Master Thesis

How geopolitical risk affects the European energy market: A TVP-VAR approach on the spillover effects of the Ukraine-Russia War

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Abstract

This thesis investigates the impact of geopolitical risk, specifically the Russia–Ukraine war, on European energy markets. Using a combination of time-varying connectedness analysis, GARCH-based volatility modelling, and predictive linear regression, we explore how geopolitical shocks affect return dynamics, volatility transmission, and short-term predictability across both stocks and commodity assets. Our analysis covers a sample of affected energy assets and a robustness group of unaffected assets, allowing for a comparative evaluation of conflict-driven versus broader market effects.

The results show that volatility connectedness increased significantly following the outbreak of the war, with energy firms and commodities acting as primary transmitters of shocks. Return connectedness also rose, though to a lesser extent, and was more irregular in nature. In contrast, unaffected assets displayed stable, low levels of connectedness and showed minimal sensitivity to geopolitical developments. Predictive regressions revealed that lagged returns held consistent forecasting power, while connectedness measures, GARCH volatility, and the Geopolitical Risk Index provided limited predictive value for short-term returns.

Overall, the findings suggest that geopolitical risk reshapes market interdependencies more through volatility and structural connectedness than through return direction. The study highlights the importance of distinguishing between risk transmission and return predictability and contributes to a growing body of work on how geopolitical uncertainty influences financial systems in real time.

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Abbreviations

ADF	Augmented Dickey-Fuller Test
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BG	Breusch-Godfrey Test
BP	Breusch-Pagan Test
CO_2	Carbon Dioxide
DCC	Dynamic Conditional Correlation
DCC	Dynamic Conditional Correlation
FEVD	Forecast Error Variance Decomposition
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GFEVD	Generalised Forecast Error Variance Decomposition
GPR	Geopolitical Risk
GPRD	Geopolitical Risk Index
JB	Jarque-Bera Test
MA	Moving Average
OLS	Ordinary Least Squares
PP	Phillips-Perron Test
RE	Renewable Energy
SD	Standard Deviation
sGARCH	Standard Generalised Autoregressive Conditional Heteroskedasticity
TCI	Total Connectedness Index
TVP-VAR	Time-Varying Parameter Vector Autoregression
VAR	Vector Autoregression

VIF	Variance Inflation Factor
VIX	Volatility Index
vMEM-X	vector Multiplicative Error Model with exogenous variables

1. Introduction

In recent years, geopolitical tensions have become a growing source of uncertainty in global financial markets. Unlike traditional market risks such as inflation or interest rate changes, geopolitical events are often sudden, difficult to predict, and capable of triggering widespread volatility. Markets tend to respond rapidly to news of political unrest, military conflicts, and policy shifts, as investors reassess risk and adjust their portfolios. For sectors closely tied to global trade and energy supply, like oil, gas, and utilities, these shocks can have immediate and heavy impacts.

We are especially interested in how these geopolitical developments affect financial returns and volatility through mechanisms such as investor sentiment, supply chain disruption, and macroeconomic uncertainty. Previous studies have shown that such events can transfer risk across assets and regions, increasing correlations and changing market dynamics (Diebold & Yilmaz, 2012). As global markets become more interconnected, the influence of geopolitical shocks is no longer limited to specific countries or regions, instead they ripple through sectors, affecting prices, risk assessment, and capital flows. From a financial research perspective, this creates a need to better understand how geopolitical risk affects asset behaviour, especially that there is value in exploring how this form of uncertainty transmits between commodities and equity markets, and how investors respond across different sections of the financial world. Our motivation for this thesis stems from the need to analyse this relationship in a timely and sector-specific context, focusing on energy markets, which have historically been among the most sensitive to geopolitical events. With most past papers focusing on oil and gas, we also decided to explore the renewable energy market and metals tied to the energy market. These assets are historically mostly unexplored in the context of spillovers and geopolitical events in research papers, giving us the fuel to charter into unexplored areas of this subject.

To see the spillover effects analysed in our thesis, we think it's important to see the key geopolitical developments in the years preceding Russia's full-scale invasion of Ukraine. In early 2021, Russia conducted a major military buildup near Ukraine's borders and in Crimea, triggering concern among NATO members. Although the troops were partially withdrawn in April, much of the equipment remained in place. During this period, diplomatic engagement, such as the June 2021 Geneva summit between Presidents Biden and Putin, failed to produce de-escalation. On 12 July 2021, President Putin published an essay asserting that Russians and

Ukrainians were ‘one people,’ effectively denying Ukraine’s sovereignty. In response, Ukraine declared its first ‘Day of Ukrainian Statehood’ on July 28, reinforcing its independent national identity. In late 2021, Russia began a second, more extensive troop buildup, while Western intelligence began warning of an imminent invasion. Diplomatic talks in early 2022 collapsed, and in February, shelling in Donbas surged significantly. On February 21, 2022, President Putin recognized the separatist regions of Donetsk and Luhansk as independent states and sent in Russian forces under the guise of peacekeeping. These developments concluded in the launch of a full-scale invasion on February 24, 2022, marking the start of a new and more destructive phase in the conflict. (BBC, 2022; NATO, 2022; OSCE, 2022; U.S. Department of State, 2022).

The start of the war on February 24, 2022, marked a pivotal moment in modern history. Once the conflict began, it immediately triggered panic across global markets. European countries especially were directly impacted due to their energy dependence on Russian oil and gas. The conflict not only disrupted supply chains but also sparked a wave of sanctions, fuelling uncertainty and volatility in financial markets. What makes this event especially relevant for our thesis is its timing and magnitude. Coming shortly after the COVID-19 recovery phase, the war added new layers of geopolitical and economic stress. Several key events shaped the early phase of the war: the imposition of SWIFT sanctions on Russian banks, massive energy price surges, and Europe’s scramble to rethink its energy security strategy. As noted by Tong (2024), the war acted as a contractionary supply shock, resulting in a spike in inflation, systemic financial stress, and price shocks across energy and commodity markets.

In financial markets, the war led to a marked rise in volatility and connectedness among assets, particularly in the energy and equity sectors. According to Sio-Chong U et al. (2024), volatility spillovers from the Ruble and Russian markets surged following the SWIFT sanctions, leading to longer-lasting instability across asset classes. The immediate reaction in Europe was especially strong, given its heavy reliance on Russian energy exports and the proximity of the conflict. The war also triggered a heightened focus on geopolitical risk indices, such as the one developed by Caldara and Iacoviello (2022), which recorded sharp spikes in investor attention to global political instability. Umar et al. (2022) observe that during this period, European equities and energy-related assets acted as both transmitters and receivers of volatility, illustrating the far-reaching impact of the conflict.

By focusing our thesis on this critical moment in history, we aim to assess how geopolitical shocks affect financial market behaviour in real time which is an area that remains underexplored in high-frequency, sector-specific studies. The Russia–Ukraine war offers a timely and relevant case to study the transmission of geopolitical risk through return, volatility, and connectedness metrics. Although there is a growing list of literature exploring how geopolitical risk affects financial markets, a lot of the existing research either focuses on broad market indices or analyses long-term effects. Studies like Assaf et al. (2023) and Wang et al. (2023) shows that the Russia–Ukraine conflict had significant impacts on global equity and commodity markets, yet these analyses often emphasize aggregate market behaviour rather than asset-level dynamics. Moreover, many previous studies rely on fixed-parameter models or rolling-window approaches, which do not fully capture how the effects of a geopolitical shock evolve over time. Another noticeable gap in the literature is the limited focus on European energy markets at a daily frequency. While several papers investigate volatility spillovers during geopolitical events, few consider both firm-level equities and energy commodities together in the same framework.

Our thesis aim is to focus on these limitations. By applying a time-varying framework to model connectedness between the GPR index and a diverse group of European energy-related assets, we can observe how transmission patterns change through different stages of the conflict. Furthermore, by including a predictive regression, we explore whether geopolitical risk and market connectedness can be used to predict asset returns, something that is quite underexplored in the literature. In this way, our study contributes to the field by offering a more dynamic and predictive perspective on geopolitical risk and financial market behaviour during one of the most disruptive events in recent history.

The main goal of our thesis is to examine how the Russia–Ukraine war affects European energy markets through return and volatility spillovers. We aim to understand not just whether these markets were impacted, but how the intensity and direction of connectedness changed over time in response to rising geopolitical tension. To do this, we focus on a group of affected assets, including both energy commodities and stocks, as well as a set of unaffected assets used for comparison. Our research focuses on two key questions. First, we ask to what extent did geopolitical risk contribute to changes in return and volatility connectedness within European energy markets during the Russia–Ukraine conflict, and secondly can connectedness measures and geopolitical risk indicators help predict short-term returns across assets.

To answer these questions, we apply a Time-Varying Parameter Vector Autoregression (TVP-VAR) model with Generalized Forecast Error Variance Decomposition (GFEVD) to estimate return and volatility connectedness over time. In addition, we use a univariate GARCH model to extract volatility, and we do a predictive regression analysis to evaluate whether past connectedness and geopolitical risk have any predictive power in finding future asset returns. This framework allows us to study both the structure of spillovers and the predictive content of geopolitical uncertainty.

This thesis is structured into five main chapters. Following this introduction, Chapter 2 presents the literature review, where we discuss key academic work on volatility spillovers, connectedness measures, and the economic consequences of geopolitical risk, with a special focus on studies related to the Russia–Ukraine war. Chapter 3 outlines the methodology, describing how we processed the data, estimated time-varying connectedness using the TVP-VAR model, calculated volatility using GARCH models and used the outcome of these two models in our predictive regression models. Chapter 4 show the results of our analysis. We report on the evolution of return and volatility spillovers, comparisons between affected and unaffected assets, and the outcomes of our predictive regressions. These results are supported with visualizations and tables show how financial markets responded overtime. In Chapter 5, we interpret and discuss the results, connecting them to the literature and providing insight into what the findings suggest for theory and practice. Finally, Chapter 6 concludes the thesis by summarizing the main findings, acknowledging limitations, and offering suggestions for future research.

2. Literature Review

As global tensions and unexpected shocks have challenged the stability and security of European energy markets, understanding how geopolitical events influence these markets is of vital importance. Our literature review outlines the key theoretical and empirical findings on the role of geopolitical risk in financial markets, with a particular focus on asset prices, volatility spillovers, and predictive dynamics. Given the Russia–Ukraine War as the central geopolitical event in our empirical analysis, we ground our discussion in the framework established by Caldara and Iacoviello (2022), whose Geopolitical Risk Index (GPRD) has become foundational in quantifying geopolitical uncertainty. The review is structured to cover various asset classes, including conventional and renewable energy, healthcare equities, and agricultural commodities, while also addressing the broader implications of GPR on market connectedness and predictability.

The chapter is structured as follows: Section 2.1. investigates GPR's effects on different asset classes, beginning with conventional energy markets which is followed by a sector over renewable energy markets. Section 2.1.3. discusses sectors typically considered 'unaffected' by geopolitical shocks, namely healthcare and agriculture. Here, we synthesize recent studies that challenge this assumption, identifying conditional vulnerabilities and emphasizing the role of regional dependencies and global trade structures. Section 2.1.5. turns to the predictive power of GPR, where research is divided on whether GPR can forecast asset returns or merely increases volatility, particularly during crises. Section 2.2. focuses on volatility spillovers and market connectedness. We highlight the importance of directional and asymmetric spillovers, particularly from oil to equities, and discuss how methodological advancements such as the vector multiplicative error model (vMEM-X) and quantile coherency networks improve our understanding of these dynamics. Section 2.3. discusses the use of Time-Varying Parameter Vector Autoregression (TVP-VAR) models, which allow researchers to capture structural breaks and evolving interdependencies. Finally, Section 2.4. introduces predictive time series regression models and the statistical challenges they face when incorporating predictors like GPR, emphasizing methods for improving forecast accuracy.

2.1. Geopolitical Risk in Financial Markets

Geopolitical risk is of upmost importance for our paper, as it builds the foundation of our empirical research where we look at how the Ukraine-Russia War as our geopolitical risk event affects the European financial markets. More specifically, we incorporate the Geopolitical Risk Index (GPRD) from Caldara and Iacoviello (2022). Hence, the authors provide a seminal indicator to quantify geopolitical risk through a sentiment analysis of newspapers and enable further research like ours to be conducted based on the index. Their findings suggest that GPR shocks are associated with lower firm-level investment, heightened macroeconomic volatility, and larger downside risks for the growth of the gross domestic product of an economy. Furthermore, do they show that these effects are stronger on companies in exposed industries. (Caldara & Iacoviello, 2022)

2.1.1. Conventional Energy Markets

Conventional energy, defined as fossil fuel-based sources such as coal, oil, and natural gas (Rao et al., 2023), is particularly exposed to geopolitical disturbances due to its strategic importance and uneven global distribution. Among these, oil markets stand out for their immediate and often pronounced reactions to geopolitical shocks, making them a focal point in recent empirical research.

Berkman et al. (2010) develop a crisis index based on international political events as a predecessor to the GPRD (Caldara & Iacoviello, 2022) and interpret them as rare disasters. They show that such crises significantly reduce stock returns and increase volatility. Additionally, no significant connection between crisis risk and future market returns were found. However, they do find support for the argument that crisis risk is already priced as industries exposed to higher crisis risk receive higher returns on average. Furthermore, the study shows a positive correlation of earnings-price ratio and dividend yield with crisis risk. (Berkman et al., 2010) However, Zhang et al. (2022) suggest that there is in fact a connection between geopolitical risk and future stock returns. The authors examine further effects of GPR on oil markets and introduce an indicator which is derived from the GPR from Caldara & Iacoviello (2022) to predict oil prices. In contrast to Berkman et al. (2010), their results indicate that GPR trends have a significantly negative impact on global crude oil demand. Thus, when a geopolitical risk event occurs, the oil price will drop (Zhang et al., 2022). Antonakakis et al. (2017) provide a long-run historical analysis using monthly data from 1899 to 2016, revealing that geopolitical risk exerts a statistically significant and negative impact on oil returns and oil market volatility, while the effect on stock markets is milder and more delayed. Primarily their results show that the oil market reacts immediately to spikes in geopolitical tension. Moreover, GPR indirectly influences the time-varying correlation between oil and stock markets, offering diversification benefits under heightened uncertainty. (Antonakakis et al., 2017) To a similar conclusion came Caldara and Iacoviello (2022) who highlight the impact geopolitical risk has on petroleum markets and precious metals as these industries are especially negatively affected by geopolitical risk. Additionally, Xu et al. (2024) analyse the transmission of volatility across markets and find that stock markets are net transmitters of volatility, whereas oil markets are net receivers when macroeconomic shocks are excluded. When included, however, they show that these shocks have a bigger impact on crude oil markets than others (Xu et al., 2024), which is in accordance with the overall opinion of science as argued before.

All in all, the reviewed literature provides evidence that geopolitical risk is not merely a background condition but a direct and quantifiable driver of volatility and returns in conventional energy markets, particularly for oil. Across studies, the one main trend that can be identified is that oil markets are more acutely sensitive to geopolitical shocks than other financial assets.

2.1.2. Renewable Energy Markets

Within financial markets, renewable energy (RE) has emerged as a distinct asset class that is both driven by and reactive to geopolitical dynamics. While much of the literature on geopolitical risk has focused on traditional energy markets, recent research reveals that renewable energy investments and stock performance are increasingly exposed to geopolitical forces.

As one of the first empirical investigations incorporating the effects of GPR on renewable energy, Yang et al. (2020) show that while GPR exerts significant risk spillovers, these are generally smaller than those from stock and oil market uncertainties. Interestingly, GPR exhibits relatively symmetric effects on renewable markets across different market states (bull and bear markets). A foundational insight is offered by Su et al. (2021), who examine the relationship between geopolitical risk and renewable energy. Based on a rolling-window framework, they identify a mutual causality between the two. Geopolitical risks, such as trade disputes and rare metal competition, stimulate investment in renewables due to concerns over energy security. On the other hand, the growth of RE can reduce geopolitical risks by decentralizing energy production and reducing fossil fuel dependencies. Thus, with greater investment in renewable energy, economies can make themselves independent of conventional energy exporting countries as no import of fossil fuel is required. Additionally, the global climate would benefit from that and with reduced geopolitical risk this effect might be even enforced. (Su et al., 2021) Hence, a lower GPR means lesser conflicts will end up in a military engagement, which results in less destruction of the environment and lower carbon emissions from war machinery. However, this relationship is currently disputed in research. There are many studies supporting the argument that higher geopolitical risk, thus higher militarisation, increases CO_2 emissions and vice versa (inter alia: Jorgensen et al., 2010; Bildirici & Gokmenoglu, 2019; Anser et al., 2021; Bildirici, 2020). Conversely, Zhao et al. (2021) find an asymmetry in the relationship between RE and GPR, meaning higher GPR does not deduce higher RE investments. Alqahtani and Taillard (2019) find a negative correlation between GPR and carbon emissions and highlight that shocks stemming from RE investments do not influence oil prices. Lastly, Flouros et al. (2022) also describe a negative effect on RE production resulting from geopolitical risk regardless of which estimator is being used.

2.1.3. Healthcare Equities & Agricultural Commodities

The impact of geopolitical risk on the healthcare and agricultural sector is analysed as part of our robustness check and will be referred to as unaffected assets in our paper. Therefore, do we want to provide an overview of the existing research in the following. However, not much research has been done exploring the effects of GPR on healthcare or agriculture assets. While agricultural commodities still show some research, healthcare or pharmaceutical equities literature is basically non-existent.

To give an overview, both Ukraine and Russia are major corn producers and exporters and rank 7th and 11th in the global corn production, respectively. Furthermore, is Russia the 9th largest producer of beef, the 5th for butter, and the 7th for eggs. (Food and Agriculture Organization of the United Nations, 2025; U.S. Department of Agriculture [USDA], 2025) Thus, to have these two countries in a war has major implication on the production of agricultural goods. Especially Ukraine is affected and does produce 34% less grain today than it did in 2021-2022 as less crops are planted. (Braun, 2025)

The effects geopolitical risk has on food is explored by Sohag et al. (2022) who distinguish between Eastern and Western Europe, showing that GPR increases food inflation in Western Europe in the long-term. Albeit, short-term effects may even be negative in Eastern Europe, suggesting that GPR reduces food prices in the east. The authors argue that these effects are due to a lack of measures handling geopolitical risk. They further establish that the Russia-Ukraine War magnifies food inflation through energy cost spillovers. Complementing these regional insights, Dai et al. (2024) and Goyal et al. (2024) show significant GPR effects on agricultural commodity market volatility and future prices. Dai et al. (2024) find that GPR significantly affects international agricultural markets by increasing volatility and dampening return predictability, especially in the long term. They discover also that GPR has a negative effect on the corn market volatility in Europe. Additionally, wheat and corn markets are vulnerable to geopolitical risks stemming from different combinations of globally influential economies involved in their production, import, and export activities. (Dai et al., 2024) On the other hand, do Goyal et al. (2024) observe a significant effect of GPR on corn and soybean future prices. Furthermore, do they indicate similar results to Sohaug et al. (2022) that an increase in oil prices stemming from the Ukraine-Russia conflict indirectly affects agricultural commodity prices. On the contrary, the findings of Mo et al. (2023) underscore that food and agricultural raw materials are not significantly affected by GPR while energy commodities are. Thus, the authors argue that geopolitical events do not influence non-energy sectors. (Mo et al., 2023) This is partly echoed by Hudecová and Rajčániová (2023) who identify no long-term connection between corn, cotton, lumber, dairy, and some other grains. However, the do find evidence of an asymmetric effect on rapeseed, sugar, sunflower oil, and wheat stemming from geopolitical risk. (Hudecová and Rajčániová, 2023) Turning to healthcare, as previously mentioned we could not find any related research about the healthcare sector. Merely, Ali et al. (2023) show a positive, yet statistically unsignificant, effect on returns in the healthcare sector.

