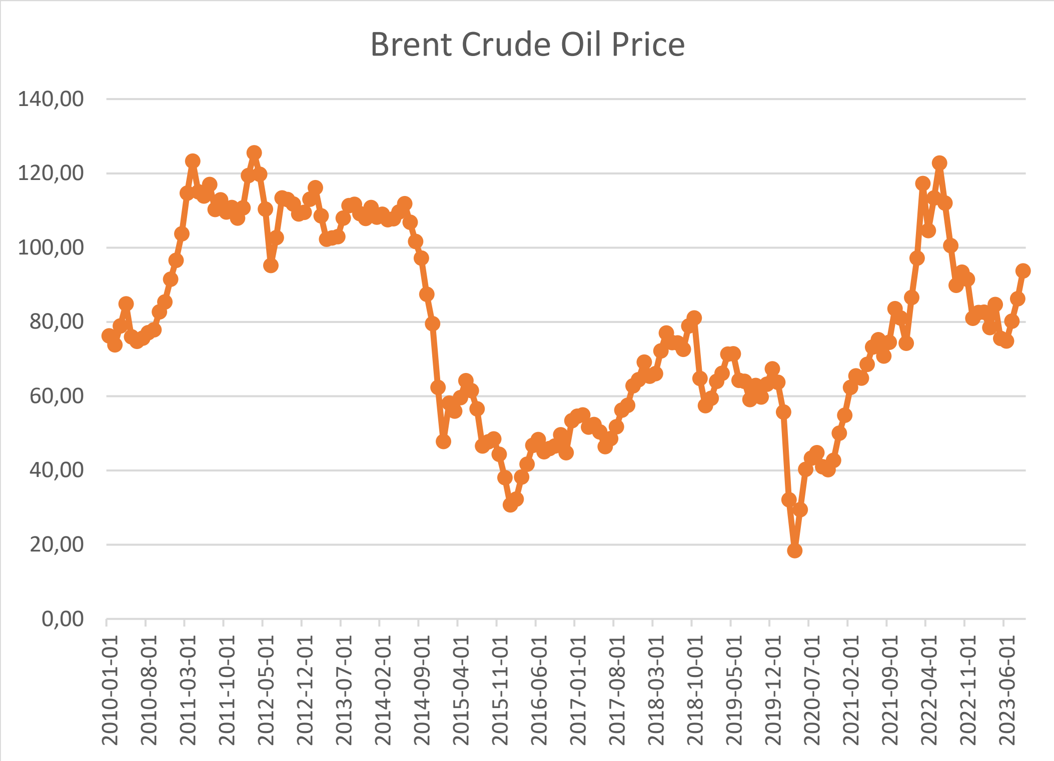


Table 5: Brent Crude Oil Price descriptive statistics

Mean	77,84787879
Standard Error	2,005970771
Median	75,17
Standard Deviation	25,7671611
Sample Variance	663,9465912
Kurtosis	-1,108541452
Skewness	0,04759703
Range	107,07
Minimum	18,38
Maximum	125,45
Sum	12844,9
Count	165
Largest(1)	125,45
Smallest(1)	18,38
Confidence Level(95,0%)	3,960858646

Stationarity

The historical development of the brent crude oil price from January 2010 until September 2023 indicates that the mean is not constant over time. The descriptive statistics table also shows that the variance of the data has changed over the years. Therefore, it can be concluded that the data being analyzed are not stationary. Non stationary time series data can be more difficult to analyze, as the patterns and trends in the data may change over time, making it challenging to make accurate estimates.

The Phillips-Perron Test is used to test whether the time series is stationary.

Null Hypothesis: Brent Crude Oil Price has a unit root

Exogenous: Constant

Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

The Phillips-Perron test statistic is -1.776750 and the p-value is 0.3910.

Test critical values:

At significance level a=1% level, the critical value is -3.470427.

At a=5% level, the critical value is -2.879045.

At a=10% level, the critical value is -2.576182.

Since p-value > a, the null hypothesis cannot be rejected and therefore it is deducted that the time series has a unit root.

Linear Trend

According to data, it seems there is a long-term linear trend with peaks in October 2011, March 2012 and June 2022. It should be mentioned that the highest price of the sample period recorded at 125.45 US dollars per barrel in March 2012.

3.1.4 Natural Gas Price

Figure 5: Global price of Natural gas, EU, U.S. Dollars per Million Metric British Thermal Unit

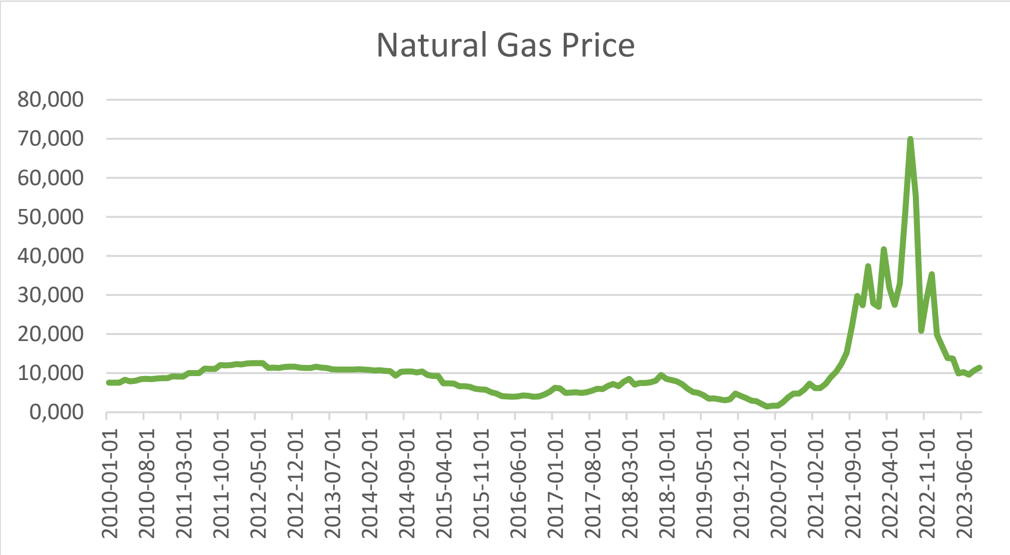


Table 6: Natural Gas Price descriptive statistics

Mean	10,80105388
Standard Error	0,744191016
Median	8,71
Mode	7,59
Standard Deviation	9,559306688
Sample Variance	91,38034436
Kurtosis	13,37544326
Skewness	3,270521431
Range	68,51462701
Minimum	1,46261232
Maximum	69,97723933
Sum	1782,17389
Count	165
Largest(1)	69,97723933
Smallest(1)	1,46261232
Confidence Level(95,0%)	1,469430893

Stationarity

The historical development of the brent crude oil price from January 2010 until September 2023 indicates that the mean is not constant over time. The descriptive statistics table also shows that the variance of the data has changed over the years. Therefore, it can be concluded that the data being analyzed are not stationary. Non stationary time series data can be more difficult to analyze, as the patterns and trends in the data may change over time, making it challenging to make accurate estimates.

The Phillips-Perron Test is used to test whether the time series is stationary.

Null Hypothesis: Natural Gas Price has a unit root

Exogenous: Constant

Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

The Phillips-Perron test statistic is -2.738563 and the p-value is 0.0698.

Test critical values:

At significance level a=1% level, the critical value is -3.470679.

At a=5% level, the critical value is -2.879155.

At a=10% level, the critical value is -2.576241.

Since p-value > a, the null hypothesis is accepted and therefore it is deducted that the time series is non-stationary.

Linear Trend

According to data, it seems there is a long-term linear trend with peaks in January 2022, August 2022 and December 2022. It should be mentioned that the highest price of the sample recorded at 69.77 US dollars per million metric British thermal unit in August 2022.

3.2 VAR Estimation Model

The standard VAR model specification for the present analysis is the following and tries to estimate the interrelation between the prices of electricity, brent crude oil and natural gas.

