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Master

Regime Shifts in European Energy Markets: An MS-BVAR Analysis Assessing the Impact of the Russo-Ukrainian War

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Preface

This thesis is the final product of the Master of Science in Business Administration at the University of Agder, specializing in Analytical Finance. The process of writing this thesis has been both challenging and rewarding, resulting in work that we can be profoundly proud of. The finished product would not have been possible without the exemplary guidance of Professor Jochen Jungeilges. His extensive knowledge and unwavering support were crucial in allowing us to expand our academic capacities beyond expectation, facilitating the completion of this thesis. Lastly, we would like to take the opportunity to thank our families and fellow students who have supported us through our five years of studies. We have taken great pride in this journey and are now looking forward to the new chapters in our lives.

Abstract

This thesis examines the frequency of high-volatility regimes in European energy and carbon markets, and their correspondence with the Russo-Ukrainian war using a Markov Switching Bayesian Vector Autoregressive (MS-BVAR) model. Utilizing monthly price data from January 2015 to February 2024, the study identifies significant shifts in volatility and market dynamics triggered by geopolitical events. The findings reveal pronounced regime-dependent variability in market responses, with high volatility regimes becoming more conspicuous post-invasion. In lower volatility regimes, markets typically stabilize quickly post-disturbance, demonstrating resilience. However, in high-volatility regimes, markets exhibit prolonged deviations from baseline levels, indicating deeper impacts of geopolitical risks. Particularly, the oil, gas, and clean energy sectors show significant sensitivity to changes in the geopolitical landscape. Additionally, the thesis highlights the crucial role of the Geopolitical Risk Index (Caldara & Iacoviello, 2022) in understanding the broader effects of geopolitical tensions on energy markets. By integrating geopolitical risk analysis into the MS-BVAR model, the research provides nuanced insights into how shifts in geopolitical stability resonate through the energy markets over time. This research contributes to the empirical literature by demonstrating the differential impacts of geopolitical events across various states of market volatility. It underscores the importance of robust risk management and energy diversification strategies to enhance the resilience of energy systems.

Keywords: Russo-Ukrainian conflict, geopolitical risk, MS-BVAR, carbon market, energy markets

Table of content

List of figures and tables

1 Introduction

The Russian invasion of Ukraine on February 24, 2022 sparked a global energy crisis of unprecedented scale (International Energy Agency, 2024b). A raft of economic sanctions, trade restrictions, government policy responses to the conflict, and Russia's energy supply cut led to an acute energy demand across an already beleaguered Europe, attempting to cope with the aftermath of the COVID-19 pandemic and spiraling energy prices (Benton et al., 2022, p. 8). Supply chain disruptions and apprehensions of supply shortfalls have further intensified the situation, and as the war continues to reshape the global energy system, there is an accelerating shift towards cleaner energy alternatives as nations seek to increase energy security (International Energy Agency, 2024b). Geopolitical risk is identified as a critical factor for driving the state of the economy and is proven to be closely related to energy markets (Liu et al., 2021; Zhang et al., 2023). In particular, work by Jiang et al. (2024) has explored the connectedness between geopolitical risk and the carbon market, offering valuable insights. Therefore, it becomes pertinent to investigate how the Russo-Ukrainian war has influenced the interplay between carbon and energy markets.

As the world's third largest oil producer, Russia's military actions in Ukraine have significantly disrupted the global energy markets (International Energy Agency, 2022b). Russia's role as a massive exporter of crude oil, natural gas, and coal, comprising nearly half of the European Union's gas imports and significant shares of oil and coal imports, rendered the EU particularly vulnerable in the aftermath of the invasion (European Commission, 2024). The EU, together with the G7 countries and their allies, responded by imposing a series of embargoes and trade restrictions targeting Russian goods and commodities. These measures precipitated a pronounced escalation in energy prices (Mahlstein et al., 2022). Despite these sanctions, Russia has continued to hold a prominent position as an exporter of fossil fuels by redirecting exports to nations such as India, China, Turkey, and the Middle East (International Energy Agency, 2024b).

The European energy sector faced a critical challenge due to its excessive dependence on energy imports from Russia, which underscored the risk of reliance on a single nation (European Commission, 2024). To mitigate the dependence on Russian energy, the European Commission developed the REPowerEU plan (European Commission, 2022). With this initiative, the European Commission aims to strengthen Europe's energy security by energy conservation measures, speed up the clean energy transition, and diversify the sources of energy imports. As nations look for alternative energy, the expansion of renewable energy has accelerated. In a time marked by escalating geopolitical risk and persistent market volatility, nations' efforts are increasingly focused on enhancing energy self-reliance through increased investments in clean energy, thereby diminishing the repercussions of the conflict.

While the conflict has implicitly contributed to the green transition in Europe, the immediate response in the price of carbon permits in the European Union Emission Trading System (EU ETS) differed. Carbon prices experienced a historical crash after the invasion, lowering the cost of pollution (Ambrose, 2022). The EU ETS emerged as the EU's strategy to achieve climate neutrality by 2050 and attain a minimum of 55% reduction in greenhouse gas emissions by 2030 (European Commission, 2019). This is facilitated through the implementation of a cap-and-trade system that governs the allocation of carbon allowances for entities such as power plants, industrial factors, and the aviation industry. Allowances are distributed via auctioning, and the standard contract unit, referred to as a lot, corresponds to 1,000 European Union Allowances (EUAs). Each EUA authorizes the holder to emit one ton of carbon dioxide or an equivalent volume of other potent greenhouse gases (European Commission, n.d.).

Typically, carbon prices are positively correlated with energy prices, but unlike oil and gas, which saw rapid price increases post-invasion, EUA prices deviated from this trend. According to Ingvild Sørhus, a lead analyst for EU Carbon Analysis, this decline was driven by investors pulling funding, prompted by uncertainties related to the conflict (Ambrose, 2022).

While it is well-documented that energy markets are interconnected with carbon markets and geopolitical risk (Chen et al., 2022; Gong et al., 2021; Liu et al., 2021; Zhang et al., 2023), there is limited literature exploring how these dynamics are specifically influenced by the Russo-Ukrainian conflict. Jiang et al. (2024) contribute to existing research by analyzing the interplay between geopolitical risk, energy markets, and carbon markets, revealing strong interconnectedness in the short term, intensified during periods of heightened geopolitical risk. Yet, within the context of the Russo-Ukrainian war, the dynamics remain underexplored.

Maneejuk et al. (2024) add to filling the research gap by studying how the conflict has affected fossil and renewable energy cycles by innovatively implementing the Russian Economic Policy

Uncertainty (REPU) index coupled with a dummy variable, following Google Trends data on "Ukraine and Russia Tensions". This approach allows them to capture complex geopolitical dimensions in their Markov Switching Bayesian Vector Autoregressive (MS-BVAR) analysis, facilitating a more profound comprehension of the long-term economic consequences spanning geopolitics and energy markets. Their findings include evidence of significant regime switching post-invasion, with high-volatility regimes appearing more frequent for both fossil energy cycles and renewable energy cycles.

Building upon the foundational research of Maneejuk et al. (2024) and Jiang et al. (2024), this thesis aims to bridge the existing research gap regarding the impact of the Russian invasion of Ukraine on energy markets, encompassing fossil fuels, clean energy, and the European carbon market. By employing an MS-BVAR model, together with impulse response function (IRF) analysis, this thesis examines the relationship between the returns on EUA carbon futures, European Brent crude oil futures, Dutch TTF natural gas futures, the S&P Global Clean Energy Index, and the Geopolitical Risk Index (Caldara & Iacoviello, 2022), by utilizing end-of-month price data spanning from January 2015 to February 2024.

The Markov switching methodology can adequately capture nonlinearities and asymmetries among variables, a challenge at which a regular VAR model would fail. This approach is particularly advantageous in the context of geopolitical instabilities and conflicts such as the Russo-Ukrainian war, where market fluctuations tend to be unpredictable. These fluctuations are a result of jumps between economic states, shifting between low and high volatility regimes, such that the distribution of the price data changes (Kim & Nelson, 1999). To understand the dynamics between the variables prior to and during the conflict, the Markov switching model allows for the definition of two distinct regimes that mirror periods of high and low market volatility. This approach enables an analysis of the shifts in the interplay between the variables as market volatility varies.

The importance of investigating these complex interactions lies in the crucial insights they provide into the broader economic and environmental strategies required to mitigate the adverse effects of geopolitical tensions. By seeking to close this research gap, this study aims to provide a nuanced perception of the changing dynamics between energy and carbon markets and their connection to geopolitical risk during high-volatility regimes. By understanding the conflict's far-reaching implications on energy security and climate policy initiatives, policymakers can develop robust responses to enhance both energy independence and environmental sustainability.

The thesis will commence with an exploration of existing literature on energy markets, carbon markets, and geopolitical risk in Section 2. Next, the data collection process and a description of the historical price data are provided in Section 3, together with descriptive statistics and tests on the underlying structure of the data. Section 4 describes the MS-BVAR model and the IRF analysis, including methodological assumptions, drawbacks, and software used. Section 5 presents the results from the MS-BVAR and IRF analysis. A discussion of these results and their implications for the research topic are explored in Section 6, followed by a conclusion of the study and suggestions for further research in Section 7.

2 Literature review

The drivers of energy and carbon markets have been extensively studied, revealing close interconnections between these markets. It is increasingly recognized that both markets are influenced by the macroeconomic environment and geopolitical tensions, emphasizing the importance of understanding these relations during crises to mitigate risks. However, there is limited research on how the Russo-Ukrainian war has impacted energy markets, and even less on its effects on carbon markets. The following section will outline relevant literature that forms the foundation of this thesis. Initially, key studies focusing on the European carbon market will be presented, followed by an exploration of the interconnectedness between geopolitical risk, clean energy, fossil fuels, and carbon markets. Finally, preliminary research addressing the impact of the Russo-Ukrainian war on these markets will be reviewed.

Alberola et al. (2008) were pioneers in their study of price drivers for EUAs, that emerged in 2005. Via regression, their efforts advance prior work by demonstrating that the prices of carbon futures respond not only to energy price forecasting errors but also to unexpected temperature changes. Their findings showed that the significant fall in EUA prices in April 2006 suggested that an insufficiently stringent cap could cause allowance prices to be too low to stimulate mitigated emissions. During Phase I of the EU ETS, it was evident that the rigor of the cap was inadequate for market participants, resulting in a collapse of the price. They claim that the post-pilot period offers enhanced insights into the institutional and market dynamics that influence allowance price movements.

Batten et al. (2021) incorporate weather, alongside energy prices, as predictors of carbon prices in Phase III of the EU ETS, to investigate the magnitude of the effect on price trends. Their study, with models based on Alberola et al. (2008) and Mansanet-Bataller et al. (2007), confirms earlier findings by showing that while the level of temperature does not influence carbon prices, unexpected temperature fluctuations do. Given the association of climate change with increased temperature volatility, their results indicate that intensified climate change is linked to increased volatility in carbon prices. However, the contribution of other energy markets to carbon price determination was minor compared to initial expectations, indicating that additional factors might be more decisive in setting prices. They encourage future studies to investigate the effect that policy uncertainty and other macroeconomic variables have on the carbon pricing dynamics.

Sun and Xu (2021) employ a modified wavelet least square support vector machine for carbon price prediction in China, the world's largest emitter, addressing the unpredictability and non-linear characteristics observed in carbon pricing series. They argue that relying solely on a single model is inadequate for achieving precise predictions, and demonstrate that implementing hybrid models significantly enhances prediction accuracy, offering valuable practical insights. Results showed that a hybrid approach for carbon price determination yielded the most accurate output. They attribute the irregularities in carbon prices to a complex interplay of policy- and market uncertainties as well as the prices of related energy markets. The researchers suggest that future work could investigate how fossil energy prices and market policies influence changes in the carbon price.

Abbas et al. (2023) establish that heightened geopolitical risks substantially obstruct green financing and environmental taxation, especially considering the global financial slowdown triggered by COVID-19. Their research underscores the critical roles of geopolitical risk, green finance, and environmental taxes on investments in renewable energy (IRE) sources. Through quantile regression and dynamic analysis techniques, the study investigates the influence of IRE on companies' energy production. The findings indicate that while green financing and environmental taxes notably enhance IRE, geopolitical risk pose barriers to such initiatives. The authors assert that green investments are vital for sustainable development, suggesting that even if energy outputs may rise in the short run, such investments are essential to address environmental change.

Zhang et al. (2023) investigate the causality dynamics between green finance and geopolitical risk by utilizing a novel time-varying causality testing framework following Nasir et al. (2021) and Shi et al. (2019) The study reveals that geopolitical risk exerts a significant influence on the volatility rather than the returns of green bonds and renewable energy. Notably, European clean energy has shown resilience to global geopolitical risk since 2015, suggesting it may act as a safe haven asset during uncertain times. Findings underscore the importance for policymakers to strengthen the green finance regulatory environment, especially in turbulent periods, to stabilize the green finance market. The authors suggest that further research could use country-level geopolitical risk or a subindex including geopolitical threats and acts.

Liu et al. (2021) empirically investigate the relationship between energy and geopolitics by utilizing the geopolitical risk index constructed by Caldara and Iacoviello (2022) to examine the volatility of fossil energy commodities. Employing the GARCH-MIDAS model, they find compelling evidence of geopolitical uncertainty significantly impacting the long-run volatility of fossil energy. Firstly, they point to geopolitical uncertainty providing explanatory power regarding the observed energy volatility, even after controlling for realized volatility, fundamental variables, financial market stress, and economic policy uncertainty. Second, the transmission mechanism indicates that the impact of geopolitical uncertainty on energy markets is more likely to occur through threats rather than actual events. Thirdly, the use of high-frequency information in the GARCH-MIDAS model enables it to capture the persistent effects of geopolitical uncertainty, significantly enhancing out-of-sample predictions of energy volatility. This study paves the way for future research into how geopolitical uncertainty impacts the decoupling of oil and gas prices.

The study by Jiang et al. (2024) examines the connectedness among geopolitical risk, fossil energy fuels, and carbon markets through a time-frequency lens, utilizing the Diebold and Yilmaz (DY), and the Baruník and Křehlík (BK) spillover index models. The results suggest a greater total connectedness in the short term, which intensifies in periods of heightened geopolitical risk, with switching pathways of connectedness. Notably, the research revealed substantial evidence that during the COVID-19 pandemic, carbon markets affected the level of geopolitical risk. The findings imply that carbon and fossil fuel markets possess inherent political attributes, enabling policymakers to adjust supply and demand strategies in response to rising geopolitical risk to mitigate market volatility. Furthermore, the researchers point out that in times of global crises with rising geopolitical tensions, it may be possible to manage the geopolitical risk by manipulating carbon prices. Results indicate that the performance of the natural gas market is inconsistent with other traditional energy markets, thus, further study of its uniqueness is recommended.

Ha (2023) studied the dynamic connectedness between the renewable energy sector and carbon risk during the Russo-Ukrainian conflict by employing a novel multivariate wavelet analysis, such as partial wavelet coherency and partial wavelet gain. The study identifies significant relationships between green bonds, clean energy, and carbon futures across various frequencies. Particularly, findings suggest that carbon risk harms renewable energy and green energy during the Russo-Ukrainian war. The study highlights the impact of geopolitical events on the renewable energy market, and how crises can reset industry growth and reshape market dynamics. Ha suggests that further analysis should examine the environmental performance of renewable energy sources in developing countries.

The study by Enescu and Szeles (2023) discusses the energy price volatility in the aftermath of the Russo-Ukrainian conflict, and policy responses to manage the high energy prices. A variety of GARCH models are utilized to capture the volatility of Brent crude oil, TTF natural gas, and UK natural gas. The analysis shows persistent high volatility in all prices, especially for TTF natural gas, which exhibited the highest range of conditional variance. The researchers underscore the EU's vulnerability due to its heavy reliance on Russian energy supplies. Despite sanctions against Russia, gas prices remain volatile. The authors suggest that a comprehensive understanding of the conflict's impact requires analysis over a longer time frame and recommend incorporating a Markov switching model to better capture non-linear and asymmetric responses of the market to geopolitical risk.

Research by Balsalobre-Lorente et al. (2023) explores how the influence of the Russo-Ukrainian conflict sentiments on the returns within the oil and gas markets of G7 nations. The researchers conducted the analysis by creating a comparative scenario between a pre- and post-conflict period of six months, employing Cross-Quantilogram and Partial Cross-Quantilogram methodologies. Findings indicated that the repercussions of the conflict were modeled by the degree of reliance on Russian oil and gas supplies, with significant differences between pre- and post-conflict scenarios. The paper underscores the critical nature of the Russo-Ukrainian conflict in the research domain, particularly from a policymaker's perspective striving to enhance energy resilience and mitigate the impact of unexpected shocks in supplies and prices for fossil fuels, by motivating renewable energy development. The proposed policy framework presented in the paper serves as a benchmark for countries dependent on Russian energy imports. For further studies, researchers suggest incorporating social dimensions to design a more robust policy framework.

By establishing the state of current literature, the intricate interconnections between energy and carbon markets are shown to be significantly influenced by geopolitical tensions. Still, a notable research gap exists concerning the specific impacts of the Russo-Ukrainian war. This thesis aims to bridge this gap by providing a detailed analysis of how this conflict has affected the dynamics between energy and carbon markets by utilizing the Geopolitical Risk index by Caldara and Iacoviello (2022) in an MS-BVAR and IRF analysis.

3 Data

3.1 Data Collection

Focusing on the dynamics of energy and carbon markets in Europe, this section contains an in-depth analysis of monthly data encompassing EUA Carbon Futures, European Brent Crude Oil Futures, Dutch TTF Natural Gas Futures, the S&P Global Clean Energy Index, and the Geopolitical Risk Index (Caldara & Iacoviello, 2022). As articulated in the introductory section, the onset of the Russian invasion of Ukraine in February 2022 has precipitated many research endeavors in this domain, examining a wide array of impacts beyond the immediate repercussions on the various European energy markets.

