CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
Institute of Economic Studies

Geopolitical risk and financial markets: trends, co-movements and effects

Master's thesis

Author: Vesna Jarina

Study program: Economics and Finance

Supervisor: Prof. Roman Horváth Ph.D.

Year of defense: 2023

Declaration of Authorship

The author hereby declares that they compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

The author grants permission to Charles University to reproduce and to distribute copies of this thesis in whole or in part and agrees with the thesis being used for study and scientific purposes.

Prague, August 1, 2023

Vesna Jarina

Abstract

This thesis explores the impact of geopolitical risk on cross-market co-movements in both global stock markets and regional foreign exchange markets over the period of 1995-2023. Employing two novel approaches, namely the return co-exceedances within the quantile regression framework and the GDCCX-GARCH model, our findings reveal that geopolitical risk has a tendency to weaken extreme return co-exceedances and dynamic conditional correlations within these markets, although there are few exceptions from this behaviour. Additionally, we emphasize the significance of considering geopolitical risk when building portfolio strategies by providing evidence for gold's hedging and safe haven properties, the resilience of clean energy investments, and the rise in crude oil prices in response to heightened geopolitical risk.

JEL Classification	C25, C26
Keywords	geopolitical risk, market co-movements, co-exceedance, dynamic conditional correlation, wavelet coherence analysis
Title	Geopolitical risk and financial markets: trends, co-movements and effects

Abstrakt

Tato práce zkoumá vliv geopolitického rizika na korelované pohyby na globálních akciových trzích a regionálních devizových trzích v období 1995-2023. S využitím dvou nových přístupů, konkrétně co-exceedance výnosů v rámci kvantilové regrese a modelu GDCCX-GARCH, docházíme k závěrům, že geopolitické riziko má tendenci oslabovat extrémní co-exceedanci výnosů a dynamické podmíněné korelace v rámci těchto trhů, ačkoli existuje několik výjimek z tohoto chování. Dále zdůrazňujeme význam zohlednění geopolitického rizika při vytváření portfoliových strategií tím, že poskytujeme důkazy o vlastnostech principu zlata jakožto bezpečného přístavu, odolnosti investic do čisté energie a nárůstu cen ropy v reakci na zvýšené geopolitické riziko.

Klasifikace JEL	C25, C26
Klíčová slova	geopolitické riziko, korelované pohyby, co-exceedance, dynamická podmíněná korelace, waveletová koherenční analýza
Název práce	Geopolitické riziko a finanční trhy: trendy, spoluhnutí a efekty

Acknowledgments

I would like to express my heartfelt gratitude to my supervisor, prof. Roman Horváth Ph.D., for his guidance, encouragement and kind approach throughout the process of writing this master's thesis. His expertise and valuable insights have been instrumental in shaping the quality of this work.

I am also deeply grateful for the unwavering support I received from my boyfriend, Tomáš Jurica, as well as my loving family, friends and colleagues. Their constant encouragement and kindness have been crucial in keeping me focused throughout the challenges of this thesis journey.

Typeset in LaTeX using the IES Thesis Template.

Bibliographic Record
Jarina, Vesna: *Geopolitical risk and financial markets: trends, co-movements and effects*. Master's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2023, pages 122. Advisor: Prof. Roman Horváth Ph.D.

Contents

List of Tables

List of Figures

Acronyms

ADF Augmented Dickey-Fuller Test

AIC Akaike information criterion

BIC Bayesian information criterion

BRICS Brazil, Russia, India, China and Sount Africa

CA Canada

CAPM Capital Asset Pricing Model

CBOE Chicago Board Options Exchange

CEE Central and Eastern Europe

CN Mainland China

DAX Deutsche Boerse AG German Stock Index

DCC Dynamic Conditional Correlation

DE Germany

ECO The WilderHill Clean Energy Index

EPU Economic Policy Uncertainty Index

ETF Exchange Traded Funds

FTSE 100 The Financial Times Stock Exchange 100 Index

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GDCCX Generalized Dynamic Conditional Correlation with Exogenous Variables

GPA Geopolitical Acts Index

GPI Global Peace Index

GPR Geopolitical Risk Index

GPT Geopolitical Threats Index

GTD Global Terrorism Database

ICB International Crises Behavior

IEP Institute for Economics & Peace

IL Israel

IN India

JP Japan

KPSS Kwiatkowski–Phillips–Schmidt–Shin Test

MIPT National Memorial Institute for the Prevention of Terrorism

MSCI Morgan Stanley Capital International World Index

MX Mexico

NYSE New York Stock Exchange Composite Index

P5 the United States, China, France, Russia, and the United Kingdom

SA Saudi Arabia

SHCOMP Shanghai Stock Exchange Composite Index

SP/BMV IPC S&P Bolsa Mexicana de Valores Index

SP BSE 500 S&P Bombay Stock Exchange 500 Index

SP/TSX S&P Toronto Stock Exchange Index

TASI Tadawul All Share Index

UK The United Kingdom

US The United States of America

VAR Vector Autoregression

VIX Volatility Index

XAU The Philadelphia Gold and Silver Index

Master's Thesis Proposal

Author	Vesna Jarina
Supervisor	Prof. Roman Horváth Ph.D.
Proposed topic	Geopolitical risk and financial markets: trends, co-movements and effects

Motivation Following 9/11, there has been a growing interest from academics in analyzing the effects of geopolitical risk on different macroeconomic variables as well as financial markets. Moreover, the Russian invasion of Ukraine showed just how fragile the political stability is and with rising geopolitical risk around the globe, the topic regained a lot of attention. Consequently, the paper of Caldara & Iacoviello (2022) introduced a new measure of geopolitical risk, the geopolitical risk index (GPR), which has opened the way to new research and has been widely applied in the recent literature.

Majority of the previous literature focused on the effects of geopolitical risk on specific types of investments. Using the GPR index and their results from CQ estimations, Sohag *et al.* (2022a) concluded that geopolitical risk measures, except geopolitical acts, transmit positive spillovers to the green investments. Baur & Smales (2018) also found that there are positive effects of these measures to gold. Będowska-Sójka *et al.* (2022) confirmed these findings using wavelet coherence analysis and considered the effects of the GPR index also on other asset types. Based on their findings, silver, CHF and real estate, in addition to green bonds and gold, are the most resilient assets to geopolitical risks. The studies of Aysan *et al.* (2019) and Singh *et al.* (2022b) extend this list of hedging tools against global geopolitical risks to Bitcoin, although this is in contradiction with the findings of Baur & Smales (2018). In addition, using data for different groups of countries and different methodological approaches Arin *et al.* (2008), Balcilar *et al.* (2018), Bouras *et al.* (2019) studied the impacts of geopolitical risk measures on stock market returns and volatility. Given their findings, geopolitical risk measures in general drive stock market volatility rather than returns and there is a cross-country variation in the magnitude of the effects. On the other hand, Liu *et al.* (2019), Cunado *et al.* (2020) as well as several other studies, concluded that oil responds negatively to geopolitical risk.

However, based on my knowledge, there has not been many attempts to examine the effects of geopolitical risk on return co-movements. Sohag *et al.* (2022b) applied the TVP-VAR approach to measure synchronization indices between the US, Russian and Chinese markets, and using the QQ framework concluded that GPR negatively affects stock market connectedness, especially at higher quantiles. Nevertheless, this topic calls for further research, taking more markets into consideration, applying other measures of financial contagion and examining them within a different methodological framework.

Therefore, this master thesis aspires to expand the previous research as I will study the effects of increased geopolitical risk on the level of contagion and return co-exceedances on different financial markets in the North America and Europe. Overall, I will aim to answer the question whether geopolitical risk undermines financial integration. In addition, I will reexamine the effect of geopolitical risk on different asset classes and examine how it is connected to the general measure of risk.

Hypotheses

> Hypothesis #1: Geopolitical risk has a significant negative effect on commodity, exchange and stock markets.
>
> Hypothesis #2: Geopolitical risk undermines financial integration.
>
> Hypothesis #3: Geopolitical risk index has a strong, significant effect on the VIX index of economic uncertainty.

Methodology First of all, to capture the geopolitical risk, I will use the recently constructed news-based daily and monthly geopolitical risk index (GPR), ranging from January 1990 until present. In addition, I will use country-specific indices, focusing on North American and European countries, as well as the sub-components of the GPR index, namely the GPA and GPT. As a result, I will be able to compare the effects driven by the threats and the realization of adverse geopolitical events. These indices, developed by Caldara & Iacoviello (2022), detect both direct and indirect geopolitical risks and are unique in their thoroughness and accuracy in the literature. Moreover, as a quantifiable measure of general risk and uncertainty, I will use the CBOE VIX. The data for commodities, exchange rates and stocks will be collected from Bloomberg, Tick Data, Inc., Yahoo! Finance or other global financial data providers.

To measure financial contagion on different markets, I will follow the approach developed by Baur & Schulze (2005) and use a modified co-exceedance measure. Then, to study the impact of geopolitical risk measures on mean and variance dynamics of returns of different asset types as well as co-movements and possible contemporaneous volatility and correlation transmissions in these markets, I will use multivariate dynamic conditional correlation (DCC) GARCH models, developed by Engle (2002) or other multivariate GARCH family models. I will also consider alternative approaches such as the structural VAR framework, the CQ and QQ frameworks used by Lyócsa & Horvath (2018) and Sohag *et al.* (2022b) or the wavelet coherence analysis which was widely used in the literature, for instance, by Bhuiyan *et al.* (2018), Będowska-Sójka *et al.* (2022), Singh *et al.* (2022b) or Cheng *et al.* (2022).

Expected Contribution The master thesis will contribute to the literature by analyzing the impact of geopolitical risks on dynamic return co-movements on different financial markets, including, for example, co-movements and volatility spillovers in the returns of euro, Czech Koruna, Hungarian Forint and Polish Złoty vis-à-vis the US dollar, which has not been addressed as yet. Moreover, the sample period will include the war in Ukraine that has significantly increased the global GPR index, as well as several country-specific indices, mostly in the CEE region. In general, the European markets and the CEE region especially, have not been considered by many relevant studies connected to the geopolitical risk, which now creates an excellent opportunity for a thorough analysis of the topic in this region. Consequently, these impacts of geopolitical threats and actions can provide new insights into how investments into these markets are resilient to those exogenous shocks and possibly even a predictive model for portfolio managers, which can be later used for hedging.

Outline

1. Motivation: To begin with, I will describe the importance of working on the topic and expected contribution to the current discussion in the academic literature.

2. Literature overview: This section will cover the previous literature related to the topic of geopolitical risk and financial markets.

3. Data: In this section, I will describe the measure of geopolitical risk index GPR and the volatility index VIX. Moreover, I will discuss the collection of commodity, exchange and stock market data.

4. Methodology: Here, I will thoroughly describe the DCC-GARCH and other multivariate GARCH models, as well as additional alternative approaches and the rest of the methodology used in the master thesis.

5. Results: In this section, I will present the main results of the analyses and the results of applied robustness checks.

6. Concluding remarks: In the conclusion, I will summarize and compare my main findings and their implications.

Core bibliography

1. Arin, K. P., Ciferri, D. & Spagnolo, N. (2008). "The price of terror: The effects of terrorism on stock market returns and volatility." Economic Letters, 101(3): pp. 164-167.

2. Aysan, A. F., Demir, E., Gozgor, G. & Lau, C. K. M. (2019). "Effects of the geopolitical risks on Bitcoin returns and volatility." Research in International Business and Finance, 47: pp. 511-518.

3. Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2018). "Geopolitical risks and stock market dynamics of the BRICS." Economic Systems, 42(2): pp. 295-306.

4. Baur, D. & N. Schulze (2005): "Coexceedances in financial markets—a quantile regression analysis of contagion." Emerging Markets Review 6(1): pp. 21–43.

5. Baur, D. & L. Smales (2018): "Gold and geopolitical risk." SSRN Electronic Journal.

6. Bhuiyan, R. A., Rahman, M. P., Saiti, B., & Ghani, G. M. (2018). "Financial integration between sukuk and bond indices of emerging markets: Insights from wavelet coherence and multivariate-GARCH analysis." Borsa Istanbul Review, 18(3): pp. 218-230.

7. Bouras, C., Christou, C., Gupta, R., & Suleman, T. (2019). "Geopolitical risks, returns, and volatility in emerging stock markets: evidence from a panel GARCH model." Emerging Markets Finance and Trade, 55(8) pp. 1841-1856.

8. Będowska-Sójka, B., E. Demir, & A. Zaremba (2022): "Hedging geopolitical risks with different asset classes: A focus on the russian invasion of ukraine." Finance Research Letters 50: p. 103192.