Estimation Proc:
===============================
LS 1 2 D(ERP) D(BRENT) D(NGP)

VAR Model:
===============================
*D(ERP) = C(1,1) *D(ERP(-1)) + C(1,2)*D(ERP(-2)) + C(1,3)*D(BRENT(-1)) + C(1,4)*D(BRENT(-2)) + C(1,5)*D(NGP(-1)) + C(1,6)*D(NGP(-2)) + C(1,7)*

*D(BRENT) = C(2,1) *D(ERP(-1)) + C(2,2)*D(ERP(-2)) + C(2,3)*D(BRENT(-1)) + C(2,4)*D(BRENT(-2)) + C(2,5)*D(NGP(-1)) + C(2,6)*D(NGP(-2)) + C(2,7)*

*D(NGP) = C(3,1) *D(ERP (-1)) + C(3,2)*D(ERP(-2)) + C(3,3)*D(BRENT(-1)) + C(3,4)*D(BRENT(-2)) + C(3,5)*D(NGP(-1)) + C(3,6)*D(NGP(-2)) + C(3,7)*

VAR Model - Substituted Coefficients:
===============================
*D(ERP) = - 0.313663329056*D(ERP(-1)) + 0.0232936703422*D(ERP(-2)) + 4.7736002968e-06*D(BRENT(-1)) - 6.18532976255e-05*D(BRENT(-2)) + 0.000238699117368*D(NGP(-1)) - 4.85563723422e-05*D(NGP(-2)) + 0.000333689281689*

*D(BRENT) = 40.6055917935*D(ERP(-1)) + 144.013580286*D(ERP(-2)) + 0.304177095518*D(BRENT(-1)) - 0.125978828883*D(BRENT(-2)) - 0.199719838016*D(NGP(-1)) + 0.147936176255*D(NGP(-2)) + 0.0167396419112*

*D(NGP) = 48.9389327018*D(ERP(-1)) + 84.2150616101*D(ERP(-2)) + 0.0412169550458*D(BRENT(-1)) + 0.127833403341*D(BRENT(-2)) + 0.0755484200922*D(NGP(-1)) - 0.465928412106*D(NGP(-2)) - 0.0195659475881*

On the vector autoregressive estimates, these are depicted in the subsequent table:

Table 7: VAR model estimation output

R-squared	0.168788	0.126195	0.269637
Adjusted R-squared	0.136612	0.092370	0.241365

Sum sq. of residuals	0.002319	5868.546	2335.036
S.E. equation	0.003868	6.153177	3.881333
F-statistic	5.245765	3.730841	9.537227
Log likelihood	673.6169	-520.6391	-445.9911
Akaike Information Criterion	-8.229839	6.514063	5.592483
Schwarz Criterion	-8.096424	6.647477	5.725898
Mean dependent	0.000247	0.091975	0.023457
S.D. dependent	0.004163	6.458698	4.456199

Determinant residual covariance (degrees of freedom adjustment)	0.008510
Determinant residual covariance	0.007454
Log likelihood	-292.7825
Akaike Information Criterion	3.873858
Schwarz Criterion	4.274102
Number of coefficients	21

According to the above findings, 16,8% of the variation of electricity price is interpreted by the variation of the crude oil price and the natural gas price. Respectively, 12,6% of the variation of the crude oil is interpreted by the variation of the electricity price and the natural gas price. Finally, 26,9% of the variation of the natural gas price volatility is explained by the volatility of the electricity and the brent crude oil price.

3.2.1 VAR Diagnostic Tests

The below table shows the VAR order selection criteria.

Table 8: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-341.4449	NA	0.014875	4.305561	4.363221	4.328975
1	-315.3099	50.96336	0.012007	4.091373	4.322011	4.185027
2	-289.7167	48.94686*	0.009760*	3.883959*	4.287576*	4.047854*
3	-286.9642	5.160988	0.010556	3.962052	4.538648	4.196188

* Indicates lag order selected by the criterion

Where LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final estimate error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

The VAR model has been estimated at 2 lags based on the above VAR lag selection criteria.

In the next table, the VAR stability condition check is shown.

Table 9: VAR Stability Condition Check

Roots of Characteristic: Polynomial	**Modulus**
0.071201 - 0.704224i	0.707814
0.071201 + 0.704224i	0.707814
0.221538 - 0.257506i	0.339688
0.221538 + 0.257506i	0.339688
-0.259708 - 0.161301i	0.305723
-0.259708 + 0.161301i	0.305723

Based on the above, no root lies outside the unit circle and therefore VAR satisfies the stability condition.

The residuals heteroskedasticity of the deployed VAR model has been tested at levels and squares as follows.

Table 10: VAR Residual Heteroscedasticity Joint Test (Levels and Squares)

Chi-squared	**Degrees of freedom**	**Probability**
189.8975	72	0.0000

Table 11: VAR Residual Heteroscedasticity Individual Components Test (Levels and Squares)

Dependent	**R-squared**	**F (12,149)**	**Probability**	**Chi-sq (12)**	**Probability**
res1*res1	0.051633	0.676013	0.7724	8.364525	0.7560
res2*res2	0.159900	2.363318	0.0082	25.90378	0.0111
res3*res3	0.395974	8.139831	0.0000	64.14773	0.0000
res2*res1	0.076123	1.023079	0.4307	12.33199	0.4194
res3*res1	0.258940	4.338610	0.0000	41.94827	0.0000
res3*res2	0.190581	2.923561	0.0011	30.87417	0.0021

Consequently, there is heteroskedasticity among the residuals both for joint and components at levels and squares.

The residuals heteroskedasticity of the deployed VAR model has been tested with cross terms included as follows.

Table 12: VAR Residual Heteroskedasticity Joint Test (Includes Cross Terms)

Chi-squared	Degrees of freedom	Probability
478.9753	162	0.0000

Table 13: VAR Residual Heteroskedasticity Individual Components Test (Includes Cross Terms)

Dependent	R-squared	F (27,134)	Probability	Chi-sq (27)	Probability
res1*res1	0.093752	0.513420	0.9771	15.18777	0.9667
res2*res2	0.362385	2.820676	0.0000	58.70641	0.0004
res3*res3	0.884812	38.12272	0.0000	143.3395	0.0000
res2*res1	0.194230	1.196315	0.2494	31.46522	0.2525
res3*res1	0.669980	10.07539	0.0000	108.5367	0.0000
res3*res2	0.724576	13.05640	0.0000	117.3813	0.0000

Hence, it can be deducted that there is heteroskedasticity among the residuals both for joint and components with cross terms included.

Moreover, the residuals are tested for autocorrelation with Portmanteau test with the null hypothesis being that there are no residual autocorrelations up to lag h.

Table 14: VAR Residual Portmanteau Tests for Autocorrelations

Lags	Q-Statistic	Probability	Adjusted Q-statistic	Probability	Degrees of freedom
1	0.377050	-	0.379392	-	-
2	1.680091	-	1.698721	-	-
3	7.300014	0.6059	7.424680	0.5930	9

The test is valid only for lags larger than the VAR lag order. The degrees of freedom are calculated for approximate chi-square distribution. Based on the above results, the null hypothesis of no vector autocorrelation up to lag order h=3 cannot be rejected at typical significance levels.

In addition, the residuals serial correlation LM tests are conducted.

Table 15: VAR Residual Serial Correlation LM Tests

Null hypothesis: No serial correlation at lag h

Lag	LRE statistic	df	Probability	Rao F-stat	df	Probability
1	5.308745	9	0.8066	0.588488	(9, 365.2)	0.8066
2	5.443369	9	0.7941	0.603522	(9, 365.2)	0.7941
3	7.079261	9	0.6289	0.786646	(9, 365.2)	0.6289

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE statistic	df	Probability	Rao F-stat	df	Probability
1	5.308745	9	0.8066	0.588488	(9, 365.2)	0.8066
2	10.89541	18	0.8987	0.601578	(18, 416.3)	0.8988
3	26.71895	27	0.4790	0.991291	(27, 421.2)	0.4795

For LRE statistic, Edgeworth expansion corrected likelihood ratio statistic.

Thus, there is no serial correlation for the residuals at lag h and at lags 1 to h.