The Geopolitical Risk Index by Caldara and Iacoviello (2022) quantifies adverse geopolitical events and measures the prevalence of associated risks using data sourced from articles in established newspaper sources. The index utilizes automated text-search results from the following newspapers: Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post. The index counts the number of articles categorized by search results that focus on terms related to wars, terrorism, and geopolitical tensions, and normalizes the results to an average of 100. Higher index values indicate an increased presence and severity of adverse events, suggesting a greater likelihood and potential intensity of such events in the future. The index graphically displays the ratio of articles that discuss geopolitical developments relative to the total article count each month, providing a graphical representation of geopolitical instability derived from journalistic coverage, enabling an empirical assessment of geopolitical threats.

Variable	Definition	Log Returns	Source
ICE EU Carbon Allowance (EUA) Futures	€ / ton of emitted CO_2 or equivalent greenhouse gases	Carbon	Bloomberg
European Brent Crude Oil Futures	$ / barrel	Oil	Federal Reserve Economics Data
Dutch TTF Natural Gas Futures	€ / MW	Gas	Bloomberg
S&P Global Clean Energy Index	€ / Index performance	Clean	Bloomberg
Geopolitical Risk Index	Ratio of newspaper articles covering geopolitical events and risk compared to the total amount of articles	GPR Index	Caldara & Iacoviello[1]

Table 1 – Research variables definitions

The analysis utilizes a transformation of five variables into logarithmic returns and logarithmic growth rates. Data on EUA carbon futures, Dutch TTF natural gas futures, and the S&P Global Clean Energy Index are retrieved from Bloomberg, while data on European Brent crude oil futures is retrieved from FRED. Monthly data on the Geopolitical Risk Index is retrieved from Caldara and Iacoviello (2022). The dataset spans from January 2015 through February 2024, yielding a sample size of 110 observations, aligned with a monthly frequency. In addressing the issue of asynchronous dates attributable to variations in trading dates, a methodological adjustment was employed. This involved the synthetic alignment of monthly closing values to the first day of each respective month, thereby standardizing the temporal aspect of the dataset for consistency.

[1] Retrieved from https://www.matteoiacoviello.com/gpr.htm on March 8th, 2024.

3.2 Description of data

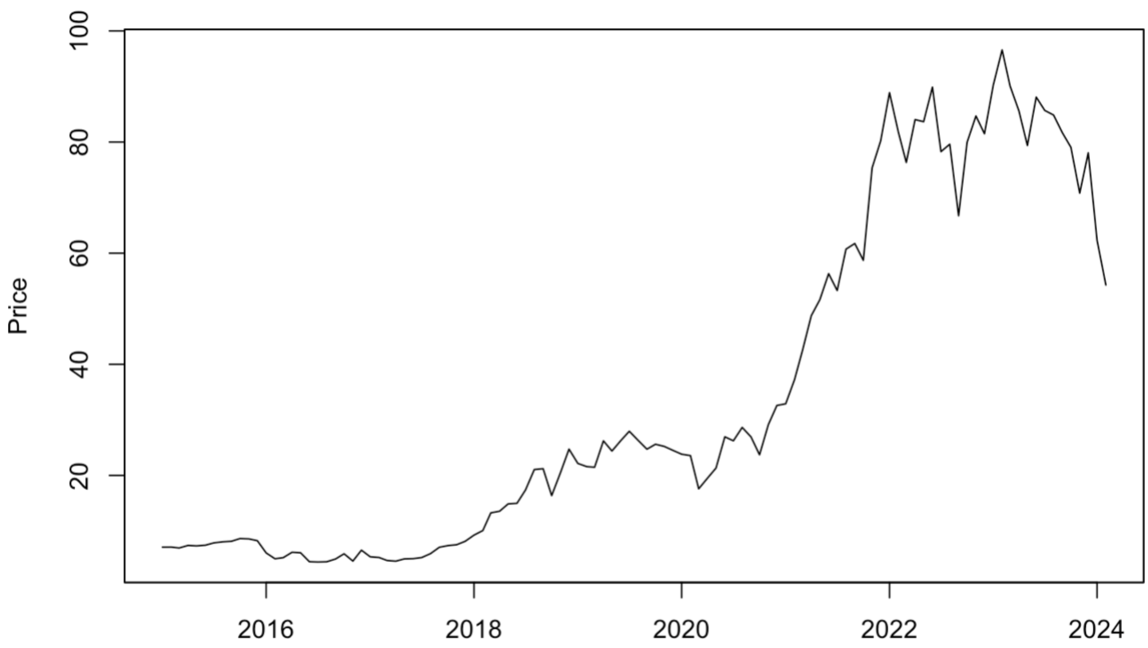

Figure 1 - Monthly EUA Carbon Future prices in EUR for the sample period (2015/01/01 – 2024/02/01)

At the onset of the sample period, the price for EUA carbon futures commenced at €7.03, peaking at an all-time high of €96.58 in February 2023. By the two years following the end of 2021, prices remained elevated, before experiencing a swift decline. The observed upward trend that can be seen in 2021 is likely due to the implementation of phase IIII of the EU ETS, which limited the supply of carbon allowances (European Central Bank, 2022). Furthermore, Europe experienced particularly cold weather conditions in 2021, which heightened the energy demand. This increased demand, coupled with the elevated prices for fossil fuels during this period, significantly contributed to a surge in carbon prices (European Central Bank, 2022).

The correlation between the price of carbon allowance and fossil fuel prices has been thoroughly studied, revealing a clear linkage where carbon prices generally track the demand and pricing dynamics of fossil fuels (Chen et al., 2022; Gong et al., 2021). However, as Russia invaded Ukraine in 2022, EUAs unexpectedly experienced a crash, decoupling from the broader energy market trends as later seen in Brent crude oil and TTF natural gas. Subsequently, carbon prices began to recover in the second half of 2022. Despite the peak in February 2023, the price of carbon allowances has since seen a rapid decline, largely attributed to falling fossil fuel prices.

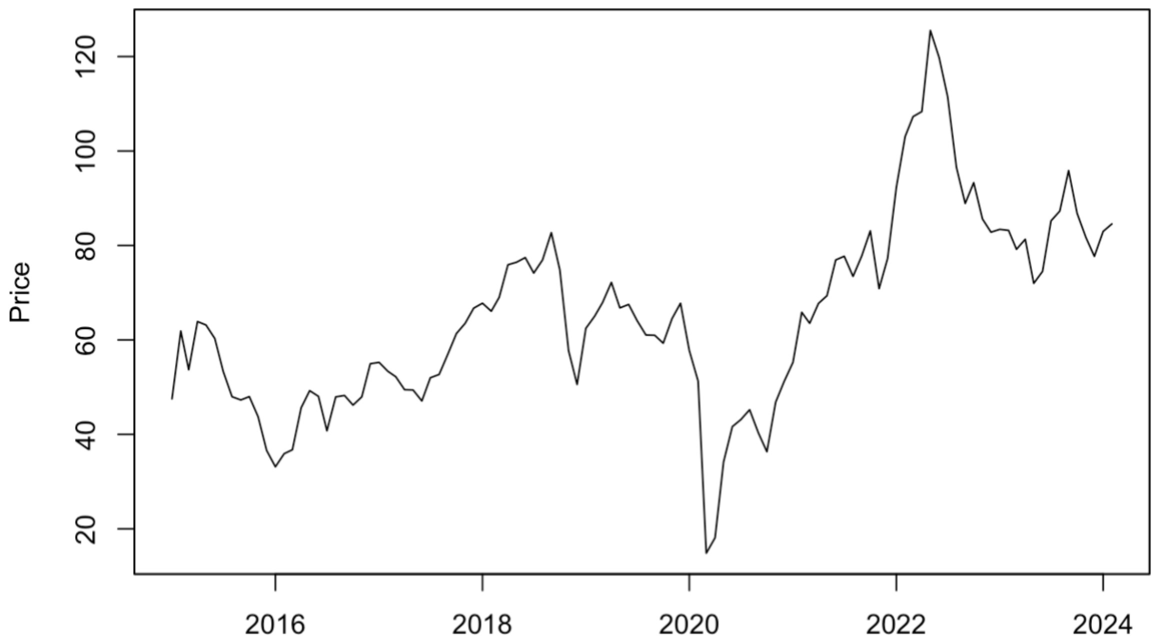

Figure 2 – Monthly European Brent Crude Oil Future prices in USD per barrel for the sample period (2015/01/01 – 2024/02/29)

Brent crude oil traded at $47.52 per barrel at the beginning of 2015 and peaked in May 2022 with a trading price of $125.53 per barrel. In a two-year period prior to the peak, the oil market was in a recovery after the unexpected demand shock triggered by the COVID-19 pandemic. The first half of 2020 was characterized by uncertainty, restrictions, and reduced economic activity, leading to a historical dip in oil demand (Ostashko, 2023, p. 12). However, in the second half of 2020, the oil price progressed as nations gradually emerged from their lockdowns. By the end of 2020, the price had recovered and was trading at $51.22 per barrel.

The year 2021 witnessed a persistent rise in trading prices, with the World Bank (2021) voicing concerns by year-end about the potential impact of escalating energy prices on short term global inflation. The rising trend in oil prices continued into 2022 as tensions of the Russo-Ukrainian conflict grew. After the invasion in February 2022, the peak was reached in May. Russia is one of the world’s largest oil exporters on the global market (International Energy Agency, 2022b), and as a reaction to the invasion, the European Commission implemented the REPowerEU plan, an initiative aimed at reducing Europe´s dependency on Russian fossil fuels (Eurostat, 2024). Thus, the reduction was compensated by an increased import from Saudi Arabia, the United States, and Norway, contributing to the rise in Brent crude oil prices. In the second half of 2022, oil prices began to decline due to the increase in interest rates by central banks, as well as growing concerns about recession (Kearney, 2022).

Throughout 2023, Brent crude oil experienced market volatility, influenced by the EU´s continued embargo on Russian crude oil imports and high interest rates. The peak oil price of the year was recorded in September, shortly after Saudi Arabia announced extended cuts in oil production. Concurrently, U.S. commercial crude oil inventories fell, which resulted in limited supply and an upward pressure in Brent crude oil prices (French, 2024).

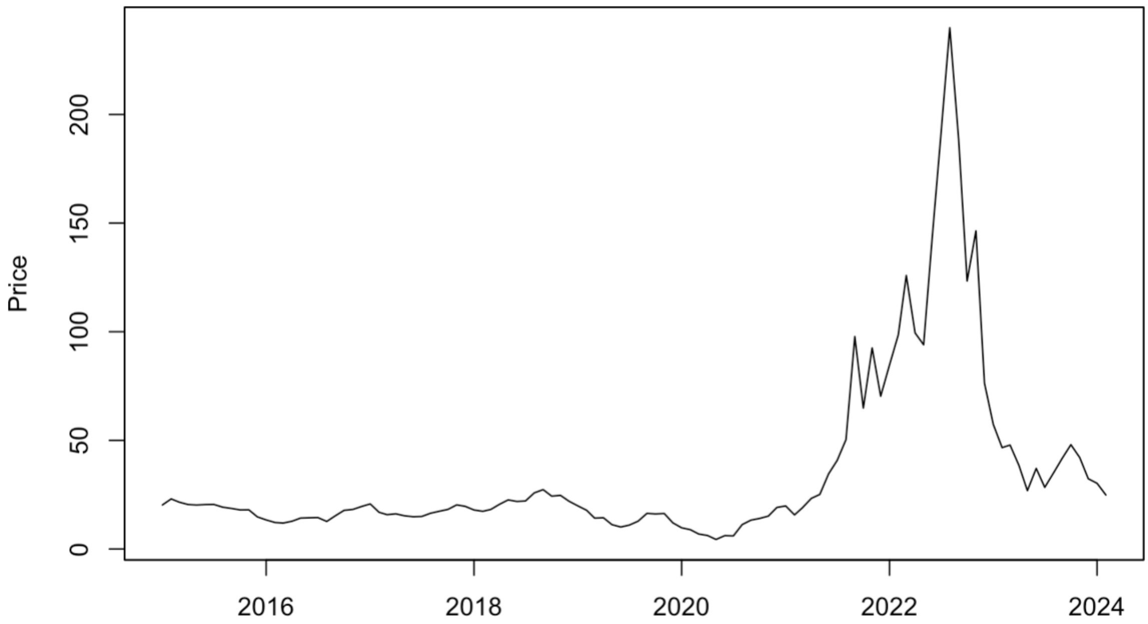

Figure 3 – Monthly Dutch TTF Natural Gas Future prices in EUR per MW for the sample period (2015/01/01 – 2024/02/29)

Figure 3 presents the end-of-month trading prices for Dutch TTF natural gas from 2015 to 2024. The time up to the end of 2021 shows a period of relative stability, with minimal price fluctuations and an average trading price of €16.2/MWh. However, a significant shift in the trend occurs towards the end of 2021. This shift reflects gradual increased economic activity and energy demand as countries were recovering from COVID-19.

The situation escalated as Russia's tapering of gas supplies to Europe in the second half of 2021 resulted in a reduction in gas supplies corresponding to a 25% reduction compared to the fourth quarter the year before (International Energy Agency, 2022a). After the invasion of

Ukraine in 2022, Russia further reduced their pipeline gas supplies with 80bcm (billion cubic meters), leading to a surge in TTF prices to €125.9/MWh (International Energy Agency, 2024b). The sharpest increase in TTF prices occurred in August 2022 when prices exploded to an unprecedented high of €239.9/MWh.

Gas prices started to stabilize in the second half of 2022, a reaction partly due to an upsurge in liquefied natural gas imports from the U.S., which bolstered European gas storage before the winter. A decrease in demand, due to mild winter conditions, also contributed to this stabilization. Additionally, the European Commission and the member states continued their work to mitigate high gas prices by improving conditions in joint gas purchasing, implementing correction mechanisms to temper episodes of extreme price surges, and fostering the growth of renewable energy infrastructure (European Commission, 2023, p. 3).

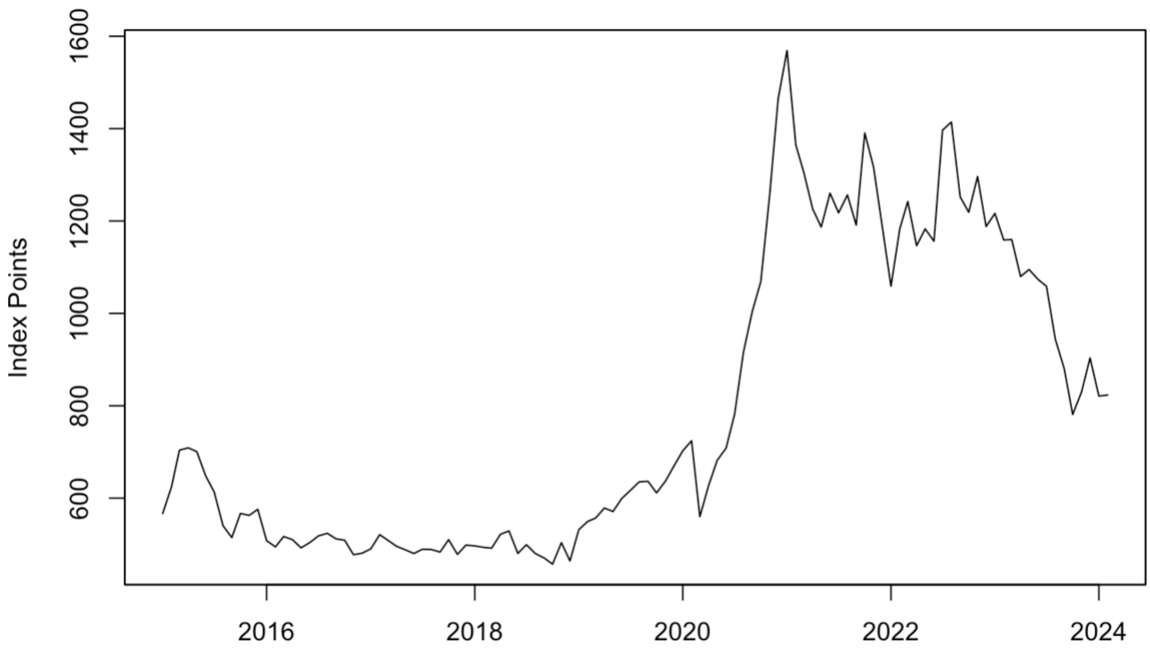

Figure 4 – Monthly S&P Global Clean Energy Index performance for the sample period (2015/01/01 – 2024/02/29)

From 2016 to 2019, the S&P Global Clean Energy Index maintained a relatively consistent development with small fluctuations in performance, averaging at 535 index points. The index displays more pronounced fluctuations after 2020, initially caused by a downturn at the outset of the COVID-19 pandemic. This downturn was followed by a swift escalation in prices towards the end of the year, cumulating in a peak in January 2021 with a record high end-of-month performance of 1569 index points.

Throughout 2020 and 2021, the global clean energy market experienced a substantial increase in prices of the production and transportation of renewables, such as solar PV modules, wind turbines, and biofuels (International Energy Agency, 2021, p. 138). However, during the same period, prices hiked for oil, gas, and coal, which strengthened renewables' overall competitiveness.

The year 2022 was characterized by pronounced price volatility, largely due to geopolitical tensions and the Russo-Ukrainian war, cumulating in the European energy crises. The European Commission's REPowerEU plan to reduce reliance on Russian fossil fuels further motivated the acceleration of renewable energy deployment (International Energy Agency, 2022a, p. 36). The 2022 peak of 1414 index points was observed in August after the U.S. Congress approved the Inflation Reduction Act (IRA) of 2022, including grants, loans, and tax provisions to accelerate the deployment of clean energy (International Energy Agency, 2023).

The capacity of clean energy reached new heights in 2023 with a 50% increase from 2022, spurred by policy support across more than 130 countries. China, in particular, emerged as a leading country with expanding capacities of solar PV and wind energy by 116% and 66%, respectively (International Energy Agency, 2024a, p. 14). Despite greater capacity and stabilization of commodity and shipping costs from prior years, financing costs remained elevated due to high interest rates, casting a shadow on the economic landscape of clean energy projects in 2023 (BloombergNEF, 2023).