2.1.4. Predictive Power of Geopolitical Risk

Research has analysed the relationship between geopolitical risk and energy assets and conclude that conventional energy, especially oil assets, as well as renewable energy are to some degree impacted by GPR. However, there is discussion whether geopolitical risk hold any predictive power on stock prices.

Ma et al. (2022) provide the strongest support for GPR's predictive power. Using a century-long dataset and a rolling-window out-of-sample forecast framework, they find that the geopolitical threats index introduced by Caldara and Iacoviello (2022) significantly predicts excess U.S. stock returns, especially during economic expansions. Their results show that GPR outperforms traditional macroeconomic predictors and improves portfolio allocation, suggesting robust economic value. In contrast, Apergis et al. (2018) find no evidence that GPR predicts stock returns of global defence companies using nonparametric methods. However, they report that GPR does significantly affect volatility, particularly realised volatility, in 50 % of the sample. This distinction between return and volatility predictability is echoed in Chatziantoniou et al. (2025), who show that GPR subcomponents (terror threats and acts) improve the explanatory power of sectoral volatility models, though their effect on returns remains limited. Furthermore, Balcilar et al. (2018) examine the BRICS markets and find that GPR impacts volatility spillovers more strongly than returns, with country-specific heterogeneity. Similarly, Plakandaras et al. (2018), focusing on emerging markets, report that GPR fails to predict stock returns, oil, or exchange rates, while gold is being the only consistently responsive asset. On the other hand, Demirer et al. (2018) find that rare disaster risks (as a proxy for GPR) strongly predict both returns and volatility in oil markets, especially at lower quantiles. This suggests that standard linear models may systematically understate GPR's predictive role, missing key nonlinear and tail-risk dynamics. Antonakakis et al. (2017) confirm this sectoral divergence. Their results show that GPR significantly affects oil markets but not stock returns, implying that commodity markets, especially oil, are more reactive to geopolitical shifts. Alqahtani and Taillard (2019) contribute to this argument by showing that shocks stemming from GPR do not influence oil prices and that there is neither causality nor any impact of GPR on oil returns.

Thus, it can be observed that science did not yet reach a consensus if GPR does hold any predictive power. However, there is a trend that GPR exhibits a higher impact on volatility than it does on (stock) returns.

2.2. Spillovers and Market Connectedness

Volatility spillovers refer to the transmission of shocks and uncertainty from one asset or market to another, potentially causing effects across financial systems. These underlying forces are especially obvious in periods of geopolitical tension and macroeconomic instability, where interconnectedness among assets such as oil, stocks, bonds, and commodities become more apparent (Diebold & Yilmaz, 2012; Smales, 2021). One famous bit of literature investigates the Influence of geopolitical risk on financial markets. Smales (2021), using the Caldara and Iacoviello (2022) GPR index, shows that GPR significantly impacts oil price volatility and, to a lesser extent, stock market volatility. Specifically, Increases In geopolitical risk tend to drive oil prices up and stock prices down, suggesting a strong supply-side influence on oil and broader sentiment-driven reactions in equity markets. This response highlights an asymmetric spillover dynamic, where oil markets absorb most geopolitical disturbances and transmit volatility to stocks in the long term.

The persistence of volatility in oil markets, coupled with their tendency to react more intensely to localized shocks, highlights a unique feature of commodity-linked spillovers. Smales (2021) finds that while both oil and equity markets exhibit short-term bidirectional volatility spillovers, long-term spillovers primarily go from oil to equities. This relationship explains the systemic role of energy markets in shaping global risk perceptions. Adding to this, Xu et al. (2024) introduced a framework to assess spillovers under the influence of macroeconomic shocks. Using a vector Multiplicative Error Model with exogenous variables (vMEM-X), they distinguish between internal volatility spillovers within financial markets and those driven by macroeconomic conditions such as inflation, interest rates, and economic policy uncertainty. Their findings reveal that the stock market often acts as the dominant transmitter of volatility, particularly toward the crude oil market. However, when macroeconomic variables are introduced, the strength of this transmission reduces—suggesting that macro-level changes largely drive observed spillovers.

This approach offers a new way for evaluating causality in volatility transmission. Contrary to earlier VAR- and GARCH-based models, which assume mutual relationships, the vMEM-X treats macroeconomic shocks as external drivers. This exogeneity assumption aligns with studies by Bali et al. (2014) and Yang and Zhou (2017), which show that financial markets respond strongly to policy-induced uncertainty and interest rate fluctuations but rarely influences these macro variables in return. Xu et al. (2024) also find that oil and stock markets are more sensitive to macroeconomic conditions compared to bonds and gold. While crude oil has the highest spillover from inflation shocks and term spread changes, confirming its role as an Indicator of global economic sentiment. In contrast, bonds and gold display relatively quiet responses, supporting their characterization as safe assets (Baur & Lucey, 2010).

Earlier studies had already laid the groundwork for spillover research. Diebold and Yilmaz (2009, 2012) developed measures to quantify spillover effects in multivariate settings. GARCH-based models further refined this by accounting for volatility clustering, though they struggled with dimensionality and asymmetry. Despite the progress, challenges remain in isolating the exact channels of spillover transmission. For example, the observed co-movement between oil and equity markets could reflect both direct transmission and shared exposure to latent macroeconomic shocks. Xu et al. (2024) acknowledge this by decomposing spillovers into those caused by internal dynamics and those triggered externally. Their impulse response analysis further shows that macroeconomic shocks have longer-lasting effects on volatility than financial market shocks—a critical insight for investors and policymakers alike.

In summary, the literature underscores that volatility spillovers are both context- and asset-specific. Geopolitical and macroeconomic shocks remain powerful triggers of financial market turbulence, with oil and equities bearing the brunt of the impact. Methodological innovations such as the Dynamic Conditional Correlation (DCC) and Vector Multiplicative Error Model with Exogenous Variables (vMEM-X) models have enhanced our understanding of these complex dynamics, offering more precise tools for measuring interconnectedness. Going forward, integrating high-frequency data, event-specific dummy variables, and more granular sectoral analysis could further refine our grasp of spillover behaviour across global markets.

The concept of market connectedness shows how financial markets influence one another through interdependencies that evolve over time. This interconnectedness becomes important during times of economic or geopolitical shocks, as changes in one market can spread to others, expanding risk and limiting diversification opportunities. Recent literature has deepened the understanding of how commodities, equities, currencies, and other asset classes are connected, both in normal periods and under shock periods.

Awartani et al. (2016) provide a detailed analysis of the connectedness between crude oil and various financial markets using implied volatility indices. Their findings reveal that oil is a significant transmitter of volatility, especially toward equity markets, with directional connectedness from oil to equities reaching as high as 20.4%. This directional nature highlights the asymmetry in market relationships where oil tends to drive changes in other markets more than it is influenced by them. Adding to this, Li et al. (2024) use a TVP-VAR model to understand global market connectedness during the Russia–Ukraine conflict. Their results show that geopolitical crises can lead to a structural shift in financial linkages, with low-frequency (long-term) components dominating total connectedness during crises. The stock and currency markets first acted as major risk transmitters, whereas the commodity markets became key risk receivers.

Khalfaoui et al. (2021) approached connectedness through a fresh method, quantile coherency networks, to explore dependencies between energy and nonenergy commodities. They find that these markets are only weakly connected under normal conditions but show stronger movements during economical and geopolitical shocks. This frequency- and quantile-specific approach allows for a fresh short-term trading-based spillovers from longer-term structural connectedness. The heterogeneity in connectedness is further emphasized by Bagirov and Mateus (2021), who examine volatility transmissions between petroleum prices and equity indices in petroleum-exporting countries and importing countries. They apply a VAR-GARCH model to demonstrate that the strength and direction of volatility spillovers vary a lot across economic sectors. This underscores how national energy profiles and economic structures shape the nature of financial interdependence.

Sectoral analysis of connectedness is also highlighted in Bagirov and Mateus (2019). They reveal that oil price shocks affect different sectors in different ways, while sectors such as technology or healthcare are less sensitive. The study further shows that listed oil and gas companies' financial performance is significantly linked to oil prices, reinforcing their role as transmission nodes in market networks. A critical takeaway from these studies is the context-specific nature of market connectedness. Connectedness increases during crises, shifts in direction depending on the origin of shocks, and varies in intensity across markets and sectors. For instance, during the Russia–Ukraine conflict, the German stock market emerged as a primary source of global spillovers, while the commodity markets played a more passive role (Li et al., 2024).

Methodologically, the field has moved beyond static models toward time-varying, quantile-based, and network-based approaches. The adoption of the TVP-VAR framework by Li et al. (2024) allows for capturing the changing structure of financial linkages, while the quantile coherency method used by Khalfaoui et al. (2021) provides a finer understanding of tail risks. These advances enable researchers and policymakers to better anticipate and manage systemic risks, especially when making diversified portfolios or assessing financial stability.

In conclusion, market connectedness is a complex phenomenon shaped by global events, economic structures, and asset characteristics. The literature demonstrates that while energy markets often serve as big sources of spillovers, their impact is not equal across sectors and time horizons. As the financial landscape becomes more integrated and sensitive to cross-border shocks, understanding the evolving patterns of connectedness is essential for effective risk management and investment strategy.

2.3. Prior Studies Using TVP-VAR

Time-Varying Parameter Vector Autoregressions have emerged as a powerful tool for studying interdependencies across financial markets, particularly when those relationships change over time. Traditional fixed-parameter VAR models often fall short in capturing structural changes or sudden market events, making TVP-VAR a natural choice for analysing volatility spillovers and market connectedness in periods of crisis or transition.

The foundational Idea of VAR models Is to capture the linear Interdependencies among multiple time series. A standard VAR(p) model of an N-dimensional vector y_t is represented as:

$$y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \varepsilon_t,$$

where $\varepsilon_t \sim N(0, \Sigma)$ is a vector of error terms and Φ_i are coefficient matrices. However, this framework assumes time-invariant coefficients Φ_i, which is often unrealistic in financial markets, especially around events like the Global Financial Crisis or geopolitical shocks such as the Russia–Ukraine conflict.

TVP-VAR models generalize this framework by allowing parameters to evolve over time:

$$y_t = \Phi_{1,t} y_{t-1} + \Phi_{2,t} y_{t-2} + \cdots + \Phi_{p,t} y_{t-p} + \varepsilon_t.$$

This setup is usually estimated using the Kalman filter, with parameter evolution modelled as:

$$\text{vec}(\Phi_t) = \text{vec}(\Phi_{t-1}) + \nu_t, \quad \nu_t \sim N(0, R_t),$$

where v_t captures the stochastic changes in coefficients.

Antonakakis et al. (2020) highlight several benefits of using TVP-VAR for dynamic connectedness analysis. Most notably, unlike rolling-window VARs, TVP-VAR avoids random window size choices and reduces observation loss. It also handles outliers better due to its probabilistic updating through the Kalman filter. These features allow researchers to trace the time-varying behaviour of financial interconnectedness more precisely, especially in turbulent periods.

The dynamic connectedness framework, originally by Diebold and Yilmaz (2012, 2014), measures how much of a variable's forecast error variance is due to shocks from itself versus from others in the system. This is achieved via generalized forecast error variance decompositions, which are ordering-invariant and suitable for systems with correlated innovations.

Given a moving average (MA) representation of the VAR

$$y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j},$$

the GFEVD for variable I due to shocks in variable j over H-steps ahead is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)},$$

where e_i is a selection vector and Σ is the variance-covariance matrix of ε_t. This measure is normalized to obtain:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}.$$

From this, four connectedness measures follow:

1. Total Connectedness Index (TCI):

$$C(H) = \frac{1}{N} \sum_{i \neq j} \tilde{\theta}_{ij}^{g}(H) \times 100,$$

2. Directional connectedness from others to i:

$$C_{i \leftarrow \bullet}(H) = \sum_{j \neq i} \tilde{\theta}_{ij}^{g}(H) \times 100,$$

3. Directional connectedness from I to others:

$$C_{\bullet \leftarrow i}(H) = \sum_{j \neq i} \tilde{\theta}_{ji}^{g}(H) \times 100,$$

4. Net connectedness of i:

$$C_i(H) = C_{\bullet \leftarrow i}(H) - C_{i \leftarrow \bullet}(H).$$

These measures allow researchers to identify not just the strength but also the direction of volatility transmission across markets.

Historically, TVP-VAR has been applied successfully to understand periods of heightened market stress. Gabauer and Gupta (2018) use it to show how economic policy uncertainty, especially monetary policy uncertainty, spreads between the U.S. and Japan, particularly during the Fukushima disaster. Similarly, Antonakakis et al. (2020) shows its robustness and sensitivity advantages over rolling-window methods.

Despite the added computational complexity and the need for careful selection of priors and forgetting factors, TVP-VAR offers many advantages in modelling evolving systems. Its flexibility makes it increasingly popular in applied macro-finance research.

In conclusion, TVP-VAR frameworks represent a significant advancement for researchers analysing dynamic relationships in finance. Their ability to handle structural shifts and produce interpretable connectedness metrics makes them vital in understanding interconnected financial systems.

2.4. Predictive Time Series Regression

Predictive time series regression models aim to forecast future values of a dependent variable using its own past values and one or more variables. These models are widely used in macroeconomics and finance to understand and forecast asset prices, GDP growth, inflation, and interest rates. Unlike standard time series models such as AutoRegressive Integrated Moving Average (ARIMA), which only uses lags of the dependent variable, predictive regressions use external regressors that are believed to have predictive power. Campbell and Thompson (2008) provide a foundational example of predictive time series regression in the context of equity returns. They argue that variables like dividend-price ratios, earnings yields, and term spreads show time-varying predictive power for stock returns. Their approach involves regressing future returns on current predictor variables, typically in the form:

$$y_{t+h} = \alpha + \beta x_t + \varepsilon_{t+h},$$

where y_{t+h} is the value of the dependent variable h periods ahead, and x_t is the predictor observed at time t. The performance of such models often varies over time, encouraging researchers to find structural instability, parameter uncertainty, and the robustness of inferences.

One common issue in predictive regressions is persistence in the predictor variable, which can lead to biased or fake inferences. Stambaugh (1999) shows that when the predictor x_t is highly persistent and correlated with the error term, standard Ordinary Least Squares (OLS) inference becomes invalid. This has motivated the development of bias-corrected estimators and robust inference methods, such as bootstrapping or local-to-unity asymptotic. Another advancement in the field involves out-of-sample forecast evaluation. Clark and West (2007) introduce a test that compares nested models, showing that in small samples, the mean squared prediction error difference can favour a model with additional predictors even when the null hypothesis of no predictive content Is true. Their test is now widely used to prove the usefulness of predictive regressions beyond in-sample fit.

Despite these innovations, predictive power remains elusive and often unstable. Researchers increasingly recognize the importance of structural breaks, nonlinear relationships, and changing economic regimes. Time-varying coefficient models and model averaging have been proposed as solutions to adapt to shifting predictive relationships (Rapach & Zhou, 2013).

3. Methodology

In this section, we will discuss in depth of how our analysis took place and give a comprehensive step by step guide on how we tackled the research question and hypotheses, along with running contingencies and looking in the future of the energy market.

3.1. Overview of Research Design

We explore in this thesis how geopolitical risk affects the European energy markets, focusing on the period surrounding the start of the Russia–Ukraine war. The conflict has created a platform to study how uncertainty starting from political events spills over into financial markets. Our thesis applies a structured empirical approach, combining time-varying connectedness analysis and predictive modelling to assess both the evolution of spillover dynamics and their impact on asset behaviour.

Our thesis stems from the idea that financial markets are not static. Relationships between different assets and economic indicators shift over time, especially during periods of geopolitical tension. Conventional models often assume a static relationship between variables, which limits their usefulness when shocks happen. This research addresses the limitation by using a Time-Varying Parameter Vector Autoregressive model (TVP-VAR), which allows model parameters to change over time. This helps in capturing the evolving nature of risk, focusing on before and after the start of the Russia–Ukraine war. The core objective is to understand how geopolitical uncertainty, captured through the Geopolitical Risk Index, affects selected European energy-related assets. This includes not only commodity prices such as Brent crude oil and natural gas but also the equity prices of major energy firms operating within Europe. The analysis is structured to identify whether these assets behave as economic shock receivers or transmitters during the examined period.

Our thesis process follows a step-by-step design, beginning with the collection and transformation of daily price data for a set of affected assets and the GPR index. To prepare the data for modelling, financial asset prices are first log-transformed to see the daily percentage returns. The GPR index, which measures geopolitical tension based on newspaper coverage and online news, is also logged. Once the transformations are done, the series are tested for stationarity to see whether they are suitable for VAR-based modelling. Stationary time series are critical in VAR frameworks to avoid false relationships and unstable results.

After data preparation, the next step was estimating the TVP-VAR model. This model captures the changing relationships between the GPR index and the selected assets over time. Unlike static or rolling VAR models, TVP-VAR does not rely on fixed parameters or arbitrarily chosen windows. Instead, it uses a Bayesian estimation method with forgetting factors, allowing the model to give more weight to recent data while still learning from the past. From there, the model generates several connectedness measures. The Total Connectedness Index (TCI) gives an overall picture of how interconnected the system is at each point in time. Directional connectedness measures show how much each variable contributes to or absorbs shocks from the rest of the system, coming from the "TO" and "FROM" connectedness metrics. The difference between the two provides the NET Connectedness, used to track the dominant behaviour of each asset. To examine how the war influenced these dynamics, the data is shown through pre- and post-invasion periods, using February 24, 2022, as the cut-off point to allow a comparison of the behaviour of energy markets during normal periods versus periods of heightened geopolitical stress. By tracking changes in connectedness before and after the war, the model highlights the change in the relationship between assets and the GPR index.

As a robustness check, we also did the same analysis on a set of unaffected assets such as healthcare stocks and agricultural commodities. The reasoning behind this is to show weaker or no response to geopolitical risk and see if their inclusion helps validate the results found in the main sample. In addition, a second connectedness model is done using GARCH-based volatility series to evaluate whether volatility spillovers mirror return spillovers. Finally, a simple predictive regression is conducted to assess whether connectedness, volatility and geopolitical risk can help forecast future asset returns.

3.2. Justification for Methodological Choices

The choice of this analysis is driven by the need to accurately capture the dynamic and directional nature of spillovers in financial markets during the Russia–Ukraine War. Hence a Time-Varying Parameter Vector Autoregression framework combined with Generalized Forecast Error Variance Decomposition was chosen. Traditional VAR models with fixed parameters often fail to reflect structural breaks or regime shifts that are typical during crisis periods. In contrast, the TVP-VAR framework allows model parameters to evolve over time, offering a more flexible and realistic representation of the market. As highlighted by Antonakakis et al. (2020), the dynamic nature of this method makes it suitable for tracking how interlinkages among variables change in response to external shocks such as geopolitical events.

The GFEVD methodology developed by Pesaran and Shin (1998) and employed in a dynamic setting by Diebold and Yilmaz (2012, 2014), was chosen for its order-invariant properties. This is particularly important in high-frequency financial data where variable ordering can significantly influence Cholesky-based decompositions. GFEVD, by contrast, treats each variable symmetrically, which ensures the robustness and credibility of directional spillover estimates. Since we included a range of energy market variables and the GPR Index, the neutrality in variable treatment helps protect the empirical validity of the results. We estimate the TVP-VAR model using a Bayesian approach, where the Kalman filter is applied to recursively update the time-varying coefficients over time, conditional on the observed data and prior assumptions. This allows for efficient tracking of structural changes and increases the model's ability to accommodate new information. Moreover, the rolling window approach previously used in Diebold and Yilmaz (2014) was avoided to prevent potential biases from arbitrary window length choices.