9. Caldara, D., & Iacoviello, M. (2022). "Measuring geopolitical risk." American Economic Review 112(4): pp. 1194-1225.

10. Cheng, S., Z. Zhang, & Y. Cao (2022): "Can precious metals hedge geopolitical risk? fresh sight using wavelet coherence analysis." Resources Policy 79: p. 102972.

11. Cunado, J., R. Gupta, C. K. M. Lau, & X. Sheng (2020): "Time-varying impact of geopolitical risks on oil prices." Defence and Peace Economics 31(6): pp. 692–706.

12. Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3): pp. 339-350.

13. Liu, J., Ma, F., Tang, Y., & Zhang, Y. (2019). "Geopolitical risk and oil volatility: A new insight." Energy Economics 84(C).

14. Lyócsa, Š. & R. Horvath (2018): "Stock market contagion: a new approach." Open Economies Review 29(3): pp. 547–577.

15. Singh, S., P. Bansal, & N. Bhardwaj (2022): "Correlation between geopolitical risk, economic policy uncertainty, and bitcoin using partial and multiple wavelet coherence in p5 + 1 nations." Research in International Business and Finance 63: p. 101756.

16. Sohag, K., S. Hammoudeh, A. H. Elsayed, O. Mariev, & Y. Safonova (2022a): "Do geopolitical events transmit opportunity or threat to green markets? decomposed measures of geopolitical risks." Energy Economics 111: p. 106068.

17. Sohag, K., R. Vasilyeva, A. Urazbaeva, & V. Voytenkov (2022b): "Stock market synchronization: The role of geopolitical risk." Journal of Risk and Financial Management 15(5).

Chapter 1

Introduction

In light of geopolitical events that have unfolded since 1995, encompassing events such as the September 11 attacks in 2001, the London Bombings in 2005 and the ongoing war in Ukraine, analyzing the effects of heightened geopolitical risk has become increasingly important. Apart from inflicting immense pain, loss of life and extensive damage to the affected areas, geopolitical conflicts have the potential to adversely impact both the national and global economies, leading to uncertainties that reverberate throughout the financial markets. Consequently, Caldara & Iacoviello (2022) introduced a new measure of geopolitical risk, the Geopolitical Risk Index (GPR), which has opened the way to new research and has been widely applied in the recent studies.

The burgeoning literature concerning geopolitical risk consistently demonstrates its substantial impact on various assets, notably leading to heightened stock and oil market volatilities. Furthermore, as Frijns *et al.* (2012) concludes, political crises have a detrimental impact on financial linkages as they introduce a *flight-to-safety* effect, prompting investors to perceive investments in countries prone to geopolitical tensions as riskier, leading to capital withdrawals. As a result, this can potentially depress these economies and affect their integration with other global markets. In addition, researchers have also found a positive effect of increased geopolitical risk on oil prices, which could favor oil-exporting countries amid heightened geopolitical uncertainty, potentially also reducing the level of integration. Therefore, in our analysis, we hypothesize that geopolitical risk undermines financial integration. On the other hand, if countries are well-integrated, as observed in the case of the Central and Eastern Europe (CEE) countries, geopolitical events may trigger contagion effects, causing rapid spillover between markets and increasing their co-movements.

Narayan *et al.* (2018b) supported this notion, finding domestic terrorism to have contagion effects in Australia, the UK, Germany, and Turkey. Therefore, we find it essential to empirically examine these contradictions and explore the effects of geopolitical risk on the co-movements between various stock markets and foreign exchange markets in more depth. To gain deeper insights into these effects, we employ a combination of two novel approaches by examining return co-exceedances within the quantile regression framework and analyzing the dynamic conditional correlations, both in the context of geopolitical risk. While the findings reveal varying effects of geopolitical risk across specific market pairs, on the whole, they consistently show a reduction in return co-movements with heightened geopolitical risk, even when considering regional foreign exchange markets. Overall, the results suggest that geopolitical risk leads to the disintegration of financial markets around the globe. Understanding these effects of geopolitical risk in the context of recent events enables policymakers, investors, and risk managers to develop more robust strategies to navigate heightened uncertainties, anticipate potential market disruptions, and effectively manage the associated risks.

To the best of our knowledge, this master thesis represents the first attempt to explore the effects of the GPR index on stock and foreign exchange market return co-movements, adding crucial insights to the current body of literature. This primary contribution is further complemented by the utilization of a multivariate dynamic conditional correlation model with exogenous variables, the GDCCX-GARCH model, and its implementation in the `R` programming language. By employing this theoretically robust and economically interesting model, we provide a valuable tool for other researchers interested in studying the effects of any exogenous variable on dynamic conditional correlations. As this model has been scarcely utilized in the current literature, our research sheds light on its potential usefulness and practical application. Another vital contribution lies in our use of the co-exceedance measure within the quantile regression framework, pioneered by Baur & Schulze (2005) and Lyócsa & Horvath (2018). This often overlooked econometric technique deserves greater attention, and our study showcases its efficacy in analyzing the effects of geopolitical risk on return co-exceedances and understanding their complex dynamics. In addition to major global stock markets, our paper focuses on foreign exchange markets in the CEE region that have not been examined in prior studies, despite their potential susceptibility to geopolitical risks, particularly in the current context of the ongoing Russia-Ukrainian war near their borders.

Moreover, the incorporation of an extensive time horizon and two distinct frameworks to reassess the effects of geopolitical risk on gold, oil and clean energy investments enhances the breadth of insights generated from our research. By combining the univariate GARCH and wavelet coherence approaches, we offer a comprehensive and nuanced understanding of how geopolitical risk impacts these asset classes and provide insights for investors seeking to protect their portfolios during geopolitical uncertainties. Furthermore, our analysis delves into the relationship between the GPR index and the comprehensive measure of financial uncertainty, the Volatility Index (VIX). The findings suggest that geopolitical risk has the ability to drive financial uncertainty, with the GPR index capturing risks that are not accounted for in the VIX index. This sheds light on the broader implications of geopolitical risk on financial markets and underscores its significance in shaping overall economic uncertainty.

The remainder of the thesis is structured in the following manner. Chapter 2 provides a comprehensive literature overview. Chapter 3 explains the data selection, collection and transformation processes. Chapter 4 is dedicated to explaining the empirical methodology employed in the thesis. Chapter 5 highlights all the main results of the analysis and discusses their potential implications. Finally, Chapter 6 offers a summary of our findings and proposes possible directions for further research.

Chapter 2

Literature review

In this chapter, we provide an overview of studies exploring the effects of geopolitical risk on different types of asset classes, an insight into the theoretical concepts of financial integration and contagion along with their measurement, and papers examining the connection between the GPR index and other economic uncertainty measures.

2.1 Exploring the effects of geopolitical risk

The following section concentrates on studies dealing with the effect of geopolitical risk on different types of investments. In the existing literature, various techniques have been introduced to analyze these impacts of geopolitical risk from different perspectives and provide new insights. Part of the previous literature approached the problem with using the quantile regression framework, such as Sohag *et al.* (2022a), Aysan *et al.* (2019) and Balcilar *et al.* (2018). This choice of framework allowed the researchers to analyze asset returns and volatility during various states of the market, focusing on their entire conditional distribution. On the other hand, majority of the studies focused on using a conditional mean-based model from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models. These studies include, for instance, Arin *et al.* (2008), Bouras *et al.* (2019), Liu *et al.* (2019), Singh *et al.* (2022b) and Dutta & Dutta (2022). Among other popular approaches are also the Vector Autoregression (VAR) framework and the non-parametric causality-in-quantile test, employed by Balcilar *et al.* (2018) and Gkillas *et al.* (2018). Despite the capability of the latter method to identify potential causality in extreme events within the joint distribution of geopolitical risk and other markets, it neglects the crucial information about the directions of the effects. Moreover, the impacts of geopolitical risk on financial assets can vary across different periods of time, influenced by a range of diverse factors. Consequently, many researchers, including Liu *et al.* (2019) and Będowska-Sójka *et al.* (2022), decided to employ the multivariate wavelet coherence analysis to investigate these impacts under different time horizons. Unfortunately, in contrast to the quantile regression or GARCH approaches, the multivariate wavelet analysis does not have the ability to capture the possible asymmetry in the effects on the lower and upper-tail distributions of the financial assets under examination.

Equity markets

A significant body of literature focused on examining the effects of geopolitical risk measures on stock markets and consistently reported their negative impact and significance, although more on stock volatility rather than returns. Important contributors in this segment of literature include Arin *et al.* (2008), Fernandez (2008), Balcilar *et al.* (2018), Gkillas *et al.* (2018), Bouras *et al.* (2019),Chowdhury *et al.* (2021) and Abakah *et al.* (2022). One of the first studies was that of Arin *et al.* (2008), which studied the effects of terrorism on stock market returns and volatility using a daily terror index, 6 different countries and the bi-variate VAR-GARCH(1,1)-in-mean model. Rather than examining geopolitical risk as a whole, the study narrowed its focused to terrorism, revealing variations in the effects across different countries. Nevertheless, it provided compelling evidence of the significant impact of terror on stock returns and their volatility. Balcilar *et al.* (2018) confirmed a strong heterogeneous impact of geopolitical risk on the stock markets of BRICS countries, with a more consistent and pronounced impact on their volatilities rather than returns. In their paper, the researchers also concluded that with an increased value of the GPR index, investments, employment and stock returns are reduced, and that geopolitical threats matter as much as geopolitical acts, based on a VAR evidence for the US. Bouras *et al.* (2019) used data for 18 emerging markets and applied a panel GARCH approach, aiming to assess the influence of geopolitical risk measures on the mean and variance dynamics of stock returns, while also capturing potential cross-sectional dependence. The results indicated no statistically significant effects on stock returns and stronger effects of the global GPR index on volatility than those of country-specific GPR indices.

Foreign exchange markets

Notable studies in the strand of the literature examining the effect on the foreign exchange market include Balcilar *et al.* (2016), Narayan *et al.* (2018a), Park & Park (2020), Hui (2020), Hui (2021), Kisswani & Elian (2021), Iyke *et al.* (2022) and Singh *et al.* (2022a). Primarily, Narayan *et al.* (2018a) concluded that terrorist attacks have a statistically significant effect on exchange rate results, although the effects are naturally heterogeneous. Employing the ARDL approach to co-integration, Hui (2020) focused on the effects of geopolitical risk on exchange rates in Indonesia and found evidence for different short-term and long-term responses. The results again indicated that while some foreign currencies can be viewed as safe havens against geopolitical risk, it is hardly true for all foreign currencies, even if they are from the same region. In his later-published study, the author focused mainly on the long-run effects and confirmed that in all four ASEAN countries, elevated geopolitical risk results in the depreciation of a domestic currency. Moreover, in order to investigate the rare disaster hypothesis, Park & Park (2020) applied a non-parametric regression and found that the South Korean currency depreciates following an increase in the number of articles reporting threatening North Korea's actions or occurrence of nuclear tests. Kisswani & Elian (2021) chose a different approach and developed their model from the association between oil price and exchange rates. Based on the results from a non-parametric ARDL model, the researchers showed that the global GPR index tends to have symmetric long-run effects on Canadian, Japanese, Chinese, British and the Republic of Korea's currencies, while having asymmetric short-run effects on the latter two. Moreover, Singh *et al.* (2022a) compared the effects of GPR to those of Economic Policy Uncertainty Index (EPU) and the results of strong wavelet coherence at lower frequencies confirmed the strong impact of GPR on exchange rate returns of the P5 countries. Other studies including Plakandaras *et al.* (2018), Iyke *et al.* (2022) focused on investigating the predictability of exchange rate returns in times of heightened geopolitical risk. The results mostly confirm that geopolitical risk provides economically important information, which helps to improve forecast accuracy of exchange rate returns. Finally, the latest paper by Będowska-Sójka *et al.* (2022) indicated that the Swiss frank currency is among the most resilient assets to geopolitical shocks using a wavelet coherence analysis.