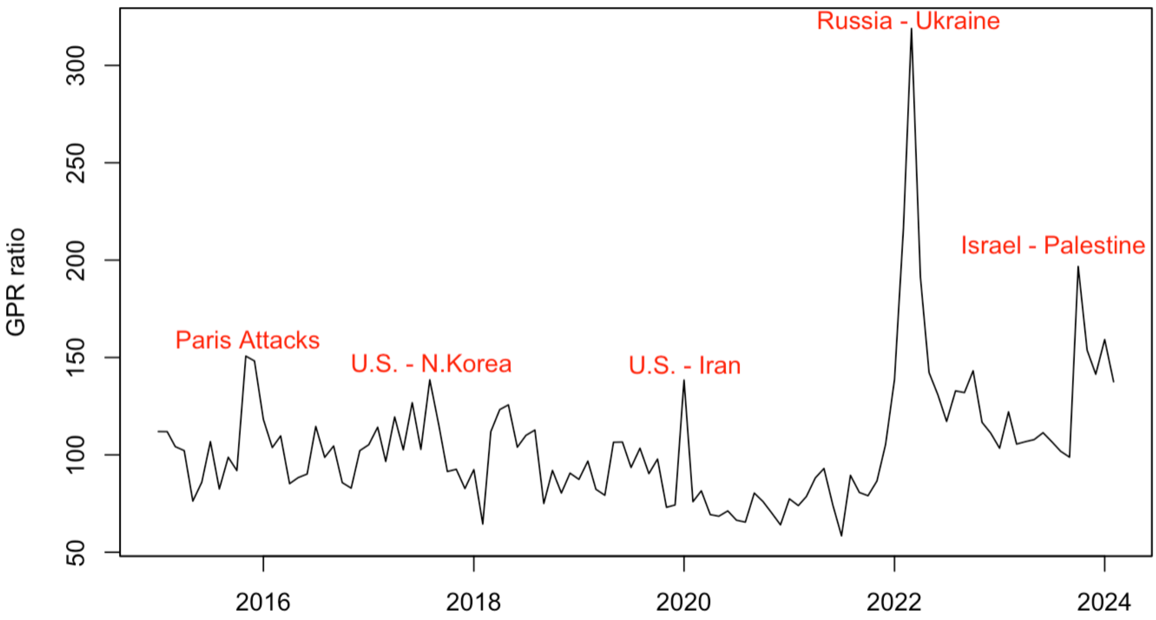

Figure 5 – Monthly Geopolitical Risk Index for the sample period (2015/01/01 – 2024/02/29)

Figure 5 illustrates a series of significant geopolitical events that have had far-reaching global repercussions over the past decade. Notably, the November 2015 terrorist attacks in Paris marked the onset of heightened global tensions. Subsequently, 2017 faced escalating tensions due to North Korea's aggressive missile and nuclear armament programs, leading to strained relations with the U.S. (Nilsson-Wright, 2017). In January 2020 the geopolitical landscape was marked by increasing tensions between Iran and the U.S. (Thomas et al., 2020). Then, in October 2023 an armed conflict between Israel and Hamas-led Palestinian military groups took place on the Gaza Strip. These episodes, among others, have significantly precipitated an acceleration in a shift toward unprecedented geopolitical changes and uncertainty.

Yet, it is the Russian invasion of Ukraine on February 24, 2022, that stands out as the most defining moment in geopolitical events in the last decade. The conflict has affected international relations, transforming global geopolitical uncertainty and the world order. The repercussions extend beyond the immediate military engagements between Russia and Ukraine, signifying a multifaced struggle and game between Russia, the U.S., and Europe (Liu & Shu, 2023).

3.3 Logarithmic returns and growth rates

To examine the interrelations among the European carbon market, energy markets, and the GPR Index, this study converts end-of-month price data into logarithmic returns. Since the GPR Index does not represent a price-based series, it makes the application of logarithmic returns unfit. Instead, variations in the GPR Index are expressed as logarithmic growth rates. The formula employed to calculate these logarithmic returns and growth rates, hereafter referred to simply as returns and growth rates, is as follows:

$$r_t = \log\left(\frac{Value_t}{Value_{t-1}}\right) \cdot 100. \tag{3.1}$$

The transformation of monthly price data to returns and GPR to growth rates provides various benefits for statistical analysis. This statistical technique stabilizes the variance of the time series data, which is effective in achieving stationarity (Brooks, 2019, p. 53). Moreover, expressing the data as logarithmic returns and growth rates allows for an interpretation of the results in terms of percentage changes. This transformation not only standardizes the comparison across different scales of data but also simplifies the comprehension of the magnitude of market movements.

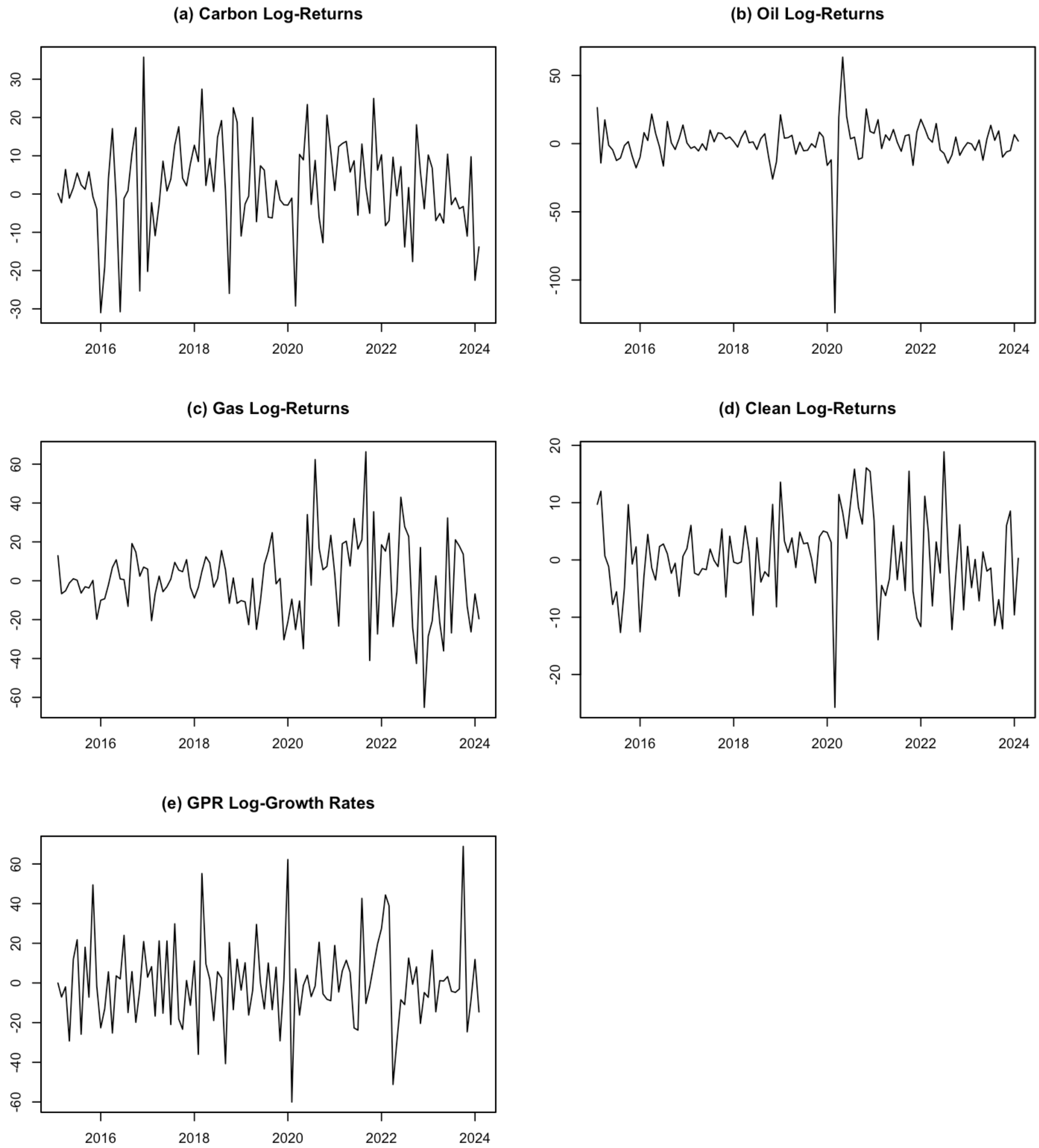

Figure 6 – Monthly logarithmic returns and growth rates for the sample period (2015/01/01 – 2024/02/29)

From figure 6, the historical monthly returns and growth rates are visualized through the sample period spanning from 2015 to February 2024. Figure 6(e) appears to have the most volatile fluctuations, reflecting the varying tensions in the geopolitical landscape. The most significant spikes from 2018, 2020, 2022, and 2024, reflect the same events as observed in figure 5.

Figure 6(a) demonstrates considerable variability throughout the sample period, with particularly significant spikes observed from 2016 to 2020. During this period, the price of EUAs was relatively low, resulting in even small price changes appearing as large return fluctuations, thereby contributing to the heightened volatility observed in this period. After 2020, variability in returns diminished as carbon prices increased. Meanwhile, returns in figure 6(b) and 6(d) exhibited relatively stable behaviors with minor fluctuations, except for 2020 when both markets exhibited significant disruptions. More notable for Oil, due to the sharp decline triggered by COVID-19. Returns on Gas remained relatively stable from 2015 to 2020 but became significantly more volatile thereafter. The European energy crises of 2021 and the repercussions of the Russo-Ukrainian conflict beginning in 2022 are visible in the plot.

The return series exhibited in figure 6 is closer to mean-variance stationarity than the raw price series, yet extreme events such as the reaction to COVID-19 and the European energy crises are visible in both price and return plots across several variables. These observations suggest that there may be substantial changes in the underlying data generating process. The extent and implications of these shifts will be further tested in Section 3.5. The next section will provide descriptive statistics for the return and growth rates.

3.4 Descriptive statistics

	Carbon	**Oil**	**Gas**	**Clean**	**GPR**
Mean	1.8672	0.5288	0.1877	0.3430	0.1887
Median	1.6261	1.2867	0.8455	0.1846	-1.2074
SD	12.3146	16.6359	20.5169	7.3963	21.3730
IQR	13.4875	12.3008	23.2911	8.6626	23.6635
Min	-31.0155	-123.9886	-65.1453	-25.7333	-60.0151
Max	35.7766	63.4298	66.3898	18.8848	68.8595
Skewness	-0.3296	-3.3298	0.1477	-0.1423	0.4915
Kurtosis	3.6129	31.6258	4.2285	3.7409	4.3120
JB p-value	0.1589	0.0000	0.0266	0.2392	0.0022

Table 2 – Descriptive statistics for the sample period (2015/01/01 – 2024/02/29)

Carbon returns display the overall highest mean and median of the variables, indicating a positive trend. A kurtosis of 3.61 is indicative of a leptokurtic nature and pronounced tails, which along with a skewness of -0.33 points to a modest asymmetry. However, with a Jarque-Bera p-value at 0.16, the evidence is not sufficiently strong to definitively discard the normality of the distribution, hence failing to reject the null hypothesis. The most prominent characteristic of Oil returns stems from the variations in extrema, along with the observation that the median is exceedingly larger than the mean, indicating a left-skewed distribution where observing negative returns is a commonality. The elevated minimum value of -123.99 aids in confirming this distributional description. This can also be read from the skewness, which at -3.33 is sufficiently negative to support the rationale of a rejected null hypothesis, as the p-value from the Jarque-Bera test is 0. An augmented leptokurtic value of 31.63 validates this decision while being synonym with frequently observed extreme values. The standard deviation of 16.64 can confirm this and is suggestive of observations widely dispersed from the mean. The same pattern regarding mean and median is also observable for Gas returns, where the discrepancy implies a non-normal distribution that is additionally corroborated by both a heightened skewness and kurtosis, therefore allowing for the rejection of normality. The elevated interquartile range, of 23.29, is telling of a large spread within the middle 50%, aligning well with the elevated standard deviation of 20.52 and the heightened kurtosis.

Clean returns display on average a marginal negative skewness of -0.14, reflecting a slightly leftward skewed distribution. Despite the leptokurtic nature of the returns, with a Jarque-Bera p-value of 0.24, there is insufficient statistical evidence to reject the hypothesis of normality. The GPR Index is on average characterized by a modestly positive average change in the ratio of geopolitically related newspaper articles to the total number of articles across the observed newspapers. However, the median value of -1.21 suggests that growth often falls on the lower end of the spectrum, highlighting a disparity between the mean and median growth rate values. However, this tendency towards lower values is offset by a positive skewness of 0.49, indicating that while lower values are more common, there are some positive extreme values in the data. Additionally, the substantial standard deviation of 21.37 highlights the index's volatility. The pronounced leptokurtosis of the index, with a value of 4.31, combined with the low Jarque-Bera p-value, strongly suggests that the distribution does not conform to normality, characterized by fat tails and a peaked distribution.

3.5 Structural Breaks and nonlinearity

3.5.1 Structural Break test

The detection of structural breaks in time series analysis is essential, as it identifies instances of substantial change in the underlying data generation. To determine if the wanted methodology is contextually appropriate, structural breaks can be identified to allow for disruption in the data stemming from significant events. Bai and Perron (2003) advanced a methodology for discerning structural breaks within an econometric framework, with parameters that may exhibit either temporal variability or constancy. This approach provides the necessary flexibility to define model specifications that are crucial for deriving accurate analytical outcomes. Neglecting these breaks can lead to forecasts that are off the mark, flawed statistical inferences, and markedly distorted interpretations of economic relationships. For example, overlooking them might lead to an incorrect assumption of non-stationarity in the series, which could in turn lead to the use of inadequate analytical models. Therefore, the identification of structural breaks plays a pivotal role in fostering a deeper understanding of the dynamics that drive changes in the data.

The constructed model analyzes logarithmic returns and growth rates of the selected variables, incorporating the allowance of both heterogeneity and autocorrelation within the residuals. Additionally, it accommodates time-varying volatility present in the dataset.

SupF(l+1|l) – Sequential F-statistic										
	Carbon		**Oil**		**Gas**		**Clean**		**GPR**	
Break Test	F	CV	F	CV	F	CV	F	CV	F	CV
0 vs. 1	4.631	18.680	10.133	18.680	5.707	9.100	4.612	9.100	1.014	9.100
1 vs. 2	16.230	20.570	99.599	20.570**	13.342	10.550**	15.641	10.550**	8.714	10.550
2 vs. 3	11.382	21.600	91.559	21.600**	1.724	11.360	8.372	11.360	8.714	11.360
3 vs. 4	21.231	22.550	91.559	22.550**	4.318	12.350	1.673	12.350	0.941	12.350
1			11/2019 [06/2018, 01/2020]		05/2020 [11/2019, 08/2021]		03/2020 [05/2019, 09/2020]			
2			09/2020 [08/2020, 01/2021]		08/2022 [10/2021, 02/2023]		01/2021 [08/2020, 08/2021]			

*Table 3 – Bai and Perron (2003) Structural Break test, where ** denotes the 95% significance level.*

The empirical analysis of the model reveals the detection of two structural breaks in the returns of Oil, Gas, and Clean, while no analogous breaks were observed in the returns of Carbon nor for the growth rate of the GPR Index. Specifically, the F-statistics associated with Carbon returns did not surpass the critical thresholds at any point, indicating a lack of statistically significant evidence for structural breaks within the time series. Similarly, the F-statistics for the GPR Index remained consistently below the threshold values required for identifying breaks, confirming the absence of such disruptions. Conversely, for the returns of Oil, Gas, and Clean, two structural breaks were identified upon setting the maximum permissible structural changes at four. Alterations to this parameter did not yield any variation in the outcomes, underscoring the robustness of these findings.

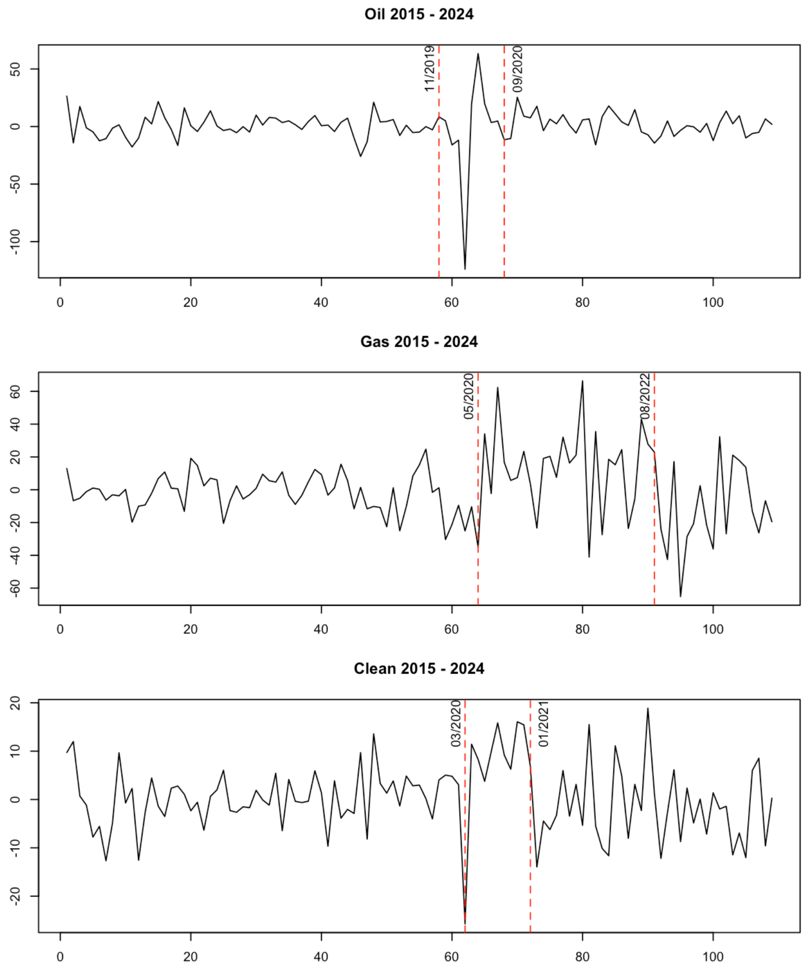

Figure 7 – Structural Breaks for Oil, Gas, and Clean for the sample period (2015/01/01 – 2024/02/29)

Figure 7 illustrates the historical returns for Oil, Gas, and Clean, marking significant structural breaks during the sample period. The test identifies two prominent breaks in the returns of Oil and Clean, notably during the COVID-19 outbreak and subsequently as market returns began to stabilize post-crises. In the case of Gas returns, the initial break occurs within the early stage of the pandemic, leading to a period marked by sustained volatility. The second break is detected shortly after the onset of the Russo-Ukrainian war. These findings highlight the importance of including the structural break test in the analysis to capture the shifts in market dynamics under external shocks. They also motivate the methodological choice of employing a Markov switching model to adequately capture the switching dynamics in the underlying data.