Also, the subsequent normality tests are done with orthogonalization Cholesky (Lutkepohl) criterion. The null hypothesis tested is the following.

H_0: Residuals are multivariate normal

Table 16: VAR Residual Normality Tests

Component	Skewness	Chi-square	DF	Probability
1	-0.126872	0.434607	1	0.5097
2	-0.368818	3.672723	1	0.0553
3	-0.833781	18.77015	1	0.0000
Joint		22.87748	3	0.0000

Component	Kurtosis	Chi-square	DF	Probability
1	5.393014	38.65400	1	0.0000
2	4.056827	7.538969	1	0.0060
3	17.14729	1350.984	1	0.0000
Joint		1397.177	3	0.0000

Component	Jarque-Bera	DF	Probability
1	39.08861	2	0.0000
2	11.21169	2	0.0037
3	1369.754	2	0.0000
Joint	1420.055	6	0.0000

Based on the above, the null hypothesis is rejected and therefore the residuals are not multivariate normal for joint and most of the components.

3.2.2 VAR Results Significance Tests

Next, the VAR Granger Causality tests are depicted for each of the variables as dependent variables of the deployed VAR model specification.

Table 17: VAR Granger Causality/Block Exogeneity Wald Test for Electricity Retail Price

Dependent variable: D(ERP)

Excluded	Chi-square	Degrees of freedom	Probability
D(BRENT)	1.585613	2	0.4526
D(NGP)	11.79502	2	0.0027
All	12.18885	4	0.0160

Table 18: VAR Granger Causality/Block Exogeneity Wald Test for Brent Crude Oil Price

Dependent variable: D(BRENT)

Excluded	**Chi-square**	**Degrees of freedom**	**Probability**
D(ERP)	1.391913	2	0.4986
D(NGP)	4.599018	2	0.1003
All	6.825203	4	0.1454

Table 19: VAR Granger Causality/Block Exogeneity Wald Test for Natural Gas Price

Dependent variable: D(NGP)

Excluded	**Chi-square**	**Degrees of freedom**	**Probability**
D(ERP)	1.264293	2	0.5314
D(BRENT)	8.856085	2	0.0119
All	10.34445	4	0.0350

For checking the VAR lag exclusion for each lag coefficient, the relevant VAR Lag Exclusion Wald Tests is conducted and the results are cited in table 13 below.

Table 20: VAR Lag Exclusion Wald Tests

	D(ERP)	**D(BRENT)**	**D(NGP)**	**Joint**
Lag 1	27.14026 [0.0000]	18.97164 [0.0003]	2.242294 [0.5237]	49.20536 [0.0000]
Lag 2	2.065622 [0.5589]	5.909810 [0.1161]	47.44556 [0.0000]	55.83361 [0.0000]
Degrees of freedom	3	3	3	9

Where numbers in [] are p values. It should be mentioned that this test checks the significance of all endogenous variables at every lag for each VAR equation either separately for each variable or joint shown in the last column.

Below the residuals of the included variables at first differences are graphically represented.

Figure 6: Electricity price VAR residuals

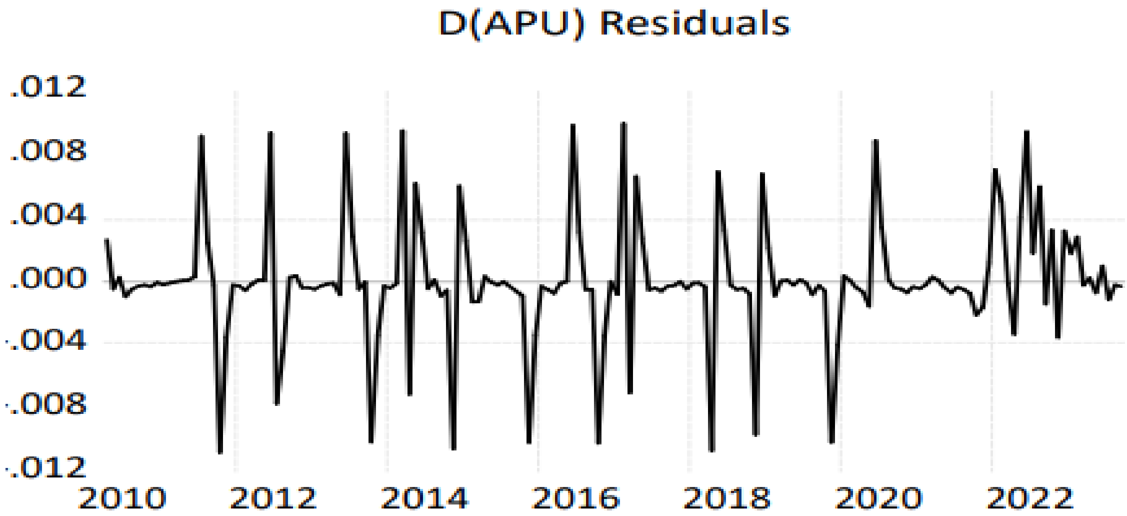


Figure 7: Brent Crude Oil price VAR residuals

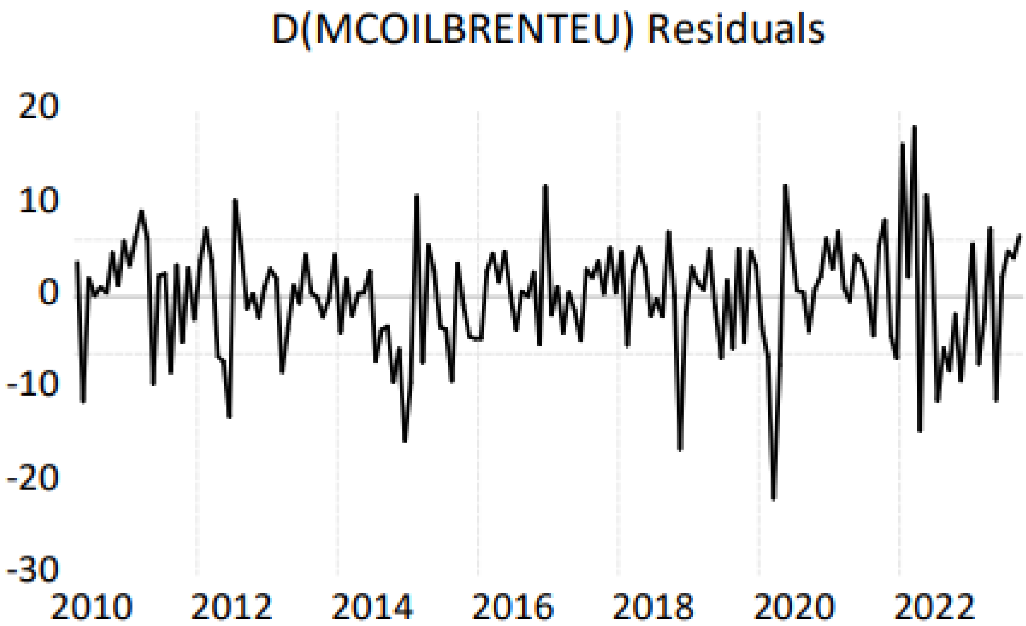
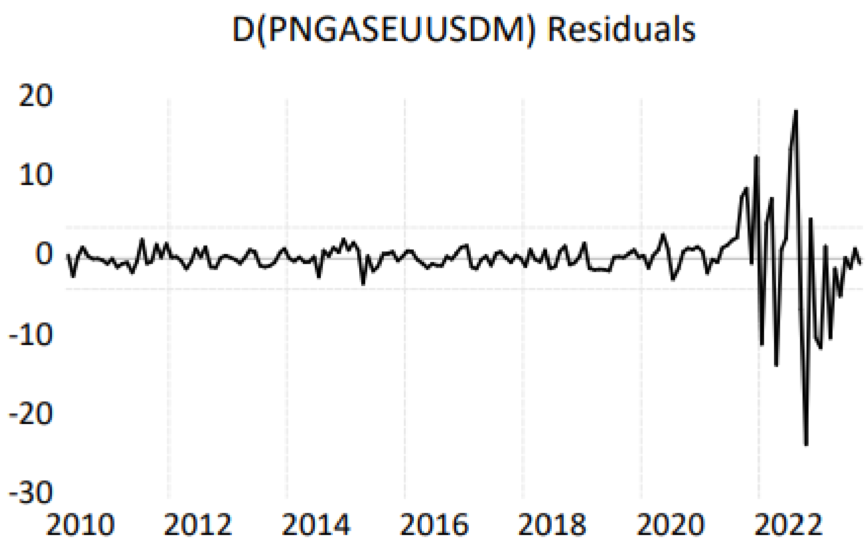


Figure 8: Natural Gas price VAR residuals



3.3 Estimating Electricity, Crude Oil and Natural Gas Prices

3.3.1 SMA Model Estimation Results

The SMA (3) model estimation results for the estimated time series are depicted in Figure 9, 10 and 11 as follows.