Oil and commodity markets

Across the literature, there is also a strong evidence of the negative effects of geopolitical risk on commodity markets, especially the crude oil market. Some of the important studies in this branch of literature include Kollias *et al.* (2013), Liu *et al.* (2019), Bouoiyour *et al.* (2019), Plakandaras *et al.* (2019), Demirer *et al.* (2019), Su *et al.* (2019), Cunado *et al.* (2020), Smales (2021), Lee *et al.* (2021), Aloui & Hamida (2021), Gu *et al.* (2021) and Lee *et al.* (2022). Among them, Kollias *et al.* (2013), Lee *et al.* (2021) and Aloui & Hamida (2021) verified the relevance and impact of geopolitical risk on oil-stock nexus. Kollias *et al.* (2013) examined the oil and stock market co-movements with a simple non-linear BEKK-GARCH model and a dummy variable for war and terrorism events. The findings indicate that war has a substantial impact on global stock and oil market co-movements, while terrorism acts affect only the relationship between oil and European stock markets CAC40 and Deutsche Boerse AG German Stock Index (DAX). The logical interpretation suggests that certain markets are able to absorb the impacts of terrorist attacks, possibly due to an effective response of the supervising authorities. Furthermore, this phenomenon creates an opportunity for diversification. After the introduction of the GPR index, the research was subsequently revisited by Antonakakis *et al.* (2017b) and validated the previous results of negative impacts of geopolitical risk on the covariance between oil and stock markets. Moreover, the choice of multivariate wavelet coherence as an estimation methodology allowed Aloui & Hamida (2021) to examine the dynamics of oil and stock markets in Saudi Arabia under heightened geopolitical risk in time-frequency domain. Their findings show that the impact of geopolitical risk on oil-stock connectedness varies across timescales and investment horizons, with a notable negative effect in the short term. Earlier, Su *et al.* (2019) followed a similar approach and presented findings that a high GPR index can cause higher connectedness between oil prices and financial liquidity in the time domain and that oil prices are dependent on the GPR index. The authors of both studies also recommend that energy-exporting countries should accelerate the global energy transition, reduce reliance on oil and hence be more safeguarded against any oil price volatility as geopolitical tensions related to oil and gas have surged in the recent decades. The conclusion that geopolitical risk causes higher oil market volatility was backed by numerous other studies including Liu *et al.* (2019), Demirer *et al.* (2019), and Cunado *et al.* (2020), who employed a time-varying parameter structural vector autoregressive (TVP-SVAR) model and argued that this negative effect is mostly transmitted via supply and demand channels. Demirer *et al.* (2019) aimed to uncover if geopolitical risk can predict oil market returns and volatility using a non-parametric causality-in-quantile test, but found that geopolitical risk primarily affects volatility and the observed casual effects on oil returns are insignificant, with the only exception of the Nigerian oil market. The additional findings of Lee *et al.* (2021) indicated a one-way causal relationship, where changes in geopolitical risk cause changes in oil prices, particularly at the extreme quantiles. The authors proposed an alternative economic interpretation that extreme events associated with geopolitical risk trigger economic fluctuations and uncertainty, consequently impacting the energy market. Similarly, other studies such as Smales (2021) and Będowska-Sójka *et al.* (2022), have also indicated a positive impact of geopolitical risk on oil prices. In addition, Bouoiyour *et al.* (2019) further investigated the separate effects of Geopolitical Acts Index (GPA) and Geopolitical Threats Index (GPT) categories of the general geopolitical risk measure utilizing the dynamic copula with Markov-switching regime. As a result, the researchers concluded that realizations of adverse geopolitical events generate strong positive effects on oil prices, while the effects of threats appear to be insignificant. However, the findings of Cunado *et al.* (2020) challenge this conclusion and advocate for a negative effect of geopolitical risk on oil returns, stemming from the decline in oil demand influenced by global economic activity. Such contrasting results create the need for additional research in this area. Furthermore, the latest study by Gu *et al.* (2021) decided employ TVP-VAR framework and confirmed the time-varying macro impact of the GPR index on the oil market, even though the results showed that the EPU shock has a more profound impact on the oil market.

Green investments

The conclusion that geopolitical risk has a strong impact on the oil market was in the literature often linked to the studies investigating its effects on green investments, since oil and clean energy markets are close substitutes in certain contexts as was indicated by numerous studies such as Marques *et al.* (2018), Song *et al.* (2019), Lee *et al.* (2021) and Lv *et al.* (2021). First, Yang *et al.* (2021) found significant geopolitical risk spillovers to five renewable, clean energy stock markets by employing the delta conditional Value-at-Risk (ΔCoVaR) with the variational mode decomposition and time-varying copula approaches.

Additionally, their findings indicate that the short- and long-run correlation coefficients between the The WilderHill Clean Energy Index (ECO) and GPR index returns sharply fluctuate over time and the risk spillovers are more pronounced in the short-run. However, the researchers conclude that the established risk measures for stock and oil market retain their significance when gauging the risk conditions of renewable energy stock markets. In addition, focusing solely on the Russian market, Rasoulinezhad *et al.* (2020) showed that geopolitical risk has a positive impact on short-term and long-term energy transition in the country. Lee *et al.* (2021) then contributed to the literature by providing evidence for unidirectional causal relationship from changes in geopolitical risk to the green bond index in case of the US economy, especially evident at lower quantiles. However, all the mentioned studies focused solely on the general geopolitical risk index and refrained from investigating the impacts of different components of geopolitical risk. Sohag *et al.* (2022a) filled this gap and concluded that the GPR index transmits positive volatility spillover shocks to green equity and bond investments and that their connectivity follows a long memory. Similarly to Yang *et al.* (2021), the researchers argued that the positive spillover is transmitted through a substitution channel as the investors prefer green investments over geopolitically exposed alternatives such as fossil fuels, thus diversifying their portfolios. On the other hand, their findings indicate that both green equity and bond markets respond negatively to a heightened GPA index. These negative spillovers are attributed to the overall postponement in consumption and investments and assumed to be transmitted through the asset price and return channels. Dutta & Dutta (2022) elaborated on these conclusions and added that geopolitical conflicts often lead to environmental pollution, which could be mitigated through the adoption of alternative energies. In their paper, the researchers decided to concentrate on the effects on the volatility of renewable energy Exchange Traded Funds (ETF) and the results from their Markov regime switching processes and different GARCH models revealed that higher GPR implies lower volatility and risk of these investments. Most recently, Będowska-Sójka *et al.* (2022) confirmed a strong resilience of green bonds to geopolitical turmoils using wavelet coherence analysis taking into the account the latest developments in geopolitical risk, including the outburst of the Russian-Ukrainian war in 2022.

Gold and precious metals

The existing literature also provides a number of studies examining the effects of geopolitical risk on gold returns and whether it could indeed be considered as a safe haven during intensified geopolitical turmoils (see, *inter alia*, Gupta *et al.* (2017), Baur & Smales (2018), Tiwari *et al.* (2020), Gkillas *et al.* (2020),Triki & Ben Maatoug (2021) and Będowska-Sójka *et al.* (2022)). Using the quantile predictive regression approach, Gupta *et al.* (2017) revealed that terror attacks hold predictive power for gold returns, particularly in the upper quantiles of the conditional distribution of gold returns. Nevertheless, it was the paper by Baur & Smales (2018) which firstly confirmed the positive relationship between geopolitical risk, proxied by the GPR or the GPT indices, and gold returns. As opposed to that, the GPA index did not show any significant effects on gold returns and overall, there were no observable effects on the volatility of gold returns. In their more recent paper, Baur & Smales (2020) confirmed the safe haven properties of silver, in addition to gold, even in times of extreme geopolitical risk. The decomposition of the GPR index into geopolitical acts and threats was later used also by Gkillas *et al.* (2020), who applied a quantile-regression heterogeneous autoregressive realized volatility model and enhanced the findings of Gupta *et al.* (2017) by confirming that geopolitical risk improves forecast accuracy of the conditional distribution of gold returns volatility. Moreover, expanding the findings presented by Baur & Smales (2018) and Baur & Smales (2020), Triki & Ben Maatoug (2021) highlighted the unique role of gold as a safe haven and a right tool for portfolio diversification in the presence of high geopolitical tensions and conflicts employing a VAR-MV-GARCH model and dynamic copula with GPR as an exogenous variable. Most recently, Będowska-Sójka *et al.* (2022) examined these effects of increased geopolitical risk after the outburst of the Russian-Ukrainian war and confirmed that gold is among the asset classes that are the most resilient to geopolitical shocks even after considering the latest geopolitical events. Finally, Tiwari *et al.* (2020) examined the gold-oil dependence dynamics with a Markov-switching time-varying copula model combined with wavelet MRA and found that geopolitical risk negatively affects the dependence structure between gold and oil, which implies further safe haven ability of gold for oil. Overall, holding gold within a diversified portfolio is expected to lower the impacts of geopolitical risk.

Cryptocurrencies

A growing literature addresses the role of geopolitical risk on alternative investments such as cryptocurrencies. One of the first studies by Baur & Smales (2018) found no evidence of a statistically significant relationship between geopolitical risk and Bitcoin prices. However, Aysan *et al.* (2019) conducted a detailed analysis of the predictive power and impact of geopolitical risk on Bitcoin returns and volatility, leading to the finding that Bitcoin may function as a hedging instrument against global geopolitical risks as their study revealed a positive relationship at upper quantiles for both Bitcoin returns and volatility. Overall, the later studies by Al-Yahyaee *et al.* (2019), Al Mamun *et al.* (2020), Chibane & Janson (2020) and Bouri *et al.* (2022) confirmed these findings, solidifying the perception of Bitcoin as a reliable hedging tool against geopolitical uncertainty. A more detailed overview of studies dealing with the impacts of the GPR index on cryptocurrencies is provided by Kyriazis (2021). Nevertheless, these findings were not confirmed by the latest wavelet coherence analysis by Będowska-Sójka *et al.* (2022) and further exploration of this subject matter falls beyond the scope of our analysis.

2.2 Financial integration and contagion

The second section of this chapter aims to provide an insight into the theoretical concepts of financial integration and contagion along with an overview of their measurement and the literature dealing with these topics. Moreover, it summarizes the current state of research on the effects of geopolitical risk on the interconnectedness of different markets.

Unfortunately, a consensus has yet to be reached on a singular unanimous definition of international market integration. Baele *et al.* (2004b) defined a fully integrated financial market as one where all potential participants operate under a unified set of rules, have equal access to all financial instruments and services, and are treated equally. Within the general context of financial integration, stock market integration is then recognized as a key component. To derive estimates of levels and trends of financial integration based on this particular definition, the authors proposed three broad categories of measures: price-based measures, news-based measures and quantity based measures[1], out of which the first two are based on the law of one price.

[1]Since the measurement of the speed or degree of financial integration through these

On its own, the law of one price is a common working definition of financial integration, applied by for example by Baele *et al.* (2004a) or Adjaouté & Danthine (2003), and even though it does not take into consideration whether there do not exist some discriminatory policies affecting the investment opportunities, it remains the main theoretical basis for most measures of financial integration. Furthermore, a broader definition was proposed by Dumas *et al.* (2003) or Cappiello *et al.* (2006b) in which markets and economies are said to be integrated when the financial and real linkages are strengthening. For instance, Cappiello *et al.* (2006b) examined the degree of integration between the stock markets of new EU member states through a new measure that coincides with return correlations and assumes that greater proportion of return variance explained by the common factor compared to the local components implies stronger level of integration. Overall, the popular techniques for analyzing financial and stock market integration include correlation analysis, co-integration analysis, causality tests, multi-factor models and multivariate GARCH models. For further information about different definitions and measures of financial integration, we refer the reader to the latest review of academic literature on financial market integration by Patel *et al.* (2022) or Akbari & Ng (2020).

Similarly, there is also a disagreement over a precise definition of financial contagion which consequently largely contributes to the discrepancy regarding the presence or absence of contagion in the literature. However, according to Forbes & Rigobon (2001), most of the definitions of the term *contagion* cover the occurrence of adverse events when market disturbances are spread from one country to another. Notably, Forbes & Rigobon (2002) defined financial contagion as a significant increase in cross-market linkages after a shock to one or more countries occurs. Given its simplicity, this definition has been widely adopted in the literature and serves as the most commonly used approach, enabling the utilization of various multivariate GARCH models to indirectly infer contagion. Such studies include Cappiello *et al.* (2006b), Chittedi (2015), Fur *et al.* (2016) and Nguyen *et al.* (2022). In addition, the paper by Corsetti *et al.* (2005) built on this definition and a single factor model of stock market returns, and linked the biased prior conclusions on contagion to the imposition of unrealistic constraints on the variance of country-specific shocks. Consequently, the authors strongly advocated for the differentiation between the common and country-specific components of market returns. Alternative approach with

---

indicators is out of scope of our analysis, we refer the reader to the source material for further details.

a strong theoretical background was proposed by Bekaert *et al.* (2005), who defined contagion as an excess correlation that cannot be explained by economic fundamentals and hence avoided the problem with bias correction proposed by Forbes & Rigobon (2002). With this definition, however, arises an additional problem of defining economic fundamentals, which can significantly affect the results. We refer the reader to the paper by Pericoli & Sbracia (2003) who cover the different definitions of financial contagion and its common measures. Moreover, Forbes & Claessens (2004) conducted an extensive review of the literature on contagion, categorizing it into five distinct frameworks: asset price correlations, conditional probabilities of currency crises, changes in volatility, extreme moments, and tests for individual channels of contagion. Additional literature that covers these empirical frameworks include Forbes & Rigobon (2001), Moser (2003) or Dungey & Fry (2004).