3.5.2 BDS test

Brock, Dechert, and Scheinkman (1986) initially developed a nonlinearity test, known as the BDS test, which was further refined in 1996. The test was introduced to evaluate the independent and identically distributed (i.i.d.) nature of time series data, thereby expanding the scope of analysis beyond merely second- or third-order dynamics. This methodology employs a correlation integral, a technique commonly used in chaotic time series analysis, to detect nonlinear dependencies in serial data. The null hypothesis of the BDS test follows a standard normal distribution, and tests if the data constitute complete randomness or the alternative, that there is a potentially forecastable structure or hidden patterns (Brock et al., 1991).

An adaptation of the test is used to check for hidden structure in the VAR(2) residuals as a diagnostic tool. By implementing first-differencing to eradicate any linear trends through the fitting of a linear model, the BDS test then assesses if the residuals are i.i.d. Should this hypothesis be refuted, it would suggest residual structures within the time series that could be indicative of underlying nonlinearities or unobserved non-stationarities.

VAR(2) residuals	Embedding dimension	BDS statistic	z-statistic	p-value
Carbon	1	5.9640	-0.0574	0.9542
	2	11.9280	1.5930	0.1112
	3	17.8920	1.4172	0.1564
	4	23.8559	0.8243	0.4098
Oil	1	7.5804	3.8937	0.0001
	2	15.1608	3.7144	0.0002
	3	22.7412	3.7287	0.0002
	4	30.3216	4.5118	0.0000
Gas	1	8.5976	2.3995	0.0164
	2	17.1951	1.3421	0.1796
	3	25.7927	1.7389	0.0821
	4	34.3903	2.0018	0.0453
Clean	1	3.5046	1.6508	0.0988
	2	7.0091	1.5432	0.1228
	3	10.5137	0.8111	0.4173
	4	14.0183	0.8037	0.4216
GPR	1	9.8684	1.8350	0.0665
	2	19.7368	1.9467	0.0516
	3	29.6052	2.6854	0.0072
	4	39.4736	1.8538	0.0638

Table 4 – Nonlinearity test by Brock, Dechert, and Scheinkman (1986) for the sample period (2015/01/01 – 2024/02/29)

The table presents the empirical findings of the BDS test applied to the residuals of a standard vector autoregressive model with two lags. For the Carbon returns and Clean energy returns, all p-values exceed the 0.05 threshold, thereby failing to reject the null hypothesis that the residuals are i.i.d. This implies that the VAR(2) model adequately captures the dynamics of these markets' returns. In contrast, the results for Gas returns and the GPR Index suggest the presence of underlying nonlinearities. This is evidenced by certain elevated test statistics being associated with p-values below the accepted significance level, signifying the remnant of forecastable structure. Specifically, for Gas returns, the BDS statistics of 8.6 and 34.4 for dimensions 1 and 4 respectively, and the GPR Index, with a test statistic of 29.6 for the third dimension, the null hypothesis is rejected, indicating clear nonlinearities and the need for a better model.

Particularly notable are the findings for Oil returns, where the p-values are consistently low across embedding dimensions, strongly suggesting a persistent nonlinear dependency not captured by the linear VAR(2). The increasing BDS statistic along the dimensions, with associated low p-values, suggests that the nonlinearity and forecastable structure is strengthened as more periods back are considered. This consistent rejection of the null hypothesis of i.i.d. across dimensions underscores a complex dynamic structure within Oil returns.

In summary, the BDS test demonstrates that while the linear VAR(2) model adequately accounts for the dynamics of the returns for the Carbon and Clean markets, it inadequately addresses the complexities observed in the returns on Oil, Gas, and the growth rate of the GPR Index, hence motivating the further study of unit roots while constructing the basis for the relevancy of the MS-BVAR.

3.6 Unit Root tests

The examination of unit roots within time series data is a fundamental prerequisite for establishing cointegrated relationships. In situations where structural breaks are present within the series under investigation, the standard Dickey-Fuller unit root test may yield unreliable results. This unreliability stems from its diminished power in such scenarios, which may lead to an incorrect failure to reject the null hypothesis. Specifically, the presence of an unaccounted structural break biases the slope parameter in the regression toward unity, consequently affecting the accuracy of the test (Perron, 1989). The influence of the structural break on the power of the test is directly proportional to the magnitude of the break, and inversely proportional to the size of the sample. Larger breaks and smaller samples tend to reduce the power of the test significantly.

In response to the limitations of the standard Dickey-Fuller (DF) unit root test in the presence of structural breaks, the Augmented Dickey-Fuller (ADF) test is often employed as a more robust alternative. The test addresses the key issue of reduced test power, especially in cases of structural breaks, by incorporating additional lagged difference terms of the dependent variable into the testing equation. The added terms help to control for autocorrelation and serial correlation that might be present in the error term, a common occurrence in the presence of structural breaks. By conducting this adjustment the reliability of the test in differentiating between a true unit root and a stationary process affected by structural breaks is enhanced. (Dickey & Fuller, 1979)

The Phillips-Perron (PP) test advances the methodology of the standard DF test, which hypothesizes a unit root under the condition $\rho = 1$ within the model $\Delta y_t = (\rho - 1)y_{t-1} + u_t$ (Dickey & Fuller, 1979). It addresses the limitations of the DF test that arise from the potential existence of autocorrelation within the data-generating process for y_t , which is not accommodated within the DF test equation. Such autocorrelation may induce endogeneity in y_{t-1}, thereby rendering the DF t-statistic unreliable. To mitigate this issue, the DF test has been augmented to include lagged differences of the dependent variable Δy_t as additional regressors. Conversely, the PP test employs a non-parametric method to adjust the t-statistic, enhancing the robustness against unspecified forms of autocorrelation and potential heteroskedasticity within the error term (Phillips & Perron, 1988).

	ADF	**p-value**	**PP**	**p-value**
Carbon	-3.0876	0.1254	-6.3093	0.0000
Oil	-5.962	0.0000	-80.052	0.0000
Gas	-3.7699	0.0230	-118.95	0.0000
Clean	-3.9122	0.0161	-100.04	0.0000
GPR	-6.3093	0.0000	-85.222	0.0000

Table 6 - Augmented Dickey-Fuller and Phillips-Perron unit root tests

Table 6 displays the test statistics belonging to the ADF test and the PP test, alongside the p-values that determine whether the null hypothesis of a unit root is rejected or not. The predominance of significant test statistics, except for Carbon returns under the ADF methodology, affords a robust basis to deduce stationarity within the series under review at the 95% confidence level. It is noteworthy that, despite the intrinsic differences in their methodologies, the ADF and PP tests often arrive at analogous inferential outcomes concerning unit root presence. Although the p-values from the PP test yield constant 0, the conclusion on the hypothesis is similar on all except for Carbon returns.

The identification of structural breaks and nonlinearities, alongside the predominant rejection of unit roots confirming stationarity, underscores the complexities inherent in the return series. While the predominant absence of unit roots facilitates the use of conventional VAR models, the presence of structural breaks challenges their capacity to consistently capture dynamic changes. Thus, underscoring the complexities of market behaviors and necessitating the application of more advanced methodologies that can accommodate these intricacies for a deeper analysis.

4 Methodology

4.1 Markov Switching Bayesian Vector Autoregressive Model (MS-BVAR)

Granger (1996) emphasizes the importance of addressing structural breaks and regime shifts in macroeconomic time-series analysis, and in this thesis, a Markov Switching Bayesian Vector Autoregressive Model (MS-BVAR) is employed to examine the impact of the Russo-Ukrainian war on the dynamics of the European carbon and energy markets. Building upon the foundational VAR model by Sims (1980), the MS-BVAR integrates the features of a Markov chain, as originally proposed by Hamilton (1989). Krolzig (1997) further integrated the Markov chain with the multivariate VAR framework, efficiently addressing the limitations that linear models face in capturing market asymmetries as shown by Kunitomo and Sato (1999).

The MS-BVAR model is able to adequately capture the dynamic and multifaced nature of the carbon and energy markets, as well as identifying distinct states or regimes, each reflecting different phases of market behavior. This methodological choice enables a comprehensive exploration of the underlying factors driving these markets by scrutinizing the behavior and interplay of the variables within different regimes (Krolzig, 1997).

For this analysis, a two-regime MS model is assumed to describe the dynamic interactions between the carbon and energy market before and during the Russo-Ukrainian war. The empirical literature sufficiently demonstrates that a two-regime MS model is comprehensive enough to capture the regime switching behavior observed in macroeconomic time series data (Balcilar et al., 2015; Filardo & Gordon, 1998; Hamilton, 1989; Maneejuk et al. 2024). Based on preliminary tests, such as the likelihood ratio test and the Akaike Information Criterion (AIC), the order of two lags is chosen to sufficiently capture the dynamics from the data.

A reduced form MS**IAH**(2)-BVAR(2) specified by Krolzig (1997) has been employed, where "**I**" refers to the intercept, "**A**" is for the autoregressive coefficients, and "**H**" refers to heteroskedasticity in the variance-covariance matrix. All parameters of the two-regime model are assumed to be conditioned on the unobservable regime variable s_t. The model specification of the two-state MS-BVAR model, where $y_t = (\mathrm{Carbon}_t, \mathrm{Oil}_t, \mathrm{Gas}_t, \mathrm{Clean}_t, \mathrm{GPR}_t)$ is a 5 by 1 vector of endogenous variables at time t, is outlined as follows:

$$y_t = \begin{cases} \alpha_1 + \sum_{i=1}^{p=2} \beta_{i1} y_{t-i} + u_t, & if\ s_t = 1 \\ \alpha_2 + \sum_{i=1}^{p=2} \beta_{i2} y_{t-i} + u_t, & if\ s_t = 2 \end{cases}. \tag{4.1}$$

Each regime is characterized by an intercept α_i, autoregressive coefficients β_{ij} of lagged endogenous variables, and error term $u_t|s_t \sim NID(0, \Sigma_{s_t})$. The regime-dependent error terms are assumed to follow a normal and independent distribution with a mean of zero and a positive definite 5 by 5 variance-covariance matrix that can change depending on the state at time t. The number of lags of the autoregressive terms are represented in p.

The foundational concept of the MS-BVAR model is that the parameters of the underlying data generating process of the observed time series vector y_t depend on the unobservable regime variable s_t, which represents the regime prevailing at time t (Krolzig, 1997, p. 11). For this specific case, the regime variable $s_t = 1, 2$, indicates if the market is in a low-volatility regime or in a high-volatility regime.

4.1.2 The Hidden Markov Chain

To further complete the description of the data-generating process, Markov switching models assume that the unobservable realization of the regime variable, s_t, is dictated by a discrete time, discrete state Markov stochastic process, which is defined by the transition probabilities,

$$p_{lh} = \Pr(s_{t+1} = h \mid s_t = l), \sum_{h=1}^{2} p_{lh} = 1,\ l, h = 1,2, \tag{4.2}$$

where p_{lh} is the conditional probability of moving from a low-volatility regime *l* at time *t*, to a high-volatility regime *h,* at time *(t+1).* The s_t is assumed to follow a two-state Markov process that is irreducible and ergodic. The transition probabilities between states are collected in the transition matrix *P*,

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}. \tag{4.3}$$

The transition matrix presents the probability of transitioning from the current state to any future state. For further description, it is convenient to collect all information on the realization of the Markov chain in the vector ξ_t to denote the unobserved state of the system

$$\xi_t = \begin{bmatrix} I(s_t = 1) \\ I(s_t = 2) \end{bmatrix}, \qquad I(s_t = m) = \begin{cases} 1 \; if \; s_t = m \\ 0 \; otherwise \end{cases}, \tag{4.4}$$

where the different states are denoted through an indicator function with m = 1, 2. Relevant information about the future state of the Markov process depends exclusively on the current state ξ_t,

$$\Pr(\xi_{t+1}|\xi_t,\ \xi_{t-1}, \dots; y_t, y_{t-1}, \dots) = \Pr\,(\xi_{t+1}|\xi_t), \tag{4.5}$$

where the past and additional variables such as y_t where the past and additional variables, such as y_t do not provide additional information beyond what is captured by the current state of the system. A Markov chain is said to be ergodic if one eigenvalue of the transition matrix *P* is unity, with all others residing inside the unit circle, ensuring that each state is aperiodic and recurrent (Krolzig, 1997, p. 17). When this assumption holds, the ergodic probability vector of the Markov chain represents the unconditional probability distribution for s_t, which is denoted by $\bar{\xi} = \mathrm{E}[\xi_t]$. When solving the stationarity condition $P'\bar{\xi} = \bar{\xi}$, while honoring the adding up restriction of $1_2'\bar{\xi} = 1$, one finds

$$\bar{\xi} = \begin{bmatrix} I_{2-1} - P'_{1,1} & P'_{1,2} \\ 1'_{2-1} & 1 \end{bmatrix}^{-1} \begin{bmatrix} 0_{2-1} \\ 1 \end{bmatrix}, \tag{4.6}$$

$$\bar{\xi} = \begin{bmatrix} 1 - p_{11} & p_{21} \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ 1 \end{bmatrix}. \tag{4.7}$$

The first row is derived from the stationarity condition by transposing the transition matrix P, and the second row reflects the adding up restriction which ensures that the sum of probabilities equals 1. If $\bar{\xi}$ is strictly positive, such that all regimes have a positive unconditional probability

$\bar{\xi}_i > 0, i = 1,2$, the respective Markov process is called irreducible. This attribute of irreducibility suggests that the process is capable of entering alternative states. The assumptions of ergodicity and irreducibility are vital for the property of stationarity of the MS-BVAR model to ensure that the process converges to a steady state distribution regardless of the initial state (Krolzig, 1997, p. 17).

4.2 Bayesian Estimation

In Bayesian estimation within the MS-BVAR model, the inferential process is conducted through the application of Bayes' theorem to deduce the joint posterior distribution of the model parameters given the observed data. The joint posterior distribution is a combination of the prior distribution, representing prior knowledge about the parameter space, and the likelihood function, which is derived from the observed data specific to the MS-BVAR model (Frühwirth-Schnatter, 2006). The integration of Bayesian inference is especially useful due to its provision of complete posterior distributions rather than point estimates, a feature particularly crucial when estimating nonlinear models with regime switches, such as the MS-BVAR with its dynamic nature.

The application of Bayesian inference begins by positing a prior distribution, $p(\Theta, P)$, over the space of the regime-dependent VAR model parameters $\Theta = \left(\alpha(s_t), \beta(s_t), \mathrm{u}(s_t)\right)$ and the transition matrix P of the Markov process. The prior captures historical beliefs about model parameter values before considering the observed data. The likelihood function, $p(Y_t|\Theta(s_t), P)$, indicates the likelihood of the observed values of y_t, namely $Y_t = (y_t', y_{t-1}', \cdots, y_{t-p}')'$, given the set of regime-dependent VAR parameters Θ and the transition matrix P.

By combining the two via Bayes' theorem, the joint posterior distribution over the VAR parameters and the regime states can be formulated as:

$$p(\Theta, \mathrm{P}|Y_t) \propto p(Y_t|\Theta(s_t), P)p(\Theta, P). \tag{4.8}$$

The estimation process for the posterior mode is computed via an iterative maximum likelihood (ML) function, known as an expectation-maximization (EM) algorithm (Navidi, 1997). In models with numerous variables or multiple regimes, the EM algorithm grapples with nonlinear complexities, often requiring extensive iterations for full posterior distribution convergence, with the risk of not reaching a definitive solution. Consequently, to help reach the full posterior distribution, the next section introduces the Monte Carlo Markov Chain (MCMC) algorithm, namely the Gibbs sampler.

4.2.1 Gibbs Sampler

Gibbs sampling, developed by Geman and Geman (1984) and later expanded by Gelfand and Smith (1990), emerged as a Monte Carlo Markov Chain (MCMC) method of dealing with "missing values" in data analysis. As an MCMC method, Gibbs sampling has substantially expanded the scope of Bayesian inference, especially for complex and multi-dimensional space models (Frühwirth-Schnatter, 2006, p. 54). This method has gained increasing prevalence in parameter estimation for models with missing values as it treats the unobservable states as additional unknown parameters. Subsequently, Markov chain simulations are employed to derive the joint posterior distribution of parameters and regimes (Krolzig, 1997).

The Gibbs sampler procedure involves four steps. Initially, the state-space for the Markov process is drawn from the full conditional distribution, utilizing the Baum-Hamilton-Lee-Kim (BHLK) filter and smoother to estimate the regime probabilities (Kim & Nelson, 1999). Secondly, the posterior distribution of the transition probability matrix P is drawn, where a Dirichlet prior is assumed for P (Frühwirth-Schnatter, 2006, pp. 432-433). Thirdly, the posterior of the covariance matrices of Σ_{s_t} is drawn utilizing the inverse-Wishart distribution (Frühwirth-Schnatter, 2006, p. 439). In the last step, the regression coefficients $\beta(s_t)$ are drawn assuming a Sims-Zha prior (Sims & Zha, 1998).

The Gibbs sampler performs 25,000 iterations of parameter sampling, with the initial 5,000 iterations discarded to account for the burn-in period. This ensures that the sampling process adequately represents a random and stationary distribution. The remaining 20,000 iterations allow the distribution of the sampled parameters to closely approximate the true joint posterior distribution. This approach does not only facilitate precise parameter estimation but also yields credible probabilistic inferential statistics for the analysis.