Figure 9: Electricity Retail Price SMA (3) Estimate

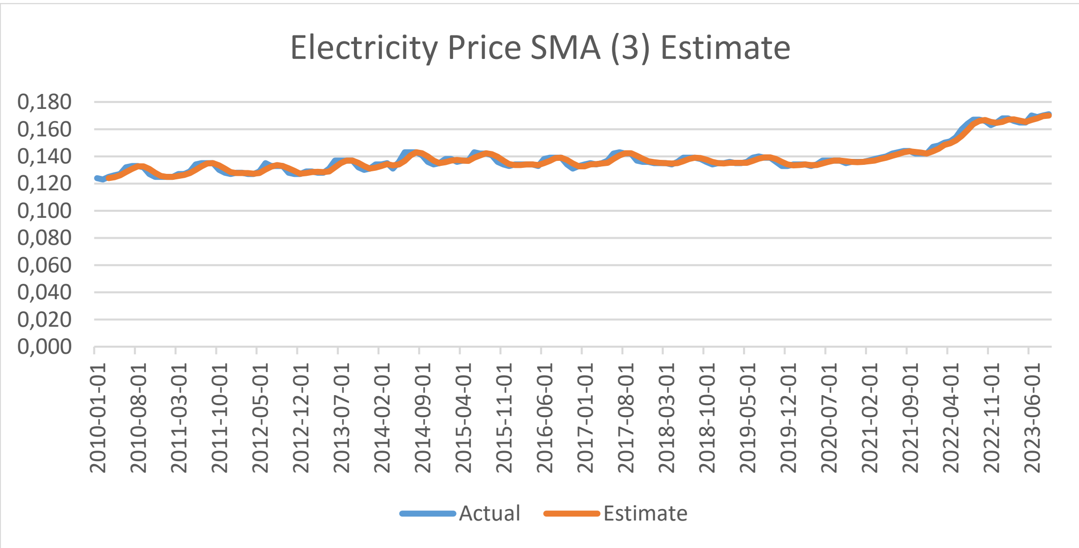


Figure 10: Natural Gas Price SMA (3) Estimate

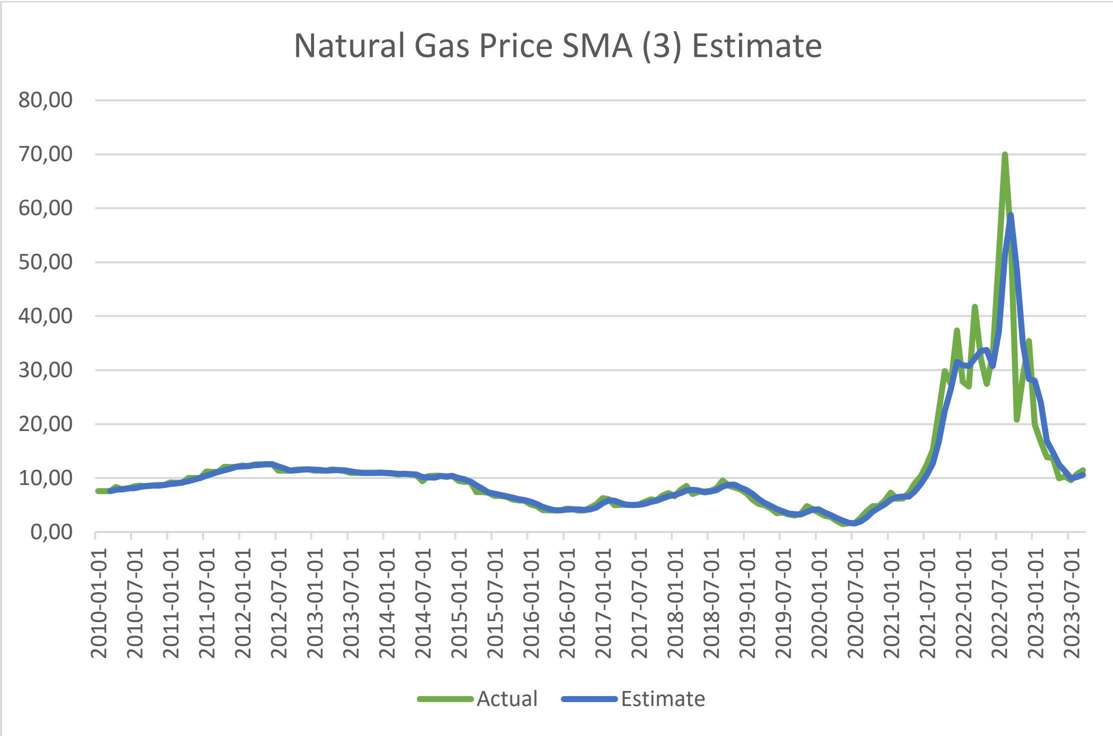


Figure 11: Brent Crude Oil Price SMA (3) Estimate

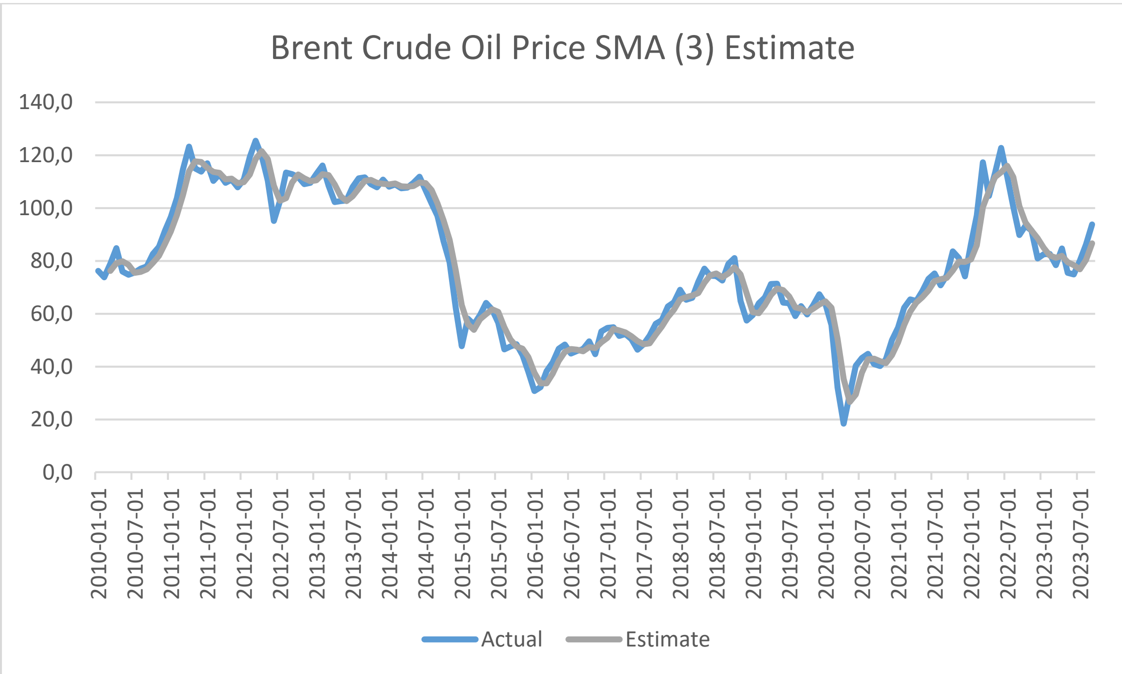


Table 21: SMA Estimate Evaluation Table

SMA (3) Estimate Errors	**Electricity Retail Price**	**Natural Gas Price**	**Brent Crude Oil Price**
MAE	0,001	1,219	3,889
MAPE	0,010	0,085	0,061
MSE	0,000004	11,516	27,650
RMSE	0,001908	3,394	5,258

According to afore cited estimation results, it seems that the SMA (3) model has produced the best estimation results for electricity price whilst the worst estimation results have been produced for brent crude oil price. It is worth mentioning here that the estimation accuracy of the SMA (3) model is very good in regards to electricity price estimates of the actual prices since the estimate errors are very low.