On the whole, financial integration and contagion are interconnected concepts that relate to the interdependence and transmission of financial risks across different countries and markets. By enabling the flow of capital, information and financial services, financial integration creates channels through which contagion can spread and therefore, the more are financial systems interconnected, the faster are shocks and disturbances in one market transmitted to other markets. For example, many studies have shown that highly integrated markets played a crucial role in transmitting the effects of the 2008-2009 financial crisis throughout global markets. Conversely, financial contagion episodes can have a retroactive impact on financial integration, as crises or disruptions can lead to a reassessment of risks, increased regulatory measures, or changes in market behavior, potentially affecting the level and nature of integration in subsequent periods. Therefore, understanding the dynamics between financial integration and contagion is crucial when examining the cross-market linkages and the role of geopolitical risk in their changes.

The typically employed approach of asset price correlations, for examining both financial integration and contagion, relies on the assumption of linear changes of market associations and gives the same weight to all the returns regardless of their magnitude. Consequently, this often leads to underestimation of the impacts caused by larger returns. Additionally, Forbes & Rigobon (2002) demonstrated that correlation coefficients are conditional on market volatility and therefore, increases in market co-movements do not necessarily mean financial contagion, but suggest an interdependence. As many authors, including Baele *et al.* (2004a) or Pukthuanthong & Roll (2009), highlight, this also implies that an increase in unconditional correlations cannot be straightforwardly interpreted as an increase in financial integration. Therefore, the use and interpretation of unconditional correlation coefficients should generally be approached very cautiously. As Pericoli & Sbracia (2003) encapsulates, the related econometric concerns of heteroskedasticity, omitted variables and endogeneity, have been addressed by a number of studies, some of which decided follow the volatility spillovers framework and employ multivariate GARCH models that allow for asymmetry, while other, including Boyer *et al.* (2006), Ye *et al.* (2016), Zhang *et al.* (2022) decided to employ Markov regime-switching models or other models within the jump contagion framework.

Perhaps the most common approach for analyzing the integration of financial markets and the occurrence of contagion remains using the multivariate GARCH family models within the volatility spillovers framework. This approach facilitates the analysis of the evolution of financial linkages, effectively addressing the developments in financial integration. An example of a study have adopted this approach can be Carrieri *et al.* (2007). Moreover, it assesses the occurrence and direction of volatility spillovers, cross-market movements in the second moments, that can be linked to occurrences of some market shocks or financial crises and become evidence for contagion. One of the most important contributions has been the paper of Engle (2002), which introduced the DCC-GARCH model allowing for time-varying conditional correlation that has been later used by many relevant studies including Chittedi (2015), Nguyen *et al.* (2022) and Gunay & Can (2022). The initial model was furthermore refined by numerous authors including Bonga-Bonga (2018), who focused on the BRICS equity markets and introduced a VAR-DCC-GARCH model for uncovering stock market contagion. On the other had, Cappiello *et al.* (2006a) extended the DCC-GARCH model and developed a ADCC-GARCH model to allow for asymmetric effects of positive and negative innovations. The model was later used by Fur *et al.* (2016) and Samitas *et al.* (2022), who decided to employ a ADCC model together with copula functions with the similar aim of identifying financial contagion in stock markets. In order to facilitate the study of the effects of different exogenous variables on conditional correlations, the ADCC model was later modified by Li (2011) and Schopen (2012). Li (2011) introduced the GARCH-ADCCE model by adding absolute changes in interest rate differentials into the evolution of conditional correlations while permitting asymmetry. Moreover, the GDCCX model with exogenous variables developed by Schopen (2012) was recently applied by Pineda *et al.* (2022) to study the financial contagion under the recent Covid-19 crisis. A survey of different multivariate GARCH models is provided by Laurent *et al.* (2006), although, keeping pace with the rapidly expanding literature becomes challenging.

Alternatively, Bae *et al.* (2003) proposed a new approach for measuring financial contagion through return co-exceedances, which they define as joint simultaneous occurrences of extreme returns within a specific region or across different regions within a group of markets. This way, co-exceedances enable the capturing non-linear associations between macroeconomic or financial market events and can be considered as evidence of financial contagion. Subsequently, Baur & Schulze (2005) further enhanced this approach by estimating the co-exceedances conditional on the dependence structure. In contrast to Bae *et al.* (2003), Baur & Schulze (2005) applied a quantile regression model for analyzing the return co-exceedances instead of a multinomial logit model, which facilitated the analysis of degrees of co-exceedances and their evolution over time. The refined measure and approach align conceptually with Bekaert *et al.* (2005) and have subsequently been used in different studies including Christiansen & Ranaldo (2009), Horváth *et al.* (2018) and Lyócsa & Horvath (2018).

Theoretically, when geopolitical tensions escalate in a specific region or a country, investors can become more cautious of investments and their exposure to this particular region. Moreover, geopolitical events such as trade conflicts or sanctions can disrupt global supply chains and operations, which can lead to general disruption in the market interconnectedness. Therefore, increased geopolitical risk can create an environment of uncertainty and instability in global financial markets and can undermine financial integration. On the other hand, when the markets are well interconnected, the effects of increased geopolitical risk can quickly spread between the markets, triggering a contagion effect. The transmission of geopolitical risk can amplify the volatility and co-movement of stock prices, as investors react to unfolding events with a flight to quality and save havens and adjust their portfolios accordingly.

However, there has not been many attempts to examine the role of geopolitical risk on financial integration or contagion. An early paper by Frijns *et al.* (2012) revealed that political crises have an adverse impact on stock markets due to heightened investor risk aversion, which consequently leads to reduction in the level of financial integration. The authors based their measure of financial integration on stock market integration and the concept that if a market is fully integrated, assets should be priced identically when employing both a domestic

CAPM and an international CAPM. In addition, Narayan *et al.* (2018b) estimated the dynamic conditional correlations using a simple DCC-GARCH model and subsequently estimated the impact of terrorism risk factor on these correlations after controlling for other determinants of stock market integration by applying the pool ordinary least squares panel regression estimation. The results indicated a fight-to-safety effects of foreign terrorism on dynamic conditional correlations of several market pairs and a contagion effect of domestic terrorism for pairs with Australia, UK, Germany and Turkey as the originators. Among the few other exceptions is the paper by Hedström *et al.* (2020), which studied stock market return and volatility spillovers from developed to 10 emerging markets, while controlling for geopolitical uncertainty. For this reason, the researchers created a spillover index from a VAR model with generalized error variance decomposition and found that geopolitical risk shows no significant spillover to the examined emerging stock markets. Another important finding is that regional emerging markets generally show high risk of contagion, which dominates over the spillover effects from developed markets. These conclusions have important diversification implications between developed and emerging markets, and provide insights into the role of geopolitical risk in the emerging market contagion. In addition, Sohag *et al.* (2022b) applied a TVP-VAR approach to measure total and bilateral connectedness indices between the US, Russian and Chinese markets. Using the quantile framework, the researchers concluded that GPR negatively affects stock market connectedness, especially at higher quantiles.

For the purposes of this thesis, our focus lies on the stock market integration and its broad definition by Cappiello *et al.* (2006b) as increasing interconnectedness between two markets. In addition, we will focus on the broad definition of market contagion as suggested in Forbes & Rigobon (2001), which covers the vulnerability of one country or market to adverse events occurring in other countries or markets, whether some direct cross-market linkages though finance and trade exist or not. Overall, our primary objective is to examine the dynamics of return co-exceedances and conditional correlations among selected market pairs, aiming to shed light on the interdependencies between these markets. On top of that we investigate the role of geopolitical risk in these interdependencies, and if its effect is significant, we debate whether it can serve as evidence that contagion between these countries has occurred.

2.3 Comparison of geopolitical risk with economic uncertainty

To understand the importance and added value of geopolitical risk in economic research, a significant strand of literature examined the relationship between geopolitical risk and other commonly used general measures of economic uncertainty, comparing their impacts (see, *inter alia*, Baur & Smales 2018, Baur & Smales 2020, Gu *et al.* 2021, Singh *et al.* 2022b). We will primarily focus on two measures, namely the EPU index and the VIX index. The EPU index, constructed by Baker *et al.* (2016) is another text-based measure, which aims to capture the economic policy uncertainty. On the other hand, the VIX index, commonly known as the *investor fear gauge*, is a S&P's options-based Chicago Board Options Exchange (CBOE) index, reflecting the overall investor aversion to market fear Whaley (2000). Intuitively, we would expect that geopolitical events would lead higher financial volatility and policy uncertainty, thus indicating a causation from the GPR index to the VIX and the EPU indices.

The authors of the GPR index, Caldara & Iacoviello (2022), were naturally the first ones to provide a graphical evidence that in comparison to the VIX and the EPU indices, the GPR index captures events that are less likely to have an economic origin and as expected, could be causing higher stock market volatility and policy uncertainty. Moreover, a number of studies, including Baur & Smales (2018) and Baur & Smales (2020), compared and differentiated the GPR index with the VIX index as part of their broader analyses. The results confirmed the previous assumptions since even after controlling for the VIX and EPU measures of uncertainty, there remained a positive association between the GPR index and precious metal returns under examination. In addition, Gu *et al.* (2021) compared the macroeconomic effects of the GPR and EPU indices on the oil market and concluded that quantitatively, the latter has a more significant adverse impact on oil returns and volatility. Employing various wavelet coherence analyses, the study of Singh *et al.* (2022b) examined the time-frequency relationship between EPU, GPR and Bitcoin returns. The results confirmed both short-term and long-term co-movements between EPU and GPR across the P5+1 countries. Moreover, Singh *et al.* (2022a) found evidence of a cyclical relationship between EPU and GPR.

Chapter 3

Data

The first part of this chapter focuses on the GPR index and provides a brief introduction into the measures of geopolitical risk. In the second part, we introduce all the endogenous and exogenous variables and provide an insight into their properties through descriptive statistics and basic diagnostic tests. Our research is focused on the period from 1995 until the recent past of March 2023, including the start of the ongoing war in Ukraine in 2022.

3.1 Geopolitical risk measures

Some of the prior papers, including Arin *et al.* (2008) and Kollias *et al.* (2013), focused only on events connected to terrorism and modeled the terrorist attacks via a dummy variable or a constructed index. The information about the terrorism events was collected from open databases such as the National Memorial Institute for the Prevention of Terrorism (MIPT) Terrorism Knowledge Base's Database or the Global Terrorism Database (GTD). Another popular quantitative proxy of war intensity and terrorism-related events is the International Crises Behavior (ICB) crises index, which contains information on all international crises that occurred between 1918 and 2015, regardless of their press coverage. The index was compared to the GPR index in the paper by Caldara & Iacoviello (2022) and showed a significantly lower high-frequency variation. Clearly, these war and terrorism-based measures, however, are not able to capture all the components of geopolitical risk.

Other approaches to geopolitical risk measures include empirical models of asset prices, ratings by geopolitical and financial analysts, and textual analysis of news. Karagozoglu *et al.* (2022) compared these three approaches and concluded that measures based on asset prices are able to capture changes in geopolitical risk the most promptly, however, the text-based measures are also able to incorporate these changes in a timely manner. It follows that analyst ratings appear to react with a slight delay.

Presumably the most complex and popular ratings-based measure of global peacefulness is the Global Peace Index (GPI) index published by the Institute for Economics & Peace (IEP), based on the insights and analyses by geopolitical risk experts who rely on 23 different qualitative and quantitative indicators. The main disadvantage of this index is the low frequency of its updates and subsequent delayed reaction to adverse geopolitical events.

The alternative text-based approach was used by Caldara & Iacoviello (2022), who introduced a new measure of geopolitical risk, the GPR index, aiming to create an indicator which is consistent over time and able to measure the geopolitical tensions and the overall geopolitical situation as is perceived by the public. In contrast to other measures of geopolitical risk, the GPR index includes a wider array of events that are not necessarily connected to actual acts of violence or competition over territories, however, are still negatively affecting the peaceful course of international relations. Moreover, Caldara & Iacoviello (2022) visually compared the GPR index to two popular proxies of economic uncertainty, the VIX and the EPU indices, in order to demonstrate that GPR index is able to capture events of other than economic origin and could even explain some of the periods of higher economic uncertainty and financial volatility. One of its drawbacks, however, is that it underestimates the importance of events that receive little press coverage. Nevertheless, since this measure of geopolitical risk is unique in its thoroughness and accuracy, it has been widely applied in the recent literature and has even been used by important institutions such as the European Central Bank, the International Monetary Fund, and the World Bank. Consequently, this measure will be adopted also in this master thesis.