4.3 Impulse Response Function

Since the seminal work of Sims (1980), impulse response functions (IRF) have emerged as an analytical tool for exploring the dynamic interactions between variables and disturbances in VAR models. IRFs quantify the magnitude and persistence of the effects that a shock to one variable imposes on all other variables in the system, mapping out the recovery trajectory (Koop et al., 1996, pp. 120-121). By defining generalized impulse response functions, Koop et al. (1996), established a methodological basis for applying IRFs within nonlinear models. In the development of IRFs for MS-VAR models, two principal methodologies have emerged. Ehrmann et al. (2003) proposed a model where regime switching is not assumed to occur beyond the horizon of the IRF, an assumption that poses a limitation as regime switches are likely to happen during the propagation of shocks, thereby potentially misrepresenting the dynamics of the system. In contrast, Krolzig (2006) introduced an approach that accounts for any regime changes within the time horizon, enabling a more realistic depiction of how shocks influence the system's behavior. However, Krolzig's approach does not incorporate the construction of confidence intervals, hence motivating the choice of a Bayesian approach for IRFs.

In this thesis, Bayesian impulse response functions as described by Sims and Zha (1999) and Waggoner and Zha (2003) are utilized. To provide interpretable shocks, a Cholesky decomposition is employed to identify and estimate the effects of the shocks within the MS-BVAR model. This process involves decomposing the variance-covariance matrix into a lower triangular matrix and its transpose, creating a recursive system where a shock to each variable affects only itself and the subsequent variables in the MS-BVAR model. Initially, the identification matrix L_{s_t} is derived from the decomposition of the variance-covariance matrix using the Cholesky decomposition, satisfying $\Sigma_{s_t} = L_{s_t} L'_{s_t}$. Subsequently, by using the matrix L_{s_t}, the orthogonalized shocks are computed by transforming u_t into a structural form:

$$u_t = L_{s_t} \epsilon_t, \tag{4.9}$$

$$\epsilon_t = L_{s_t}^{-1} u_t, \quad \text{with } \epsilon_t \sim NID(0, I_{(5,5)}). \tag{4.10}$$

The structural residuals ϵ_t represent the orthogonalized shocks, which are assumed to follow a normal and independent distribution with a mean of zero and a variance-covariance matrix taking the form of a 5 by 5 identity matrix.

To estimate the IRFs, the Gibbs sampler is employed to simulate the posterior densities for the MS-BVAR parameters, joint with the simulations of its identification matrix L_{s_t}, which directly yields the posterior densities of the IRFs. The Gibbs sampler provides accurate probabilistic statistical inference by simulating 5,000 burn-ins and 20,000 sample iterations, yielding confidence intervals for the IRF.

The method allows for the possibility of regime switches throughout the duration of the impulse responses, providing a more dynamic depiction of how the shocks influence the variables under varying conditions. It also overcomes the limitations in Krolzig (2006) by assessing the uncertainty associated with the IRFs through direct computation of confidence intervals.

4.4 Drawbacks of the MS-BVAR Model

Droumaguet (2012) discusses an acknowledged set of methodological constraints within MS-BVAR models. First, the incorporation of multiple regimes injects a layer of complexity through the introduction of nonlinearities, which complicates interpretation as the output escalates unidirectionally with the presence of additional regimes, each characterized by distinct dynamic properties. Furthermore, MS-BVAR models inherently embrace a higher degree of uncertainty in economic shock analysis, a byproduct of their capacity to encompass various regime transitions, leading to broader confidence intervals when assessing shock effects. This intricacy is however deemed essential for accuracy in the portrayal of economic phenomena and is not uniquely attributed to MS-BVAR.

In MS-BVAR model specification it is important to balance analytical rigor with intuitive judgment. This sensitivity in model specification often merges subjective data interpretation with empirical evidence, possibly impacting the outcome. Similarly, the selection of regimes may be dependent on external considerations, including specific aims and research context. This approach may skew results, as the determination of regimes is not solely based on intrinsic data characteristics but is also influenced by the research objective.

4.5 Computational framework and software

In this thesis, RStudio (version 2023.12.1+402) was employed as the main software. The primary statistical analysis was carried out using the “MSBVAR” package (version 0.9-3), obtained from the Comprehensive R Archive Network CRAN (Brandt, 2016). This package is equipped with a wide range of tools for estimating various models, including VAR, Markov switching, and Bayesian framework. For this specific study, the Markov Switching Bayesian VAR model was utilized, along with methods for generating posterior inference and impulse response functions.

Due to the complexity of the MS-BVAR methodological approach, some parts of the estimation procedure within the “MSBVAR” package are executed as a mixture of native R code and compiled Fortran. To specify, the sampling of MS-BVAR coefficients, transition matrix, and error covariances for each regime is conducted using native R coding. The most computationally intense parts, such as the state-space filtering algorithms and the forward-filtering-backward-sampling procedures of the Markov switching process are handled in compiled Fortran (Brandt, 2016).

The “MSBVAR” package was last updated in 2016, which posed a complication with the reliance on code from the “bit” package in some essential functions, as they were no longer compatible. The problem was resolved by downloading an older version of the "bit" package (version 1.1-8), that was compatible with the newest version of “MSBVAR”.

Overall, the integration of the “MSBVAR” package in RStudio, together with compiled Fortran for computational efficiency, provides a powerful analytical toolkit. It is especially advantageous for interpreting and visualizing the output of such a complex statistical methodology as the MS-BVAR. The reproducibility of the analysis is fortified by documenting the specific software versions of RStudio and related packages, as well as the script utilized for the analysis.

5 Results

A detailed assessment of the methodological framework supports that the selected approach is relevant for the intended analysis. This section utilizes the Markov Switching Bayesian Vector Autoregressive model with two regimes and two lags to explore whether there is a noticeable increase in the frequency of high-volatility regimes in European energy and carbon markets following the Russian invasion of Ukraine. The MS-BVAR model is instrumental in differentiating between market regimes, allowing for a nuanced understanding of how market conditions shift in response to external geopolitical events. This capability makes the MS-BVAR particularly suitable for examining the impacts of such shocks on market volatility.

This section will thoroughly assess whether the underlying theories that motivated this thesis hold, using the MS-BVAR as a critical analytical tool. By applying this model, the analysis aims to identify the specific characteristics and triggers of regime shifts, thereby providing insights into the resilience and responsiveness of European energy and carbon markets under geopolitical stress. The outcomes of this model will seek to enhance the understanding of complex market dynamics under crisis conditions.

5.1 MS-BVAR analysis

	REGIME 1				
Dependent variable	**Carbon**	**Oil**	**Gas**	**Clean**	**GPR**
$\boldsymbol{\alpha_1(s_1)}$	1.3720**	-0.0820	-1.5839**	-0.4879**	-0.8427**
$\mathbf{Carbon_{t-1}}$	0.0008	0.1456**	0.2012**	-0.0490**	-0.1090**
$\mathbf{Oil_{t-1}}$	-0.0109	0.2050**	0.0810**	0.0785**	0.0867**
$\mathbf{Gas_{t-1}}$	-0.0319**	0.0263**	0.4215**	-0.0936**	-0.0333**
$\mathbf{Clean_{t-1}}$	-0.1028**	-0.1227**	0.0057	0.0861**	0.5543**
$\mathbf{GPR_{t-1}}$	-0.0065	-0.0326**	-0.0601	0.0563**	-0.4101**
$\mathbf{Carbon_{t-2}}$	-0.0138	-0.0131	0.0602	0.0835**	0.2391**
$\mathbf{Oil_{t-2}}$	0.1226**	-0.0463**	-0.0505	-0.0432	-0.0356
$\mathbf{Gas_{t-2}}$	0.0243**	0.0071	0.0535	0.0669**	0.0306
$\mathbf{Clean_{t-2}}$	-0.2358**	0.2130**	-0.2354**	-0.0229	-0.9594**
$\mathbf{GPR_{t-2}}$	-0.0254**	-0.0032	-0.1344**	-0.0344**	-0.3260**

*Table 7 – Estimated coefficients from the MS-BVAR model in regime 1, where ** denotes the 95% significance level.*

	REGIME 2				
Dependent variable	**Carbon**	**Oil**	**Gas**	**Clean**	**GPR**
$\boldsymbol{\alpha_2(s_2)}$	2.6248**	0.5781	6.6038**	1.7756**	2.5369**
$\mathbf{Carbon_{t-1}}$	0.1386**	-0.2718**	0.1384	-0.1246**	-0.1218
$\mathbf{Oil_{t-1}}$	0.0606**	0.4175**	0.2065**	0.0372**	0.0532
$\mathbf{Gas_{t-1}}$	-0.2213**	0.1001**	-0.1264**	0.1537**	0.0314
$\mathbf{Clean_{t-1}}$	0.0284	-0.3277**	0.2784**	0.0607	0.1897**
$\mathbf{GPR_{t-1}}$	0.0756**	0.7459**	-0.0353	0.0402**	0.4161**
$\mathbf{Carbon_{t-2}}$	0.0946	0.4301**	-0.3468	-0.1204**	0.4178**
$\mathbf{Oil_{t-2}}$	-0.0762**	-0.5849**	0.5898**	0.0493**	-0.0722**
$\mathbf{Gas_{t-2}}$	0.0696**	-0.1651**	0.3895**	0.0134	-0.1141**
$\mathbf{Clean_{t-2}}$	0.1142	0.2081**	-1.2257**	-0.2598**	-0.0990
$\mathbf{GPR_{t-2}}$	-0.1521**	-0.5194**	-0.4342**	-0.1102**	0.2363**
$\boldsymbol{\rho_{11}}$	0.9717				
$\boldsymbol{\rho_{22}}$	0.9614				

*Table 8 – Estimated coefficients from the MS-BVAR model in regime 2 and transition probabilities, where ** denotes the 95% significance level.*

The findings from the MS-BVAR are compelling for the hypothesis of distinctive regime characteristics in the investigated time frame. Regime 1 is associated with low volatility, while regime 2 depicts periods of high volatility. There is an enlarged spread in the estimated intercept terms associated with high volatility in regime 2, as opposed to the small, negative but significant intercepts observed in regime 1. The estimated coefficients for the second lag, which are elevated and often statistically significant, affirm the robustness of the initial model selection, particularly in regime 2. Various information criteria and preliminary likelihood-ratio tests favored the inclusion of two lags as exerting substantial influence on the data. The prevalence of heightened coefficient estimation for the second lag is more common across both regimes when compared to the first lag. This suggests that regardless of volatility-state, the value two months prior has a higher predictive power for the current value than the immediate month, although with exceptions. For instance, in regime 2, The GPR Index' influence on Oil returns, with an estimated effect of 0.75% movement in the same direction per percentage point change, demonstrates that an increased amount of newspaper articles linked to geopolitical risk can positively affect Oil returns in the immediate period with everything else being fixed.

The GPR Index is included to allow for the bidirectional effect of time-varying volatility, measured by the ratio of geopolitically related newspaper articles to the total number of articles across the established news outlets, on energy markets, yielding notable findings. A noteworthy finding for the fluctuations in the current value of the GPR Index revealed that the direction of the growth rate both one and two months prior has a heightened impact on itself, demonstrating an inverse relationship in low-volatility regimes. This is suggestive of a predictable pattern for the succeeding months. The same relationship is observable for the estimated coefficients for the GPR Index in regime 2. This implies that when economic conditions are marked by instability, the current level of geopolitical risk can provide insights into the future geopolitical environment. Specifically, a one percent change in the subsequent month is associated with a 0.42% estimated movement in the same direction for the current value, assuming other factors remain constant. Regime 1 exhibits a similar trend, where the direction for the growth rate one and two months prior is estimated to predict the current movement in the opposite direction by 0.41% and 0.33% given everything else being fixed.

In volatile conditions, regime 2 shows a greater cumulative impact for coefficients from two months earlier compared to the preceding month, suggesting that the current energy market values are more influenced by values from two months ago. This lagged effect can indicate a delay in repercussions when the markets are exposed to shocks. In contrast, regime 1 shows negligible differences in the impacts between the first and second months' effect on the current value, with only a slight amplification observed in the estimated coefficients related to two months prior. For instance, a one percentage point change in Oil returns two months prior is estimated to correspond with a 0.59% movement in the same direction for current Gas returns in regime 2. This contrasts the marginal estimated impact of 0.05% in the opposite direction observed in regime 1 if all factors are assumed constant. Similarly, in regime 2, a one percentage point change in Clean returns from two months prior is estimated to affect the current value of Gas returns by 1.23% in the opposite direction. This inverse relationship suggests that positive returns for Clean are estimated to have a negative effect on Gas returns.

Changes in the GPR Index influence Oil returns and Gas returns in regime 2, particularly for a two-month lag. A one percent change in the GPR Index is linked to an estimated 0.52% movement in the opposite direction for Oil returns and 0.43% for Gas returns. Thus, it appears that when there is an increase in the amount of geopolitically related newspaper articles as compared to the total amount of articles, the returns for Oil and Gas tend to fall. Conversely, a decrease in geopolitical media coverage is associated with an increase in returns for Oil and Gas. The heightened, yet significant estimated coefficients in regime 2 for the GPR Index' impacts on the other variables two months prior enable conclusive inference on the strong connection between geopolitical risk and energy markets. In regime 2, Gas returns feature a notably high intercept term at 6.60%, significantly aligning with the sharp, manifold surge in gas prices initially driven by intracontinental energy politics, and further escalated by the invasion of Ukraine. This high baseline is more pronounced than those estimated for other variables and presents a stark contrast to the intercept of -1.59% for Gas returns in low-volatility regimes.

Analyzing Carbon returns across regimes underscores its distinct response patterns and interactions with the other variables. While Carbon's return dynamics remain stable in regime 1, regime 2 shows sensitivity to rapid economic and policy changes, influenced by intensified market fluctuations. Furthermore, the coefficients reveal that Carbon returns two months prior have a substantial impact on current returns on Oil, Gas, and the GPR Index. This interaction suggests a dynamic interplay where changes in Carbon prices could lead to substantial adjustments in the two energy markets. For instance, an increase in the price of carbon, potentially reflecting tighter emission regulations or increased demand for emission credits, could drive the oil price up. This is depicted in table 8, as a one percentage change in Carbon returns two months prior affect current Oil returns and growth rates in the GPR Index by 0.43% and 0.42% respectively, in the same direction. However, Gas returns are estimated to move 0.35% in the opposite direction, assuming other factors held constant. Additionally, in regime 2, Carbon returns show autocorrelation from the previous month's performance to the current value, reflecting pronounced self-impact during unstable market conditions.

The transition probabilities indicate the likelihood of persisting in each regime, with compelling results that underscore the presence of distinct regimes. With regime 1 showing a 97.17% likelihood of continuity, and regime 2 not far behind at 96.14%, there is consistency serving as evidence of regime stability, emphasizing the clear differentiation between the two regimes. These rates are also informative about the expected tenure of each regime, estimating an average span of 35 months for regime 1 and 26 months for regime 2. Nonetheless, the higher probability of remaining in regime 1, coupled with its longer average duration, indicates that periods of economic stability are more frequently observed in the sample period and last longer than those marked by economic volatility.

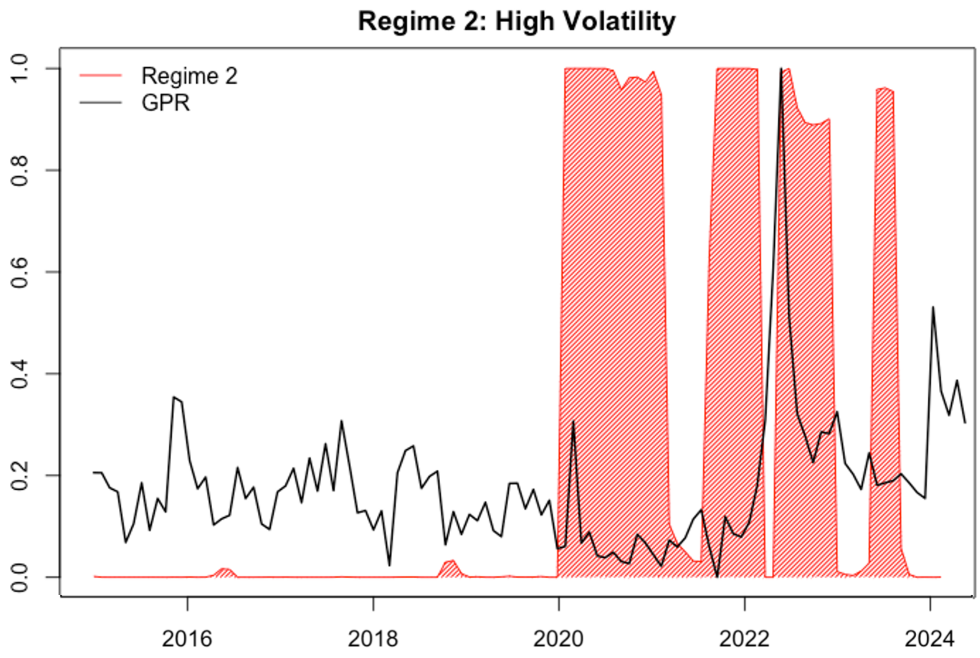

Figure 8 – Smoothed transition probabilities for regime 2 and Geopolitical Risk Index for the sample period (2015/01/01 – 2024/02/29)

Figure 8 presents the smoothed transition probabilities for regime 2, identified by significant volatility in carbon and energy markets, prominently observed during periods of increased uncertainty. The initial significant appearance of regime 2, in 2020, could be linked to the onset of economic turbulence triggered by COVID-19. Although this period was characterized by economic instability, COVID-19 has no geopolitical relevance. The enduring regime shift may be related to the instabilities following the pandemic, but is also supported by the spike in the GPR Index in 2020, coinciding with the tensions between the U.S. and Iran. This phase persisted for a prolonged period before reverting to regime 1. The correction was transient, as the second and third regime shifts in the plot are associated with the tensions initiated by the invasion of Ukraine and the energy market instabilities that followed. The black line on the graph represents the trajectory of the GPR Index, underscoring its concurrent trends with the spikes observed in the high-volatility regime, thereby emphasizing the synchronous fluctuations and hence the validation of regimes.

The visualization of regime 2 reveals a notable increase in high-volatility states beginning in 2020 and persisting in later years, validating the estimated high transition probabilities of remaining within the same regime. To conclude, there is a clear association between the timing of the Russian invasion and the frequency of the estimated high-volatility states.