3.3.2 EWMA Model Estimation Results

The EWMA model is used with weight λ=0,10 and its estimation results are illustrated in Figure 12, 13 and 14 as shown below.

Figure 12: Electricity Retail Price EWMA Estimate

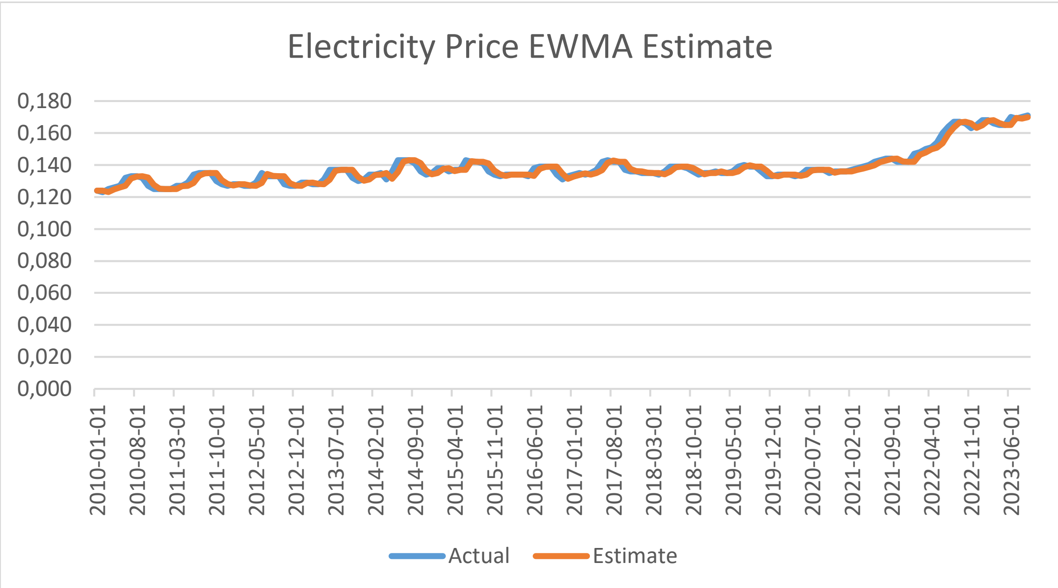


Figure 13: Natural Gas Price EWMA Estimate

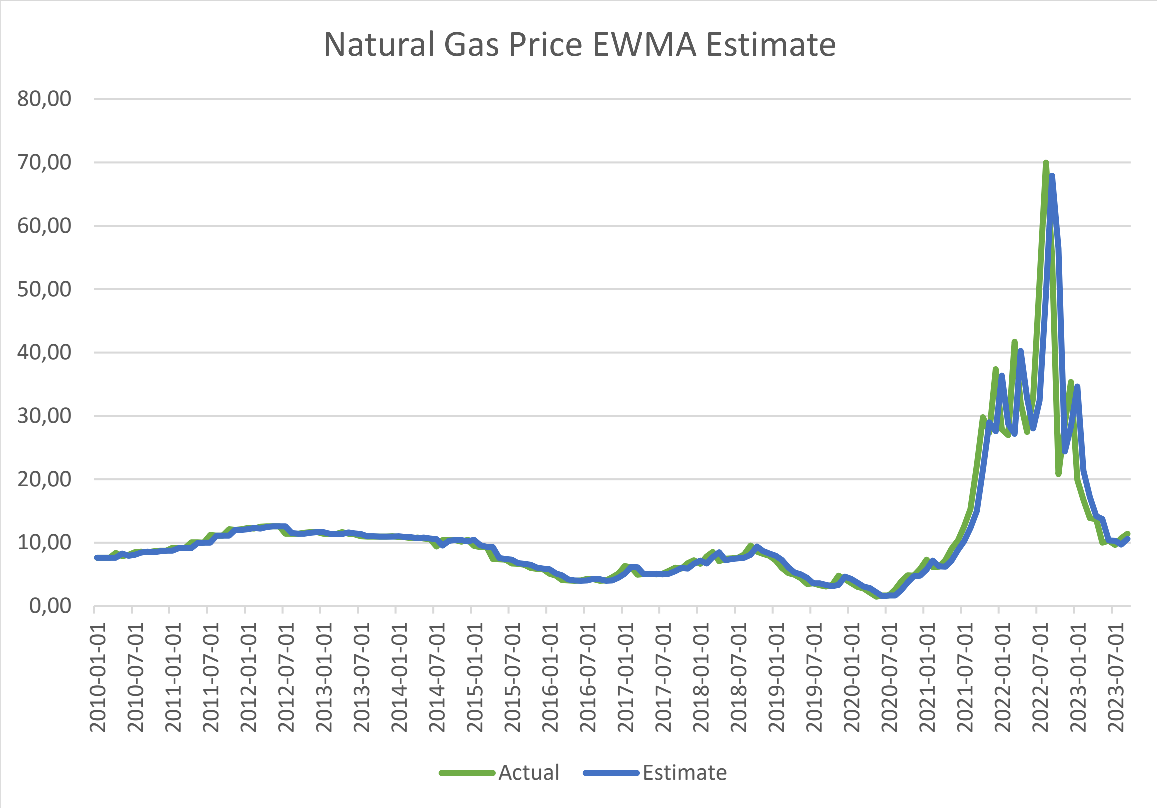


Figure 14: Brent Crude Oil Price EWMA Estimate

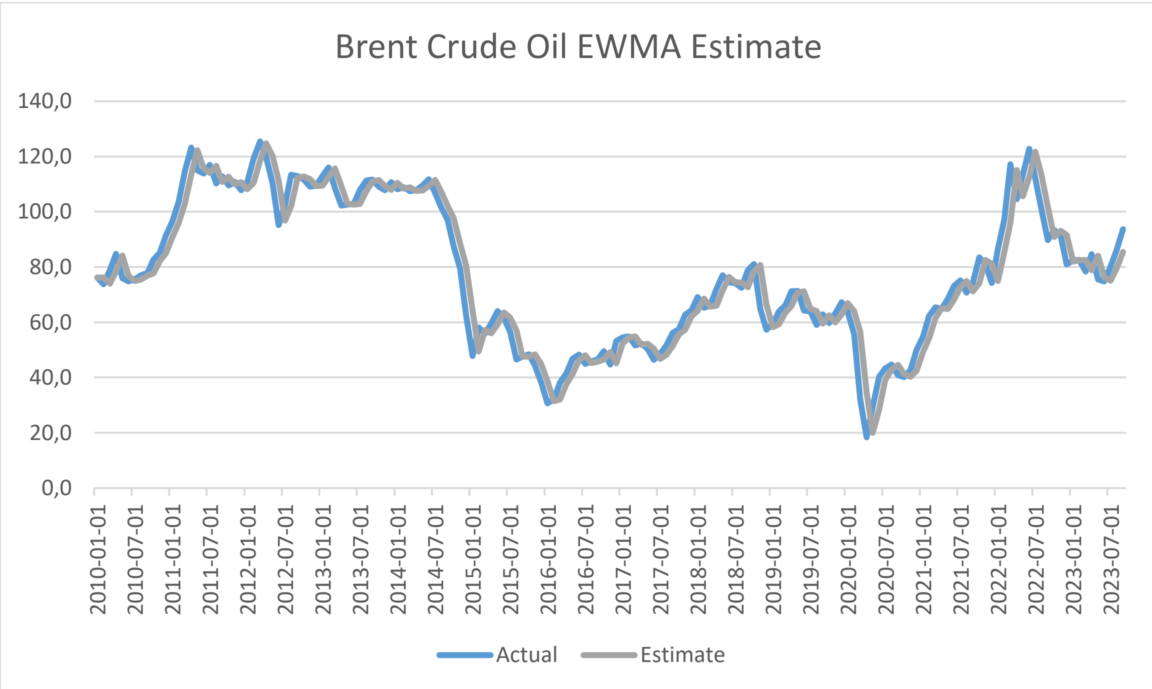


Table 22: EWMA Estimate Evaluation Table

EWMA Estimate Errors	Electricity Price	Natural Gas Price	Brent Crude Oil Price
MAE	0,002	1,596	5,046
MAPE	0,012	0,105	0,077
MSE	0,00001	19,782	43,629
RMSE	0,002	4,448	6,605