3.3. Data and Sample Selection

Starting with the collection of data, we decided to choose assets of different classes and from different countries to have our analysis as comprehensive as possible. Our decision to choose both stocks and commodities was to get a broad picture of how far a geopolitical shock can spillover.

3.3.1. Geopolitical Risk Index (GPRD)

The primary source of geopolitical uncertainty in our thesis is captured through the Geopolitical Risk Index, developed by Caldara and Iacoviello (2022). The index is sourced from https://www.matteoiacoviello.com/gpr.htm and is widely used in economic and financial research for its transparent methodology and historical consistency. It measures the intensity of geopolitical tensions by analysing news article content and assigning standardized risk scores across time. This is why the GPRD index is treated as a key input to identify how the war affects financial assets with varying exposure to energy markets.

3.3.2. Affected Asset Group

The affected asset group consists of commodities, utility companies, energy firms, and precious metals that are expected to react strongly to geopolitical risk particularly when it threatens supply chains and pricing. This group includes:

- Commodities: Brent Crude Oil, Diesel, Dutch Natural Gas, and Heating Oil
- Energy Firms and Utilities: Equinor, Repsol, Shell, TotalEnergies, Fortum, Ørsted, RWE, Verbund
- Metals: Aluminium, Cobalt, Copper, Nickel

These assets were selected based on their role in the European energy market and their historical sensitivity to disruptions in global supply and political risk. Their prices reflect not only internal financial dynamics but also geopolitical narratives, making them suitable candidates for spillover analysis.

3.3.3. Data Sources and Time Frame

Daily price data for all assets were extracted from FactSet, with the timeline spanning from February 1st, 2021, to March 1st, 2023, offering over two years of daily observations. This period was chosen to provide sufficient data both before and after the start of the Russia–Ukraine war on February 24th, 2022.

3.4. Data Transformation and Preprocessing

Before estimating the TVP-VAR model, we took several pre-processing steps to ensure the data were clean, consistent, and suitable for time series analysis. This section will explain how missing values were addressed, how variables were transformed, and how stationarity was tested and achieved.

3.4.1. Cleaning and Filling

The data of the assets had multiple empty values given the presence of public holidays and different trading days across different countries which need to be filled and fixed in order to start our analysis. To do this, all series were first aligned with the dates of the GPRD index which resemble all weekdays for the two-year timeframe. This was done on excel using a simple IF(ISNA(VLOOKUP)) formula, aligning GPRD dates with asset dates and having the empty values be shown as zero for filling. Where data was missing for a given asset but available for others on the same day, the missing values were filled using a forward-filling approach. We used a moving average approximation with a time window of the last seven days prior to the missing value, ensuring that the continuity of each time series was maintained without changing the trend. This approach was chosen over listwise deletion or backward-filling to avoid introducing artificial shocks or inconsistencies into the returns.

3.4.2. Log Transformation

To prepare the data for modelling, all asset prices were transformed into logarithmic percentage returns. This was done using the transformation:

$r_t = 100 \times \text{diff}(\log(x_t))$

This log-difference transformation has two main benefits. First, it stabilizes the variance of the data, reducing the impact of extreme values and making the time series more homoscedastic. Second, it approximates the continuously compounded return, which is standard in financial time series analysis and improves comparability across assets.

3.4.3. Stationarity Testing

Once the transformations were applied, the next step was to verify that all variables met the stationarity requirement necessary for vector autoregressive modelling. Two well-established unit root tests were applied: the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Both tests were used to check whether the series had a unit root, i.e., whether they were non-stationary. The ADF test accounts for autocorrelation in the time series by adding lagged difference terms, while the PP test corrects for serial correlation and heteroskedasticity using non-parametric methods. Using both tests provides a robust validation of stationarity assumptions.

3.5. Model Setup: TVP-VAR Estimation

With the data cleaned, transformed and tested, it was time to start working on our TVP-VAR model to see spillovers and connectedness.

3.5.1. Preparing the Data Matrix: zoo Object Creation

After data transformation and cleaning, the dataset was structured as a zoo object in R, which is required by the ConnectednessApproach package (created by Antonakakis et al., 2020) we used for our TVP-VAR model. The zoo format ensures that each variable is indexed by time, allowing the model to treat all series as synchronized daily observations. This is crucial for consistent lagging, forecasting, and decomposition in time series estimation. The final zoo matrix contained the differenced log returns of 16 affected assets along with the first-differenced GPRD index. A similar matrix was later created for the robustness check using unaffected assets.

3.5.2. Model Framework and Lag Length

A lag length of four (nlag = 4) was chosen. This decision is based on two factors: the structure of daily financial data and prior empirical evidence. As stated in Zhou et al., 2020, responses to geopolitical risk shocks are strongest around the 4th lag and tend to diminish at higher lags. A four-day lag strikes a balance between capturing meaningful short-term dynamics and avoiding overfitting, especially given the high frequency of the data.

3.5.3. Forecast Horizon and Window Size

The forecast horizon was set to 10 days (nfore = 10). This allows the model to capture both immediate and slightly delayed responses to shocks, which is essential for understanding volatility transmission in periods of uncertainty. A 10-day horizon also ensures compatibility with the GFEVD. The window size was fixed at 100 observations, which defines the sample length used to update the model over time. This rolling window makes sure that the model remains responsive to recent changes while maintaining enough data for a stable estimation. In periods of market stress, shorter windows would be too reactive, and longer ones might smooth over important shifts.

3.5.4. Prior Specification and Estimation Method

The model uses a Bayesian prior, done with the BayesPrior function. This prior is taken from the early part of the sample and serves as the starting point for the Kalman filter, which updates the time-varying parameters throughout the estimation. The Bayesian prior is preferred because it allows the model to incorporate initial beliefs about the system while using these beliefs as new data become available.

Two important forgetting factors were used, as used by Koop and Korobilis (2014), denoted as κ_1 (kappa1) and κ_2 (kappa2), to control the rate at which the model updates its parameter estimates:

- $\kappa_1 = 0.99$ controls the evolution of the coefficient matrices. A high value means that the model updates slowly, giving more weight to past relationships and allowing for smoother transitions in market behaviour.

- $\kappa_2 = 0.96$ governs the evolution of the variance-covariance matrix, which captures the volatility dynamics. A slightly lower value for κ_2 allows the model to respond more quickly to sudden changes in volatility.

These settings are consistent with best practices in financial applications of TVP-VAR models, as discussed by Antonakakis et al. (2020). They allow the model to remain stable without being too slow to adapt to sharp changes.

3.5.5. Model Estimation Process

Once the prior, lag structure, and decomposition settings are specified, the TVP-VAR model was estimated using the ConnectednessApproach package in R. The model produces a series of dynamic connectedness measures, including:

- Total Connectedness Index (TCI)
- Directional “TO” and “FROM” Connectedness
- Net Connectedness
- Forecast Error Variance Decomposition (FEVD) Matrix

These outputs form the core of the connectedness analysis and are further used in robustness checks, volatility modelling, and predictive regressions described in the following sections after chapter 3.6.

3.5.6. Justification for Time-Varying Parameters

The choice of a time-varying framework over a static or rolling-window VAR is fixed in its ability to flexibly capture evolving spillover dynamics without losing observations. Unlike rolling-window approaches that require arbitrary window selections and waste data at the start of the sample, the TVP-VAR model regularly updates parameters using the full sample. Moreover, using GFEVD instead of Cholesky-based variance decomposition avoids the problem of variable ordering. The GFEVD treats all variables symmetrically and captures the correlation structure in the residuals without the need for orthogonalization. This ensures that the connectedness results are robust and not driven by arbitrary modelling decisions.

3.6. Robustness Check: Unaffected Assets

To validate the findings of the main analysis and ensure that the observed spillover effects are not simply reflective of broader market dynamics, we did a robustness check using a separate group of assets that we thought to be unaffected by geopolitical risk in the energy sector. This additional step was taken to help us confirm whether the geopolitical spillovers identified in the affected asset group are specific to energy-related markets, or whether similar patterns are seen in seemingly unrelated sectors. The purpose of including a robustness check is twofold. First, it provides a benchmark for comparison: if the unaffected assets show significantly lower levels of connectedness to the GPRD, this will support the conclusion that the energy sector was more sensitive to the Russia–Ukraine war. Second, it tests the consistency of the TVP-VAR framework itself, by verifying that it does not generate artificial connectedness patterns in assets that should, by theory, be insulated from such events.

The unaffected asset group consists of equities from large European healthcare and pharmaceutical firms, as well as prices of core agricultural commodities:

- Healthcare and Pharma companies: AstraZeneca, Bayer, Novartis, Novo Nordisk
- Food Commodities: Beef, Butter, Corn, Eggs

These assets were chosen for their historically defensive behaviour and low direct exposure to geopolitical disruptions. While broader economic uncertainty may influence these markets to some degree, they were not expected to exhibit the same pattern of spillovers from GPRD as energy-related assets.

3.7. GARCH-Based Volatility Estimation

In addition to analysing return spillovers using the TVP-VAR framework, we also see volatility spillovers by modelling and comparing the time-varying volatility of each asset. The purpose of this second layer of analysis is to determine whether the volatility of affected assets is also influenced by geopolitical risk, and to test whether these volatility linkages are alike or different from return-based connectedness. Return-based connectedness captures how price movements in one asset influence others, but it does not directly show fluctuations in risk or uncertainty. Since studies show that geopolitical events increase market volatility (inter alia: Apergis et al., 2018; Balcilar et al., 2018; Chatziantoniou et al., 2025), it is important to assess and verify whether the volatility patterns of energy assets also replicate exposure to geopolitical risk. Modelling volatility separately helps identify whether certain assets act as volatility transmitters or absorbers, independent of their return movements.

3.7.1. Model Specification

To achieve this, a univariate GARCH(1,1) model was applied to each asset in both the affected and unaffected groups. The GARCH framework was well-suited for financial time series as it accounts for volatility clustering.

For each asset, a GARCH(1,1) model is estimated using the following settings:

- Model Type: Standard GARCH (sGARCH)
- ARMA Order: (0, 0) – no mean component included
- Distribution: Student t-distribution
- Mean Structure: Mean included = FALSE

The choice of a simple GARCH(1,1) structure is deliberate. While more complex models exist, the standard form was enough for estimating daily volatility series in a consistent manner. Additionally, we employ the Jarque-Bera test to look for autocorrelation in the variables. Due to strong non-normality, we make use of the student-t distribution which better reflects the heavy tails that are usually found in asset return distributions, especially during crisis periods.

3.7.2. Estimation and Volatility Matrix Construction

The GARCH model was applied to each asset individually using a looped estimation routine for each point in time. For each time series:

1. The model is fitted to the log return series.
2. The estimated conditional standard deviation (volatility) is extracted.
3. These volatility series are compiled into a matrix, where each column represents a single asset's daily volatility values.

This process results in a new zoo matrix of volatility, which replaces the return matrix used in the earlier TVP-VAR estimation. The GPRD index is added to this matrix as an external series, preserving the original modelling logic.

3.7.3. Volatility TVP-VAR Analysis

Once the volatility matrix is complete, the same TVP-VAR estimation procedure is applied to this dataset. This includes the same lag length (4), forecast horizon (10), window size (100), Bayesian prior, and forgetting factors. The output yields connectedness measures based on the forecast error variance of volatility, rather than returns.

The resulting indicators, TCI, TO, FROM, and NET, reveal how volatility is transmitted between the GPRD and energy markets over time. These results are later compared to those from the return-based model to assess whether volatility behaves similarly or differently.

3.8. Predictive Regression Analysis

In the final stage of our thesis, a predictive regression framework was used to test whether key indicators can help forecast the next day returns of the affected assets. This works well with the spillover analysis by evaluating the predictive power of the transmission mechanisms already observed in the TVP-VAR results.

3.8.1. Model Structure and Variables

The dependent variable y_t is the log return of each asset at time t as a matrix. The independent variables include:

- x_1: Log return at time t_{-1}
- x_2: NET connectedness at time t_{-1}
- x_3: NET volatility at time t_{-1}
- x_4: Log value of the GPRD index at time t_{-1}

This setup allows for the inclusion of both financial (return and volatility) and macro-political (geopolitical risk) predictors, along with the connectedness metric derived from the TVP-VAR. The regression is run as a matrix of all affected assets, keeping identical specifications for comparability and processing efficient.

3.8.2. Model Estimation Approach

A standard Ordinary Least Squares (OLS) regression was used to ensure interpretability and transparency in measuring the relationship between asset returns and the four lagged predictors. Since financial time series often exhibit non-normal errors and autocorrelation, several diagnostic tests and corrections were implemented to validate the results.

3.8.3. Diagnostic Testing and Justification

To ensure robustness and reliability, the following statistical tests were applied to the residuals of the model:

- Jarque-Bera (JB) Test: Assesses whether the residuals are normally distributed.
- Breusch-Pagan (BP) Test: Tests for heteroskedasticity, i.e., whether the variance of the residuals is constant across time.

- Breusch-Godfrey (BG) Test: Checks for autocorrelation in the residuals.
- Variance Inflation Factor (VIF): Used to detect multicollinearity among predictors.

The diagnostic tests confirmed some deviations from ideal conditions existed, which were expected in financial time series, leading us to fix for the possible heteroskedasticity and autocorrelation. Newey-West standard errors were applied to all coefficient estimates which adjusts the standard errors to remain consistent even when the assumptions of homoskedasticity and no autocorrelation are violated.

3.8.4. Output and Interpretation Framework

The key output for the regression included the coefficient estimates and p-values for all four predictors. The final regression results were compiled into structured tables showing the Newey-West-adjusted estimates, as well as the results of the diagnostic tests (JB, BP, BG) and VIF scores. These outputs enable side-by-side comparison across different assets and are discussed in detail in the next chapter.

4. Empirical Results

This chapter presents the empirical findings from our analysis of return and volatility spillovers, as well as the predictive regression models developed to assess short-term return behavior. The analysis is structured to first explore descriptive statistics, followed by connectedness results for returns and volatilities, and finally the regression-based evaluation of return predictability.

4.1. Results Connectedness - Affected Returns

In the following, the descriptive statistics, correlation matrix, and connectedness table of affected returns are analysed and put into context.

4.1.1. Descriptive Statistics - Returns

Before analysing the dynamic connectedness results, it is important to look at the underlying characteristics of the data. This provides us an overview of the dataset and lets us identify normal distribution and stationarity of the data.

Table 1 presents the descriptive statistics for the daily log returns of the affected variables, covering 542 observations per asset. These include, as mentioned earlier, conventional and renewable energy commodities, European energy companies, and the Geopolitical Risk Index. The mean returns of all assets are close to zero, as expected for daily financial returns. Most assets display mean returns ranging between -0.12 and 0.20, with Dutch Gas (0.20) and Diesel (0.12) on the higher end, while Ørsted, Fortum, and Cobalt are the only assets that show slightly negative averages (-0.12, -0.06, and -0.01, respectively). The GPRD portraits a slight positive mean of 0.08, indicating that the index is experiencing a higher geopolitical risk over the reference period which is naturally true given the war event of our analysis.

The standard deviation (SD) highlights the volatility of the series. The GPRD stands out with a SD of 40.95 way above the other variables. The next highest degree of volatility occupies Dutch Gas at 7.65, Diesel at 4.23, and Heating Oil at 3.50. A trend can be recognised, showing that conventional energy assets, and especially commodities demonstrate a higher SD in comparison to RE assets. Notably, Nickel (3.26) exhibits a similar degree of volatility as oil and gas commodities. On the lower end we find Copper (1.57), Cobalt (1.81) and surprisingly TotalEnergies (1.74) from the conventional energy equity sample. Another trend is identifiable in RE equities being generally lower in volatility.

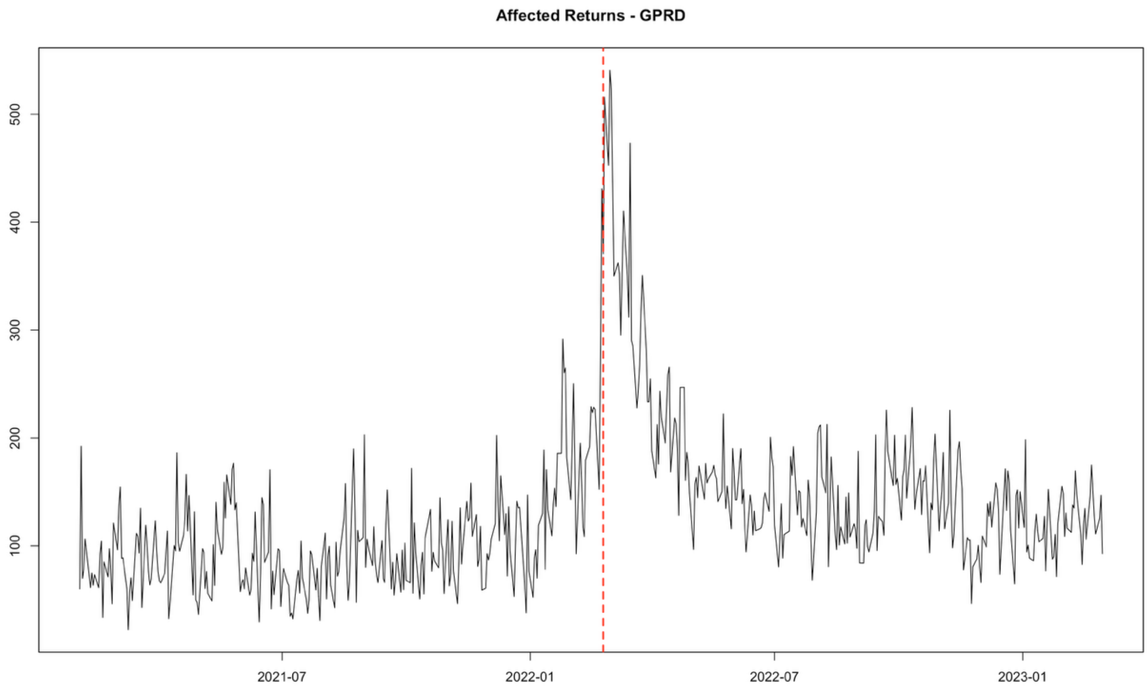
Diesel (1.92) and Nickel (2.54) exhibit significant positive skewness, implying that large upward price movements occur more frequently than equivalent downward movements. In contrast, Cobalt (–4.06) and Equinor (–1.80) show pronounced negative skewness, suggesting that downside risk events are more prevalent for these assets. The kurtosis values are high across all variables, with Diesel (78.15), Cobalt (42.56), and Nickel (34.77) exhibiting particularly extreme leptokurtic behaviour. This implies the presence of fat tails and a high probability of observing extreme negative or positive events. This is consistent and expected when dealing with macroeconomic shocks. Even on the lower end, we see excess kurtosis > 3, suggesting leptokurtic behaviour in all variables.

We employ the Jarque–Bera test to test for normal distribution. This is especially important for the volatility series which applies the GARCH model. We find that all series are not normally distributed as we reject the null hypothesis at statistical significance level. Thus, every variable shows non-normal distributed behaviour, indicating heavier tails. We therefore employ the student-t distribution model for our GARCH.

Lastly, we test for stationarity utilising unit root tests such as the ADF and PP tests. The results show that all variables are stationary at the 1% significance level, as evidenced by highly negative ADF test statistics and large absolute PP test values. These results confirm that all return series are mean-reverting and suitable for use in the TVP-VAR connectedness framework without further differencing.

To give a better overview of the GPRD, we included the time series in Figure 1. The red line marks the day of the Russian invasion of Ukraine, representing February 24th, 2022. The index clearly shows the news sentiment reporting the war on the war date which signifies the highest extent of geopolitical risk in the whole series. Although the news sentiment decreases shortly after, it remains on a higher level than before the war, depicting the ongoing conflict and following economic consequences.