5.2 Regime-dependent Impulse Response analysis

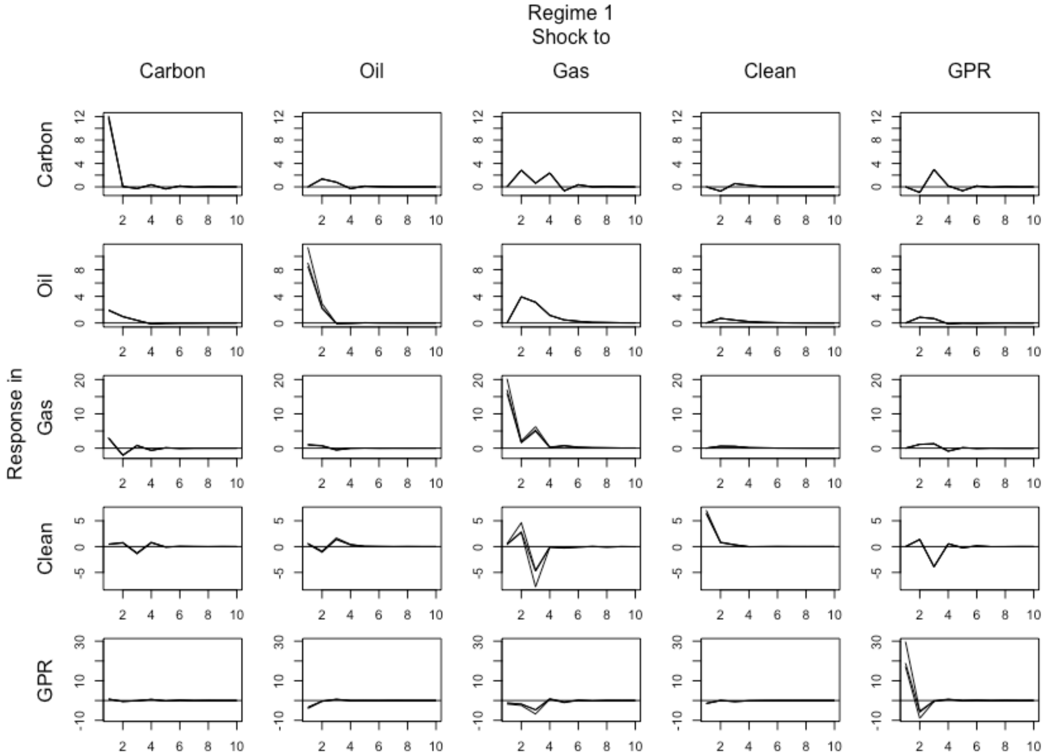

Figure 9 – Impulse Response plots for regime 1

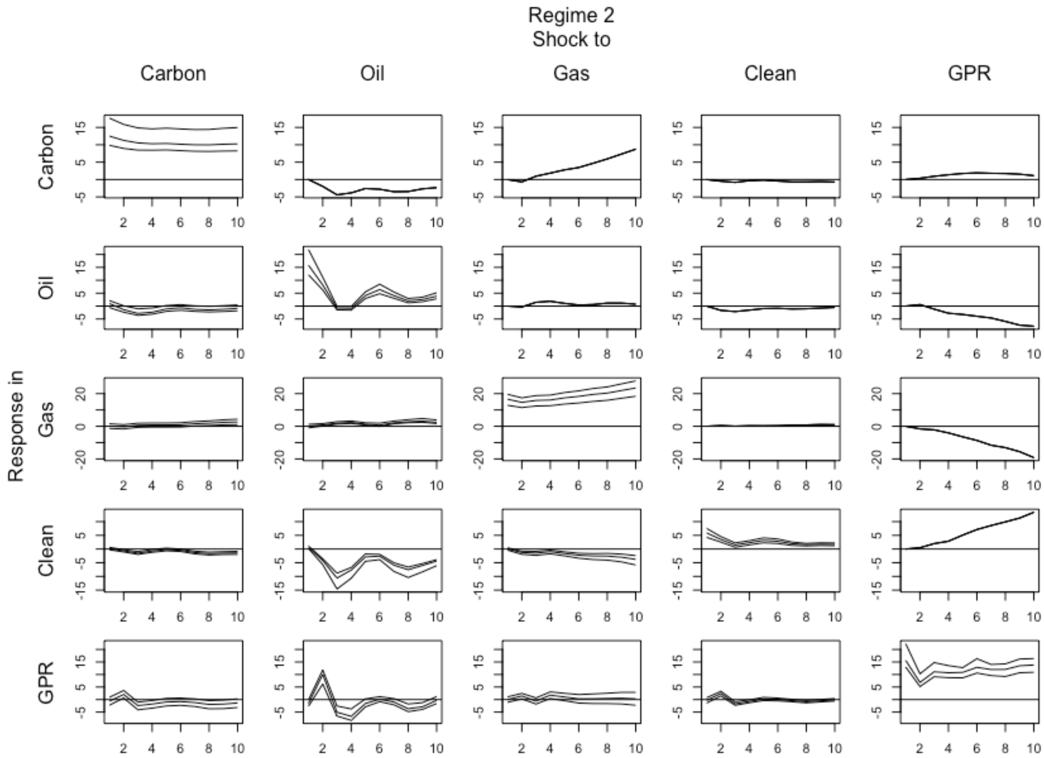

Figure 10 – Impulse Response plots for regime 2

Figure 9 and 10 show the impulse response plots generated from the MS-BVAR, incorporating error bands for the posterior in the manner of Waggoner and Zha (2003). The results reveal divergent responses between regime 1 and regime 2, corroborating the existence of distinct behavioral regimes in the European carbon and energy markets during the period from January 2015 to February 2024. In regime 1, the impact of shocks appears to be more transient, stabilizing back to baseline levels within 10 months. Conversely, regime 2 demonstrates a tendency not to revert as consistently to baseline, often displaying a prolonged deviation over the course of 10 months.

The persistence of shock effects in regime 2 is notable, with deviations from equilibrium continuing beyond 10 months. This pattern is consistent across the impulse response plots, and particularly pronounced for shocks to the GPR Index, with an observed negative impact on Oil and Gas returns, and positive for Clean returns. These observations support the notion that significant geopolitical shocks may have long-lasting impacts. Furthermore, the wider error bands observed in high-volatility regimes reflect the uncertainty related to the precision of impulse response estimates. This visual representation of uncertainty can be interpreted as supporting the regime-dependent nature of market responses as it is not visibly present in regime 1.

The impulse response functions highlight the robustness of the MS-BVAR model, and conveniently visualize responses to shocks, in order to capture the prolonged dynamics of the European energy and carbon markets. The consistent impact of the shocks underscores the importance of considering temporal dependencies in market behavior, which are crucial for understanding how shocks propagate through the energy and carbon markets, alongside the GPR Index.

6 Discussion

This section explores the results of the MS-BVAR analysis and the associated financial implications. It seeks to connect these findings with relevant literature to better understand the underlying forces shaping the pricing dynamics in European carbon and energy markets in a geopolitical context. The discussion includes insights that reveal distinct behavioral patterns of the variables across two separate regimes. This section sets the stage for a deeper examination of how these regime-specific differences influence market behavior, further elaborating on the practical implications of these findings for policy formulation and market prediction in the volatile landscape of energy economics.

The detection of structural breaks in the time series prompted a deeper exploration of the underlying mechanisms influencing pricing dynamics that are not adequately addressed by conventional linear modeling. This led to the introduction of the MS-BVAR model, to examine the interconnectedness of the variables, while allowing for distinctive regime characteristics. The initial theory proposed that high-volatility regimes would occur more frequently following the significant disruptions to the energy landscape caused by Russia invading Ukraine, and the results validate this belief. Comparing the results from the different regimes, the analysis highlights how specific market dynamics, such as sudden shifts in oil prices or rapid changes in gas demand, tend to align with notable fluctuations in geopolitics. For instance, the elevated volatility in regime 2 could be contextualized as reflecting markets becoming increasingly erratic and sensitive to external shocks during periods of heightened geopolitical tension.

The ADF test uniquely identified unit root presence in the returns of Carbon, which may be attributable to the market's artificial nature. The EUA Carbon market involves trading emission allowances, a mechanism progressively transitioning from full subsidization towards full market-driven pricing. This gradual shift influences the distinct behavior observed in Carbon returns dynamics, compared to the other markets investigated in this thesis. The persistence of non-stationarity in Carbon returns, as indicated by the ADF test, is likely mirroring the unique pricing mechanisms affecting this market, with policy changes, regulatory updates, and significant shifts in demand leading to the stochastic trend. This might also be suggestive of the carbon market experiencing shocks with permanent effects that go beyond short-term ramifications.

Preliminary data testing, along with practicalities linked to desired research objectives, facilitated landing on two regimes as a solid choice. This is however arbitrarily fixed within the MS-BVAR, which fundamentally shapes the analysis and interpretation of the interconnectedness across the investigated variables. This is a methodological choice, where the sensitivity of the results and regime-specific boundaries are introduced by pre-determined regime classifications. This approach does allow for a structured examination of regime-specific dynamics but may also obscure the dynamic nature of economic relationships under different geopolitical or economic conditions.

The high transition probabilities of 97.17% for regime 1 and 96.14% for regime 2 reflect substantial persistence within each market regime. This suggests that once markets enter a specific state, such as one characterized by high volatility, they are likely to remain in that state until interventions or natural market corrections trigger a shift to a low-volatility state. Previously noted durations, with regime 1 typically lasting 35 months and regime 2 enduring for 26 months within the selected time frame, emphasize the necessity for policies and strategies that minimize periods of instability and steer the markets back towards states of reduced volatility.

Jiang et al. (2024) found the carbon market to differ from the more conventional energy markets by unidirectionally affecting the GPR Index. Like the findings from this thesis, the GPR Index is found to be the volatility spillover receiver in high-volatility periods, while Carbon acts as the transmitter. It is seen that a one percentage change in Carbon returns from two months prior, corresponds to a 0.42% movement in the same direction in the GPR Index. Intriguingly, this suggests that shifts in Carbon returns could serve as an indicator of fluctuations in geopolitical trends, a distinctive correlation relative to other variables examined. If this relationship is established through further study, the precise quantification of the carbon market's influence on the GPR Index may offer an advanced forecasting tool, potentially aiding in the anticipation of geopolitical events based on observable market trends. This insight would be valuable in the formulation of energy policies, particularly as global markets navigate the challenges of transitioning to low-carbon economies.

Findings identified by Jiang (2024), serve as an intricate study of the connectedness between the GPR Index, carbon and energy markets as it encompasses geopolitical events and tensions beyond Russia's invasion of Ukraine. While this study specifically examines the observed increased frequency of high-volatility regimes following the invasion, it is important to note that the GPR Index captures a broader range of geopolitical events. Consequently, this wider scope may influence the interpretation of the results, as the estimated effects and relationships could be attributed to other influences, and not solely the Russo-Ukrainian war. This broader array of geopolitical events reflected in the GPR Index is essential to recognize when assessing the predictive capacity of the carbon market on geopolitical trends.

Initially, there was consideration to use a more targeted index, such as the Russian Economic Policy Uncertainty (REPU) Index, which could tailor the analysis more closely to the specific geopolitical context of interest, as seen in Maneejuk et al. (2024). However, the core objective of the analysis is not to align variables to a preconceived outcome but rather to examine whether the included variables demonstrate clear trends corresponding to periods of high or low volatility. By utilizing the comprehensive GPR Index, the analysis can explore whether there are unique dynamics in the variables that emerge specifically during times of heightened geopolitical tensions, regardless of their specific origin. This approach allows for a broader investigation into how global geopolitical unrest influences market volatility, providing insights into the overall resilience and sensitivity of these markets to external shocks. This could reveal underlying patterns that are crucial for understanding the broader implications of geopolitical risks on energy markets.

During periods of high volatility, the GPR Index was observed to respond to changes in Carbon returns, while simultaneously functioning as a transmitter influencing Oil returns. Balsalobre-Lorente et al. (2023) studied the effect of the Russo-Ukrainian war on oil and gas returns in a pre- and post-invasion period. They found that oil returns exhibited a prolonged impact in the post-invasion scenario, compared to the pre-invasion period. Although this thesis does not explicitly analyze the periods before and after the invasion, the findings from the MS-BVAR model somewhat align with their observations. The interconnectedness between the lagged coefficients of the GPR Index on Oil returns has intensified from -0.03% and -0.003% in the low-volatility regime, to 0.75% and -0.52% in the high-volatility regime. These findings suggest that during periods of heightened geopolitical tensions, the impacts on Oil returns are greater. Given that high-volatility regimes have become more frequent following COVID-19 and the Russo-Ukrainian war, it could be argued that the intensified relationship between the GPR Index and Oil returns reflects a post-invasion effect.

The MS-BVAR analysis revealed that if Clean returns two months prior experience a one percentage change, current Gas returns will move 1.23% in the opposite direction during high volatility regimes, as observed after the invasion. In response to the surging energy prices, the REPowerEU plan was introduced to mitigate the risk of future critical energy crises in Europe, emphasizing the importance of diversifying energy sources to enhance security and decrease reliance on fossil fuels during crises. The estimated inverse relationship between Clean and Gas returns in regime 2 may be due to increased investments and capacity of renewable energy sources, hence lowering the returns of Gas. Conversely, a reduced emphasis on clean energy could lead to heightened returns for Gas. This dynamic suggests that shifts in investment priorities between renewable and fossil fuel sources are likely to influence the respective financial performance of these energy sectors.

The impulse response plots depict the mildest volatility spillover transmissions from Carbon to the other variables comparably, which is intriguingly identified in both low- and high-volatility regimes. The motivation for including Carbon in the analysis stemmed from its underrepresentation in previous literature, which allowed for curiosity about how this market behaved in connection with others under distinct regime behaviors. In addition to Carbon's unwavering role as a volatility spillover transmitter, it is also notable how shocks to the other investigated variables barely impact Carbon returns, indicating a weak reception from shocks to the other variables. As previously mentioned, the price of carbon futures is driven by partially artificial pricing mechanisms, controlled by regulatory and policy frameworks, which likely insulates it from the pure supply-demand dynamics that drive conventional energy markets. These pricing mechanisms of the carbon market may provide a stabilizing effect, secluding it from the immediate impacts of market volatility seen in other energy sectors. These findings may suggest that the carbon market operates with a degree of independence from the fluctuations affecting traditional energy markets.

In high volatility regimes, shocks to the GPR Index demonstrate a lasting negative effect on Oil and Gas returns, with little indication that the system will revert to normal. These observations align with the research by Liu et al. (2021) which found that geopolitical uncertainty has a significant impact on the long-run volatility in fossil fuels. Another noteworthy finding from the impulse response functions during high-volatility regimes are the effect shocks to Oil returns have on Clean returns, exhibiting a sustained negative impact. This extended recovery period for clean energy during high-volatility states implies a critical vulnerability within the renewable energy sector. It suggests that these markets are perhaps more sensitive to global political instability or may lack the robustness that more established energy markets have. However, shocks to the GPR Index exhibited a positive lasting impact on Clean returns, which might indicate that heightened geopolitical risk boosts the clean energy markets, a development observed following the invasion of Ukraine. Abbas et al. (2023) on the other hand, found that heightened geopolitical risk obstruct green financing, while Zhang et al. (2023) argues that geopolitical risk exert significant influence on the volatility rather than returns on green bonds and renewable energy, suggesting clean energy as a safe haven asset during uncertain times.

The estimated prolonged impact of the GPR Index and Oil returns on Clean energy returns in regime 2, as compared to the transient instabilities observed in regime 1, has significant implications for energy security, policies, and strategic planning. This is particularly relevant for countries and institutions committed to transitioning to renewable energy sources or those heavily reliant on a singular energy source. To enhance energy security and ensure a stable transition towards renewable energy, it becomes imperative to invest more substantially in the development of renewable energy markets. By broadening the spectrum of energy sources to include a variety of renewables such as solar, wind, hydro, and bioenergy, it is possible to reduce susceptibility to shocks from any singular source and more effectively distribute geopolitical risk across their entire energy infrastructure, thereby fortifying energy security. These initiatives would help cushion clean energy markets from the immediate impacts of geopolitical shocks and support quicker corrections.

The analysis yields a broad insight into the interconnections between energy markets, carbon markets, and geopolitical risk, but it is important to note the limitations posed by this study. Firstly, many considerations were weighing in when ultimately deciding on monthly data. It was convenient due to the time frame that was decided upon, and necessary for several of the functions needed for the MS-BVAR analysis. Moreover, the GPR Index is available as monthly data, simplifying the decision. However, the choice of monthly data inherently impacts the results and necessitates several considerations. Utilizing only the final observation of each month means that daily fluctuations within the month are condensed into a single data point. This aggregation might obscure significant short-term volatility and the immediate impacts of market-altering events. Consequently, substantial developments that resolve within a month's time may not be adequately captured, potentially overlooking crucial market dynamics. This smoothing effect could understate the true volatility and responsiveness of the markets to immediate geopolitical or economic events, which might lead to an underestimation of risk or an oversimplification of market behaviors in the analysis. As such, while the use of monthly data aids in managing large datasets and aligns with the availability of key indices, it also introduces a layer of abstraction that may distance the analysis from the nuances of real-time market fluctuations.

Secondly, there are limitations associated with the use of a fixed number of regimes. Predetermined regimes might not fully capture the dynamic nature of markets, as they may not account for unexpected economic shifts or new geopolitical developments that necessitate a regime change (Psaradakis & Spagnolo, 2003). This static approach could lead to a failure in detecting critical transitions that would be obvious if a more flexible regime model was used, potentially leading to different interpretations of market relationships. Both overfitting and underfitting the model could result in markedly different conclusions, highlighting the importance of thorough preliminary testing and the rationale from other studies in determining the number of regimes. These challenges are not exclusive to the specific model employed in this thesis, nor to the generalized MS-BVAR model, but are common across econometric methodologies that incorporates regimes. While integrating a more flexible approach into a time-constrained thesis like this one may be complex, future applications involving machine learning algorithms could potentially overcome these limitations. By allowing for regime adjustments based on real-time data, such technologies could enhance the model's precision and responsiveness, offering a more accurate and dynamic understanding of market behaviors and their underlying drivers.