According to afore cited estimation results, it seems that the EWMA model has produced the best estimation results for electricity price whilst the worst estimation results have been produced for brent crude oil price. It is worth mentioning here that the estimation accuracy of the EWMA model is very good in regards to the electricity price estimates of the actual prices since the estimate errors are very low.

3.3.3 VAR Model Estimation Results

Regarding the estimation results of the deployed VAR model, these are the subsequent as depicted in Figure 15, 16 and 17. In these figures, the vertical axis represents the estimated price of energy and the horizontal axis shows the time period in which the estimation is conducted.

Figure 15: Electricity Price VAR Estimation

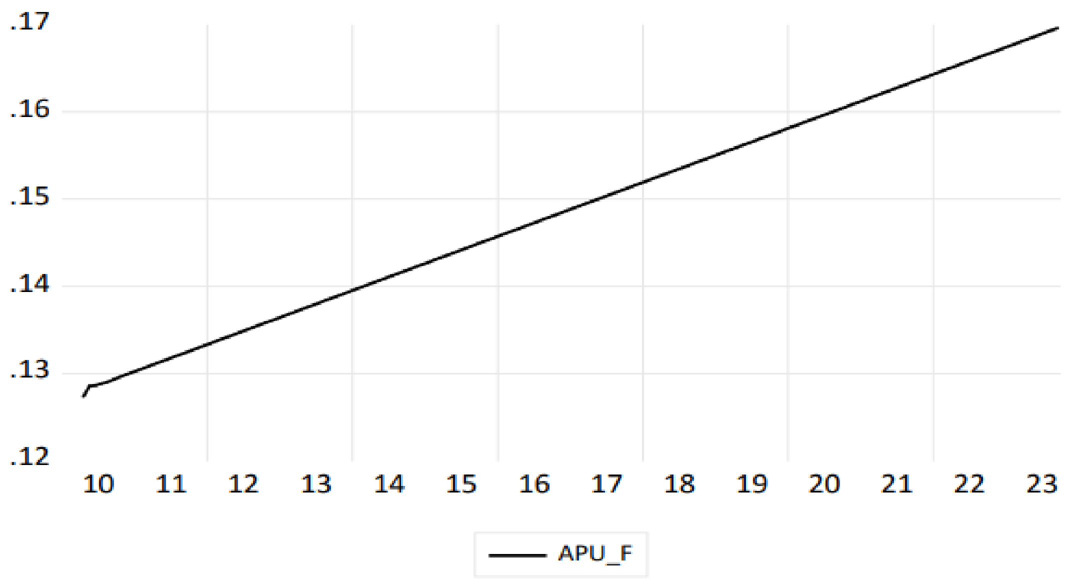


Figure 16: Natural Gas Price VAR Estimation

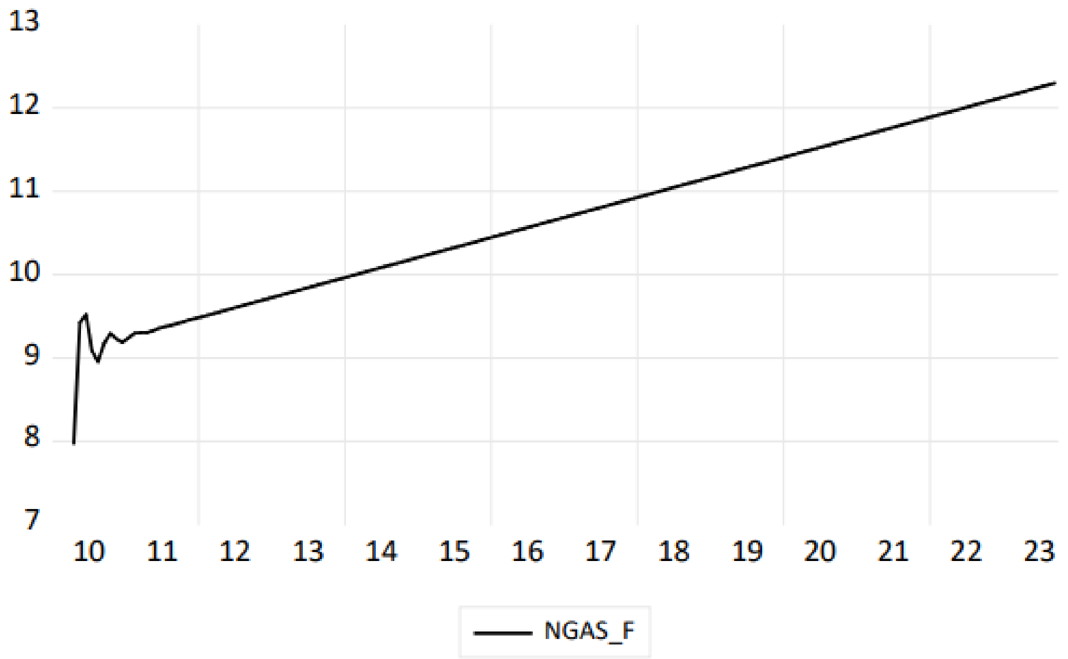


Figure 17: Brent Crude Oil Price VAR Estimation

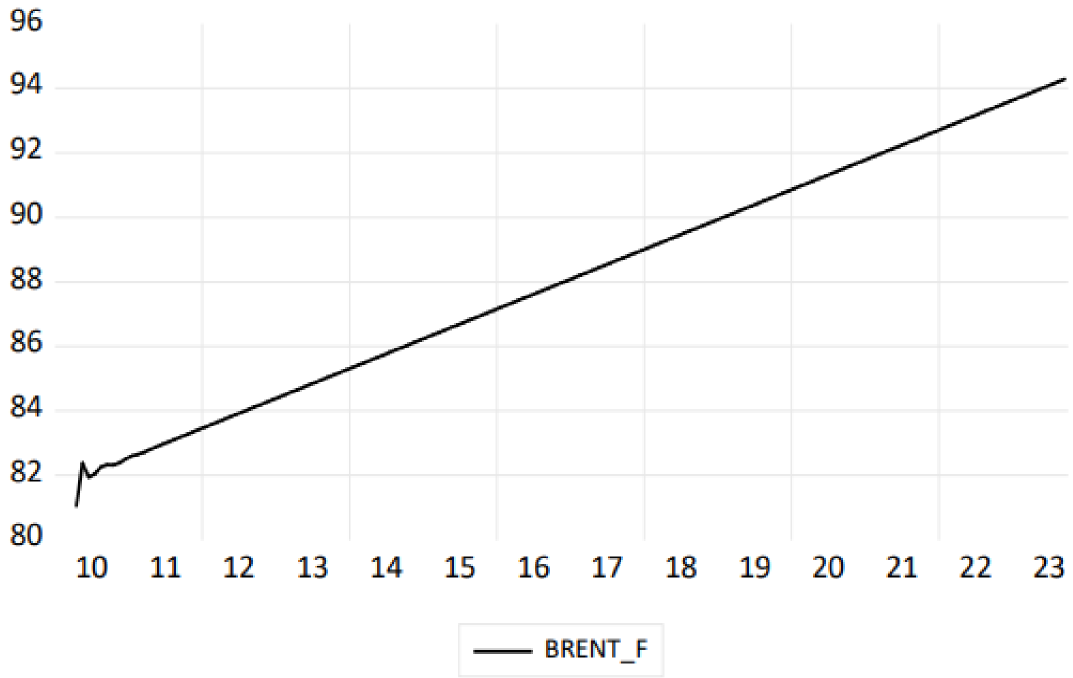


Table 23: VAR Estimate Evaluation Table

Variable	RMSE	MAE	MAPE	Theil
Electricity Retail Price	0.013221	0.010432	7.614871	0.045746
Brent Crude Oil Price	29.34507	25.99560	44.32140	0.172378
Natural Gas Price	9.378454	5.510713	75.27672	0.371782

Where Theil is the Theil inequality coefficient.