The geopolitical risk measure proposed by Caldara & Iacoviello (2022) is based on the following definition of the term *geopolitical risk*:

Definition 3.1. Geopolitical risk is the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations.

As a result, the set of terms used in the textual analysis is created based on this definition, human reading and textual analysis of the *New York Times* front pages since 1990, and an analysis of key dates and time-specific language differences in each period. The index is then created based on the frequency of articles covering the topics connected to geopolitical risk. Moreover, while the historical GPR index, which covers the period from 1990 until 1985, is based on only three newspapers, the *Chicago Tribune*, the *New York Times* and the *Wall Street Journal*, the recent GPR takes into consideration seven additional newspapers, namely the *Daily Telegraph*, the *Financial Times*, the *Globe and Mail*, the *Guardian*, the *Los Angeles Times*, the *USA Today*, and the *Wall Street Journal*. In addition, the index is a continuous measure of the geopolitical risk, therefore, higher values indicate higher ongoing intensity of negative events and their higher probability and expected intensity in the future. Figure 3.1 shows the daily GPR index annotated with the major geopolitical events causing the highest peaks in the index around the 9/11, followed by the subsequent Iraq war in 2003, London bombings in 2005, Paris terrorist attacks in 2015 and the start of Russian-Ukrainian war in 2022. Nevertheless, even without the annotations, the spikes corresponding to the historically significant events can be readily identified. The various impacts of geopolitical risk will be examined throughout the period from January 4, 1995 until March 30, 2023, which already includes the outburst and course of the Russian-Ukrainian war and overall consists of more than 3,000 daily observations. Therefore, the sample should be sufficiently diverse and long to efficiently capture any dependency structures or contagious tendencies among the markets under analysis. Furthermore, the war significantly increased the GPR index, which, aside from the terror and devastation it has caused, presents an intriguing opportunity for research.

In addition, Caldara & Iacoviello (2022) introduced also sub-components of the general GPR index, namely the GPA and GPT indices. As a result, it is possible to compare the effects driven by the threats or expectations of future adverse geopolitical events and the actual realization or escalation of current adverse geopolitical events, as both of which will be utilized in our analysis. However, we will not incorporate the country-specific indices, as they are calculated only on a monthly basis, leading to a significant reduction in our sample size and potentially limiting the observability of effects under daily granularity. Moreover, some researchers, such as Bouras *et al.* (2019) have emphasized that the effects of the broad global GPR index hold more significance compared to those of country-specific indices, emphasizing the dominance of world events in influencing global equity markets. This finding further supports our decision to exclude country-specific indices from our analysis.

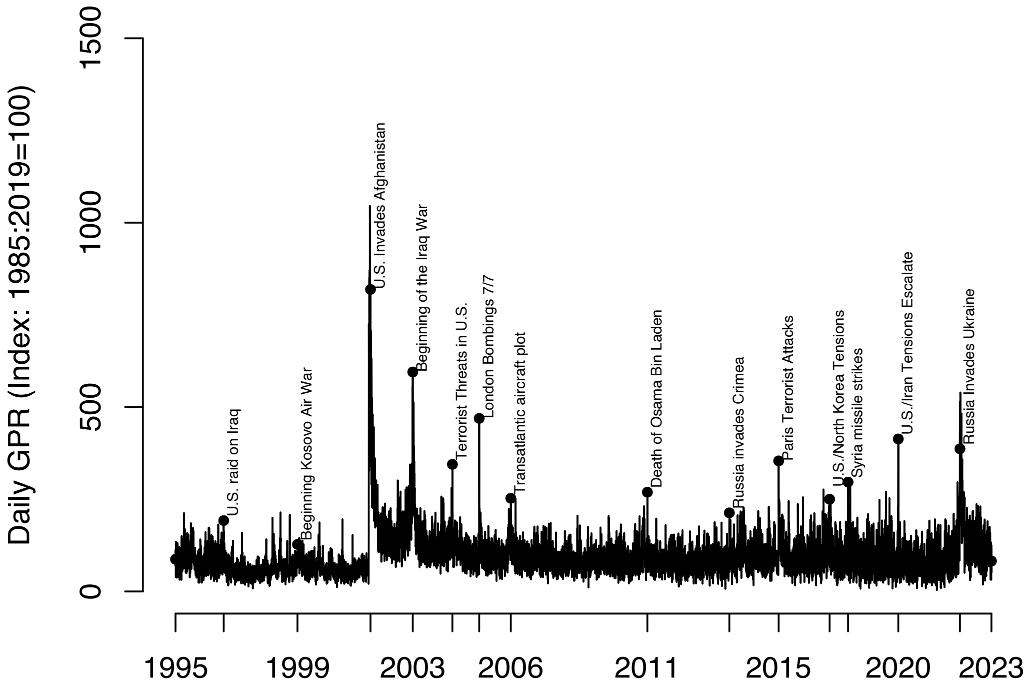


Figure 3.1: **Daily GPR Index**: The figure displays the daily GPR index with the annotation of major events during the sample period from January 1995 to March 2023.

To address the stationarity issues, we will follow the most common approach followed by other studies such as Aysan *et al.* (2019), Baur & Smales (2020) and Lee *et al.* (2021), and employ daily logarithmic first differences for all the geopolitical risk measures and thus compute their continuous daily returns. For this, we must exclude observations where the index value is zero. However, this means sacrificing some pieces of information, as a zero value still provides valuable insight by indicating the absence of geopolitical news articles published on that particular day. Moreover, due to the nature of the construction of the geopolitical risk measures and the delay in publication of news events, we will adjust the series by introducing a 1 day forward lag, adopting the approach by Smales (2021) or Baur & Smales (2020)[1]. Therefore, the final series for the geopolitical risk measures will be $\Delta\log(GPR_t) = \log(GPR_{t+1}) - \log(GPR_t), \Delta\log(GPA_t) = \log(GPA_{t+1}) - \log(GPA_t)$ and $\Delta\log(GPT_t) =$

[1]Conversely, some studies including Antonakakis *et al.* (2017b) decided to introduce backward lags. The assumption behind this approach could be that markets exhibit a significantly delayed reaction to geopolitical risks, making it suitable for examining periods further in the past. However, considering the present state of instantaneous information sharing and easy access to information at any time, we believe that the market reaction is of a more immediate nature.

$\log(GPT_{t+1}) - \log(GPT_t)$ and the summary statistics for these series are presented in Table 3.4. The series display positive skewness and exhibit excess kurtosis. In addition, the Augmented Dickey-Fuller Test (ADF) confirms the stationarity of the data.

3.2 Financial markets data

To study the effects of geopolitical risk on return co-exceedances and dynamic conditional correlations between global stock markets, we will focus on the sample of the following countries: The United States of America (US), Mainland China (CN), Japan (JP), Germany (DE), India (IN), The United Kingdom (UK), Canada (CA), Mexico (MX), Israel (IL) and Saudi Arabia (SA). The selection of countries for the analysis was based on several criteria. These included the incorporation of major world economies, determined by their gross domestic product or stock market capitalization, as well as incorporation of major oil exporters and importers. In addition, to ensure data variety, we have chosen countries from various continents and avoided including highly correlated markets such as Germany and France. Lastly, we modified the selection to ensure a sufficient sample size by excluding countries like Brazil or South Korea. The development of the chosen stock markets is measured via standardized continuous daily index returns computed from daily close-to-close index prices of the following market indices: New York Stock Exchange Composite Index (NYSE), Shanghai Stock Exchange Composite Index (SHCOMP), Nikkei 225 Index, DAX, S&P Bombay Stock Exchange 500 Index (SP BSE 500), The Financial Times Stock Exchange 100 Index (FTSE 100), S&P Toronto Stock Exchange Index (SP/TSX), S&P Bolsa Mexicana de Valores Index (SP/BMV IPC), TA-35 Index and Tadawul All Share Index (TASI). The standardization was introduced by demeaning the observed returns and dividing them by their standard deviation to ensure that the high volatility markets do not substantially influence the return co-exceedance measure. The same approach was adopted by previous studies such as Baur & Schulze (2005) and Lyócsa & Horvath (2018). Since each market has different local holidays and trading schedule, the data are not synchronous and the use of close-to-close prices introduces a bias. However, since we assume that geopolitical risk should have rather long-standing effects on return co-exceedances and dynamic conditional correlations, this potential bias is considered less significant. In addition, the different trading schedules cause a significant reduction of our sample size as the days, on which at least one of the examined markets is closed, are omitted. The biggest complication is introduced by including the Israel and Saudi Arabia markets, whose trading days are from Sunday to Thursday while the trading days for other examined markets are typically from Monday to Friday. Nevertheless, we find it crucial to include them in the sample as they represent countries from the Middle East region, which frequently serves as the focal point of geopolitical tensions. Consequently, the sample covers the period from January 4, 1995 until March 29, 2023 and consists of 3,780 observations.

Similarly, standardized continuous daily returns of foreign exchange prices will be used to explore the possible financial contagion in the foreign exchange markets in the CEE region. To be exact, the foreign exchange prices between the US dollar and the corresponding local currency in the countries of interest, namely: the Czech republic (USD/CZK), Euro-zone countries (USD/EUR), Poland (USD/PLN), Hungary (USD/HUF), Bulgaria (USD/BGN) and Romania (USD/RUB). Since the CEE countries share the same trading hours, the data are synchronuous and the sample size is significantly bigger, with 6,311 observations covering the period from January 3, 1995 until March 31, 2023.

The descriptive statistics for all stock market returns and foreign exchange returns are shown in Table 3.5. As can be seen, while stock market returns for all markets except China, and USD/EUR returns are negatively skewed, Chinese stock market returns and all other foreign exchange market returns exhibit positive skewness. This property of foreign exchange returns is often linked to the popular forex carry trade strategy, *fight-to-quality* phenomenon or effects of interventions of local central banks. The *carry trade strategy* in particular is a very important factor, since borrowing in lower-interest-rate currencies and investing in high-interest-rate currencies has a tendency to generate positive average returns. Moreover, all returns exhibit a high degree of excess kurtosis, especially USD/BGN and USD/RON currency pairs, which is considered a typical property of asset prices returns as there is a relatively high chance of extreme events. Consequently, the excess kurtosis is the main driver of rejecting the null hypothesis of the Jarque Bera Test for normality for all examined market returns and justify the use of a GARCH model with non-normal innovations. The table shows also the results of two stationarity tests, the ADF test and the Kwiatkowski–Phillips–Schmidt–Shin Test (KPSS) for level and trend stationarity and confirm the stationarity of all the times series.

	US	CN	JP	DE	IN	UK	CA	MX	IL	SA
US	1.00									
CN	0.05	1.00								
JP	0.19	0.17	1.00							
DE	0.62	0.06	0.26	1.00						
IN	0.24	0.16	0.29	0.29	1.00					
UK	0.60	0.06	0.29	0.79	0.31	1.00				
CA	0.78	0.07	0.23	0.56	0.26	0.56	1.00			
MX	0.59	0.05	0.16	0.44	0.21	0.44	0.54	1.00		
IL	0.36	**0.03**	0.24	0.48	0.23	0.46	0.36	0.27	1.00	
SA	0.16	0.09	0.18	0.18	0.15	0.18	0.16	0.11	0.16	1.00

Table 3.1: **Correlations between stock market returns**: The table presents unconditional correlations between 10 standardized stock market returns during the examined period between January 1995 and March 2023. All correlation estimates are statistically different from zero except the CN-IL pair.

	USD/CZK	USD/HUF	USD/PLN	USD/BGN	USD/RON	USD/EUR
USD/CZK	1.00					
USD/HUF	0.05	1.00				
USD/PLN	0.19	0.17	1.00			
USD/BGN	0.62	0.06	0.26	1.00		
USD/RON	0.24	0.16	0.29	0.29	1.00	
USD/EUR	0.60	0.06	0.29	0.79	0.31	1.00

Table 3.2: **Correlations between foreign exchange market returns**: The table presents unconditional correlations between 6 standardized foreign exchange market returns during the examined period between January 1995 and March 2023. All correlation estimates are statistically different from zero.