Lastly, while this thesis provides a comprehensive empirical analysis of market reactions to the Russo-Ukrainian war, it primarily operates within an empirical framework without a corresponding theoretical framework. Further research could benefit from the incorporation of theoretical models that offers a deeper conceptual understanding of the observed dynamics. For instance, theoretical economic models could serve to predict potential outcomes under different scenarios or explain the causal mechanisms driving market behaviors during geopolitical conflicts. Including a theoretical approach would enhance the robustness of predictive models and deepen the understanding of the complex interplay within energy and carbon markets.

7 Conclusion

Motivated by the research of Maneejuk et al. (2024) and Jiang et al. (2024), this thesis has explored the connectedness among the EUA Carbon futures, European Brent crude oil futures, Dutch TTF natural gas futures, S&P Global Clean Energy Index, and the Geopolitical Risk Index by Caldara and Iacoviello (2022). The thesis employs a Markov Switching Bayesian Vector Autoregressive model and impulse response analysis, with a specific focus on the period marked by the initiation of the Russo-Ukrainian war in 2022. The study converted monthly price data into logarithmic returns and growth rates spanning from January 2015 to February 2024. The findings indicate a significant regime-dependent variability in the response of these markets to geopolitical shocks, with high volatility regimes becoming more pronounced post-invasion.

The study has demonstrated that there is compelling evidence for the existence of distinct regime-specific characteristics, where regime 1, characterized by lower volatility and less instability, typically sees quicker market stabilizations after being exposed to shocks. This behavior underscores the resilience of energy markets under less turbulent conditions. In contrast, regime 2, which corresponds with periods of heightened volatility, exhibits a prolonged adjustment period. This is particularly evident by the effect of shocks to the GPR Index on the returns of Oil, Gas, and Clean, which suggests a long-lasting impact of heightened geopolitical risk on the stability of these markets.

Moreover, the thesis has highlighted the importance of considering a wider geopolitical context to capture the broader implications on energy markets. The inclusion of the GPR Index in the MS-BVAR model has allowed for a nuanced analysis of how shifts in geopolitical stability propagate through the energy markets over time. The analysis confirms that significant geopolitical events, such as the invasion of Ukraine by Russia, not only disrupt immediate market conditions but also instigate long-term shifts in market dynamics and volatility regimes.

This research enhances the existing literature by providing empirical evidence on the varying impacts of European energy markets and geopolitical risk across different market volatility states, offering insights into the underlying mechanisms of these impacts. The findings highlight the critical importance of robust energy security and the need for diversified energy sources to bolster resilience against geopolitical shocks. This is especially relevant in today's interconnected and politically volatile global landscape. The European Commission's REPowerEU plan, which seeks to reduce dependency on Russian energy, exemplifies proactive measures aimed at mitigating such risks.

Looking ahead, there is a clear necessity for ongoing research into the complex relationship between geopolitical events and energy markets. This should particularly focus on employing advanced econometric models capable of handling regime switches and nonlinear dynamics. Future studies could expand upon this analysis by integrating a theoretical model and include variables that incorporate economic policy uncertainty or environmental policy changes. An enhanced understanding of these dynamics is vital to assist the development of strategies that not only ensure energy security and market stability but also contribute to climate change mitigation. A continued investigation will provide deeper insights into global energy dynamics, facilitating more informed decisions.

To conclude, this thesis highlights the intricate links between geopolitical risks and the dynamics of energy markets, delivering thorough insights into the evolution of these relationships under diverse market conditions. It establishes a strong foundation for additional empirical research and strongly advocates for the inclusion of geopolitical risk analysis within energy market assessments. This integration is vital in an increasingly interconnected and politically volatile global landscape.

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9 Appendix

9.1 R Script

```
rm(list=ls(all=TRUE))

#install_version("MSBVAR", version="0.9-3", repos = "http://cran.us.r-project.org")
#install_version("bit", version = "1.1-8", repos = "http://cran.us.r-project.org")

library(MSBVAR)
library(bit)
library(remotes)
library(zoo)
library(lmtest)
library(readxl)
library(moments)
library(ggplot2)
library(stats)
library(tidyr)
library(urca)
library(tseries)
library(coda)
library(MTS)
library(mbreaks)
library(strucchange)

# DATA IMPORTS -----------------------------------------------------------------------------------------

setwd("~/Documents/masteroppg/data")

CARBON <- read_excel("~/Documents/masteroppg/data/EUAmonthly.xlsx", col_types = c("date",
"numeric"))
OIL <- read_excel("~/Documents/masteroppg/data/OILmonthly.xls", col_types = c("date",
"numeric"))
GAS <- read_excel("~/Documents/masteroppg/data/GASmonthly.xlsx", col_types = c("date",
"numeric"))
CLEAN <- read_excel("~/Documents/masteroppg/data/SPCLNmonthly.xlsx", col_types = c("date",
"numeric"))
GPR <- read_excel("~/Documents/masteroppg/data/GPRmonthly.xls", col_types = c("date",
"numeric"))

carbon <- zoo(CARBON[,2], order.by = CARBON$Date)
oil <- zoo(OIL[,2], order.by = OIL$Date)
gas <- zoo(GAS[,2], order.by = GAS$Date)
clean <- zoo(CLEAN[,2], order.by = CLEAN$Date)
gpr <- zoo(GPR[,2], order.by = GPR$Date)

data <- merge(carbon, oil, gas, clean, gpr)
names(data) <- c("Carbon", "Oil", "Gas", "Clean", "GPR")

plot(data[,1], main = "", ylab = "Price", xlab = "", lwd = 1)
plot(data[,2], main = "", ylab = "Price", xlab="", lwd = 1)
```

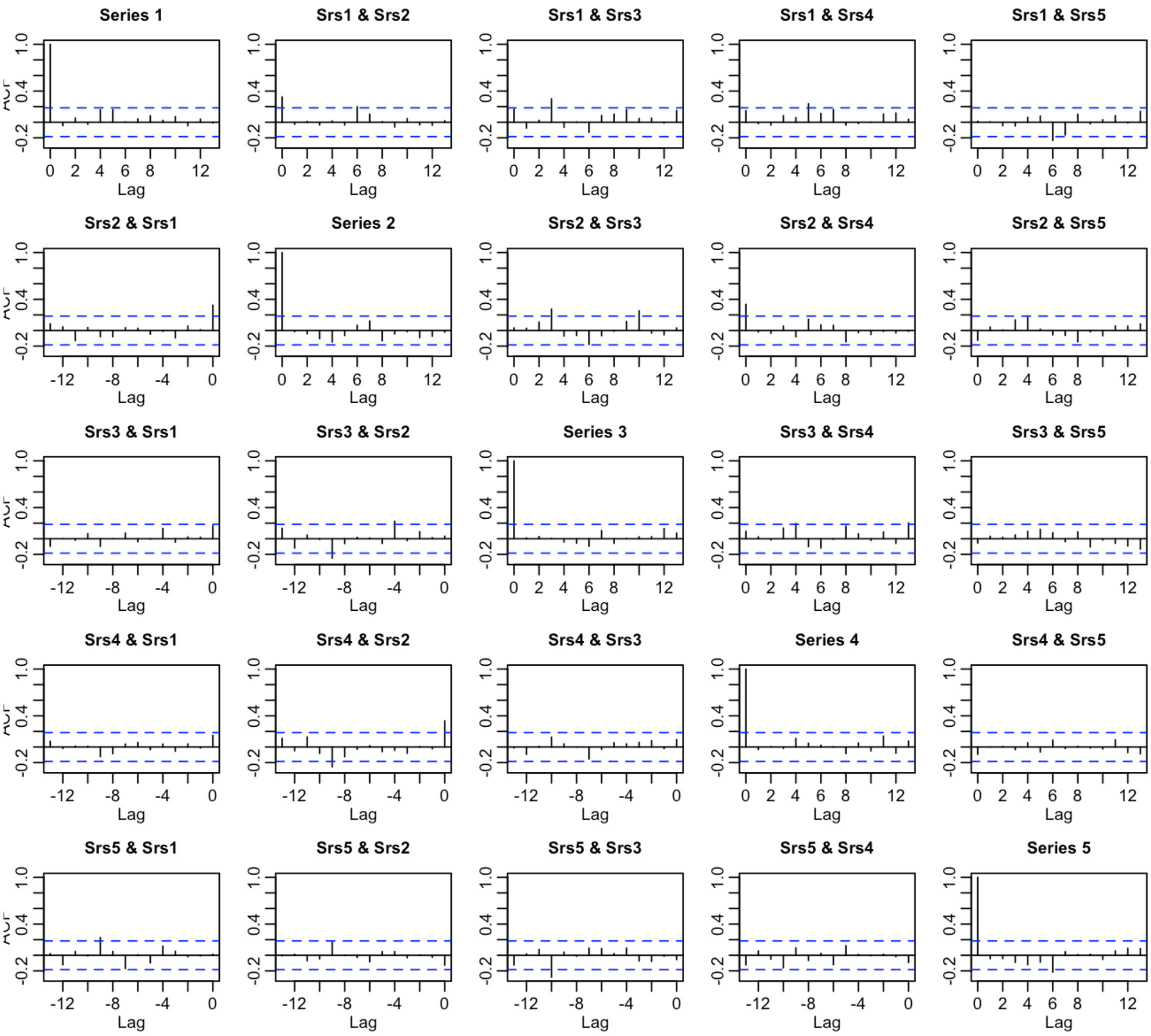
```
plot(data[,3], main = "", ylab = "Price", xlab = "", lwd = 1)
plot(data[,4], main = "", ylab = "Index Points", xlab = "", lwd = 1)

plot(data[,5], main = "", ylab = "GPR ratio", xlab = "", lwd = 1)
points <- locator(n=5)
text(points$x, points$y, labels= c("Paris Attacks", "U.S. - N.Korea", "U.S. - Iran",
                          "Russia - Ukraine", "Israel - Palestine"), col="red")

# LOG-RETURN TRANSFORMATION ------------------------------------------------------------------

returns <- 100*diff(log(data))

par(mfrow=c(3,2), mar = c(3,3,4,2))
plot(returns[,1], main = "(a) Carbon Log-Returns", ylab = "", xlab = "", lwd = 1)
plot(returns[,2], main = "(b) Oil Log-Returns", ylab = "", xlab="", lwd = 1)
plot(returns[,3], main = "(c) Gas Log-Returns", ylab = "", xlab = "", lwd = 1)
plot(returns[,4], main = "(d) Clean Log-Returns", ylab = "", xlab = "", lwd = 1)
plot(returns[,5], main = "(e) GPR Log-Growth Rates", ylab = "", xlab = "", lwd = 1)

ret <- ts(returns)

# DESCRIPTIVE STATISTICS ---------------------------------------------------------------------

stat.desc(ret, desc = TRUE, norm = TRUE)

IQR(ret[,1])
IQR(ret[,2])
IQR(ret[,3])
IQR(ret[,4])
IQR(ret[,5])

jarque.bera.test(ret[,1])
jarque.bera.test(ret[,2])
jarque.bera.test(ret[,3])
jarque.bera.test(ret[,4])
jarque.bera.test(ret[,5])

# NONLINEARITY - STRUCTURAL BREAKS TEST ------------------------------------------------------

mdlCarbon <- mdl("Carbon", z_name = c("Oil", "Gas", "Clean", "GPR"), data = ret, hetvar = 1,
robust = 1, m = 4, eps1 = 0.1); mdlCarbon
mdlOil <- mdl("Oil", z_name = c("Carbon", "Gas", "Clean", "GPR"), data = ret, hetvar = 1, robust =
1, m = 4, eps1 = 0.1);mdlOil
mdlGas <- mdl("Gas", x_name = c("Carbon", "Oil", "Clean", "GPR"), data = ret, hetvar = 1, robust =
1, m = 4, eps1 = 0.1); mdlGas
mdlClean <- mdl("Clean", x_name = c("Carbon", "Oil", "Gas", "GPR"), data = ret, hetvar = 1, robust
= 1, m = 4, eps1 =  0.1); mdlClean
mdlGPR <- mdl("GPR", x_name = c("Carbon", "Oil", "Gas", "Clean"), data = ret, hetvar = 1, robust =
1, m = 4, eps1 =  0.1); mdlGPR

# Plot structural breaks

par(mfrow=c(3,1), mar = c(2,5,4,4))
offset <-  2
```

```
oildate <-  mdlOil$KT$date
plot(ret[,2], main = "Oil 2015 - 2024", ylab = "", lwd = 1)
for (i in 1:2) {
  abline(v = oildate[i,1], col = 'red', lty = 2)
}
text(x = oildate[1,1], y = par("usr")[4], pos = 2, labels = "11/2019", srt = 90)
text(x = oildate[2,1] + offset, y = par("usr")[4], adj = 1 , labels = "09/2020", srt = 90)

#---------------------------------------------------------------------------------------------------------------------

gasdate <-  mdlGas$KT$date
plot(ret[,3], main = "Gas 2015 - 2024", ylab = "", lwd = 1)
for (i in 2:3) {
  abline(v = gasdate[i,1], col = 'red', lty = 2)
}
text(x = gasdate[2,1], y = par("usr")[4], pos = 2, labels = "05/2020", srt = 90)
text(x = gasdate[3,1], y = par("usr")[4], pos = 2, labels = "08/2022", srt = 90)

#---------------------------------------------------------------------------------------------------------------------

cleandate <-  mdlClean$KT$date
plot(ret[,4], main = "Clean 2015 - 2024", ylab = "", lwd = 1)
for (i in 1:2) {
  abline(v = cleandate[i,1], col = 'red', lty = 2)
}
text(x = cleandate[1,1], y = par("usr")[4], pos = 2, labels = "03/2020", srt = 90, adj = 1, xpd = TRUE)
text(x = cleandate[2,1] + offset, y = par("usr")[4], labels = "01/2021", srt = 90, adj = 1, xpd = TRUE)

# NONLINEARITY - BDS TEST -----------------------------------------------------------------------------

# Optimal lag number

var.lag.specification(ret, lagmax = 10)
VARorder(ret, maxp = 10)

VARmod <- VAR(ret, p = 2, output = T, include.mean = T, fixed = NULL)
VARres <- residuals(VARmod)

bds.test(VARres[,1], m = 4)
bds.test(VARres[,2], m = 4)
bds.test(VARres[,3], m = 4)
bds.test(VARres[,4], m = 4)
bds.test(VARres[,5], m = 4)

# UNIT ROOT TESTS -----------------------------------------------------------------------------------------

# Augmented Dickey-Fuller test for stationarity
adf.test(ret[,1],alternative="stationary")
adf.test(ret[,2],alternative="stationary")
adf.test(ret[,3],alternative="stationary")
adf.test(ret[,4],alternative="stationary")
adf.test(ret[,5],alternative="stationary")

# Phillips-Perron test for stationarity
pp.test(ret[,1], alternative ="stationary", type ="Z(alpha)", lshort =TRUE)
```

```
pp.test(ret[,2], alternative ="stationary", type ="Z(alpha)", lshort =TRUE)
pp.test(ret[,3], alternative ="stationary", type ="Z(alpha)", lshort =TRUE)
pp.test(ret[,4], alternative ="stationary", type ="Z(alpha)", lshort =TRUE)
pp.test(ret[,5], alternative ="stationary", type ="Z(alpha)", lshort =TRUE)

# TEST FOR OPTIMAL MODEL - BAYES FACTOR-------------------------------------------------------

mod1 <- msbvar(ret, p=1, h=2,
        lambda0=0.8, lambda1=0.85, lambda3=1, lambda4=1,
        lambda5=1, mu5=0.1, mu6=0.1, qm=12, prior=0, max.iter=40,
        initialize.opt=NULL)

res1 <- mod1$init.model$residuals
acf(res1)

gib1 <- gibbs.msbvar(mod1, N1 = 5000, N2 = 20000, permute = TRUE,
            Beta.idx = NULL, Sigma.idx = NULL, Q.method = "Gibbs")

plot(ts(mod1$fp))
print(mod1$Q)

mod2 <- msbvar(ret, p=2, h=2,
         lambda0=0.8, lambda1=0.85, lambda3=1, lambda4=1,
         lambda5=1, mu5=0.1, mu6=0.1, qm=12, prior=0, max.iter=40,
         initialize.opt=NULL)

res2 <- mod2$init.model$residuals
acf(res2)

gib2 <- gibbs.msbvar(mod2, N1 = 5000, N2 = 20000, permute = TRUE,
             Beta.idx = NULL, Sigma.idx = NULL, Q.method = "Gibbs")

#MS-BVAR(1) vs MS-BVAR(2)
post1 <- posterior.fit(gib1, A0.posterior.obj=NULL, maxiterbs=500); post1
post2 <- posterior.fit(gib2, A0.posterior.obj=NULL, maxiterbs=500); post2

mlr <- post1$marglik.BS/post2$marglik.BS; mlr

# MSBVAR MODEL ------------------------------------------------------------------------------------------

gibb <- gibbs.msbvar(mod2, N1 = 5000, N2 = 20000, permute = FALSE,
             Beta.idx = c(5,1), Sigma.idx = NULL, Q.method = "Gibbs")

summary <- regimeSummary(gibb)

# PLOT REGIME 2 -----------------------------------------------------------------------------------------

# Apply min-max normalization to GPR
min_gpr <- min(GPR$GPR, na.rm = TRUE)
max_gpr <- max(GPR$GPR, na.rm = TRUE)
normalized_values <- (GPR$GPR - min_gpr) / (max_gpr - min_gpr)

# Adding the normalized values back to GPR data
GPR$Normalized <- normalized_values
gprline <- ts(GPR$Normalized)
```

```
# Extracting high-volatility regime probabilities
regime <- mean.SS(gibb)[,2]
regime <- ts(regime)
regime <- as.matrix(regime, nrow=109, ncol=1, byrow=TRUE)
x_values <- 1:107

# Regime plot
par(mar=c(1, 4, 2, 1) + 0.1)
plot.ts(regime, col="red", ylab="Probabilities", main="Regime 2: High Volatility")
polygon(c(x_values[1], x_values, x_values[length(x_values)]),
        c(0, regime, 0), col = "red", border = NA, density=40)
lines(gprline, col="black", lwd=1.5)
legend("topleft", legend=c("Regime 2","GPR"), col=c("red","black"), lty=1, bty="n")

# AUTOREGRESSIVE COEFFICIENTS ---------------------------------------------------------------------

ar <- summary(gibb$Beta.sample);ar

Beta.sample <- gibb$Beta.sample
Beta.sample <- mcmc(Beta.sample)

interval <- HPDinterval(Beta.sample, prob = 0.95)
print(interval)

lower_bounds <- interval[,"lower"]
upper_bounds <- interval[,"upper"]

significant_coeffs <- (lower_bounds * upper_bounds) > 0

# Print the results
print(significant_coeffs)

# Average regime durations
1/(1-0.9614) # Regime 1
1/(1-0.9717) # Regime 2

# IMPULSE RESPONSE FUNCTIONS ------------------------------------------------------------------------

irf <- mc.irf(gibb, nsteps=20, draws=20000)
plot.mc.irf(irf)
```

9.2 Autocorrelation from initial model residuals



9.3 Discussion Paper

9.3.1 Maria Rimestad Orre - International

This discussion paper serves as my concluding remark of my Master's Degree in Business Administration with a specialization in Analytical Finance at the University of Agder. After five years of intensive study, my academic journey concludes with this master thesis, as I have written together with Anna Jeppedal Moen. The process of writing this thesis has been both challenging and rewarding, as I have learned a lot about myself and developed myself academically. This paper aims to discuss how our research and findings engage with the broad concept of "international". Initially, it will provide a brief overview of our thesis, followed by how it relates to global trends and forces.