According to above estimate results, the VAR model has produced the best estimation results for electricity price whilst the worst estimation results have been produced for brent crude oil price. The estimate errors of the VAR model are very low as regards electricity price but they are quite high on what it concerns the brent crude oil price.

Table 24: Estimation Models MAE Comparison Table

Estimation Model	Electricity Retail Price	Natural Gas Price	Brent Crude Oil Price
SMA	0.001	1.219	3.889
EWMA	0.002	1.596	5.046
VAR	0.010432	5.510713	25.99560

Therefore, SMA is the estimation model with the lowest MAE produced as regards electricity price, natural gas price and crude oil price estimates.

Table 25: Estimation Models RMSE Comparison Table

Estimation Model	Electricity Price	Natural Gas Price	Brent Crude Oil Price
SMA	0.001908	3.394	5.258
EWMA	0.002	4.448	6.605
VAR	0.013221	9.378454	29.34507

Based on the above data, SMA has produced the lowest RMSE concerning all the estimated energy prices.

Table 26: Estimation Models MAPE Comparison Table

Estimation Model	Electricity Retail Price	Natural Gas Price	Brent Crude Oil Price
SMA	0.010	0.085	0.061
EWMA	0.012	0.105	0.077
VAR	7.614871	75.27672	44.32140

Regarding MAPE, the lowest error has been produced with SMA model with respect to electricity price, natural gas price and crude oil price.

In addition, on what it concerns the correlation between the selected probed energy prices, the deployed VAR model has calculated the below coefficient of determination for the probed energy prices.

Table 27: VAR Model Equations Comparison Table

VAR Equations Values	**Electricity Retail Price**	**Brent Crude Oil Price**	**Natural Gas Price**
R-squared	0.168788	0.126195	0.269637
Adjusted R-squared	0.136612	0.092370	0.241365
Sum sq. of residuals	0.002319	5868.546	2335.036
S.E. equation	0.003868	6.153177	3.881333
F-statistic	5.245765	3.730841	9.537227

According to the above table, 26.9% of the variation of the natural gas price is explained by the variation of the crude oil price and the variation of electricity price, whilst the respective R-squared for crude oil price VAR equation is 12.6% and for the R-squared for electricity price equation of the VAR model is 16.8%. That means that among the used VAR equations, the one for natural gas price has the highest coefficient determination and hence it is explained by the VAR model by this percentage, while the VAR equation with lowest coefficient of determination is the one for crude oil price which is 12.6%. Therefore, only 12.6% of the volatility of the crude oil price is interpreted by the utilized VAR model.

4. CONCLUSIONS AND FURTHER RESEARCH

The research findings of this study have shown that the Russia-Ukraine conflict has affected the global supply chain network negatively in terms of transport and energy cost across the globe. This fact is presented by the GSPI which quantifies the global supply chain disruptions and supply constraints.

It is calculated using global transportation cost data and manufacturing indicators focusing on seven interlinked large economies which are the following: the United States, the United Kingdom, the Eurozone area, Taiwan, China, South Korea and Japan.

Based on the historical data of GSPI, it seems that the global supply chain has been pressured heavily during the first months of the year 2022 by eventual shocks one of which could be the Russian-Ukraine conflict. It should be noted that the conflict started in February 2022 and it has been continued until now.

Apart from that, it is observed in the research data that there is also a significant supply chain disruption which starts in January 2020 and ends with the normalization of the index's variation during the last months of 2021. It could be inferred that this pressure is ensued by the pandemic crisis of Covid-19. Nevertheless, it seems that this pressure is not so heavy as the pressure ensued by the Russian-Ukraine war which is more robust and has reduced the GSPI to significant negative values.

On what it concerns the estimates made by the used models, the VAR model specification deployed in the dissertation has shown that there is correlation to a certain extent between the volatility of the electricity retail price, the brent crude oil price and the natural gas price but the estimation accuracy of the VAR model differs significantly for the estimated energy prices. Although, the VAR model has produced very good estimation results for the electricity retail price with low estimation errors, this is not the case for the rest estimated energy prices which is brent crude oil price and natural gas price.

Apart from that, as regards the estimation results of the moving average methods, these concur the findings on the VAR model estimation precision. More specifically, both the SMA and the EWMA model used have managed to estimate the electricity retail price to a pretty satisfying level producing low estimation errors. Nevertheless, they have produced much higher estimation errors for the other two energy prices with brent crude oil price to be the hardest energy price to be estimated accurately among the probed ones. These conclusions on the estimation results of the deployed models are depicted in the above estimation models accuracy comparison tables cited in the results section.

4.1 Proposal for Further Research

As regards the implications of the Russia-Ukraine conflict on the global supply chain network, this dissertation has revealed that the GSPI has been affected heavily by the ongoing military conflict between the two nations. However, further research could be directed towards the investigation of the other factors that may have affected the global supply chain as well, especially during the period from the first months of 2020 until the last months of 2021. One possible influencing factor which has also affected the GSPI during this period is the pandemic crisis of Covid-19. Thus, further research which will focus on the effects of the global coronavirus pandemia on the global supply chain network could reveal some interesting findings as well.

Given the fact that the calculated coefficients of determination for all the VAR equations have been calculated by the used model to less than 50%, perhaps some addition regression models could be run with different model specifications including selected energy prices which affect the supply chain network on the whole world. In this way, there might be stronger interrelation between these selected energy prices.

Finally, in regards to the estimate of the examined energy prices, further research could be conducted on the estimation of the crude oil price as well as the natural gas price more accurately. Since, the price of crude oil is a time series variable which is affected by various political and financial parameters but also exogenous factors, the model specification which will be selected should take into account those parameters and factors that influence the variation of the crude oil price to a great extent.

The same logic should also be applied in modelling natural gas prices estimation methods more accurately achieving lower estimate errors. This research endeavor should be conducted whilst bearing in mind that natural gas is a fossil fuel with different market structure comparatively to the crude oil market. Since the fossil fuels market is considered to be very volatile and the price movements are deemed hard to be estimated, then it is of high importance that the deployed estimation models are adjusted accordingly following the market’s price movements to the highest evitable level.

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Appendix A: Johansen Cointegration Test

Sample (adjusted): 2010M06 2023M09

Included observations: 160 after adjustments

Trend assumption: Linear deterministic trend

Series: ERP BRENT NGP

Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized number of CE(s)	**Eigenvalue**	**Trace Statistic**	**Critical Value (0.05)**	**Probability***
None	0.102538	23.60615	29.79707	0.2176
At most 1	0.030062	6.296697	15.49471	0.6605
At most 2	0.008792	1.412980	3.841465	0.2346

*MacKinnon-Haug-Michelis p-values

Trace test indicates that there is no cointegration at the 0.05 level.

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized number of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value (0.05)	Probability*
None	0.102538	17.30945	21.13162	0.1579
At most 1	0.030062	4.883716	14.26460	0.7565
At most 2	0.008792	1.412980	3.841465	0.2346

*MacKinnon-Haug-Michelis p-values

Max-Eigen value test indicates that there is no cointegration at the 0.05 level.