Figure 1: Geopolitical Risk Index - Affected Returns



Source: Caldara and Iacoviello (2022) (https://www.matteoiacoviello.com/gpr.htm)

4.1.2. Correlation Matrix - Returns

The correlation matrix for the affected daily log returns is shown in Table 2. It captures the linear relationships among the Geopolitical Risk Index, energy commodities, rare metals, and European energy companies. This matrix is central to understanding the underlying return dynamics prior to the TVP-VAR estimation and sheds light on how different asset classes interact under geopolitical and market stress.

The GPRD shows low overall correlation with all other assets, with values ranging from –0.02 to 0.07. The highest correlation is observed with Nickel (0.07), followed by Cobalt (0.05) and Heating Oil (0.04). These weak correlations are expected, as GPRD is an exogenous indicator that captures media-reported geopolitical tensions, and not a traded asset. Its low correlation with market-based returns suggests that its influence likely operates through lagged spillover effects rather than synchronous movement which seems logical as news report past events. This also justifies the use of lag structures in the TVP-VAR framework.

The correlation among fossil fuel commodities reveals a clear pattern of interconnectedness. Brent Crude Oil and Heating Oil exhibit a particularly strong correlation (0.68), reflecting their shared upstream inputs and high co-dependence on global crude supply chains. Conversely, Diesel and Dutch Gas appear to behave more independently, with generally negligible correlations across the matrix.

Conventional energy stocks display high internal correlations, which reflects their similar business models, geographic exposure, and investor bases. For instance, Shell and TotalEnergies are strongly correlated (0.79), as are Repsol and Shell (0.76) and Equinor and Repsol (0.61). This interconnectedness indicates that these companies are collectively responsive to shifts in crude oil prices, macroeconomic sentiment, and global energy supply shocks. While all show moderate correlations with Brent crude (0.40 – 0.49), the values are not excessively high, suggesting that firm-specific factors, diversification strategies, and risk management play a role in dampening direct commodity exposure.

The industrial metals segment, comprising of Aluminium, Cobalt, Copper, and Nickel, shows moderate to high internal correlations, particularly between Aluminium and Copper (0.62), and Copper and Nickel (0.41). Notably, they are only weakly correlated with fossil fuel commodities and energy equities, confirming their value as a diversification tool.

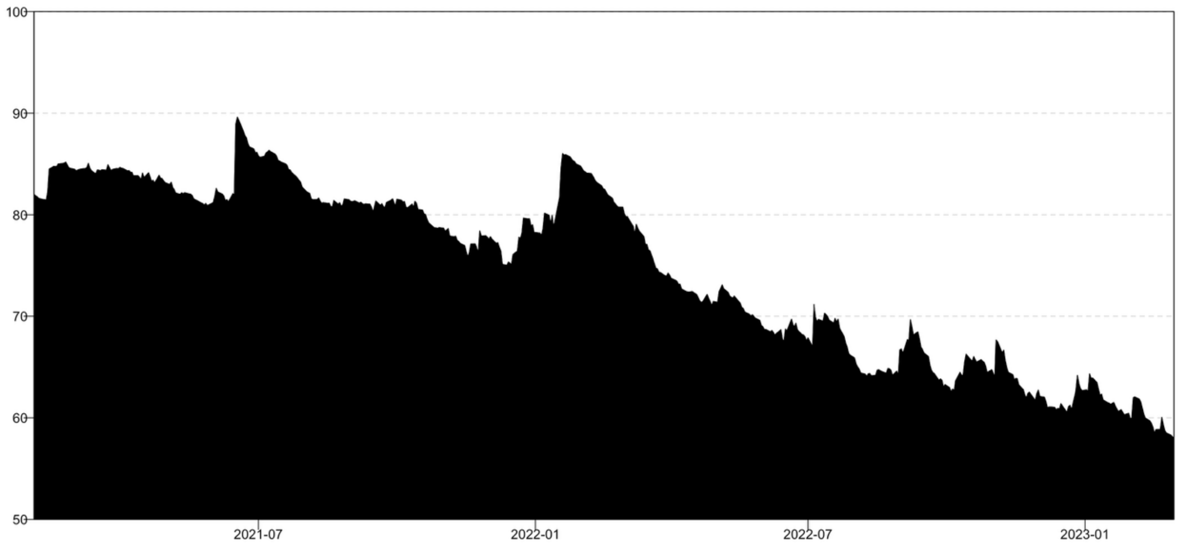
Renewable energy companies form a moderately correlated cluster, with notable co-movements between RWE and Ørsted (0.45), RWE and Verbund (0.48), and Ørsted and Verbund (0.42). Interestingly, Fortum demonstrates a higher correlation with TotalEnergies (0.27) than other renewables, likely due to its continued involvement in gas energy assets. Overall, renewable stocks are only weakly or negatively correlated with traditional fossil fuel firms, suggesting that they operate under different risk structures and may offer hedging or diversification benefits in energy-focused portfolios.

4.1.3. Connectedness Results - Returns

Overall, we find a TCI of 74.60%, indicating a high level of interconnectedness among the examined assets as illustrated in Figure 2. This suggests that a substantial portion of return variation across these markets is driven by cross-variable spillovers. Throughout the sample period, the TCI fluctuates between approximately 55% and 90%, reflecting periods of both high systemic interaction and relative decoupling.

In early 2021, the TCI remains elevated, fluctuating around 82–85%. This is likely influenced by post-COVID recovery dynamics and synchronized responses to global macroeconomic drivers such as inflation, central bank policy signals, and energy market volatility. A notable spike in mid-to-late 2021 pushes the TCI close to 90%, reflecting mounting geopolitical tension which was further provoked by the imperial ambitions seen in the essay from Putin on July 12th, 2021. As the series approaches the end of 2021, a steady decline in the TCI becomes evident, pointing to a partial decoupling across asset classes. However, an incline in connectedness can be observed beginning in the late months of 2021, stemming from further increase of geopolitical tensions as more and more Russian troops gather along the Ukrainian border in November 2021. Then by February 2022, Russia first starts its biggest military exercise since the Cold War and two weeks later begins its invasion into Ukraine which makes up the spike in TCI in that time. Following the initial war shock, the TCI undergoes a sustained decline throughout the remainder of 2022, dropping to approximately 55 – 60% by early 2023. This trend indicates a normalization in market behaviour, with return dynamics increasingly governed by asset- or sector-specific fundamentals rather than global shocks. The presence of several short-lived spikes suggests that secondary events, such as energy sanctions, policy responses, or companies having their assets seized unlawfully by the Russian state, briefly reignited connectedness, but these episodes were not persistent. (the information for the conflict events were gathered from Walker, 2023)

Figure 2: TCI - Affected Returns



The results of the NET connectedness from our TVP-VAR framework are depicted in Table 3 and visualised in Figure 3. The plot in Figure 3 shows the time-varying net spillover roles of each asset, indicating whether the variable is a shock transmitter or receiver. It offers insights into how these roles evolved in response to geopolitical shocks and market transitions.

The GPRD is a moderate net transmitter (+10.52), meaning it transmits more return volatility to other markets than it receives. While not the strongest contributor overall, its influence peaks around early 2022, as seen in Figure 3, precisely around the time of the start of the Russia–Ukraine War. This confirms GPRD's role as an external systemic risk factor, particularly during periods of geopolitical escalation. Moreover, does the index show a net positive from January 2022 onwards after a period of being a shock receiver. It also remains a shock transmitter most of the time throughout the rest of our timeframe.

Conventional energy equities show the highest and most sustained net spillover roles. The companies are strongly interconnected with both commodities and other equities and serve as dominant transmitters of return spillovers throughout the period. Their role intensifies during major commodity price shocks (i.e. Diesel and Dutch Gas in late 2021) and peaks again with the war in early 2022. This suggests that investors interpret oil and gas equities as leading indicators or amplifiers of broader return dynamics during crises. On the commodity side we find that Brent (+0.10) and Heating Oil (+3.05) are only marginal net transmitters despite their centrality in global energy pricing. This somewhat surprising result reflects their dual role: while they influence downstream markets, they also absorb shocks from upstream producers and geopolitical drivers. The NET plot shows these commodities become short-term transmitters during crisis periods (especially Brent around February–March 2022) but otherwise play a more balanced or reactive role. Furthermore, are both Diesel (-1.63) and Dutch Gas (-4.70) mild net receivers. Their NET connectedness remains slightly negative throughout the period, with brief spikes in late 2021 and early 2022, suggesting momentary reactivity to larger market or geopolitical events.

We also discover that rare metals are clear net receivers. The NET plot shows little sustained transmission power for these assets, although brief upward spikes occur during inflationary pressure and energy crises. Copper, while averaging a slightly positive NET value (+4.09), also largely follows the same pattern.

However, the strongest net receivers from our sample are the RE equities. The companies consistently absorb return shocks from fossil fuels and geopolitical risk, particularly during 2022. Ørsted's NET plot shows a distinct downturn at the time of the war as does the plot of RWE, indicating heightened vulnerability to market-wide spillovers despite their clean energy focus. This reflects a broader trend as renewables are not isolated from fossil fuel volatility, particularly when energy systems are stressed or rebalanced. However, their lack of spillover transmission also supports their classification as defensive or diversifying assets under certain conditions. Nevertheless, Fortum shows only a slight negative net of -2.71 and its NET plot illustrates a larger transmitting period before the war than after. This is likely due to Fortum's diversified business model employing multiple RE services and producing nuclear energy as a non-renewable energy alternative (Fortum, 2025).

Table 1: Descriptive Statistics - Affected Returns

	GPRD	***Brent***	***Diesel***	***Dutch Gas***	***Heating Oil***	***Equinor***	***Repsol***	***Shell***	***Total Energies***	***Aluminium***	***Cobalt***	***Copper***	***Nickel***	***Fortum***	***Ørsted***	***RWE***	***Verbund***
Minimum	-149.93	-15.64	-42.50	-36.42	-26.29	-7.32	-8.91	-8.79	-6.63	-12.97	-19.38	-5.37	-16.16	-10.92	-9.10	-8.99	-18.57
Mean	0.08	0.10	0.12	0.20	0.13	0.12	0.12	0.12	0.10	0.06	-0.01	0.05	0.09	-0.06	-0.12	0.02	0.00
Median	0.05	0.29	0.03	0.48	0.28	0.14	0.12	0.23	0.16	0.09	0.03	0.10	0.08	0.00	-0.20	0.03	0.12
Maximum	135.73	9.14	50.45	43.15	12.36	7.51	6.60	7.52	7.86	7.59	6.61	5.55	37.06	10.50	14.65	7.98	12.53
Kurtosis	3.76	6.23	78.15	7.84	16.24	3.61	4.54	4.82	4.29	7.13	42.56	3.87	34.77	6.62	5.74	5.51	10.50
Skewness	-0.13	-0.67	1.92	-0.08	-0.17	-1.80	-0.40	-0.29	-0.22	-0.48	-4.06	-0.20	2.54	-0.30	0.53	0.01	-0.93
Range	285.66	24.78	92.95	79.57	38.65	14.83	15.52	16.31	14.49	20.56	25.99	10.92	53.22	21.43	23.75	16.97	31.10
SD	40.95	2.68	4.23	7.65	3.50	2.46	2.01	1.93	1.74	1.97	1.81	1.57	3.26	2.45	2.54	1.82	2.62
Count	542	542	542	542	542	542	542	542	542	542	542	542	542	542	542	542	542
Jarque-Bera* **	14.492	276.52	127869	528.81	4254.1	11.006	67.98	82.24	41.753	405.34	36842	20.552	23384	303.87	195.27	141.84	1347.1
ADF test***	-11.11	-9.61	-9.15	-8.09	-9.78	-8.30	-7.47	-7.95	-7.30	-9.04	-5.53	-8.15	-8.57	-6.97	-7.59	-8.24	-8.41
PP test***	-50.02	-25.86	-32.12	-23.92	-24.36	-25.55	-24.05	-25.08	-25.01	-27.35	-23.26	-26.89	-20.11	-22.87	-24.44	-23.71	-25.86

Note: *** suggests a p-value of 0.01.

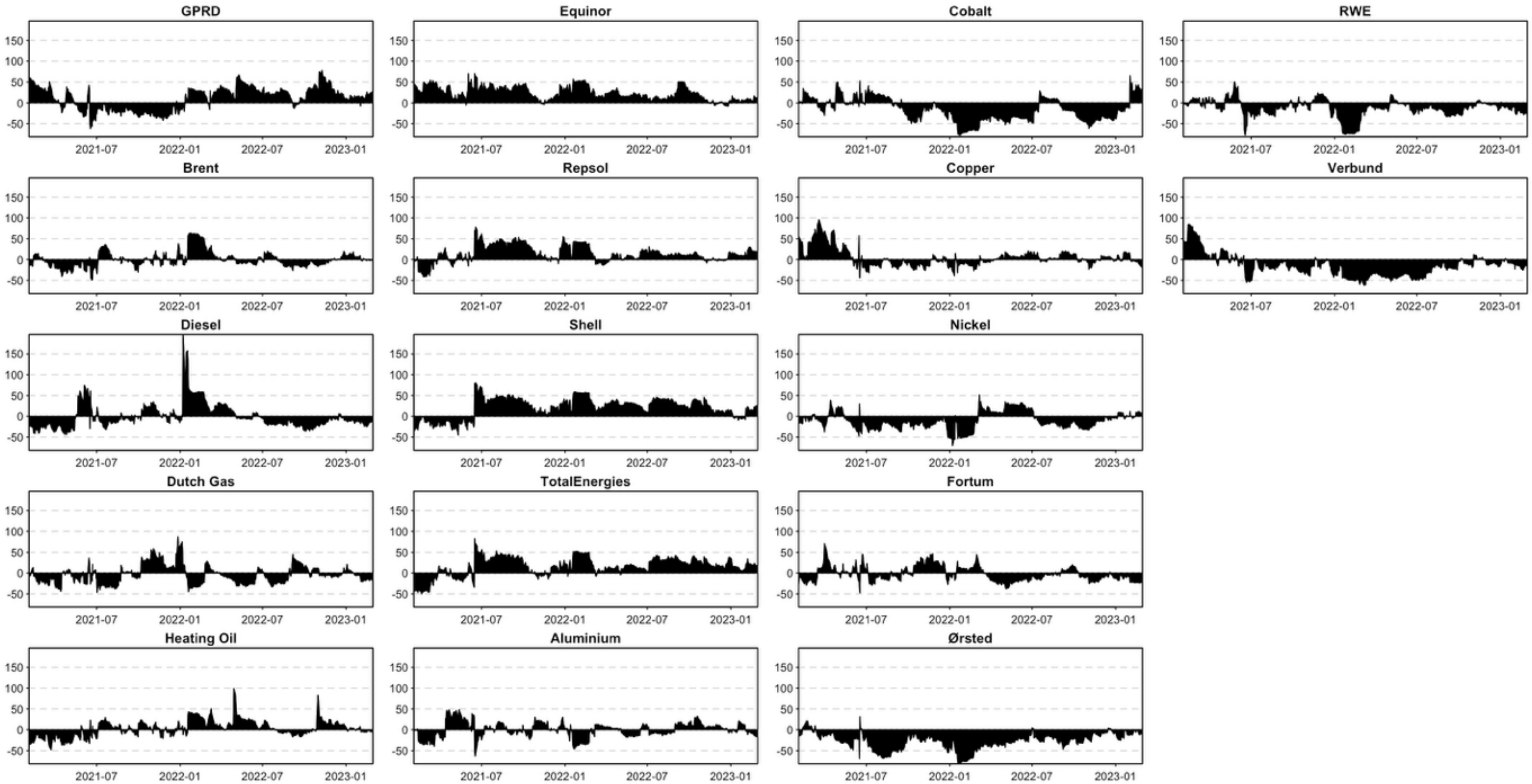
Table 2: Correlation Matrix - Affected Returns

	GPRD	Brent	Diesel	Dutch Gas	Heating Oil	Equinor	Repsol	Shell	TotalEnergies	Aluminium	Cobalt	Copper	Nickel	Fortum	Ørsted	RWE	Verbund
GPRD	1.00	0.05	-0.02	0.00	0.04	0.02	0.02	0.03	0.03	0.00	0.05	0.02	0.07	-0.01	-0.02	0.02	-0.01
Brent	0.05	1.00	0.07	0.10	0.68	0.46	0.49	0.47	0.40	0.30	0.07	0.31	0.15	-0.01	0.01	-0.04	-0.03
Diesel	-0.02	0.07	1.00	0.05	0.07	0.04	-0.02	-0.05	-0.04	0.04	0.07	0.01	0.04	0.01	0.01	-0.05	0.01
Dutch Gas	0.00	0.10	0.05	1.00	0.15	0.27	0.01	0.06	-0.05	0.12	0.10	0.04	0.09	-0.19	0.01	-0.11	0.03
Heating Oil	0.04	0.68	0.07	0.15	1.00	0.34	0.35	0.35	0.27	0.17	0.16	0.21	0.14	-0.06	-0.01	-0.03	0.00
Equinor	0.02	0.46	0.04	0.27	0.34	1.00	0.61	0.61	0.56	0.26	0.02	0.32	0.15	0.06	0.06	0.06	0.11
Repsol	0.02	0.49	-0.02	0.01	0.35	0.61	1.00	0.76	0.75	0.17	0.04	0.28	0.13	0.16	0.01	0.08	0.05
Shell	0.03	0.47	-0.05	0.06	0.35	0.61	0.76	1.00	0.79	0.15	0.00	0.27	0.15	0.20	0.05	0.11	0.05
TotalEnergies	0.03	0.40	-0.04	-0.05	0.27	0.56	0.75	0.79	1.00	0.11	-0.02	0.23	0.09	0.27	-0.03	0.16	0.05
Aluminium	0.00	0.30	0.04	0.12	0.17	0.26	0.17	0.15	0.11	1.00	0.04	0.62	0.31	-0.03	-0.01	0.02	-0.01
Cobalt	0.05	0.07	0.07	0.10	0.16	0.02	0.04	0.00	-0.02	0.04	1.00	0.03	0.14	-0.06	-0.09	-0.10	-0.04
Copper	0.02	0.31	0.01	0.04	0.21	0.32	0.28	0.27	0.23	0.62	0.03	1.00	0.41	-0.04	-0.04	-0.01	-0.02
Nickel	0.07	0.15	0.04	0.09	0.14	0.15	0.13	0.15	0.09	0.31	0.14	0.41	1.00	-0.06	0.03	-0.09	-0.03
Fortum	-0.01	-0.01	0.01	-0.19	-0.06	0.06	0.16	0.20	0.27	-0.03	-0.06	-0.04	-0.06	1.00	0.13	0.32	0.27
Ørsted	-0.02	0.01	0.01	0.01	-0.01	0.06	0.01	0.05	-0.03	-0.01	-0.09	-0.04	0.03	0.13	1.00	0.45	0.42
RWE	0.02	-0.04	-0.05	-0.11	-0.03	0.06	0.08	0.11	0.16	0.02	-0.10	-0.01	-0.09	0.32	0.45	1.00	0.48
Verbund	-0.01	-0.03	0.01	0.03	0.00	0.11	0.05	0.05	0.05	-0.01	-0.04	-0.02	-0.03	0.27	0.42	0.48	1.00