In addition, correlation tables 3.1 and 3.2 present respectively unconditional contemporaneous correlations between stock market returns and foreign exchange market returns. The statistical significance of the correlation between two markets was assessed using the Pearson correlation test. Unsurprisingly, the US market returns are highly correlated with German, British, Canadian and Mexican market returns. Other western markets also exhibit high level of unconditional correlation, while Saudi Arabia, India and Israel markets appear to be the least correlated with the other markets in the sample. Among the foreign exchange market returns, USD/BGN and USD/EUR or USD/BGN and USD/CZK are the most correlated.

Apart from geopolitical risk measures, we will consider other exogenous variables including continuous daily returns computed from well-recognized benchmarks of gold, crude oil and global stock prices. Namely, the gold XAU prices, oil ICE Brent Crude prices will be employed to control for shocks in the main commodity markets and continuous daily returns of the Morgan Stanley Capital International World Index (MSCI) World index for both emerging and developed world equity markets will be used to control for developments on the global stock markets. In addition, we will include changes in market yields on 10-year US Treasury securities to measure market conditions on the low-risk fixed income markets and as a proxy for the global monetary policy. Ultimately, the option-based CBOE VIX index will be considered as a quantifiable measure of general risk and uncertainty. In a supplementary part of the analysis, it will be compared to the geopolitical risk measures. In the examination of return co-exceedances and dynamic conditional correlations, we will again employ their daily first differences to mitigate any stationarity concerns.

The summary statistics for all exogenous variables, including the geopolitical risk measures, are depicted in Table 3.4, while Table 3.3 shows their correlation statistics. All measures are constructed using the longer sample of 6,311 observations covering the period from January 3, 1995 until March 31, 2023 that is used for the analysis of co-movements between the foreign exchange markets, since it is significantly bigger than that for stock markets. In addition, this sample will be used also for the examination of the effects of geopolitical risk measures on oil and gold returns and volatility. As can be seen, there is a positive correlation between gold and oil returns, oil and MSCI returns, gold and MSCI returns and MSCI returns and changes in 10Y US market yields. Unsurprisingly, significant negative correlation can be observed between MSCI returns and changes in the VIX index, changes in the VIX index and changes in 10Y US market yields, changes in the VIX index and oil returns, and gold returns and changes in 10Y US market yields. Based on the Pearson correlation test, for the correlations between $\Delta \log(GPR)$ and MSCI returns, changes in 10Y US market yields and changes in the VIX index are not statistically different from zero at 1% significance. The same holds true also for the correlation between gold returns and changes in the VIX index. Moreover, Table 3.4 provides evidence that MSCI returns and oil returns exhibit typical negative skewness and that all variables except $\Delta US10$ exhibit significant excess kurtosis. The results of the ADF tests and both KPSS tests confirm that all variables are constructed in a way to ensure stationarity of the data.

	$\Delta\log(GPR)$	r_{GOLD}	r_{OIL}	r_{MSCI}	ΔVIX	$\Delta US10$
$\Delta\log(GPR)$	1.00					
r_{GOLD}	0.03	1.00				
r_{OIL}	0.03	0.18	1.00			
r_{MSCI}	-0.02***	0.11	0.28	1.00		
ΔVIX	0.01***	-0.02***	-0.22	-0.73	1.00	
$\Delta US10$	-0.00***	-0.17	0.14	0.28	-0.24	1.00

Table 3.3: **Correlations between exogenous variables**: The table presents unconditional correlations between six exogenous variables used in the analysis of return co-exceedances and co-movements between examined foreign exchange market. The correlation estimates, where we cannot confirm at 1% significance level that they are statistically different from zero are denoted with *** superscripts.

For the first part of this master thesis, which focuses on reexamining the effects of geopolitical risk on different asset classes and their safe haven quality against geopolitical tensions, we will use the ECO index as a proxy for green investments. The index aims to track the clean energy sector, focusing on the business that stand to benefit from a societal shift towards the use of cleaner energy and decarbonization and is considered among the best indices to capture climate change solutions. The selection of stocks and sectors in the index is based on their importance for clean energy, technological influence and relevance. Moreover, the rationale behind adopting the ECO index in our analysis is to facilitate a comparison of our results with previous studies like Yang *et al.* (2021) and Dutta & Dutta (2022), which have also used this particular index. Even though the ECO index has the longest record among its peers, it was still launched live only in 2004 and its historic prices were available from

2000. Therefore, the sample will differ from the sample used for the analysis of the effects of geopolitical risk measures on oil and gold returns and will cover the period from December 28, 2000 until March 31, 2023. We will again work with both with index prices and continuous daily returns that were constructed to avoid stationarity issues.

Lastly, Figures 3.2 and 3.3 display the daily gold and oil prices, and daily clean energy ECO index, respectively. Additionally, we plot along the daily GPR index for comparison. Upon initial observation, we would assume that oil prices and the ECO index prices react positively to increased geopolitical risk. For gold prices, such a clear pattern is not immediately evident. These figures serve as a motivating factor for further investigation into the relationships between geopolitical risk and the prices of gold, oil, and clean energy assets.

	Mean	SD	Skew	Kurt	Min	Max	ADF	$KPSS_L$	$KPSS_T$
Table A: Geopolitical risk measures									
$\Delta\log(GPR)$	0.08	0.42	0.47	4.93	-1.88	2.49	-15.29	1.92**	0.14*
	0.08	0.43	0.47	5.51	-3.00	2.74	-17.79	2.54**	0.43**
$\Delta\log(GPA)$	0.04	0.62	0.11	4.53	-2.63	2.78	-16.56	0.52**	0.11
	0.05	0.62	0.10	4.57	-2.63	2.78	-18.97	0.24	0.11
$\Delta\log(GPT)$	0.09	0.52	0.35	4.24	-2.13	2.47	-15.70	1.19**	0.07
	0.09	0.53	0.30	4.47	-3.45	2.66	-18.11	0.93**	0.14*
Table B: Other exogenous variables									
r_{MSCI}	0.00	0.97	-0.89	13.83	-10.00	8.06	-16.95	0.09	0.07
	0.02	1.00	-0.68	12.22	-10.00	8.06	-17.79	0.04	0.03
$\Delta US10$	-0.00	0.06	-0.14	6.47	-0.51	0.29	-15.63	0.15	0.03
	-0.00	0.06	-0.01	5.55	-0.51	0.29	-16.65	0.12	0.04
ΔVIX	0.06	1.69	1.86	25.10	-13.10	21.57	-17.84	0.07	0.03
	-0.00	1.78	1.56	27.53	-17.64	24.86	-18.84	0.03	0.02
r_{OIL}	-0.05	2.31	-1.10	16.43	-27.98	13.48	-14.23	0.14	0.07
	0.03	2.36	-0.57	12.92	-27.98	19.08	-17.44	0.09	0.04
r_{GOLD}	-0.01	0.99	0.05	11.08	-7.24	10.25	-16.60	0.11	0.06
	0.03	1.06	-0.11	9.74	-9.51	10.25	-18.79	0.14	0.11

Table 3.4: **Descriptive statistics for explanatory variables**: The table presents the summary statistics of the daily changes in logged global GPR index and its components GPA and GPT in Table A, and the summary statistics of the other exogenous variables used in our models in Table B. Among these, VIX and US10 variables are computed as first differences, while daily continuous returns are used for the other variables. In the table, the mean, standard deviation, minimum and maximum values for the daily continuous returns r_{MSCI}, r_{OIL}, and r_{GOLD} are multiplied by 100. SD denotes standard deviation, Skew skewness and Kurt kurtosis. ADF, $KPSS_L$ and $KPSS_T$ denote respectively the test statistics of the ADF test and the KPSS test for level and trend stationarity. The null hypothesis of the ADF test is rejected for all examined variables at the significance level of 1%. Significance of rejecting the null hypothesis of the two KPSS tests at 10%, 5% and 1% levels is denoted by *, ** and *** superscripts, respectively.

Market	Mean	SD	Skew	Kurt	Min	Max	ADF	$KPSS_L$	$KPSS_T$
Table A: Stock market standardized returns									
United States	-0.02	1.03	-0.85	15.42	-9.42	8.76	-16.92	0.10	0.07
China	-0.01	0.79	0.44	26.77	-8.25	12.39	-15.28	0.11	0.02
Japan	-0.01	0.96	-0.15	6.61	-7.52	5.22	-15.79	0.41*	0.10
Germany	-0.01	1.02	-0.27	8.89	-9.32	7.59	-16.66	0.16	0.08
India	-0.01	0.97	-0.85	10.97	-9.54	5.32	-15.41	0.08	0.04
UK	-0.03	1.02	-0.53	11.40	-10.44	7.84	16.34	0.13	0.09
Canada	-0.03	1.07	-1.38	22.02	-13.05	11.15	-15.67	0.07	0.07
Mexico	-0.03	1.00	-0.50	9.77	-10.16	7.01	-15.42	0.04	0.04
Israel	-0.02	0.87	-0.38	6.50	-6.53	5.34	-16.06	0.06	0.06
Saudi Arabia	0.02	0.87	-1.20	16.91	-7.79	6.41	-15.42	0.27	0.15**
Table B: Foreign exchange market standardized returns									
USD/CZK	-0.01	1.04	0.29	7.77	-6.49	11.15	-17.54	0.14	0.07
USD/HUF	-0.01	1.05	0.26	6.83	-6.74	8.37	-17.92	0.09	0.07
USD/PLN	-0.01	1.04	0.23	7.53	-8.32	6.54	-17.03	0.09	0.08
USD/BGN	-0.04	0.57	5.57	219.55	-9.76	19.05	-15.32	0.42*	0.29***
USD/RON	-0.03	0.37	4.47	147.04	-5.36	10.94	-15.49	2.30***	0.78***
USD/EUR	-0.00	0.99	-0.05	4.57	-5.79	4.18	-17.45	0.12	0.08

Table 3.5: **Descriptive statistics for stock and foreign exchange market returns**: The table summarizes the descriptive statistics of the daily standardized continuous returns for stock markets in Table A and for foreign exchange markets in Table B. SD denotes standard deviation of the returns, Skew skewness and Kurt kurtosis. ADF, $KPSS_L$ and $KPSS_T$ denote respectively the test statistics of the ADF test and the KPSS test for level and trend stationarity. The null hypothesis of the ADF test is rejected for all returns at the significance level of 1%. Significance at 10%, 5% and 1% levels for the two KPSS tests are denoted by *, ** and *** superscripts, respectively.