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

ERP	BRENT	NGP
-64.40425	-2.28E-05	0.182481
115.6851	4.71E-05	-0.090221
-111.7660	1.63E-05	0.046390

Unrestricted Adjustment Coefficients (alpha):

D(ERP)	0.000544	-4.33E-05	0.000102
D(BRENT)	153.2044	-1007.163	-128.7648
D(NGP)	-0.689204	-0.161012	0.273566

1) Cointegration Equation: Log likelihood -1282.954

Normalized cointegrating coefficients (standard error in parentheses)

ERP	BRENT	NGP
1.000000	3.54E-07	-0.002833
	(1.8E-07)	(0.00052)

Adjustment coefficients (standard error in parentheses)

D(ERP)	-0.035056
	(0.01043)
D(BRENT)	-9867.012
	(31907.0)
D(NGP)	44.38765
	(19.6071)

2) Cointegration Equation: Log likelihood -1280.512

Normalized cointegrating coefficients (standard error in parentheses)

ERP	BRENT	NGP
1.000000	0.000000	-0.016541
		(0.00478)

0.000000	1.000000	38741.47
		(12598.2)

Adjustment coefficients (standard error in parentheses)

D(ERP)	-0.040069	-1.44E-08
	(0.02145)	(8.5E-09)
D(BRENT)	-126380.8	-0.050893
	(64660.4)	(0.02554)
D(NGP)	25.76089	8.13E-06
	(40.2704)	(1.6E-05)

Appendix B: Phillips Perron Unit Root Tests

Phillips-Perron Unit Root Test on GSPI (Global Supply Pressure Index)

Null Hypothesis: GSPI has a unit root

Exogenous: Constant

Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adjusted t-Stat	P-value
Phillips-Perron test statistic		-2.209770	0.2037
Test critical values:	1% level	-3.471192	
	5% level	-2.879380	
	10% level	-2.576361	
Residual variance (no correction)		0.153642	
HAC corrected variance (Bartlett kernel)		0.178094	

Phillips-Perron Test Equation

Dependent Variable: D(GSPI)

Method: Least Squares

Date: 01/07/24 Time: 11:04

Sample (adjusted): 2 164

Included observations: 161 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Probability
GSPI(-1)	-0.052800	0.025738	-2.051437	0.0419
C	0.015673	0.032563	0.481314	0.6310

R-squared 0.025785	Mean dependent var -0.004224
Adjusted R-squared 0.019658	S.D. dependent var 0.398365
S.E. of regression 0.394430	Akaike info criterion 0.989594
Sum squared resid 24.73641	Schwarz criterion 1.027872
Log likelihood -77.66228	Hannan-Quinn criterion 1.005136
F-statistic 4.208392	Durbin-Watson stat 1.686344
Probability (F-statistic) 0.041865	

Phillips-Perron Unit Root Test on ERP

Null Hypothesis: ERP has a unit root

Exogenous: Constant

Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		Adjusted t-Stat	P-value
Phillips-Perron test statistic		0.275269	0.9764
Test critical values:	1% level	-3.470427	
	5% level	-2.879045	
	10% level	-2.576182	
Residual variance (no correction)		5.20E-06	
HAC corrected variance (Bartlett kernel)		4.41E-06	

Phillips-Perron Test Equation

Dependent Variable: D(ERP)

Method: Least Squares

Sample (adjusted): 2010M02 2023M09

Included observations: 164 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Probability
ERP(-1)	0.000698	0.017198	0.040563	0.9677
C	0.000190	0.002380	0.079954	0.9364

R-squared 0.000010	Mean dependent var 0.000287
Adjusted R-squared -0.006163	S.D. dependent var 0.002288
S.E. of regression 0.002295	Akaike info criterion -9.303739
Sum squared resid 0.000854	Schwarz criterion -9.265935
Log likelihood 764.9066	Hannan-Quinn criterion -9.288392
F-statistic 0.001645	Durbin-Watson stat 1.439749
Probability (F-statistic) 0.967694	

Phillips-Perron Unit Root Test on Brent

Null Hypothesis: Brent has a unit root

Exogenous: Constant

Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adjusted t-Stat	P-value
Phillips-Perron test statistic		-1.776750	0.3910
Test critical values:	1% level	-3.470427	
	5% level	-2.879045	
	10% level	-2.576182	

Residual variance (no correction) 40.56102

HAC corrected variance (Bartlett kernel) 53.33226

Phillips-Perron Test Equation

Dependent Variable: D(BRENT)

Method: Least Squares

Sample (adjusted): 2010M02 2023M09

Included observations: 164 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Probability
BRENT(-1)	-0.029910	0.019442	-1.538460	0.1259
C	2.432581	1.592286	1.527729	0.1285

R-squared 0.014400	Mean dependent var 0.107012
Adjusted R-squared 0.008316	S.D. dependent var 6.434757
S.E. of regression 6.407946	Akaike info criterion 6.565075
Sum squared resid 6652.007	Schwarz criterion 6.602878
Log likelihood -536.3361	Hannan-Quinn criterion 6.580421
F-statistic 2.366860	Durbin-Watson stat 1.458695
Probability (F-statistic) 0.125887	

Phillips-Perron Unit Root Test on NGP

Null Hypothesis: NGP has a unit root

Exogenous: Constant

Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adjusted t-Stat	P-value
Phillips-Perron test statistic		-2.738563	0.0698
Test critical values:	1% level	-3.470679	
	5% level	-2.879155	
	10% level	-2.576241	

Residual variance (no correction) 18.54694

HAC corrected variance (Bartlett kernel) 14.86688

Phillips-Perron Test Equation

Dependent Variable: D(NGP)

Method: Least Squares

Sample (adjusted): 2010M02 2023M08

Included observations: 163 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Probability
NGP(-1)	-0.106928	0.035398	-3.020762	0.0029
C	1.173764	0.511161	2.296269	0.0229

R-squared 0.053637	Mean dependent var 0.019187
Adjusted R-squared 0.047759	S.D. dependent var 4.440619
S.E. of regression 4.333282	Akaike info criterion 5.782722
Sum squared resid 3023.151	Schwarz criterion 5.820682
Log likelihood -469.2918	Hannan-Quinn criterion 5.798133
F-statistic 9.125002	Durbin-Watson stat 1.763802

Probability (F-statistic) 0.002933

Appendix C: VAR Residual Cross-Correlations

VAR Residual Cross-Correlations ordered by lags

Sample: 2010M01 2023M09

Included observations: 162

	D(ERP)	**D(BRENT)**	**D(NGP)**
D(ERP)	1.000000	0.047710	0.009601
D(BRENT)	0.047710	1.000000	0.022288
D(NGP)	0.009601	0.022288	1.000000
D(ERP(-1))	-0.001815	-0.009980	0.007400
D(BRENT(-1))	0.007030	0.001322	0.002182
D(NGP(-1))	0.004217	0.017161	0.042979
D(ERP(-2))	-0.012236	-0.011778	-0.030566
D(BRENT(-2))	0.014363	0.012282	0.040202
D(NGP(-2))	-0.038743	-0.013120	-0.055902

Asymptotic standard error (unadjusted) for lag > 0: 0.078567.

VAR Residual Cross-Correlations ordered by variables

Sample: 2010M01 2023M09

Included observations: 162

	D(ERP)	**D(BRENT)**	**D(NGP)**
D(ERP)	1.000000	0.047710	0.009601
D(ERP(-1))	-0.001815	-0.009980	0.007400
D(ERP(-2))	-0.012236	-0.011778	-0.030566
D(BRENT)	0.047710	1.000000	0.022288
D(BRENT(-1))	0.007030	0.001322	0.002182
D(BRENT(-2))	0.014363	0.012282	0.040202
D(NGP)	0.009601	0.022288	1.000000
D(NGP(-1))	0.004217	0.017161	0.042979
D(NGP(-2))	-0.038743	-0.013120	-0.055902

Asymptotic standard error (unadjusted) for lag > 0: 0.078567.

Author's Statement:

I hereby expressly declare that, according to the article 8 of Law 1559/1986, this dissertation is solely the product of my personal work, does not infringe any intellectual property, personality and personal data rights of third parties, does not contain works/contributions from third parties for which the permission of the authors/beneficiaries is required, is not the product of partial or total plagiarism, and that the sources used are limited to the literature references alone and meet the rules of scientific citations.