Table 3: Connectedness Table - Affected Returns

	GPRD	Brent	Diesel	Dutch Gas	Heating Oil	Equinor	Repsol	Shell	TotalEnergies	Aluminium	Cobalt	Copper	Nickel	Fortum	Ørsted	RWE	Verbund	FROM
GPRD	27.18	2.42	2.94	3.27	5.23	5.86	4.63	6.51	5.72	4.26	6.03	4.44	3.98	3.06	4.03	4.16	6.27	72.82
Brent	4.23	18.97	2.92	3.48	11.66	7.03	7.71	8.15	7.36	5.02	2.55	4.99	2.65	3.61	2.21	3	4.48	81.03
Diesel	4.36	3.69	39.99	2.89	3.81	4.41	4.31	4.45	3.97	4.46	3.24	3.76	2.99	4.23	3.04	2.45	3.97	60.01
Dutch Gas	4.06	3.71	3.42	39.09	4.01	4.82	3.43	4.66	4.7	2.65	3.48	3.45	3.05	6.09	1.88	4.85	2.65	60.91
Heating Oil	4.19	13.44	3.36	3.35	23.71	6.14	7.17	6.51	5.69	4.06	2.52	4.06	3.14	3.86	2.04	2.7	4.09	76.29
Equinor	3.9	6.16	3.68	3.56	4.83	19.18	10.58	10.88	10.03	4.61	2.48	5.38	2.49	3.89	2.11	2.8	3.44	80.82
Repsol	4.24	6.22	4.75	3.7	5.53	11.68	17.58	10.82	10.62	3.49	2.45	4.97	2.65	3.51	2.24	2.89	2.68	82.42
Shell	5.28	6.2	3.96	3.76	4.64	9.87	10	17.13	12.54	3.96	3.17	5.27	2.5	4.03	2.13	2.87	2.7	82.87
TotalEnergies	5.72	6.03	3.72	2.87	4.71	9.67	10.13	13.23	16.6	4.27	2.99	4.29	2.48	4.58	2.52	3.61	2.6	83.4
Aluminium	4.01	5.33	4.19	2.44	4.57	5.34	5.13	5.11	5.8	25.42	2.12	12.92	6.94	3.8	1.48	2.59	2.84	74.58
Cobalt	6.38	3.7	3.26	3.42	4.65	6.35	3.42	5.47	4.6	2.54	31.45	3.22	3.93	3.7	4.14	5.04	4.71	68.55
Copper	5.4	4.63	3.05	2.85	4.65	6.8	6.63	5.55	5.1	10.88	2.61	22.6	8.13	2.98	1.65	3.38	3.12	77.4
Nickel	5.15	3.9	3.89	3.42	5.16	4.12	4.66	3.9	3.92	7.31	2.83	9.69	30.68	2.96	2.71	3.16	2.55	69.32
Fortum	3.2	3.63	4.35	5.2	3.85	4.9	4.73	4.9	5.92	3.09	3.96	2.86	2.73	32.33	3.84	6.25	4.26	67.67
Ørsted	8.78	4	2.43	4.36	3.45	5.9	4.01	4.86	4.71	5.97	4.9	3.76	3.45	3.94	22.61	8.01	4.86	77.39
RWE	6.32	4.19	3.05	4.29	4.57	5.23	4.41	4.36	5.08	3.78	3.26	4.19	4.13	5.98	8.73	23.24	5.19	76.76
Verbund	8.13	3.87	5.4	3.36	4.03	6.38	5.42	4.49	3.99	3.94	3.28	4.26	3.29	4.74	5.18	6.18	24.05	75.95
TO	83.34	81.14	58.38	56.2	79.34	104.5	96.35	103.83	99.74	74.28	51.86	81.48	58.53	64.96	49.93	63.93	60.4	1268.19
NET	10.52	0.1	-1.63	-4.7	3.05	23.68	13.93	20.95	16.34	-0.3	-16.69	4.09	-10.79	-2.71	-27.46	-12.83	-15.54	**TCI=74.60%**

Figure 3: NET Connectedness - Affected Returns



4.2. Results Connectedness - Affected Volatility

In this part of the discussion, we focus on the patterns revealed by the connectedness of GARCH-based volatilities, which help us understand how risk was transmitted across assets during the Russia–Ukraine conflict. Unlike returns, volatility captures the perceived uncertainty and reaction intensity of the market, particularly during shocks.

4.2.1. Descriptive Statistics - Volatility

Table 4 summarises the statistical properties of the logged GARCH-filtered volatilities for the affected assets and the logged GPRD. These transformed logged volatility series are suitable for use in the TVP-VAR framework to capture time-varying connectedness in volatility. As the GPRD is the same used in previous chapter 4.1. it will not be further discussed in this section and the focus will solely be put on the logged GARCH variables.

The descriptive statistics indicate mostly negative mean values from the logged volatilities hovering around zero. Moreover, median values are notably more negative, especially for Heating Oil (-5.80), Dutch Gas (-4.40), and Ørsted (-1.52), indicating that while volatility is often low or stable, it is occasionally punctuated by large upward spikes which is expected for a GARCH model applied to a war event.

Standard deviation values further reflect these dynamics. Cobalt (31.84) and Heating Oil (17.90) show the greatest dispersion in volatility, followed by Nickel (16.30) and Dutch Gas (12.49). Conversely, conventional energy equities such as Equinor (1.46) and TotalEnergies (1.94) exhibit low standard deviations, suggesting stable conditional volatility estimates and a more muted reaction to macro shocks. Moreover, do renewable energy equities exhibit higher SD than any of the equivalents in conventional energy. To main trends can be recognised: Firstly, we see Dutch Gas and Heating Oil both with high volatility dispersion. On the other hand, do the rare metal commodities show a high value in SD as well. Thus, the commodities of our sample show increased volatility dispersion in comparison to the respective equities.

Skewness values across nearly all assets are positive and the variables showcase often extreme levels of skewness. Diesel (10.25), Verbund (6.40), and Ørsted (4.72) display particularly high positive skewness, indicating that upward volatility shocks dominate and are larger in magnitude than downward corrections. Looking at the kurtosis, we find that values are well above three for all assets, confirming strong leptokurtic behaviour.

Additionally, we employ the Jarque-Bera test and the unit root tests. We do not need to further analyse the JB test to select the correct GARCH distribution model as we already discuss the volatility dispersion in this section and do not require another GARCH.

To be sure our logged variables do still conform with being stational, we employ both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests again. All ADF statistics fall below –6, while PP statistics are also strongly negative at a significance level of 0.01. Thus, further differencing is not necessary for our volatility data.

4.2.2. Connectedness Results - Volatility

The TCI for the affected volatility amounts to 78.13% which is an increase of ca. 4% from the affected return total connectedness. As can be seen in Figure 4, the TCI for affected volatility and the affected returns TCI share a great similarity. While return connectedness peaked around the onset of the Russia–Ukraine war and gradually declined, volatility connectedness remained elevated throughout 2022 until the summer.

Figure 4: TCI - Affected Volatility

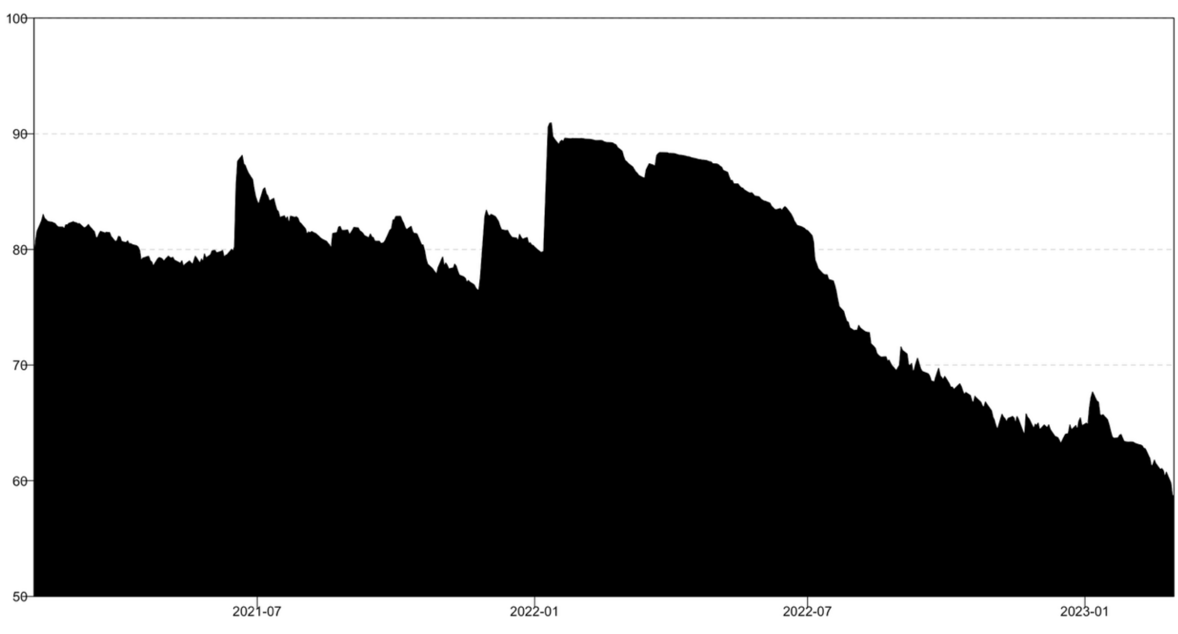


Table 5 shows the NET connectedness table for affected volatility which is illustrated in Figure 5. The empirical findings highlight a slight increase in the net of GPRD (16.27 as to previously 10.52) in comparison to the affected returns connectedness. The elevated and sustained positive NET values following this point suggest that geopolitical uncertainty continued to influence volatility across markets well beyond the initial invasion period as could be seen in the TCI plot.

Mainly, the affected volatility results show somewhat similar results in comparison to affected returns. At the start of the war, GPRD converts from being a shock receiver to a transmitter which is consistent for the remaining timeframe.

Conventional energy commodities exhibit more mixed roles. Diesel is the most dominant volatility transmitter in the system, with a net spillover of +44.67. Comparing it to its affected return value, it exhibits a stark contrast especially in the post-war period where it stays a transmitter. Whereas, in the return connectedness it changed into a shock receiver by summer 2022. Heating Oil also contributes positively (+6.23) to volatility transmission, while Brent (-6.76) and Dutch Gas (-6.63) act as mild net receivers. These mixed roles suggest heterogeneity in how different fossil fuel segments respond to and propagate volatility shocks.

Fossil fuel equities such as Shell (+14.42), Repsol (+4.03), and Equinor (+2.82) are steady net volatility transmitters. In contrast to the previous values are the values not steadily net positive after the war start. In fact, do they show inverse behaviour, becoming receivers rather than staying transmitter. Surprisingly, does TotalEnergies acts as a net receiver (-8.94), whereas previously it has shown a moderately positive value. Industrial metals are predominantly net receivers of volatility which aligns to their return connectedness values. Only Aluminium appears nearly neutral (+0.79).

RE companies are persistent and pronounced net receivers of volatility. Ørsted (-32.38), Verbund (-18.74), and Fortum (-32.38) display the most negative NET values which is consistent with previous return connectedness results. The NET plot shows that these firms consistently absorb volatility across the entire sample, particularly in response to oil and gas volatility and geopolitical spikes. Their passivity in the volatility transmission network suggests they are more exposed to external shocks than active contributors to systemic risk.

Overall, the NET plot illustrates clear cross-sectoral segmentation. Fossil fuel companies and GPRD dominate the upper range as transmitters, while renewables and metals remain largely negative throughout the period. During major geopolitical events, as can be seen at the start of the war, this segmentation becomes even more pronounced, with volatility roles polarizing sharply.

Table 4: Descriptive Statistics - Affected Volatility

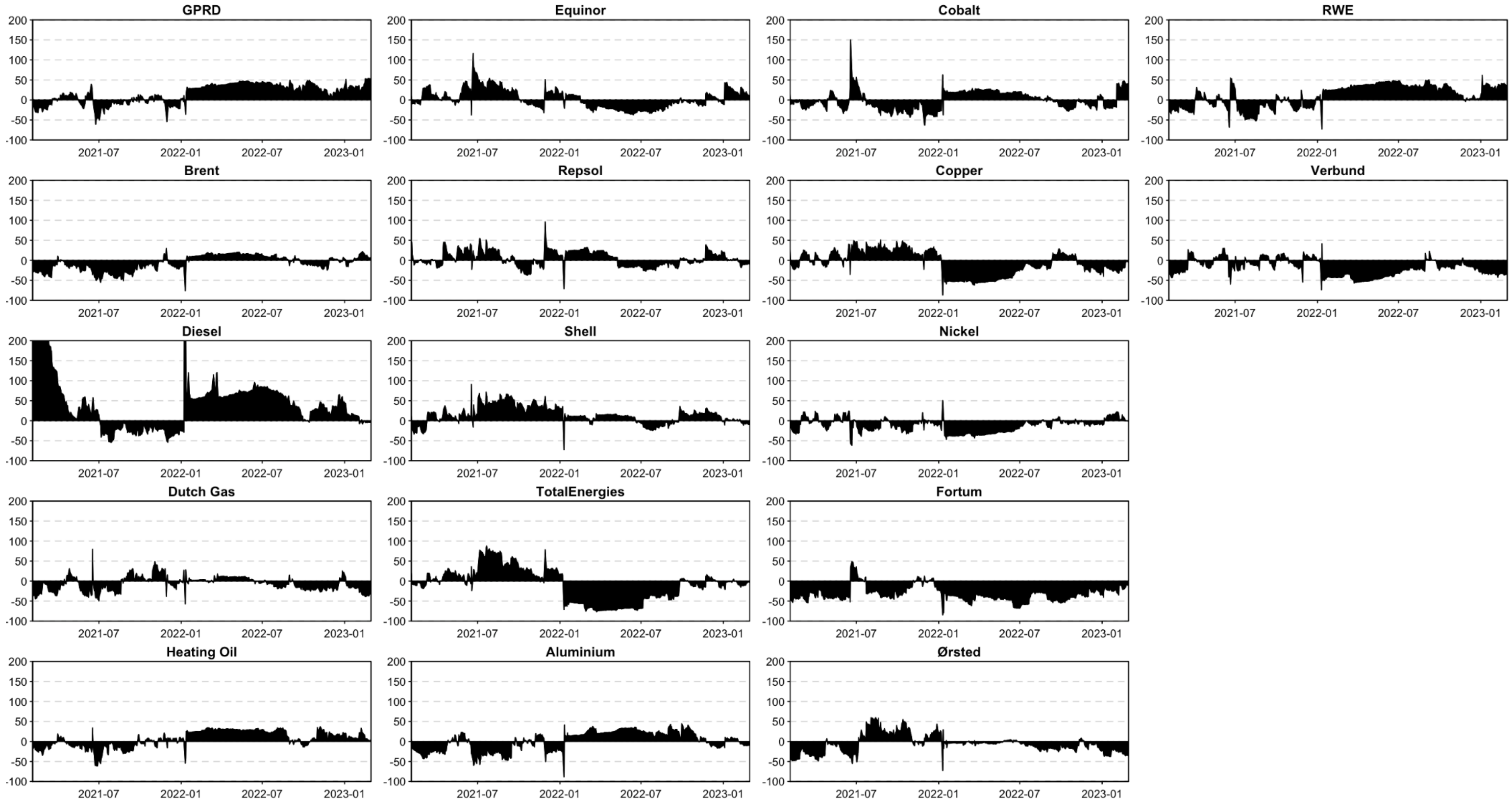
	GPRD	***Brent***	***Diesel***	***Dutch Gas***	***Heating Oil***	***Equinor***	***Repsol***	***Shell***	***Total Energies***	***Aluminium***	***Cobalt***	***Copper***	***Nickel***	***Fortum***	***Ørsted***	***RWE***	***Verbund***
Minimum	-149.93	-7.41	-9.19	-11.16	-24.22	-1.12	-1.37	-1.71	-1.28	-11.15	-91.58	-13.91	-21.21	-7.66	-6.89	-22.33	-4.36
Mean	-0.13	-0.04	-0.10	-0.06	-0.08	0.00	-0.03	-0.04	-0.02	-0.04	-0.01	-0.01	-0.08	-0.10	-0.03	-0.04	-0.03
Median	0.04	-2.44	-0.08	-4.40	-5.80	-0.59	-0.67	-0.79	-0.68	-2.71	-0.64	-2.64	-4.80	-3.48	-1.52	-2.27	-1.18
Maximum	135.73	70.92	58.07	100.32	126.02	7.93	17.71	18.44	19.38	62.66	225.47	52.06	139.36	53.68	61.04	68.38	56.71
Kurtosis	3.74	23.05	139.17	13.37	8.81	11.05	31.99	24.04	32.62	12.90	15.68	6.77	14.51	11.82	43.71	11.87	61.09
Skewness	-0.16	3.62	10.25	2.60	1.93	2.66	4.32	3.99	4.39	2.63	2.16	1.73	2.43	2.71	4.72	2.32	6.40
Range	285.66	78.33	67.27	111.48	150.24	9.06	19.09	20.15	20.67	73.81	317.05	65.96	160.56	61.33	67.93	90.71	61.07
SD	40.68	8.24	3.88	12.49	19.70	1.46	1.76	2.26	1.94	8.80	31.84	9.42	16.30	9.20	5.12	11.22	4.76
Count	541	541	541	541	541	541	541	541	541	541	541	541	541	541	541	541	541
Jarque-Bera* **	14.573	10241	427468	3034.7	1096.4	2099	20631	11412	21519	2836.2	4048.3	590.94	3515.5	2416.7	39367	2261.7	79771
ADF test* **	-11.12	-9.38	-6.24	-7.97	-10.09	-8.56	-7.69	-8.32	-8.01	-8.33	-12.39	-8.70	-8.62	-9.01	-9.81	-10.14	-8.07
PP test* **	-49.76	-22.66	-22.67	-21.85	-24.51	-22.30	-23.88	-21.79	-22.29	-23.55	-38.23	-24.66	-24.08	-21.92	-25.27	-28.34	-23.66

Note: *** suggests a p-value of 0.01.