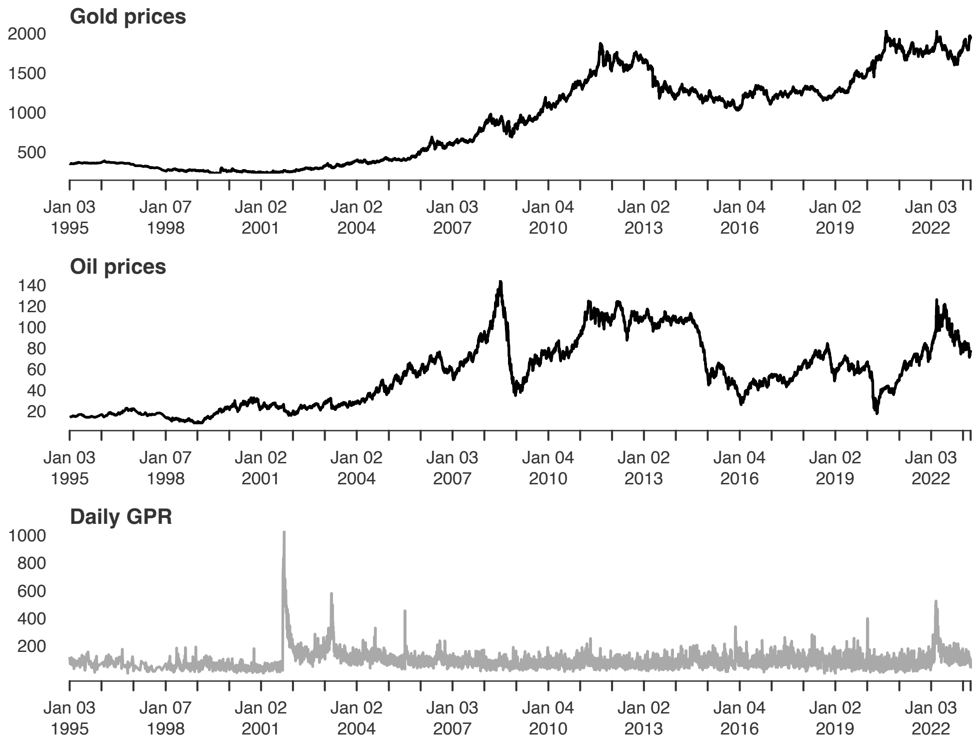


Figure 3.2: **Gold, oil prices and the daily GPR index**

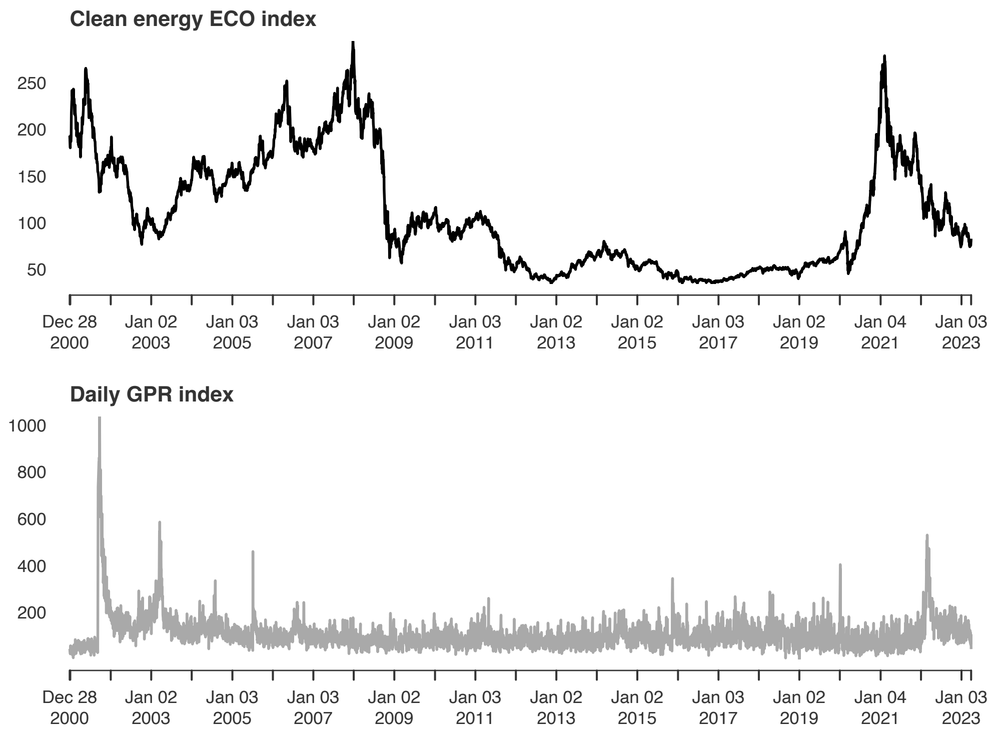


Figure 3.3: **Clean energy ECO index and the daily GPR index**

Chapter 4

Methodology

This chapter outlines all methodological frameworks that will be used in our analysis of the effects that geopolitical risk measures have on different types of investments and the co-movements between financial markets. To be specific, the chapter will present the univariate and multivariate GARCH models, the co-exceedance measure and quantile regression, and finally, the wavelet coherence analysis. Through the univariate GARCH framework, we will examine the effects of geopolitical risk measures on returns and volatility of financial assets and the wavelet coherence analysis will provide a different perspective on their time-frequency relation. Moreover, the co-exceedance measure employed within a quantile regression framework and a dynamic conditional correlation multivariate GARCH model with exogenous variables will allow for the study of co-movements between financial markets. Both of these frameworks provide valuable insights into the dynamics of co-movements between financial markets and can enhance our understanding of the possible spillover or contagion effects and financial integration among financial markets under increased geopolitical risk.

4.1 Univariate GARCH models

The GARCH models introduced by Bollerslev (1986) allow to capture the time-varying nature of volatility or heteroskedasticity of the residuals observed in financial time series data. Moreover, they allow the conditional variance σ_t^2 to be dependent on its past values $\{\sigma_{t-l}^2\}_{l=1}^p$ and the past values of residuals from the mean filtration process $\{\epsilon_{t-l}^2\}_{l=1}^q$. This formulation allows them to capture volatility clustering, which is another characteristic feature of financial time series. In addition, in the financial markets, we might observe that positive and negative news have an asymmetric effect on volatility and bad news tend to be disproportionately more important than positive ones. This is called the *leverage effect*, which causes a possible mis-specification of a simple GARCH model and can be tested for with the Sign Bias test introduced by Engle *et al.* (1987). Consequently, there have been introduced models, that try to deal with this effect. In this paper, we will namely work with E-GARCH and GJR-GARCH models that are presented below.

The GJR-GARCH model

Firstly, let us specify the individual extended GJR-GARCH(1,1) processes of Glosten *et al.* (1993) with external regressor ΔGPR_t for each of the returns $\boldsymbol{r}_i$ as

$$\begin{aligned}\varphi(L)(r_{i,t} - \mu_{i,t}) &= \vartheta(L)\epsilon_{i,t},\\ \mu_{i,t} &= \mu_i^0 + \delta_i \log(\Delta GPR_t),\\ \sigma_{i,t}^2 &= \omega_i + \alpha_i\epsilon_{i,t-1}^2 + \gamma_i I_{i,t-1}(\epsilon_{i,t-1} \leq 0)\epsilon_{i,t-1}^2 + \beta_i\sigma_{i,t-1}^2\\ &\quad + \zeta_i\Delta\log(GPR_t),\end{aligned} \tag{4.1}$$

where $\varphi(L), \vartheta(L)$ denote respectively the autoregressive operator on the demeaned returns and moving average operator on the residuals. $\mu_{t,i}, \sigma_{i,t}^2$ are respectively the conditional mean and variance of $r_{i,t}$ given the information available at time t the and $\omega_i, \alpha_i, \gamma_i, \beta_i$ are parameters of a GJR-GARCH(1,1) process for the i-th asset. As mentioned, the returns $\boldsymbol{r}_i$ are standardized daily continuous returns of the i-th asset or i-th financial market. The residual term $\epsilon_{i,t}$ is assumed to follow the Normal or Student's t-distribution. However, since financial asset returns are usually fat tailed, with a higher probability of large gains or losses in comparison to a normal distribution, we will mostly work with t-distributed innovations instead of normal. The main advantage of this type of models is that they allow for modelling positive and negative shocks on the conditional variance asymmetrically through an indicator function $I_{i,t-1}$ and a leverage term δ_i. Moreover, the vector $\Delta\log(GPR_t)$ is the vector of 1-day-lagged first differences of the logged daily GPR index or alternatively the daily GPA or GPT indices, and δ_i, ζ_i are the parameters representing the effects of this exogenous variable on the conditional mean $\mu_{i,t}$ and variance $\sigma_{i,t}^2$. In this model specification, the exogenous variable is therefore assumed to affect both the mean return and the conditional variance, however, in the final models, either effect can be omitted, depending on which specification yields the optimal result[1]. The persistence of volatility is $\alpha_i + \beta_i + 1/2\gamma_i$.

The exponential E-GARCH model

Secondly, building on the notation and the specification of the mean equation above, let us specify the variance equation of an individual exponential E-GARCH(1,1) processes, suggested by Nelson (1991) for each of the returns $\boldsymbol{r}_i$ as

$$\ln\left(\sigma_{i,t}^2\right) = \omega_i + \alpha_i z_{i,t-1} + \gamma_i(|z_{i,t-1}| - \mathbb{E}|z_{i,t-1}|) + \beta_i \ln\left(\sigma_{i,t-1}^2\right) + \zeta_i \Delta \ln(GPR_t),$$

where $z_{i,t}$ is the standardized residual term that is assumed to follow either Normal or Student's t-distribution

$$\begin{aligned} z_{i,t} &= \frac{\epsilon_{i,t}}{\sigma_{i,t}} \\ z_{i,t} &\sim \text{i.d.d. with } \mathbb{E}(z_{i,t}) = 0, Var(z_{i,t}) = 1, \\ \mathbb{E}|z_{i,t-1}| &= \int_{-\infty}^{\infty} |z| f(z, 0, 1, \dots) dz. \end{aligned}$$

Since we model the $\ln\left(\sigma_{i,t}^2\right)$ instead of $\sigma_{i,t}^2$ directly, $\sigma_{i,t}^2$ will always be positive even if these parameters are negative. Moreover, the parameters α_i and γ_i control respectively for the sign and size effects of z_t and allow the conditional variance process to respond asymmetrically to positive and negative return shocks and hence account for the leverage effect. Here, the persistence of volatility is given by β_i.

The appropriate mean equation for each asset i will be selected following the Box-Jenkins 3-step method consisting on model identification, estimation and final validation. As was already described in Chapter 2, all variables used in the models are carefully constructed and transformed to achieve stationarity of the time series, which is a necessary assumption for Box-Jenkins ARMA model specification. Moreover, in order to asses the correct specification of a GARCH model, we will conduct several diagnostics tests. These tests include

[1] In the analysis, we explored even more complex model specifications, adding a heteroskedasticity term into the mean equation or allowing the external regressor series in the mean equation to be multiplied by $\sigma_{i,t}$. However, as these modifications did not yield improved results, we have excluded them here to prevent any reader confusion.

the Weighted Ljung-Box Test on Standardized Residuals, Weighted Ljung-Box Test on Standardized Squared Residuals, Weighted ARCH LM Tests, Sign Bias Test, Nyblom stability test and the Adjusted Pearson Goodness-of-Fit Test. The Weighted Ljung-Box Test on Standardized Residuals examines whether the autocorrelation function of standardized residuals at first several lags is jointly equal to zero and therefore tests the adequacy of the ARMA fit. Similarly, the Weighted Ljung-Box Test on Standardized Squared Residuals tests for the absence of autocorrelation in squared standardized residuals up to a certain lag. The Weighted ARCH LM Test based on Fisher & Gallagher (2012) is employed to asses the adequacy of the fitted ARCH process. Lastly, the Nylom stability test by Nyblom (1989) tests if the parameter values are constant over time. Once correctly specified models are identified, the selection of the specific GARCH process will be based on the values of Akaike information criterion (AIC) and Bayesian information criterion (BIC) information criteria[2]. Moreover, in this paper, the estimation of the mean and variance equations will be carried out in a single step to ensure the best efficiency, by the maximum likelihood method.

4.2 Multivariate GDCCX-GARCH model

The presence of contagion and the impacts of its transmission channels on stock correlations and foreign exchange correlations can be also tested using various multivariate GARCH models. Specifically, this sections describes and introduces the extension of the dynamic conditional correlation model that allows for including external regressors. This methodological approach for assessing financial integration and the presence of contagion will be employed as a robustness check if our previous conclusions from quantile regression framework with co-exceedances still hold. We will mostly focus on those market pairs, where there were significant effects of geopolitical risk measures on the return co-exceedances based on the previous results.

Among the most widely used multivariate GARCH models is the Dynamic Conditional Correlation (DCC) model by Engle (2002) that takes into consideration

[2]The information criteria under consideration can be defined as

$$AIC = \frac{-2LL}{N} + \frac{2m}{N} \quad \text{and} \quad BIC = \frac{-2LL}{N} + \frac{m\log(N)}{N},$$

with N number of observations and m parameters to estimate.

that financial data exhibit conditional heteroskedasticity and at the same time allows for time-varying conditional correlations. The model can be specified as follows

$$
\begin{aligned}
&\boldsymbol{r}_t|\boldsymbol{\Omega}_t \sim N(\boldsymbol{0}, \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t), && (4.2)\\
&\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t = Var(\boldsymbol{r}_t) = \mathbb{E}(\boldsymbol{r}_t\boldsymbol{r}_t'|\boldsymbol{\Omega}_{t-1}) && \\
&\boldsymbol{D}_t^2 = \mathrm{diag}\{\omega_i\} + \mathrm{diag}\{\kappa_i\} \circ \boldsymbol{r}_{t-1}\boldsymbol{r}_{t-1}' + \mathrm{diag}\{\lambda_i\} \circ \boldsymbol{D}_{t-1}^2, && (4.3)\\
&\boldsymbol{z}_t = \boldsymbol{D}_t^{-1}\boldsymbol{r}_t, && (4.4)\\
&\boldsymbol{Q}_t = \overline{\boldsymbol{Q}} \circ (\mathbb{II}' - \boldsymbol{A} - \boldsymbol{B}) + \boldsymbol{A} \circ \boldsymbol{z}_{t-1}\boldsymbol{z}_{t-1}' + \boldsymbol{B} \circ \boldsymbol{Q}_{t-1}, && (4.5)\\
&\boldsymbol{R}_t = \mathrm{diag}\{\boldsymbol{Q}_t\}^{-1}\boldsymbol{Q}_t\mathrm{diag}\{\boldsymbol{Q}_t\}^{-1}, &&
\end{aligned}
$$

where in case of examining time series of two assets

$$
\boldsymbol{A} = \begin{bmatrix} a & 0 \\ 0 & a \end{bmatrix}, \quad \boldsymbol{B} = \begin{bmatrix} b & 0 \\ 0 & b \end{bmatrix}
$$

are diagonal parameter matrices of non-negative scalars, $\mathbb{I}$ is a vector of ones, $\boldsymbol{\Omega}_t$ contains the available information at time t and $\circ$ the Hadamard product of two matrices of the same size computed by element-by-element multiplication. The $\boldsymbol{R}_t$ matrix is a time-varying correlation matrix, which contains the conditional correlations of standardized asset returns $\boldsymbol{r}_t$ and $\overline{\boldsymbol{Q}} = \mathbb{E}(\boldsymbol{z}_t\boldsymbol{z}_t')$ is the unconditional correlation matrix of the epsilons $\boldsymbol{z}_t$, which firstly needs to be estimated. Symbol $\boldsymbol{z}_t$ denotes a vector of standardized residuals from the univariate GARCH processes for each asset $i = 1, 2, \dots, n$. As it follows from equations 4.2, 4.3 and 4.4, for the returns of examined stock markets, we assume that the conditional mean $\mu_{i,t}$ in equation 4.1 is zero. Moreover, based on the third equation 4.3, which expresses an assumption that each of the assets follows a univariate GARCH process, it can be seen that $\boldsymbol{D}_t$ is a diagonal matrix with the square roots of the conditional variances $\sigma_{i,t}^2$ on its diagonal. In case of two assets i and j, the matrix becomes

$$
\boldsymbol{D}_t = \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{j,t} \end{bmatrix}.
$$