Introduction

The Russo-Ukrainian conflict of February 2022 significantly changed the global energy system, highlighting the profound impact of geopolitical events on international energy dynamics. Russia's role as a major supplier of fossil fuels, particularly to the European Union (EU), rendered the region highly vulnerable following the invasion of Ukraine. As Russia cut the energy supply to Europe and nations agreed upon the impositions of sanctions and trade restrictions on Russian goods, the EU were forced find new energy suppliers. The EU's reliance on Russian fossil fuels resulted in a sudden shock in energy demand in Europe, which escaladed energy prices, particularly within the gas market. In response to the imperative of securing and stabilizing its energy supply, the EU introduced the REPowerEU plan, a multifaceted strategy aimed at diversifying energy imports, bolstering energy conservation efforts, and accelerating renewable energy development (European Commission, 2022). In the following years of the conflict, there has been a notable surge in the adoption and development of green energy solutions across European nations (International Energy Agency, 2024a, p. 14).

As the conflict has highlighted the consequences of nations being heavily reliant on a single energy supplier, it triggered a shift towards renewable energy sources, but this was not the immediate response. The European Union Emission Trading System (EU ETS) were developed as the EU's strategy of achieving climate neutrally by 2050 by implementing a cap-and-trade system to govern the allowance of businesses emitting carbon dioxide (European Commission, n.d). The price of EUA carbon allowances does usually follow the fluctuations in prices for fossil fuels, but when Russia invaded Ukraine, energy prices experienced a rapid incline and EUA carbon prices experienced a historical drop, decoupling from the rest of the system. When the price for carbon allowances dropped, it means that its cheaper for businesses to pollute. Ingvild Sørhus, a lead analyst for EU Carbon Analysis, attributed this decline in EUA carbon prices to investor withdrawals due to uncertainties stemming from the conflict (Ambrose, 2022). The speculation surrounding Russian investors potentially pulling out due to sanctions and the risk of frozen assets further contributed to this historical deviation in EUA Carbon Futures.

The period post invasion has witnessed intriguing market responses which has motivated this thesis to study these reactions and their implications for the intricate relationship between energy and carbon markets. Our research journey was influenced by the work of Maneejuk et al. (2024) who studied the conflict's impact on renewable and fossil energy cycles, leveraging the Russia Economic Policy Uncertainty Index. Thus, our goal is to contribute to filling the existing research gap on the effects following the Russo-Ukrainian war, by building upon the research by Maneejuk et al. (2024) by including the EUA carbon market to get an even broader understanding of the conflict's impact on the energy sector.

In this thesis, we examine whether the interplay between the European carbon and energy markets has shifted following Russia's invasion of Ukraine. We analyze monthly logarithmic returns from January 2015 to February 2024 for EUA Carbon Futures, European Brent Crude Oil Futures, Dutch TTF Natural Gas Futures, and the S&P Global Clean Energy Index. These returns are integrated into a Markov Switching Bayesian Vector Autoregressive Model (MS-BVAR) alongside the Geopolitical Risk (GPR) index by Caldara and Iacoviello (2022) to assess geopolitical influences on market returns. The MS-BVAR model, which alternates between high and low volatility regimes based on transition probabilities, is particularly suited to capture the nonlinear dynamics and asymmetries in the markets. Our findings highlight a pronounced increase in the occurrence of high volatility regimes post-invasion which underscores the critical need to understand the dynamics between geopolitical risks and energy and carbon markets to effectively mitigate the impacts of future crises.

Discussion

The research topic of this master thesis is related to international trends and forces in various ways. Firstly, Russia's invasion of Ukraine sparked a global energy crisis which still has a significant impact on economic growth, straining the finances of households and businesses in many parts of the world (International Energy Agency, n.d). The conflict underscored how sensitive important commodities, such as oil and gas, are to geopolitical uncertainty and events, and the importance of understanding these market reactions in times of crises to mitigate future consequences. By utilizing the GPR index, which encompasses a wide spectrum of geopolitical tensions which goes beyond the Russo-Ukrainian war. This expanded scope has the potential to influence the interpretation of our findings, as the observed enhancements in estimated effects and relationships may be influenced by various geopolitical developments, not solely limited to the Russo-Ukrainian conflict. But by incorporating the GPR index, we aimed to adopt a robust approach that captures the multifaceted nature of global geopolitical dynamics, recognizing their far-reaching impacts on international tensions and disruptions.

Secondly, the thesis relates to the development of renewable energy sources which contributes to nations energy security and combating climate change. By including the S&P Global Clean energy index in the analysis, we are able to get a comprehensive understanding of the performance of clean energy related businesses form both developing and emerging countries. Thus, reactions in the clean index gives us a perspective on how geopolitical shocks affects the investments in renewable energy sources in a global scale, and its implications in the broader environmental context. The thesis also considers the market reactions in the EU ETS, which is the world's largest carbon pricing mechanism (European Commission, n.d). The system was developed to limit the amount of greenhouse gas emissions to combat climate change and reach climate neutrally. As the cornerstone of the EU's policy to reduce emissions, it becomes important to examine if the Russo-Ukraine war has changed the interconnectedness between carbon prices and fossil fuels, reducing the effectiveness of such environmental policies. Especially after the observed decoupling in prices at the outbreak of the war, which can indicate that the European carbon market is exposed to geopolitical shocks.

The MS-BVAR analysis revealed high transition probabilities, indicating a substantial persistence within each regime. Which mean that if the system was currently in a low volatility regime, there is a 97.17% chance of the system remaining in the same regime in the next period.

While if the system were in a high volatility regime, there is a 96.14% probability that the system continues to be in a volatile state for the following period. The high transition probabilities suggests that when a geopolitical event such as the Russo-Ukraine conflict triggers the markets to enter a high volatility state, they are most likely to remain in this state for the following months. These findings can help nations to understand the duration and long-term effects of such crises.

Another interesting finding were the connectedness between carbon returns and the GPR growth rates. Overall, the analysis showed mild volatility spillovers between carbon returns and the other variables included, which might suggest that the pricing mechanisms for carbon allowances operates with a degree of independence form the fluctuations driving fossil and clean energy markets. But there was one exception, because carbon returns were found to be a volatility spillover transmitter for the GPR index during high volatility regimes, so a one percentage change in the returns of carbon futures from two months back, would lead to a 0.42% change in the same direction in today's growth rates for GPR. Meaning, a decrease in carbon returns could result in reduced geopolitical risk. These findings suggests that fluctuations in European carbon market could serve as an indicator of geopolitical risks.

Findings from the impulse response analysis reveals a lasting effect in Oil and Gas returns after a shock to the GPR index during high volatility regimes. Meaning, when a shock occurs in the GPR index, which may correspond to heightened geopolitical risk, it will have a long-term impact on the returns on Oil and Gas. It was also found that shocks to Oil, Gas, and GPR had a lasting impact on Clean returns, suggesting these markets to be particularly vulnerable to global political instability or lack the robustness that more established energy markets has, during high volatility regimes. The lasting impact on Clean returns could serve as a motivation for nations to prioritize investments and strategies that enhances the resilience of renewable energy sources against geopolitical shocks.

The thesis topic and findings are useful in an international context for various reasons. The high transition probabilities underscore the need for strategic planning to mitigating the negative impact of geopolitical tensions and events, as when the system enters a high volatility state, it is most likely to remain in this state for a long time. By understanding how the interconnectedness between energy markets and carbon markets changes during periods of heightened geopolitical risk, policy makers, investors, and heavy-carbon enterprises will be better prepared to cope with future fluctuations of geopolitical risks.

Conclusion

This thesis examines the profound interconnections between geopolitical events and the dynamics of energy and carbon markets. The Russo-Ukrainian conflict, which has served as our central focus, exemplifies the vulnerability of the global energy system to political instability. By utilizing the MS-BVAR model, together with an impulse response analysis, we have investigated how geopolitical risk affects fluctuations in energy and carbon markets, and how the dynamics between these market changes between high and low volatility regimes.

Our findings indicate a pronounced tendency in the occurrence of high volatility regimes post-invasion, and high transition probabilities for the system to remain in the high volatility state for the coming periods. It was also shown that energy markets were particularly vulnerable during heightened geopolitical risk, which underscored the importance for nations to diversify its energy sources and become more self-reliant on renewable energy sources. By diversifying and investing in more renewable energy, nations could increase their energy security while reducing emissions. These findings mark the importance of understanding changing dynamics during high volatility regimes to be able to develop strategies and policies to tackle future crises as geopolitical risk emerges.

In conclusion, I find the research topic of how the dynamics between energy and carbon markets changes during heightened geopolitical risk, especially during the Russo-Ukrainian conflict, to be highly relevant, connecting intricately with international trends and forces. The Russo-Ukrainian war has had profound and far-reaching implications at a global scale, highlighting the critical role of geopolitical events and energy dynamics. By contributing to filling the research gap regarding implications following this conflict, we have seen the importance of energy security in a world increasingly shaped by frequent geopolitical tensions.

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9.3.2 Anna Jeppedal Moen - International

This discussion paper marks the completion of my Master of Science in Business Administration at the University of agder, specializing in Analytical Finance. The master's thesis represents the culmination of my accumulated knowledge after five years at UiA, finalized with a thesis co-authored by Maria Rimestad Orre. The creation of this thesis has been immensely challenging yet rewarding throughout the process, leading to both academic and personal growth. This discussion paper starts with an introduction of the thesis and the geopolitical context that inspired it, along with the research objectives that guided its development. I then discuss the findings and related research, focusing on the theme of 'international' throughout.

The recency of the Russian invasion of Ukraine has profoundly reshaped global energy supply chains and needs (International Energy Agency, 2024). This geopolitical event caused significant disruptions of established energy flows, which has particularly affected Europe, due to its substantial dependence on Russian energy exports. The decision of curtailing energy supplies to Europe was aimed at undermining European support for Ukraine, but instead led to a dramatic escalation in gas prices and raised acute demands for alternative energy sources. Russia redirected the energy flow towards Asian markets, while Europe urgently had to address the resulting energy shortfall (International Energy Agency, 2024). This necessitated a rapid and unplanned shift back to fossil fuel sources, impacting both the energy security and green investments. This disruption in supply chains highlighted the vulnerability of Europe's energy infrastructure, underscoring the risk related to over-reliance on a single supplier. Consequently, this event has prompted a re-evaluation of energy policies while emphasizing the strategic importance of diversifying energy sources and sustained investments in renewable energy. Such diversification is essential not only for enhancing energy security but also for mitigating long-term risks associated with geopolitically induced energy market volatility, to ensure a stable transition towards a sustainable energy future.

The thesis employs the Markov Switching Bayesian Vector Autoregressive (MS-BVAR) model to examine whether there is an observed increase in the frequency of high-volatility regimes in European carbon and energy markets following the Russian invasion of Ukraine. The geopolitical landscape saw a major shift when Russia initiated aggressive actions against Ukraine in February 2022, leading to significant disruptions in international energy markets and further straining the already precarious energy situation in Europe (Benton et al., 2022, p. 8). This act of war triggered widespread consequences, and the implementation of trade embargoes and restrictions on Russia, a key supplier of crude oil, natural gas, and coal, intensified the already escalating energy crisis.

To explore these dynamics, the MS-BVAR analysis includes the study of benchmarked energy markets, namely EUA carbon futures, European Brent crude oil futures, Dutch TTF natural gas futures, the S&P Global Clean Energy Index, and the Geopolitical Risk (GPR) Index by Caldara and Iacoviello (2022). This approach helps reveal the patterns and frequency of high-volatility periods following the invasion. By conducting an in-depth analysis of market dynamics and incorporating changes in the geopolitical landscape, this thesis aims to understand how geopolitical events like the Russo-Ukrainian war have increased volatility in the post-invasion period. This thesis adds to the academic discussion by investigating the development in the European carbon market, a previously understudied market in collaboration with shocks to geopolitics.

The GPR Index has become increasingly prevalent in empirical research in recent years, highlighting the necessity of integrating the evolving geopolitical landscape into the analysis of economic relationships. Liu et al (2023) and Zhang et al. (2023) establish geopolitical risk to be a critical factor for driving the state of the economy and have proven its relation to energy markets. The GPR Index quantifies geopolitical risk by measuring the proportion of articles from major newspapers that mention geopolitical tensions or risks relative to the total number of articles (Caldara & Iacoviello, 2022). An increase in the index signifies heightened geopolitical uncertainty. Although the index is artificially constructed, its interaction with conventional energy markets provides valuable insights into addressing the growing geopolitical uncertainties that significantly impact the market. By understanding these dynamics, policymakers and researchers can better anticipate and mitigate the effects of geopolitical risks on economic stability and energy security. The implications are profound, as a higher GPR Index can signal potential market disruptions, prompting the need for preemptive measures such as diversifying energy sources and enhancing international cooperation to ensure energy resilience.

The findings demonstrate the interconnectedness of the European carbon and energy markets, particularly during high-volatility periods, underscoring the extensive international implications of geopolitical events. The results indicate that in times of increased market instability, shocks to the growth rate of the GPR Index have a prolonged impact on oil and natural gas returns, amplifying the global effects of actions taken by a major military power against another country. The impulse response plots reveal negative consequences that persist well beyond the investigated 10-month period, suggesting that during heightened volatility, markets are unable to return to equilibrium in the short term due to the severity of these impacts.

The thesis findings affirm the critical importance of sustained investments in renewable energy, not only for mitigating climate risks but also for enhancing energy security. This necessity is highlighted by the fact that singular events can drastically reshape the energy landscape with international repercussions. Furthermore, empirical analysis reveals that the GPR Index has a substantial influence on the clean energy market. The magnitude of this effect is significant, with shocks to the GPR Index causing persistent impacts that extend beyond ten months without reverting to baseline. This enduring influence underscores the interconnectedness between political stability and the performance of the clean energy market. Therefore, continuous investments in renewable energy are not only an environmental necessity but also a strategic imperative for mitigating the effects of geopolitical fluctuations and their extensive implications.

Regime 1 is characterized by low volatility and stable markets, while regime 2 is marked by high volatility. The analysis estimates that regime 1 typically lasts for 35 months, whereas regime 2 persists for 26 months. The transition probabilities for these regimes are 97.17% and 96.14%, respectively, indicating a high likelihood of remaining within each state. These high probabilities indicate the persistence of distinct regimes over the investigated period. This implies that once markets enter a specific state, they are likely to remain in that state for an extended period. If a geopolitical shock can push markets into a prolonged high-volatility state, it emphasizes the critical need for enhanced energy security and diversification to expedite the return to normal conditions. Remaining in a high-volatility state over time leads to increased uncertainty, which can potentially harm economic growth. Additionally, prolonged volatility can strain energy resources and infrastructure, complicating the task of ensuring consistent supply and fair pricing on an international scale.

The unforeseen international impact of the Russo-Ukrainian war on European carbon and energy markets underlines the critical importance of understanding the persistence and implications of shocks in these markets. Drawing on knowledge from the master’s program, this research investigates the crucial role that international dynamics play in shaping market responses. By examining the effects of geopolitical events on conventional energy markets and their interconnectedness over time, the findings highlight the need for robust analytical frameworks to ensure that singular events do not destabilize intercontinental energy markets.

The REPowerEU plan, developed to mitigate this risk, was specifically designed to reduce dependence on Russian energy supplies (European Commission, 2022). The creation of this plan was crucial not only for addressing the immediate impact of geopolitical shocks but also for enhancing long-term resilience and sustainability in the global energy system. Our analysis provides valuable insights into the resilience of energy markets under geopolitical tensions and shocks, emphasizing the need to bolster energy security and diversify energy sources to effectively manage varying levels of volatility through initiatives like the REPowerEU plan. Furthermore, the results highlight the importance of sustained investments in renewable energy sources to avoid reliance on fossil fuels in situations such as when a major energy exporter cuts off supply.

The findings in this thesis highlight the complex dynamics and interconnectedness of the European carbon and energy markets, particularly in relation to the GPR Index. These complexities are especially pronounced when examining the increased frequency of high-volatility regimes following Russia's invasion of Ukraine. The MS-BVAR analysis robustly evidences the heightened prevalence of these regimes in subsequent years, highlighting the urgent need for enhanced international energy security measures and policies aimed at mitigating climate change through sustained investments in renewable energy sources. This approach is crucial to avoid reverting to fossil fuels as a resort when the geopolitical landscape shifts unexpectedly. The prolonged impact of shocks, as observed in the impulse response plots, highlight the critical necessity of promptly implementing strategies to enhance energy security, such as the REPowerEU plan. These initiatives are vital to prevent scenarios where a single geopolitical disruption can significantly alter international energy dynamics. The analysis clearly indicates that delayed responses to geopolitical shifts can hinder economic growth and divert focus from investing in renewable energy sources, leading to adverse environmental consequences. Furthermore, the research elucidates how geopolitical shocks not only trigger immediate market responses but also induce long-lasting volatility in energy markets. This highlights the importance of robust, proactive strategies to ensure energy security and stability in the face of global geopolitical challenges.

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