Table 5: Connectedness Table - Affected Volatility

	GPRD	Brent	Diesel	Dutch Gas	Heating Oil	Equinor	Repsol	Shell	TotalEnergies	Aluminium	Cobalt	Copper	Nickel	Fortum	Ørsted	RWE	Verbund	FROM
GPRD	20.98	4.36	6.91	4.73	5.47	3.99	4.69	4.73	3.18	5.04	6.61	5.63	5.46	3.09	4.45	7.2	3.47	79.02
Brent	4.4	19.7	4.25	3.12	16.5	5.35	4.93	5.07	2.85	4.29	5.79	3.79	3.55	3.81	3.23	4.67	4.69	80.3
Diesel	2.88	3.42	39.78	3.75	4.65	4.46	3.34	5.17	4.02	4.52	3.35	3.88	3.72	2.32	4.95	2.35	3.45	60.22
Dutch Gas	7.06	3.67	15.32	19.76	4.3	4.15	3.46	4.82	3.29	3.51	4.1	4.38	4.05	2.69	4.67	7.21	3.57	80.24
Heating Oil	5.59	15.13	3.86	3.2	21.65	4.95	5.19	4.07	2.49	5.65	6.27	3.29	2.57	3.91	4.27	4.36	3.56	78.35
Equinor	5.56	3.9	5.59	4.1	5.15	20.45	7.74	7.21	7.08	5.15	4.22	4.66	3.5	3.11	4.37	6.16	2.05	79.55
Repsol	5.62	5.17	3.4	4.27	6.01	7.06	21.12	11.22	9.65	3.49	3.72	3.24	2.71	2.82	3.52	4.19	2.79	78.88
Shell	5.67	4.14	4.31	4.71	5.1	6.69	11.07	19.52	9.51	3.79	3.98	3.52	2.99	2.63	3.68	4.99	3.71	80.48
TotalEnergies	5.02	4.58	4.6	4.2	5.12	7.38	9.33	10.65	16.74	3.8	5.22	4.66	4.36	3.03	4.43	4.34	2.55	83.26
Aluminium	6.01	3.39	9.64	4.06	3.75	5.19	3.97	5.7	3.49	25.52	4.66	4.75	3.64	2.31	6.21	4.65	3.07	74.48
Cobalt	7.15	4.17	6.8	5.98	5.12	4.56	4.38	4.76	3.82	6.12	20.93	4.53	4.42	3.1	5.43	5.26	3.47	79.07
Copper	6.15	2.65	6.58	4.04	3.68	4.95	5.34	6.35	4.83	5.09	3.43	19.07	9.77	2.84	4.73	5.73	4.77	80.93
Nickel	6.32	3.27	9.71	3.61	3	6.57	3.94	5.39	3.95	3.11	3.76	10.26	20.87	2.34	3.49	6.83	3.58	79.13
Fortum	7.37	4.06	3.48	5.87	4.23	4.81	4.09	4.58	4.41	6.58	7.59	4.65	3.3	20.22	4.77	7.21	2.8	79.78
Ørsted	5.64	3.83	5.83	6.41	4.53	4.43	3.59	5.21	4.38	6.64	4.28	5.26	5.42	3.01	19.17	8.76	3.63	80.83
RWE	8.84	4.17	5.51	6.5	4.37	4.66	4.65	6.07	4.13	3.95	6.5	2.69	3.53	2.77	7.68	20.08	3.89	79.92
Verbund	6	3.63	9.11	5.07	3.62	3.16	3.2	3.92	3.23	4.53	4.05	4.88	4.47	3.63	4.73	6.55	26.22	73.78
TO	95.29	73.54	104.9	73.61	84.59	82.37	82.91	94.9	74.32	75.27	77.52	74.07	67.44	47.4	74.62	90.46	55.04	1328.23
NET	16.27	-6.76	44.67	-6.63	6.23	2.82	4.03	14.42	-8.94	0.79	-1.54	-6.86	-11.69	-32.38	-6.21	10.54	-18.74	**TCI=78.13%**

Figure 5: NET connectedness - Affected Volatilities



4.3. Linear Regression

To investigate whether the results of the TVP-VAR analysis and the GARCH model can help predict future asset returns, we ran a series of linear regressions for each asset in the affected group. Each asset was modelled individually, resulting in a total of 16 regressions. This setup allowed us to evaluate the short-term predictive contribution of both financial and geopolitical indicators. Since financial time series data often violates the OLS assumptions due to issues like autocorrelation and heteroskedasticity, we applied robust standard errors using the Newey-West correction. This adjustment helps ensure that our coefficient estimates and p-values are reliable.

4.3.1. Pre-diagnostic Results

Before applying any corrections or robust standard errors, we reviewed the initial regression outputs to evaluate model fit and reliability. The adjusted R-squared values varied across all assets, showing differences in how well the selected variables forecast returns.

Table 6: Pre-diagnostic Results

	R_squared	Adj_R_squared	x1_coef	x1_pval	x2_coef	x2_pval	x3_coef	x3_pval	x4_coef	x4_pval
Brent	0.210	0.204	-0.455	0.000	0.000	0.175	0.000	0.910	0.000	0.443
Diesel	0.216	0.210	-0.465	0.000	0.000	0.833	0.000	0.115	0.000	0.182
Dutch Gas	0.148	0.142	-0.384	0.000	0.000	0.783	0.000	0.360	0.000	0.188
Heating Oil	0.182	0.176	-0.426	0.000	0.000	0.384	0.000	0.504	0.000	0.789
Equinor	0.124	0.118	-0.352	0.000	0.000	0.883	0.000	0.784	0.000	0.507
Repsol	0.025	0.017	-0.153	0.000	0.000	0.398	0.000	0.755	0.000	0.805
Shell	0.052	0.045	-0.228	0.000	0.000	0.861	0.000	0.998	0.000	0.857
TotalEnergies	0.063	0.056	-0.249	0.000	0.000	0.469	0.000	0.819	0.000	0.858
Aluminium	0.185	0.179	-0.427	0.000	0.000	0.119	0.000	0.224	0.000	0.640
Cobalt	0.232	0.227	-0.480	0.000	0.000	0.071	0.000	0.426	0.000	0.151
Copper	0.118	0.112	-0.338	0.000	0.000	0.115	0.000	0.607	0.000	0.227
Nickel	0.145	0.139	-0.380	0.000	0.000	0.162	0.000	0.431	0.000	0.706
Fortum	0.092	0.085	-0.299	0.000	0.000	0.275	0.000	0.164	0.000	0.460
Ørsted	0.064	0.057	-0.251	0.000	0.000	0.578	0.000	0.724	0.000	0.678
RWE	0.011	0.004	-0.100	0.020	0.000	0.856	0.000	0.359	0.000	0.722
Verbund	0.078	0.071	-0.273	0.000	0.000	0.085	0.000	0.791	0.000	0.487

We observed, as can be seen in Table 6, that commodities generally showed a stronger model fit compared to company stocks. As seen in table 6 above, the adjusted R^2 was the highest for Diesel (20.96%), Brent (20.36%), and Heating Oil (17.61%). In comparison, Equinor (11.79%), RWE (0.41%), and Orsted (5.65%) had lower explanatory power, which shows that company-specific factors outside the model may play a more dominant role in their price movements compared to the selected variables.

In terms of individual variable significance, the lagged returns were highly significant across nearly all assets, with p-values close to zero. This points to short-term momentum or autocorrelation in returns. On the other hand, net connectedness, net volatility and GPRD were insignificant across the board. In net connectedness, Verbund and Cobalt reached marginal significance with p-values less than 0.1 but still above the target. Net volatility also showed a similar story, with high p-values across all assets, none being in the marginal significance category. The same went for all the assets with GPRD, showing us major problems with the model.

We then assessed the models using diagnostic tests to check for violations of classical linear regression assumptions:

- The Breusch-Pagan test for heteroskedasticity revealed non-constant variance in the residuals of several assets. Heteroskedasticity was most evident in models for Diesel, Dutch Gas, Repsol, Equinor, and Shell.
- The Breusch-Godfrey test for autocorrelation identified serial correlation in the residuals for most companies, especially for Brent, Repsol, Shell, Fortum, and Heating Oil.
- The Jarque-Bera test for normality indicated that residuals for several assets exhibited skewness and excess kurtosis. While normality is not strictly required for consistent estimation, non-normal residuals may signal that some model assumptions are not fully met.

These diagnostic findings confirmed the need for using Newey-West standard errors to address heteroskedasticity and autocorrelation in the residuals. We applied these corrections to all models in the final stage to ensure the validity of the coefficient estimates and p-values.

4.3.2. Post-diagnostic Results

After confirming the presence of heteroskedasticity and autocorrelation in multiple models during the diagnostic phase, we re-estimated all regressions using Newey-West standard errors. This correction adjusts the standard errors for both autocorrelation and heteroskedasticity by accounting for serial correlation in the residuals and allowing error variances to vary over time, resulting in more robust statistical inference.

The use of Newey-West corrections led to several shifts in the statistical significance of variables. For instance, in models like Repsol and Shell, which showed autocorrelated residuals in the Breusch-Godfrey test, standard errors became wider after the adjustment, leading to some variables losing their initial significance. In contrast, in assets like Fortum and Orsted, where heteroskedasticity was more prominent, the correction improved the reliability of p-values without changing coefficient direction.

The final regression outputs, including Newey-West adjusted coefficients and their p-values, are reported in Table 7 below.

Table 7: Regression Outputs

	x1_coef	x1_pval	x2_coef	x2_pval	x3_coef	x3_pval	x4_coef	x4_pval
Brent	-0.455	0.000	0.000	0.136	0.000	0.885	0.000	0.195
Diesel	-0.465	0.000	0.000	0.936	0.000	0.175	0.000	0.095
Dutch Gas	-0.384	0.000	0.000	0.729	0.000	0.081	0.000	0.019
Heating Oil	-0.426	0.000	0.000	0.427	0.000	0.263	0.000	0.694
Equinor	-0.352	0.000	0.000	0.786	0.000	0.730	0.000	0.136
Repsol	-0.153	0.154	0.000	0.266	0.000	0.681	0.000	0.730
Shell	-0.228	0.006	0.000	0.701	0.000	0.997	0.000	0.720
TotalEnergies	-0.249	0.055	0.000	0.308	0.000	0.736	0.000	0.817
Aluminium	-0.427	0.000	0.000	0.087	0.000	0.196	0.000	0.452
Cobalt	-0.480	0.000	0.000	0.082	0.000	0.233	0.000	0.066
Copper	-0.338	0.000	0.000	0.040	0.000	0.502	0.000	0.132
Nickel	-0.380	0.000	0.000	0.202	0.000	0.415	0.000	0.563
Fortum	-0.299	0.001	0.000	0.189	0.000	0.081	0.000	0.287
Ørsted	-0.251	0.002	0.000	0.464	0.000	0.622	0.000	0.606
RWE	-0.100	0.177	0.000	0.795	0.000	0.159	0.000	0.628
Verbund	-0.273	0.000	0.000	0.054	0.000	0.743	0.000	0.320

The lagged return variable remained the most consistently significant predictor across the affected assets. In 13 out of 16 models, the coefficient was statistically significant at the 5% level or better, with coefficients generally ranging between –0.25 and –0.47. The results for net connectedness changed a bit but still show no major significance. The only to be significant after the adjustment is copper, with Aluminium, Cobalt and Verbund being marginally significant. These cases highlight that while connectedness is not a universal predictor, it carries useful information for certain assets. Moving to net volatility, the results were clear to show that no assets were statistically significant or even marginally significant, showing that this variable has no predictive power whatsoever. The GPRD index displayed mostly insignificant results after the Newey-West correction. For 15 out of 16 assets, the variable was not statistically meaningful with Dutch gas being the only statistically significant asset. Diesel and Cobalt do achieve marginal significance however as a whole, the variables failed to have any predictive power in most assets.

Lastly, to ensure our models were not affected by multicollinearity, we computed Variance Inflation Factors for each regression.

Table 8: Variance Inflation Factors

	x1_vif	x2_vif	x3_vif	x4_vif
Brent	1.001	1.014	2.025	2.029
Diesel	1.007	1.073	1.613	1.568
Dutch Gas	1.005	1.050	1.085	1.047
Heating Oil	1.001	1.269	1.088	1.189
Equinor	1.001	1.407	1.527	1.844
Repsol	1.003	1.131	1.271	1.138
Shell	1.000	1.089	1.046	1.131
TotalEnergies	1.001	1.384	1.291	1.405
Aluminium	1.004	1.106	1.339	1.271
Cobalt	1.006	1.270	1.603	1.407
Copper	1.001	1.083	1.038	1.117
Nickel	1.003	1.151	1.369	1.215
Fortum	1.004	1.096	1.022	1.097
Ørsted	1.001	1.025	1.024	1.037
RWE	1.002	1.037	1.020	1.050
Verbund	1.002	1.318	1.999	1.776

As seen in Table 8 above, across all assets the VIF values for each independent variable remain below the conventional threshold of 10, with most ranging between 1 and 2.1. This confirms that there was no problematic correlation among predictors, and that the estimates were not distorted due to multicollinearity.

4.4. Robustness Check

To assess whether the patterns observed in the affected assets were specific to sectors directly exposed to geopolitical risk, we conducted a robustness check using a group of unaffected assets. By analyzing their return behavior, volatility dynamics, and connectedness patterns over the same timeline, we aim to determine whether the changes we observed in the energy sector were systemic or localized. Comparing the unaffected group to the affected assets also helps to validate the significance of our findings by providing a stable reference point that is not expected to exhibit strong responses to the war.

4.4.1. Unaffected Returns

Looking into the descriptive statistics given in table 9, we observe that volatility varies across assets. Among the commodities, eggs display the highest standard deviation at 5.51, followed by corn (2.02) and butter (1.98), showing a wider range of daily return fluctuations. In comparison, equities like Novartis and Bayer exhibit lower volatility, with standard deviations of 1.02 and 1.75, respectively. These differences align with the expectation that food commodities are more exposed to seasonal and supply-side shocks, while healthcare firms tend to behave more defensively.

The average returns are close to zero across all assets, with most means ranging between 0.01 and 0.15. Novonordisk and eggs report the highest mean returns at 0.15, while assets like Novartis and Bayer show minimal returns. Median values also remain near zero, suggesting that return distributions are generally centred and not strongly skewed in either direction.

However, the shape of the distributions reveals more complexity. Many of the unaffected assets exhibit high kurtosis, indicating fat tails and a higher likelihood of extreme return values. For example, butter has a kurtosis of 53.44, beef reports 29.75, and eggs 21.34. These values reflect the abnormal nature of return distributions, especially among agricultural commodities. Additionally, skewness values show some assets leaning toward large positive outliers (e.g., beef and eggs), while others like Novonordisk and Bayer lean slightly negative.

The Jarque-Bera test confirms that none of the return distributions are normal. Each asset's test statistic far exceeds the critical threshold for rejection at the 1% level. The most extreme departures from normality are seen in butter (57,500), beef (16,322), and eggs (7,766.8), further highlighting the presence of non-Gaussian return behaviour.

Lastly, we test for stationarity using both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. All test statistics were significantly negative and well beyond the critical values, indicating that the return series are stationary. This confirms that the data meet the requirements for the TVP-VAR analysis.

Table 9: Descriptive Statistics - Unaffected Returns

	GPRD	*Astrazeneca*	*Bayer*	*Novartis*	*Novonordisk*	*Beef*	*Butter*	*Corn*	*Eggs*
Minimum	-149.93	-6.78	-7.90	-4.13	-12.47	-7.41	-17.32	-9.71	-23.75
Mean	0.08	0.07	0.02	0.01	0.15	0.03	0.11	0.05	0.15
Median	0.05	0.14	0.01	0.03	0.15	0.02	0.11	0.08	0.02
Maximum	135.73	5.51	6.99	5.56	7.17	9.79	19.35	6.20	47.50
Kurtosis	3.76	4.71	5.72	5.52	9.62	29.75	53.44	5.67	21.34
Skewness	-0.13	-0.24	-0.29	-0.10	-0.77	1.36	0.70	-0.49	1.37
Range	285.66	12.29	14.89	9.69	19.64	17.20	36.67	15.91	71.25
SD	40.95	1.56	1.75	1.02	1.78	1.05	1.98	2.02	5.51
Count	542	542	542	542	542	542	542	542	542
Jarque-Bera* **	14.492	71.199	174.75	143.9	1044.8	16322	57500	182.75	7766.8
ADF test* **	-11.11	-7.38	-7.07	-7.85	-8.76	-8.55	-8.28	-7.58	-5.48
PP test* **	-50.02	-24.25	-24.16	-21.88	-25.68	-29.69	-24.14	-25.32	-24.37

Note: *** suggests a p-value of 0.01.

Going into the correlation matrix, table 10 shows that correlations with the GPRD are extremely weak as expected. The correlation values range from -0.05 with corn to 0.07 with Novartis, all of which are close to zero. This supports our assumption that the selected unaffected assets were largely disconnected from direct geopolitical shocks during the Russia–Ukraine war period.

Within the pharmaceutical group, we observe moderate positive correlations, suggesting a degree of common movement within the sector. AstraZeneca and Novartis show the strongest correlation at 0.47, followed by AstraZeneca and Novonordisk at 0.40, and Novartis and Novonordisk at 0.31. These values indicate that while the assets are not highly synchronized, they do share similar trends that may be influenced by broader healthcare market trends or investor sentiment. In comparison, the agricultural commodities show much weaker correlations with each other. The highest correlation in this group is between beef and corn at 0.21, while most others are close to zero or slightly negative. This shows that these commodities generally move independently, which is consistent with their pricing being influenced by distinct supply and demand factors. We also find very low correlation between the pharma and commodity assets. For instance, Bayer and eggs have a correlation of -0.04, and AstraZeneca and butter have a correlation of -0.04. This shows that these two sectors are not driven by similar forms of risk.

Overall, the correlation matrix confirms that the unaffected assets do not display strong interdependence either within or across sectors, and they show little to no relationship with the GPRD. This strengthens their role as a stable benchmark group in our analysis and supports our assumption that they were indeed “unaffected” by the Russia–Ukraine war.

Table 10: Correlation Matrix - Unaffected Returns

	GPRD	Astrazeneca	Bayer	Novartis	Novonordisk	Beef	Butter	Corn	Eggs
GPRD	1.00	-0.03	0.00	0.07	0.05	0.05	0.06	-0.05	0.00
Astrazeneca	-0.03	1.00	0.28	0.47	0.40	0.03	-0.04	0.03	-0.01
Bayer	0.00	0.28	1.00	0.30	0.12	-0.03	0.00	-0.03	-0.04
Novartis	0.07	0.47	0.30	1.00	0.31	0.06	0.02	0.08	-0.02
Novonordisk	0.05	0.40	0.12	0.31	1.00	-0.03	-0.11	0.01	0.03
Beef	0.05	0.03	-0.03	0.06	-0.03	1.00	0.13	0.21	0.06
Butter	0.06	-0.04	0.00	0.02	-0.11	0.13	1.00	0.06	0.00
Corn	-0.05	0.03	-0.03	0.08	0.01	0.21	0.06	1.00	-0.02
Eggs	0.00	-0.01	-0.04	-0.02	0.03	0.06	0.00	-0.02	1.00

The connectedness results for the unaffected asset group are presented in Table 11 and visualised in Figures 6 and 7. Overall, the behaviour of this group is quite different from the affected assets, especially how the assets respond to external shocks. The TCI averages at 40.49%, which is significantly lower than the TCI of the affected group that averaged at 74.60%. This lower TCI shows that these assets are not as heavily linked in terms of return spillovers, and their reactions to the Russia–Ukraine war are far more subtle.

Figure 6 shows how the TCI evolved over time. We observe that the connectedness across the unaffected group peaked during 2021 in the start of the year, reaching to almost 60%, but gradually declined after. Although we do see a sharp increase around February 2022, it still differs strongly with the TCI behaviour of the affected assets as shown in figure 2. While the affected group experienced a surge in connectedness around the war's outbreak and during key escalation phases, the unaffected group remained somewhat stable. This supports our expectation that these assets are less sensitive to geopolitical stress and were largely shielded from its direct financial consequences.

Figure 6: TCI - Unaffected Returns

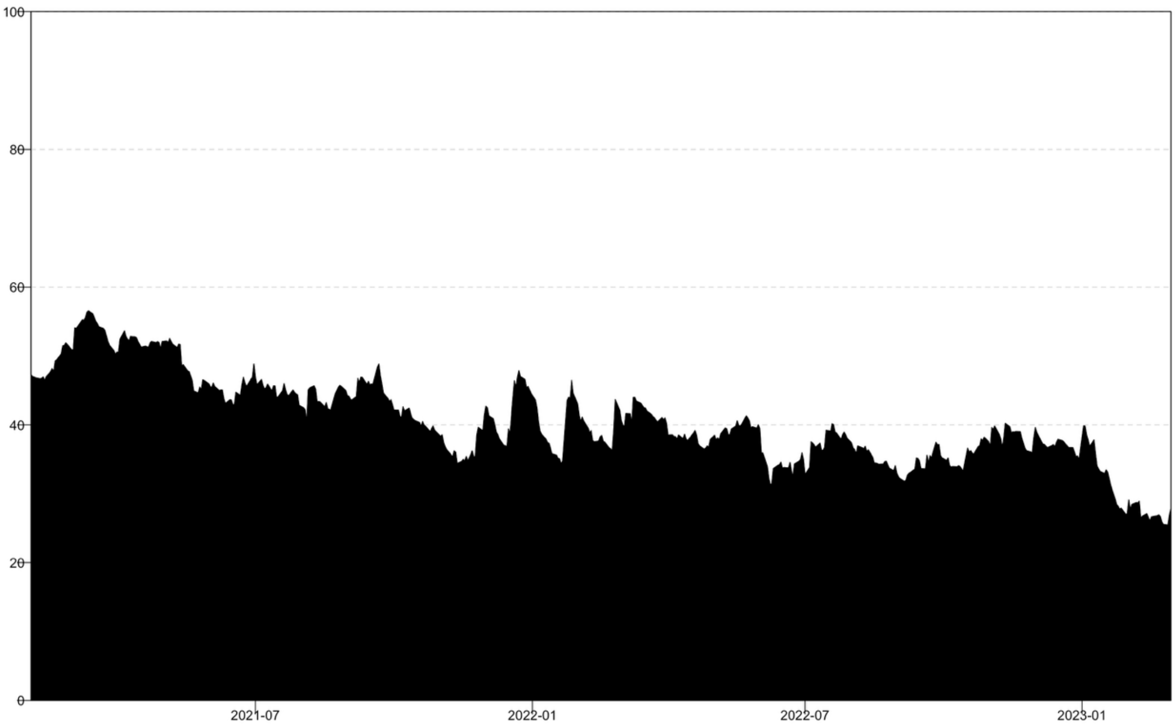


Table 11 highlights the relative roles of different assets within the network. Among the pharmaceutical stocks, Astrazeneca and Novartis are seen as dominant contributors to return spillovers. AstraZeneca has a TO value of 56.64, followed closely by Novartis at 53.80, showing that these assets frequently transmit return shocks to others in the network. The FROM values, 46.79 and 47.72, respectively, are also high, suggesting they are equally exposed to incoming shocks. This two-way dynamic is consistent with the sector's integrated behaviour and reflects the fact that investor sentiment often links large-cap pharmaceutical firms during market-wide events, even in the absence of geopolitical shocks.

In comparison, the agricultural commodities in the group show consistently lower connectedness. Corn, butter, beef and eggs exhibit TO values ranging between 31 and 33, with FROM values ranging from 30 to 43, a slightly higher range specially for beef (43.08). These figures indicate a relatively low level of engagement with the rest of the assets. For instance, corn has a NET score close to zero, Butter has a NET of -9.77, beef at -10.16 and eggs stand at 2.51, which classifies them largely as shock receivers rather than active transmitters. These results align with the assumption that food commodities are driven more by supply-side conditions, seasonal cycles, and localized factors than by global financial market shocks.

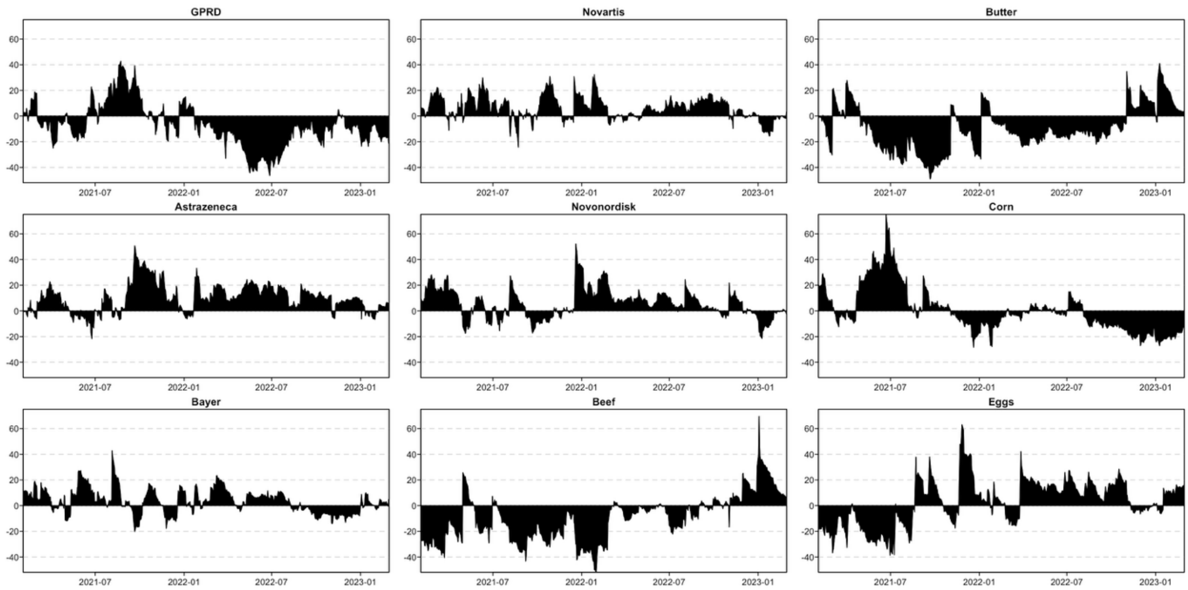
An especially notable difference from the affected asset group lies in the behaviour of the GPRD. In the unaffected group, GPRD is not a dominant player. It has a TO value of 38.24 and a FROM value of 45.53, giving it a NET score of -7.29, which clearly positions it as a net receiver. This is the reverse of what we saw in the affected group, where GPRD served as a strong transmitter of return spillovers to energy firms and commodities. The finding here reinforces the idea that GPRD's role as a shock source is context-dependent and that these unaffected assets were indeed a good source of comparison. This is further supported by Figure 7, with most spikes being consistent throughout the timeline rather than around the war date.

Altogether, the results confirm that the unaffected assets form a relatively low-connected and stable network. Their lower TCI, weak response to GPRD, and lack of consistent directional spillovers highlight their exclusion from the effects of the Russia–Ukraine war. These findings support our initial motivation for including this group as a control sample.

Table 11: Connectedness Table - Unaffected Returns

	GPRD	Astrazeneca	Bayer	Novartis	Novonordisk	Beef	Butter	Corn	Eggs	FROM
GPRD	54.47	7.94	3.74	3.56	5.99	4.38	5.07	3.71	11.15	45.53
Astrazeneca	4.7	53.21	6.09	13.2	10.14	2.63	3.45	3.99	2.59	46.79
Bayer	3.21	7.51	62.53	9.78	5.17	3.37	2.46	2.31	3.67	37.47
Novartis	3.95	13.95	9.07	52.28	7.35	2.94	4.06	2.83	3.58	47.72
Novonordisk	3.15	10.93	4.37	8.37	60.06	2.64	4.07	3.23	3.17	39.94
Beef	6.96	4.21	6.15	4.44	5	56.92	5.21	8.69	2.43	43.08
Butter	7.48	4.2	4.42	4.87	5.4	6.56	59.15	4.92	2.99	40.85
Corn	3.85	2.98	4.02	4.58	2.47	8.59	3.3	67.11	3.11	32.89
Eggs	4.95	4.93	2.94	5	3.96	1.82	3.46	3.13	69.82	30.18
TO	38.24	56.64	40.8	53.8	45.47	32.92	31.08	32.79	32.69	364.45
NET	-7.29	9.86	3.33	6.08	5.53	-10.16	-9.77	-0.09	2.51	**TCI=40.49%**

Figure 7: NET connectedness - Unaffected Returns



4.4.2. Unaffected Volatility

Going into Table 12 which provides the descriptive statistics for the logged GARCH volatilities of the unaffected asset group, we see that the overall volatility characteristics here differ noticeably from those of the affected group. The mean and median values are relatively close to zero across most assets, which is typical of GARCH-filtered series. However, a few assets, including Novonordisk and Astrazeneca, show more negative median values than others. For example, the median volatility for Novonordisk is -0.86 and for Astrazeneca is -1.74, showing that while volatility was mostly low, these assets experienced occasional sharp increases. Agricultural commodities like corn and eggs also reflect this pattern, with median values of -2.35 and -1.56, respectively.

The standard deviation of logged volatility varies widely. Corn (6.72), Astrazeneca (6.47), and eggs (5.89) show relatively high volatility dispersion, which shows greater sensitivity to changing market conditions. On the other hand, assets like Bayer (0.02), butter (0.03), and beef (0.08) display a much lower variation in volatility, showing a more stable behaviour over time. This supports our assumption that the unaffected assets are generally less reactive to external shocks, particularly geopolitical ones.

Looking at the distribution, we see that the volatility series show strong deviations from normality. Most assets display positive skewness, meaning large positive shocks in volatility occurred more frequently than negative ones. This is particularly clear in the pharmaceutical firms, where Novartis and Novonordisk show extremely high skewness values of 9.19 and 9.55, respectively. The kurtosis values are also extremely high. Novartis has a kurtosis of 128.31 and Novonordisk 124.02, which indicates fat tails and a high likelihood of extreme values.

As mentioned previously in section 4.2.1. we do not need to further discuss the Jarque-Bera test because we already use GARCH volatilities. Lastly, the results of the ADF and PP unit root tests confirm all test statistics are strongly negative and well below critical thresholds meaning the volatility series is stationary.

Overall, the unaffected group shows a different volatility profile compared to the affected group. While volatility remains non-normal and at times extreme, the lack of strong upward trends or sustained volatility further solidifies our claim that these assets are unaffected by the GPRD.

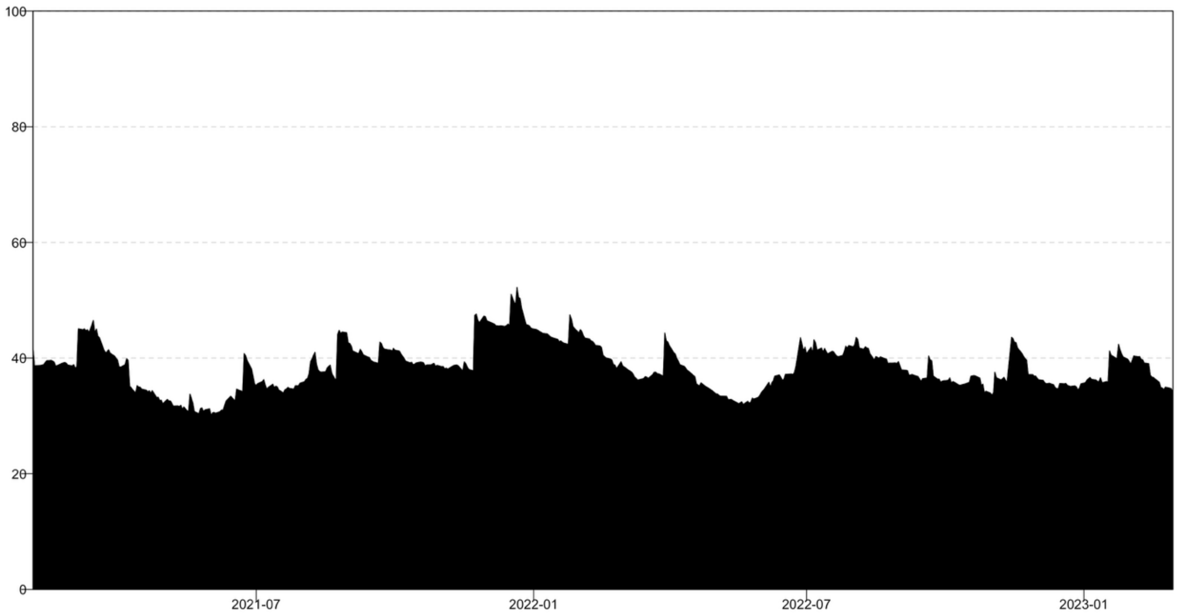
Table 12: Descriptive Statistics - Unaffected Volatility

	GPRD	***Astrazeneca***	***Bayer***	***Novartis***	***Novonordisk***	***Beef***	***Butter***	***Corn***	***Eggs***
Minimum	-149.93	-8.74	0.03	-0.54	-1.75	0.05	0.04	-6.35	-1.56
Mean	-0.13	0.00	0.05	0.01	-0.03	0.14	0.07	-0.05	-0.12
Median	0.04	-1.74	0.05	-0.33	-0.86	0.11	0.06	-2.35	-1.56
Maximum	135.73	53.75	0.09	19.60	51.28	0.40	0.13	47.63	64.35
Kurtosis	3.74	18.90	2.21	128.31	124.02	3.87	2.42	16.47	57.17
Skewness	-0.16	3.24	0.58	9.19	9.55	1.29	0.71	3.06	6.60
Range	285.66	62.49	0.06	20.14	53.03	0.34	0.09	53.98	65.91
SD	40.68	6.47	0.02	1.23	3.38	0.08	0.03	6.72	5.89
Count	541	541	541	541	541	541	541	541	541
Jarque-Bera* **	14.573	6646.1	44.139	361606	338390	167.97	53.086	4937.1	70078
ADF test* **	-11.12	-9.56	-2.68	-7.73	-7.57	-16.37	-11.71	-8.02	-7.26
PP test* **	-49.76	-24.82	-132.18	-23.24	-22.60	-61.94	-108.38	-23.06	-24.33

Note: *** suggests a p-value of 0.01.

The TCI of the unaffected volatility connectedness amounts to just 38.44% which is roughly half of that from the affected volatility. Thus, it verifies our assumption that healthcare and agricultural assets are indeed unaffected or rather less affected. The TCI plot in Figure 8 visualises the overall behaviour of the index throughout the series. In comparison to the affected TCI plots, one cannot distinguish trends on the first glance. There are spikes visible, however difficult to interpret. One spike is seen at the end of 2022 which perhaps shows a similar increase in volatility connectedness as could be seen in the affected volatility section. Nevertheless, if put into contrast the affected total connectedness showed easily recognisable peaks at the war date. Here, these peaks are absent. Furthermore, does the whole TCI plot exhibit a rather stagnant linearity. Hence, Figure 8 depicts a TCI plot of actual from GPR unaffected assets.

Figure 8: TCI - Unaffected Volatility



With a net spillover of -12.94, the GPRD emerges as a moderate net receiver of volatility in this sample. While it transmits volatility to assets like Novartis (12.69) and Eggs (17.65), it also absorbs considerable spillovers, particularly from pharma and food sectors. The NET plot reflects this: GPRD oscillates around the zero line for most of the sample, with no sustained periods of dominance as a transmitter and rather larger periods of negative connectedness. This indicates that in markets less directly tied to energy or less prone to be affected from conflicts, geopolitical risk plays a less decisive role in driving volatility interdependence.

Within the pharmaceutical sector, Novartis is the most prominent transmitter (+16.19), particularly around the early stages of the war, as visible in the NET plot. AstraZeneca and Novonordisk remain near-neutral, with only mild fluctuations in their net spillover roles. Bayer, in contrast, is a net receiver (–4.03), displaying relatively low average TO values and absorbing more volatility than it transmits.

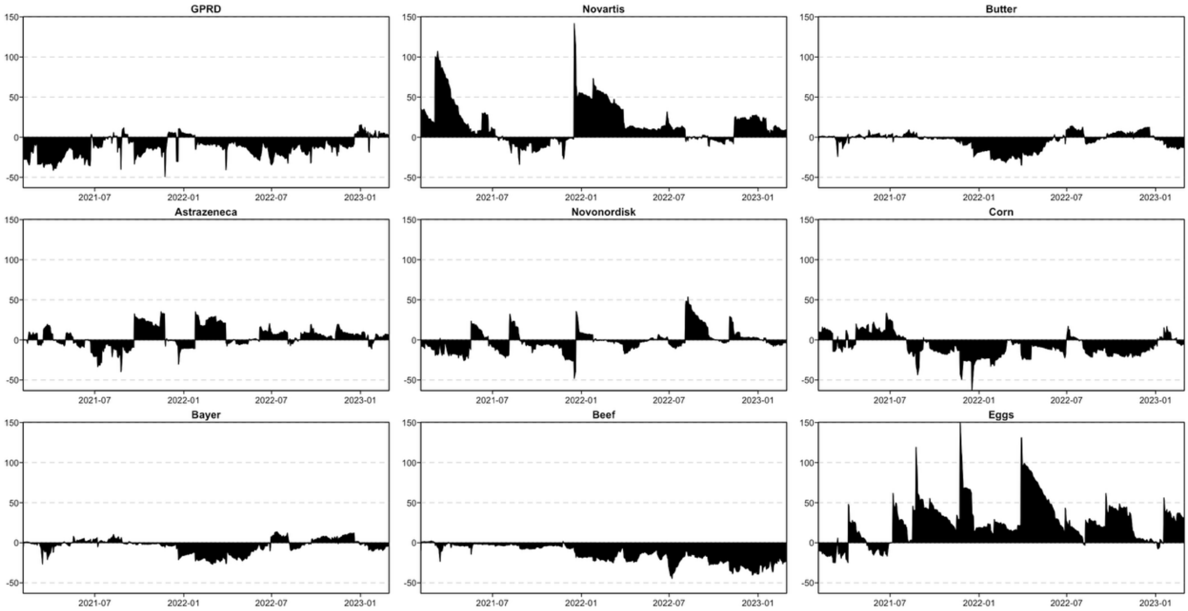
The commodity segment also exhibits heterogeneous patterns. Eggs emerges as the strongest net transmitter in the entire system, with a net spillover of +26.17. The NET plot confirms this behaviour, showing sustained periods of elevated transmission, particularly in 2022. This may reflect food supply chain disruptions, input price inflation, or broader agricultural volatility during the war and post-pandemic periods. Other commodities such as Butter and Corn, display relatively high TO values but end up as net receivers, suggesting that their volatility is driven more by external conditions than by internal propagation. Beef exhibits the most persistent net receiver profile (-14.67), with the NET plot showing consistently negative values throughout the period.

Overall, the connectedness structure in the unaffected sample reveals a lower, more fragmented, and asymmetric volatility transmission network. Only Novartis and Eggs serve as consistent sources of volatility spillovers, while others either play passive roles or alternate between minor sending and receiving. The NET plot highlights that these roles are more variable and less crisis-driven compared to the affected sample, confirming the relative isolation of these markets from systemic volatility contagion.

Table 13: Connectedness Table - Unaffected Volatility

	GPRD	**Astrazeneca**	**Bayer**	**Novartis**	**Novonordisk**	**Beef**	**Butter**	**Corn**	**Eggs**	**FROM**
GPRD	50.22	8.59	2.12	12.69	4.02	0.84	1.81	2.07	17.65	49.78
Astrazeneca	6.81	72.63	0.88	6.3	3.37	0.76	0.82	2.51	5.91	27.37
Bayer	2.53	2.02	35.66	2.21	1.92	14.61	35.2	1.71	4.14	64.34
Novartis	3.52	6.6	0.98	79.92	2.35	0.55	0.91	2.69	2.48	20.08
Novonordisk	5.64	3.01	1.16	3.55	77.66	0.87	1.2	4.77	2.15	22.34
Beef	3.8	1.92	17.04	1.87	1.6	51.53	16.48	2.51	3.26	48.47
Butter	2.58	2.04	35.08	2.31	1.98	14.29	35.69	1.8	4.24	64.31
Corn	7.08	4.27	1.3	5.63	3.3	0.98	1.44	70.19	5.81	29.81
Eggs	4.88	2.74	1.76	1.72	2.26	0.9	1.69	3.53	80.53	19.47
TO	36.84	31.2	60.31	36.27	20.79	33.81	59.54	21.58	45.64	345.97
NET	-12.94	3.83	-4.03	16.19	-1.55	-14.67	-4.77	-8.23	26.17	**TCI=38.44%**

Figure 9: NET connectedness - Unaffected Volatility



5. Discussion

Here we compare and analyse our findings in the previous section and put it into a broader academic context. We revisit the results not only to highlight where our findings support existing literature but also to point out where they diverge or offer new perspectives.

5.1. Connectedness

Geopolitical Risk as a Volatility Transmitter

Our results confirm that GPRD acts as a moderate yet consistent net transmitter of volatility, particularly during periods of heightened geopolitical stress. Across both affected and unaffected samples, we observe that volatility connectedness is not only stronger but more persistent than return connectedness, particularly during and after the geopolitical shock. This aligns with the findings of Awartani et al. (2016), Apergis et al. (2018), Balcilar et al. (2018), Xu et al. (2024), and Chatziantoniou et al. (2025), who emphasize that geopolitical risk tends to impact volatility transmission more strongly than returns. While the GPRD's return-based connectedness was present but not dominant, its volatility transmission role intensified notably around the onset of the Russia–Ukraine war in February 2022, confirming that geopolitical shocks are a primary driver of systemic uncertainty. Thus, our results confirm that while asset prices begin to differentiate as markets stabilize post-crisis, volatility interlinkages remain elevated for the energy market.

Sectoral Segmentation and Asymmetry as Transmitter

A central empirical finding is the clear segmentation between conventional energy assets and renewables in both return and volatility connectedness networks. Fossil fuel companies emerged as strong net transmitters, both in terms of returns and volatilities, particularly during the war period. This confirms the literature consensus (Antonakakis et al., 2017; Zhang et al., 2022; Xu et al., 2024) that oil markets are disproportionately sensitive to geopolitical shocks, reacting immediately and feeding risk into the broader financial system. In contrast, renewable equities consistently appeared as net receivers of both return and volatility spillovers. While Yang et al. (2020) and Su et al. (2021) suggest that GPR can affect renewables, our results show that renewables predominantly absorb volatility, rather than amplify it. This asymmetry aligns our results with Zhao et al. (2021) and indicate that despite their rising strategic importance, renewables remain relatively insulated from acting as systemic transmitters of geopolitical risk.

Affected vs. Unaffected

The empirical segmentation between affected and unaffected assets further validates our methodological approach. Assets classified as unaffected i.e. pharmaceuticals and agricultural commodities, displayed significantly lower TCI values, and the NET plots revealed less pronounced and temporary spillover effects. For instance, GPRD did not dominate volatility transmission in this sample, and Eggs was the only significant net transmitter. This finding supports the arguments made by Mo et al. (2023) and Hudecová & Rajčániová (2023), who suggest that non-energy sectors are less sensitive to GPR, with only selected food commodities showing regional and product-specific effects. Additionally, Corn being a shock receiver is in line with Dai et al. (2024) and Goyal et al. (2024), who showcase a negative effect of GPR on the asset. Furthermore, do we find that Eggs exhibits a moderate shock transmission to the GPR at 17.65 within the unaffected volatility sample group.

5.2. Linear Regression

Our regression analysis set out to investigate whether lagged returns, net connectedness, net GARCH-based volatility, and the GPRD index could help predict short-term asset returns for the selected affected group. While the regression models were originally designed to evaluate predictability at the asset level, what they highlighted was the relative strength or weakness of these predictors when set against the backdrop of the Russia–Ukraine war.

One of the clearest findings we see from this analysis was the strength of past return behaviour in forecasting future movements. The presence of return autocorrelation across much of our sample aligns with what we might expect in periods of heightened uncertainty. In contrast, the role of connectedness and volatility in explaining returns was virtually non-existent. While our connectedness analysis showed clear transmission patterns in the affected assets group, those spillovers did not serve as strong predictors of returns. This difference suggests that while connectedness may reflect how markets interact, it does not necessarily indicate where they are headed next. Similarly, GARCH-based volatility did not offer predictive power either. This reinforces the theory that volatility and connectedness serve better as diagnostic tools than as predictive ones in the context of daily return forecasting.

The role of GPRD was the most interesting to see. Existing research offers a mixed view: some studies suggest that GPR can forecast returns, particularly in equity markets or under specific economic regimes (e.g., Ma et al., 2022), while others argue that its impact is stronger on volatility or sectoral risk (Apergis et al., 2018; Antonakakis et al., 2017). Our findings lean toward the latter. Although the GPRD index played a clear role in connectedness dynamics, it offered limited value in predicting next-day returns. This tells us that geopolitical risk serves more as a force shaping risk perception and cross-asset behaviour than as a short-term driver of returns.

What we see through these regressions is a confirmation of our thesis' broader position: geopolitical risk, though powerful, may not behave like conventional market variables. It disrupts, reshapes, and distorts, but does not easily predict.

5.3. Future Research & Limitations

First, the analysis relies on the Geopolitical Risk Index by Caldara and Iacoviello (2022) as a unidimensional proxy for geopolitical uncertainty. While the GPRD is widely used and well-documented, it is constructed from a newspaper-based sentiment framework and may not fully capture the nuances of all geopolitical events. Future research could complement the GPRD with alternative or disaggregated measures of geopolitical risk, such as sub-indices for geopolitical threats vs. acts which is available on their website or incorporate conflict-specific indicators that account for regional heterogeneity.

Additionally, the division of assets into affected and unaffected groups was based on logical sectoral and geographical relevance to the Ukraine–Russia War. However, this binary classification may oversimplify reality, as some assets may be only indirectly or intermittently influenced by geopolitical developments. Future studies could refine this classification by applying data-driven clustering to allow more flexible segmentation based on actual spillover behaviour. Furthermore, the sample includes a specific subset of European assets and commodities. While this provides a focus on how geopolitical risk affects the European energy market, it limits the generalisability of the findings to global markets or emerging economies. Future work could expand the asset group to include North American, Asian, Middle Eastern, or any other non-European markets. Another idea would be to focus only on country-specific spillovers, where only GPR effects on equities in one economy are being observed.

6. Conclusion

This thesis set out to explore how geopolitical risk, specifically triggered by the Russia–Ukraine war, affects the European energy markets. Using a TVP-VAR model, a GARCH-based volatility estimation, and a predictive regression analysis, we examined both return and volatility spillovers, identifying how these financial metrics evolved before, during, and after the onset of the war. Our main aim was to uncover the extent to which geopolitical shocks transmit through financial markets and whether they carry predictive power for short-term asset returns.

One of the key insights from our connectedness analysis is that GPRD played a significant role as a net transmitter of volatility, especially during the early phase of the conflict. Volatility spillovers were consistently stronger and more persistent than return spillovers, reinforcing the idea that uncertainty often travels faster than price movements in times of crisis. This dynamic was especially pronounced in energy assets, which functioned as primary transmitters of both return and volatility shocks. Meanwhile, renewable energy equities mainly absorbed shocks and rarely functioned as dominant transmitters. The clear segmentation between fossil fuel and renewable energy markets emphasizes the differentiated response within the energy sector itself.

Our robustness check using unaffected assets served to confirm that the elevated spillovers observed in the affected group were not systemic. The lower total connectedness and weaker links to the GPRD in the unaffected group strengthened our confidence in the sector-specific relevance of geopolitical risk transmission.

The predictive regression analysis offered a different angle. While the models showed that past returns held strong predictive power, connectedness, volatility, and geopolitical risk showed limited ability to forecast next-day asset returns. This distinction highlights that while these variables explain current interdependencies and risks well, they do not necessarily guide future price directions. Our results echo parts of the literature that argue GPR is more useful as a risk indicator than a return predictor. In particular, the fact that the GPRD variable remained insignificant across almost all assets suggests that investor sentiment and market pricing incorporate geopolitical risk in complex, possibly nonlinear ways that standard regressions cannot fully capture.

Overall, this thesis contributes to the growing field of geopolitical finance by applying a multi-layered methodology to one of the most significant geopolitical events of the decade. By comparing different asset classes and testing predictive value, we have provided new evidence that geopolitical risk reshapes market structures more through connectedness and volatility than through immediate return effects.

References

Ali, S. R. M., Anik, K. I., Hasan, M. N., & Kamal, M. R. (2023). Geopolitical threats, equity returns, and optimal hedging. *International Review of Financial Analysis*, *90*, 102835. https://doi.org/10.1016/j.irfa.2023.102835

Alqahtani, A., & Taillard, M. (2019). Global energy and geopolitical risk: behavior of oil markets. *International Journal of Energy Sector Management*, *14*(2), 358–371. https://doi.org/10.1108/ijesm-04-2019-0005

Anser, M. K., Syed, Q. R., & Apergis, N. (2021). Does geopolitical risk escalate CO2 emissions? Evidence from the BRICS countries. *Environmental Science and Pollution Research*, *28*(35), 48011–48021. https://doi.org/10.1007/s11356-021-14032-z

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84. https://doi.org/10.3390/jrfm13040084

Antonakakis, N., Gupta, R., Kollias, C., & Papadamou, S. (2017). Geopolitical risks and the oil-stock nexus over 1899–2016. *Finance Research Letters*, *23*, 165–173. https://doi.org/10.1016/j.frl.2017.07.017

Apergis, N., Bonato, M., Gupta, R., & Kyei, C. K. (2018). *Does geopolitical risks predict stock returns and volatility of leading defense companies? Evidence from a nonparametric approach*. http://hdl.handle.net/2263/59358

Assaf, A., Mokni, K., & Yoon, S.-M. (2023). The price of war: Effect of the Russia-Ukraine war on the global financial market. *Finance Research Letters*, 55, 104865. https://doi.org/10.1016/j.frl.2023.104865

Awartani, B., Maghyereh, A., & Guermat, C. (2016). The connectedness between crude oil and financial markets: Evidence from implied volatility indices. *Journal of Commodity Markets*, 4, 56–69. https://doi.org/10.1016/j.jcomm.2016.11.002

Bagirov, M., & Mateus, C. (2019). Oil prices, stock markets and firm performance: Evidence from Europe. *International Review of Economics and Finance*, 61, 270–288. https://doi.org/10.1016/j.iref.2019.02.007

Bagirov, M., & Mateus, C. (2021). Petroleum prices and equity sector returns in petroleum exporting and importing countries: An analysis of volatility transmissions and hedging. *Applied Economics*, 53(48), 5560–5580. https://doi.org/10.1080/00036846.2021.1990846

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2018). Geopolitical risks and stock market dynamics of the BRICS. *Economic Systems*, *42*(2), 295–306. https://doi.org/10.1016/j.ecosys.2017.05.008

Bali, T. G., Brown, S. J., & Caglayan, M. O. (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics*, 114(1), 1–19.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45(2), 217–229.

BBC. (2022, February 24). Ukraine conflict: Russia launches full-scale invasion. https://www.bbc.com/news/world-europe-60503037

Berkman, H., Jacobsen, B., & Lee, J. B. (2010). Time-Varying Rare Disaster Risk and Stock Returns. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1572042

Bildirici, M. E. (2020). Terrorism, environmental pollution, foreign direct investment (FDI), energy consumption, and economic growth: Evidences from China, India, Israel, and Turkey. *Energy & Environment*, *32*(1), 75–95. https://doi.org/10.1177/0958305x20919409

Bildirici, M., & Gokmenoglu, S. M. (2019). The impact of terrorism and FDI on environmental pollution: Evidence from Afghanistan, Iraq, Nigeria, Pakistan, Philippines, Syria, Somalia, Thailand and Yemen. *Environmental Impact Assessment Review*, *81*, 106340. https://doi.org/10.1016/j.eiar.2019.106340

Braun, K. B. (2025, April 24). Ukraine's once-booming grain industry teetering on being a war casualty. *reuters.com*. https://www.reuters.com/markets/commodities/ukraines-once-booming-grain-industry-teetering-being-war-casualty-braun-2025-04-23/

Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, *112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, 21(4), 1509–1531.

Chatziantoniou, I., Gabauer, D., & Stenfors, A. (2025). US sectoral stock market volatility and geopolitical risk categories. *Finance Research Letters*, 106916. https://doi.org/10.1016/j.frl.2025.106916

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1), 291–311.

Dai, Y., Dai, P., & Zhou, W. (2024). The impact of geopolitical risk on the international agricultural market: Empirical analysis based on the GJR-GARCH-MIDAS model. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2404.01641

Demirer, R., Gupta, R., Suleman, T., & Wohar, M. E. (2018). Time-varying rare disaster risks, oil returns and volatility. *Energy Economics*, *75*, 239–248. https://doi.org/10.1016/j.eneco.2018.08.021

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119(534), 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Flouros, F., Pistikou, V., & Plakandaras, V. (2022). Geopolitical risk as a determinant of renewable energy investments. *Energies*, *15*(4), 1498. https://doi.org/10.3390/en15041498

Food and Agriculture Organization of the United Nations. (2025, June 1). *Egg production – FAO: Production: Crops and livestock products*. Our World in Data. Retrieved June

1, 2025, from https://ourworldindata.org/grapher/egg-production-thousand-tonnes?tab=table&tableFilter=countries

Fortum. (2025). *Our energy production | Fortum*. Retrieved June 2, 2025, from https://www.fortum.com/energy-production

Gabauer, D., & Gupta, R. (2018). On the transmission mechanism of country-specific and international economic uncertainty spillovers: Evidence from a TVP-VAR connectedness decomposition approach. *Economics Letters*, 171, 63–66. https://doi.org/10.1016/j.econlet.2018.07.004

Goyal, R., Steinbach, S., & Mensah, E. R. (2024). The interplay of geopolitics and agricultural commodity prices. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4888749

Hudecová, K., & Rajčániová, M. (2023). The impact of geopolitical risk on agricultural commodity prices. *Agricultural Economics (Zemědělská Ekonomika)*, *69*(4), 129–139. https://doi.org/10.17221/374/2022-agricecon

Jorgenson, A. K., Clark, B., & Kentor, J. (2010). Militarization and the Environment: A panel study of carbon dioxide emissions and the Ecological Footprints of Nations, 1970–2000. *Global Environmental Politics*, *10*(1), 7–29. https://doi.org/10.1162/glep.2010.10.1.7

Khalfaoui, R., Baumöhl, E., Sarwar, S., & Výrost, T. (2021). Connectedness between energy and nonenergy commodity markets: Evidence from quantile coherency networks. *Resources Policy*, 74, 102318. https://doi.org/10.1016/j.resourpol.2021.102318

Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross section. *Journal of Financial Economics*, 135(2), 271–292.

Li, K., Shen, D., & Zhang, W. (2024). Financial market spillovers and investor attention to the Russia–Ukraine war. *Finance Research Letters*, 58, 104989. https://doi.org/10.1016/j.frl.2023.104989

Li, P., Zhang, P., Guo, Y., & Li, J. (2024). How has the relationship between major financial markets changed during the Russia–Ukraine conflict? *Humanities and Social Sciences Communications*, 11(1), 1731. https://doi.org/10.1057/s41599-024-04231-7

Ma, F., Lu, F., & Tao, Y. (2022). Geopolitical risk and excess stock returns predictability: New evidence from a century of data. *Finance Research Letters*, *50*, 103211. https://doi.org/10.1016/j.frl.2022.103211

Mo, B., Nie, H., & Zhao, R. (2023). Dynamic nonlinear effects of geopolitical risks on commodities: Fresh evidence from quantile methods. *Energy*, *288*, 129759. https://doi.org/10.1016/j.energy.2023.129759

NATO. (2022, February). Russia's war against Ukraine: NATO response and support. https://www.nato.int/cps/en/natohq/topics_192640.htm

OECD. (2022). Impacts of the Russian invasion of Ukraine on financial market conditions and resilience: Assessment of global financial markets. OECD Publishing. https://www.oecd.org/finance/financial-markets/financial-markets-resilience.htm

OSCE. (2022, February 21). Daily report 39/2022: Ceasefire violations in eastern Ukraine. Organization for Security and Co-operation in Europe. https://www.osce.org/special-monitoring-mission-to-ukraine/513064

Plakandaras, V., Gogas, P., & Papadimitriou, T. (2018). The Effects of Geopolitical Uncertainty in Forecasting Financial Markets: A Machine Learning approach. *Algorithms*, *12*(1), 1. https://doi.org/10.3390/a12010001

Rao, A., Lucey, B., Kumar, S., & Lim, W. M. (2023). Do green energy markets catch cold when conventional energy markets sneeze? *Energy Economics*, *127*, 107035. https://doi.org/10.1016/j.eneco.2023.107035

Rapach, D. E., & Zhou, G. (2013). Forecasting stock returns. In G. Elliott & A. Timmermann (Eds.), *Handbook of Economic Forecasting* (Vol. 2, pp. 328–383). Elsevier.

Sio-Chong U, S., Wong, W.-K., & Dai, L. (2024). The impact of the Russia–Ukraine war on volatility spillovers. *Finance Research Letters*, 58, 104988. https://doi.org/10.1016/j.frl.2023.104988

Smales, L. A. (2021). Geopolitical risk and volatility spillovers in oil and stock markets. The *Quarterly Review of Economics and Finance*, 80, 358–366.

Sohag, K., Islam, M. M., Žiković, I. T., & Mansour, H. (2022). Food inflation and geopolitical risks: analyzing European regions amid the Russia-Ukraine war. *British Food Journal*, *125*(7), 2368–2391. https://doi.org/10.1108/bfj-09-2022-0793

Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics*, 54(3), 375–421.

Su, C., Khan, K., Umar, M., & Zhang, W. (2021). Does renewable energy redefine geopolitical risks? *Energy Policy*, *158*, 112566. https://doi.org/10.1016/j.enpol.2021.112566

Tong, M. H. (2024). Repercussions of the Russia–Ukraine war. *Economics Letters*, 230, 111104. https://doi.org/10.1016/j.econlet.2023.111104

U.S. Department of Agriculture [USDA]. (2025). *Corn | USDA Foreign Agricultural Service*. https://www.fas.usda.gov. Retrieved June 1, 2025, from https://www.fas.usda.gov/data/production/commodity/0440000

U.S. Department of State. (2022, February). Russia's buildup and pretexts for invasion. https://www.state.gov/russias-buildup-and-pretexts-for-invasion/

Umar, Z., Gubareva, M., & Teplova, T. (2022). The impact of the Russia-Ukraine conflict on the connectedness of financial markets. *Finance Research Letters*, 46, 102373. https://doi.org/10.1016/j.frl.2022.102373

Walker, N. W. (2023). *Conflict in Ukraine: A timeline (2014 - eve of 2022 invasion): Research Briefing*. Retrieved June 1, 2025, from https://researchbriefings.files.parliament.uk/documents/CBP-9476/CBP-9476.pdf

Wang, Y., Zhang, D., & Wang, Y. (2023). Estimating the impact of the outbreak of wars on financial assets: Evidence from Russia-Ukraine conflict. Emerging Markets Finance and Trade, 59(3), 825–843. https://doi.org/10.1080/1540496X.2022.2158074

Xu, Y., Guan, B., Lu, W., & Heravi, S. (2024). Macroeconomic shocks and volatility spillovers between stock, bond, gold and crude oil markets. Energy Economics, 136, 107750.

Xu, Y., Guan, B., Lu, W., & Heravi, S. (2024). Macroeconomic shocks and volatility spillovers between stock, bond, gold and crude oil markets. *Energy Economics*, *136*, 107750. https://doi.org/10.1016/j.eneco.2024.107750

Yang, K., Wei, Y., Li, S., & He, J. (2020). Geopolitical risk and renewable energy stock markets: An insight from multiscale dynamic risk spillover. *Journal of Cleaner Production*, *279*, 123429. https://doi.org/10.1016/j.jclepro.2020.123429

Yang, L., & Zhou, G. (2017). Market reactions to macroeconomic announcements: Evidence from implied volatility. Review of Finance, 21(1), 329–367.

Zhang, Z., He, M., Zhang, Y., & Wang, Y. (2022). Geopolitical risk trends and crude oil price predictability. *Energy*, *258*, 124824. https://doi.org/10.1016/j.energy.2022.124824

Zhao, W., Zhong, R., Sohail, S., Majeed, M. T., & Ullah, S. (2021). Geopolitical risks, energy consumption, and CO2 emissions in BRICS: an asymmetric analysis. *Environmental Science and Pollution Research*, *28*(29), 39668–39679. https://doi.org/10.1007/s11356-021-13505-5