The author Engle (2002) proves that provided that the condition $a + b < 1$ holds, the $\boldsymbol{Q}_t$ matrix and the $\boldsymbol{R}_t$ correlation matrix are positive definite, which is a necessary condition for the model estimation procedure introduced later in this chapter. Furthermore, this model specification describes a multivariate normal case, however, when considering a multivariate Student's t-distribution instead, there would be an additional shape parameter which enters the density equation.

In addition, if we denote $q_{ij,t}$ elements of the symmetric matrix $\boldsymbol{Q}_t$ defined in equation 4.5, the conditional correlation between returns i and j at time t can be expressed as

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}. \tag{4.6}$$

Schopen (2012) introduced an extension of this baseline model specification, alternative to the equation 4.5, which allows the incorporation of exogenous variables $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_P$. The specification of the new Generalized Dynamic Conditional Correlation with Exogenous Variables (GDCCX) model becomes

$$\boldsymbol{Q}_t = \overline{\boldsymbol{Q}} \circ (\mathbb{I}\mathbb{I}' - \boldsymbol{A} - \boldsymbol{B}) - \sum_{p=1}^{P} \boldsymbol{C}_p \overline{x}_p + \boldsymbol{A} \circ \boldsymbol{z}_{t-1}\boldsymbol{z}'_{t-1} + \boldsymbol{B} \circ \boldsymbol{Q}_{t-1} + \sum_{p=1}^{P} \boldsymbol{C}_p x_{p,t-1}, \tag{4.7}$$

where $\overline{x}_p = \frac{1}{T}\sum_{t=1}^{T} x_{p,t}$ and $\boldsymbol{C}_p, p = 1, \ldots, P$ denotes a matrix containing the effects of each of the P exogenous variables on correlations, allowing for the identification of the marginal effects that the exogenous variables have on each co-movement between markets. Moreover, these variables affect only correlations, instead of both correlations and volatilities, by having zeros on the diagonal and are present only in the DCC process. This makes, apart from accounting for the asymmetry, the biggest difference between the presented GDCCX model and the ADCCX model introduced by Vargas (2008), ADCCE model by Li (2011), ADCCEX model by Kleinbrod & Li (2017). In its basic form, the ADCCX model proposed by Vargas (2008) implies that the exogenous variables drive only conditional variances and restricts them to have only a positive impact, which would not align with our specific requirements and specifications for conducting the analysis.

For more clarity, in case of one exogenous variable, $p = P = 1$, and two time series i and j, the matrix $\boldsymbol{C}_p$ becomes

$$\boldsymbol{C}_{1,ij} = \boldsymbol{C}_{ij} = \begin{bmatrix} 0 & c_{ij} \\ c_{ij} & 0 \end{bmatrix},$$

and the exogenous variable $\boldsymbol{x}_1$ are naturally the 1-day lagged daily changes in the logged geopolitical risk index $\Delta\log(GPR_t)$ or another geopolitical risk measure.

The equation 4.7 can be furthermore rewritten by specifying the elements of the $\boldsymbol{Q}_t$ matrix as

$$\begin{aligned} q_{ii,t} &= (1-a-b)\overline{q}_{ii} + a\epsilon^2_{i,t-1} + bq_{ii,t-1}, \\ q_{ij,t} &= (1-a-b)\overline{q}_{ij} - c_{ij}\overline{\Delta\log(GPR)} + az_{i,t-1}z_{j,t-1} + bq_{ij,t-1} \\ &\quad + c_{ij}\Delta\log(GPR_{t-1}) \end{aligned} \tag{4.8}$$

with

$$\boldsymbol{Q}_t = \begin{bmatrix} q_{ii,t} & q_{ij,t} \\ q_{ji,t} & q_{jj,t} \end{bmatrix}.$$

From the model specification, the necessary condition $a + b < 1$ no longer holds and consequently, the conditional correlation matrix $\boldsymbol{Q}_t$ is not ensured to be positive definite. Therefore, a constrained MLE has to be employed to make parameter estimation feasible. Following the approach by Schopen (2012), we will impose constraints on the parameter space for the GDCCX model so that the smallest eigenvalue of any estimated $\boldsymbol{Q}_t$ and $\boldsymbol{R}_t$ matrices is positive. This creates an optimization problem with inequality constraints, which can be solved by introducing a penalty function for constraints that are near or over the boundary or by applying quadratic programming methods focusing on the solution of Karush-Kuhn-Tucker equations. In our analysis, we tested both methods and concluded that both yield comparable estimates, which aligns with Schopen (2012). However, the penalty function approach, despite its higher sensitivity to initial parameters, is favored due to its faster estimation speed. Furthermore, as Schopen (2012) highlights, the major drawback of using a constrained maximum likelihood estimator is that both the true and estimated parameters have to be assumed to fall within the defined parameter space, otherwise the asymptotic standard errors cannot be considered valid.

The whole estimation procedure is based on the DCC model estimation procedure thoroughly described in Engle (2002) and can be consistently performed in two steps. Under the normality condition 4.2, the model can be estimated by the quasi-maximum likelihood method, with the log-likelihood function

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + \log|\boldsymbol{H}_t| + \boldsymbol{r}_t'\boldsymbol{H}_t^{-1}\boldsymbol{r}_t\Big) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + \log|\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t| + \boldsymbol{r}_t'\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{r}_t\Big) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \log|\boldsymbol{R}_t| + \boldsymbol{z}_t'\boldsymbol{R}_t^{-1}\boldsymbol{z}_t\Big) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \boldsymbol{r}_t'\boldsymbol{D}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{r}_t - \boldsymbol{z}_t'\boldsymbol{z}_t + \log|\boldsymbol{R}_t| + \boldsymbol{z}_t'\boldsymbol{R}_t^{-1}\boldsymbol{z}_t\Big),
\end{aligned}
$$

where the symbol $|\ |$ denotes a determinant of a given matrix.

Moreover, let $\boldsymbol{\theta} = (\boldsymbol{\phi}, \boldsymbol{\psi})^T$ be the set of all parameters, with $\boldsymbol{\phi} = (\boldsymbol{\phi}_1, \boldsymbol{\phi}_2)^T = (\omega_1, \alpha_1, \beta_1, \gamma_1, \omega_2, \alpha_2, \beta_2, \gamma_2)^T$ being the set of parameters in $\boldsymbol{D}_t$ from the univariate GARCH models and $\boldsymbol{\psi} = (dcca, dccb, c)^T$ the set of additional DCC parameters in $\boldsymbol{R}_t$. The log-likelihood function can be expressed as a sum of a volatility part and a correlation part as

$$
L(\boldsymbol{\phi}, \boldsymbol{\psi}) = L_v(\boldsymbol{\phi}) + L_c(\boldsymbol{\phi}, \boldsymbol{\psi}),
$$

where the volatility part is the sum of individual GARCH likelihoods

$$
\begin{aligned}
L_v(\boldsymbol{\phi}) &= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \boldsymbol{r}_t'\boldsymbol{D}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{r}_t\Big) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{n}\left(n\log(2\pi) + 2\log(\sigma_{i,t}^2) + \frac{r_{i,t}^2}{\sigma_{i,t}^2}\right)
\end{aligned}
$$

and the correlation part is

$$
L_c(\boldsymbol{\phi}, \boldsymbol{\psi}) = -\frac{1}{2}\sum_{t=1}^{T}\Big(-\boldsymbol{z}_t'\boldsymbol{z}_t + \log|\boldsymbol{R}_t| + \boldsymbol{z}_t'\boldsymbol{R}_t^{-1}\boldsymbol{z}_t\Big). \tag{4.9}
$$

The volatility part can be jointly maximized by separately maximizing each individual term. By estimating an univariate GARCH process, as described in section 4.1, separately for each return time series i, we will get the conditional variances $\sigma_{i,t}^2$, which can be then transformed into standardized residuals $z_{i,t}$ and used in the second stage[3].

[3] It should be again emphasized that in the formulation of the multivariate GARCH models, we have for simplicity assumed that the returns $r_{i,t}$ have a zero conditional mean $\mu_{i,t} = 0$.

The second estimation step involves estimating the correlation parameters $\boldsymbol{\psi}$ using the correlation part $L_c(\boldsymbol{\phi}, \boldsymbol{\psi})$

$$\max_{\boldsymbol{\psi}} \Big\{ L_c(\hat{\boldsymbol{\phi}}, \boldsymbol{\psi}) \Big\}$$

given

$$\hat{\boldsymbol{\phi}} = \arg\max_{\boldsymbol{\phi}} \Big\{ L_v(\boldsymbol{\phi}) \Big\}$$

is the set of parameters in $\boldsymbol{D}$ estimated in the previous step, specifically, the estimated standardized residuals $\hat{\boldsymbol{z}}_t = \hat{\boldsymbol{D}}_t^{-1} \boldsymbol{r}_t$. Since we will maximize the correlation part in respect to the set of parameters $\boldsymbol{\psi}$, the $-\boldsymbol{z}_t' \boldsymbol{z}_t$ part of the function 4.9 will not influence the selection of parameters. Therefore, the estimation of the DCC parameters becomes easier when we remove the constant terms and the correlation part of the log-likelihood functions becomes

$$L_c(\hat{\boldsymbol{\phi}}, \boldsymbol{\psi}) = -\frac{1}{2} \sum_{t=1}^{T} \Big(\log |\boldsymbol{R}_t| + \hat{\boldsymbol{z}}_t' \boldsymbol{R}_t^{-1} \hat{\boldsymbol{z}}_t \Big).$$

Moreover, given that the GDCCX model is not available in any existing `R`[4] package, we have taken the initiative to implement the whole model estimation, particularly the maximization of the $L_c(\hat{\boldsymbol{\phi}}, \boldsymbol{\psi})$ function, ourselves by utilizing the solver by Ye (1987)[5][6]. The corresponding code is included in the Appendix A.1.

The asymptotic theory of the GDCCX model is largely based on the theory of the asymptotic distribution for two-stage QMLE estimators introduced by White (1996) and Bollerslev & Wooldridge (1992). Moreover, under the set of assumptions outlined in Engle & Sheppard (2001), the parameters estimated through the described two stage procedure are consistent. The authors also introduce the sufficient regularity conditions to allow for the asymptotic normality of the estimated parameters, which can be specified as follows

$$\sqrt{T}(\hat{\boldsymbol{\theta}}_T - \boldsymbol{\theta}_0) \overset{as.}{\sim} N(\boldsymbol{0}, \boldsymbol{A}^{-1} \boldsymbol{B} \boldsymbol{A}'^{-1}),$$

[4]The symbol `R` denotes the R Core Team (2023) programming language.

[5]The solver is implemented in the `Rsolnp` package for `R` by Ghalanos & Theussl (2015). As the estimation process is sensitive to the selection of starting parameters, we have experimented with iterative random initialization of the solver, aiming to enhance our chances of identifying the optimal global maximum solution.

[6]While we did not rely on it directly, we drew some inspiration from the `rmgarch` package developed by Galanos (2022) during our implementation process.

with

$$\boldsymbol{A} = \begin{bmatrix} \nabla_{\phi\phi} L_v(\boldsymbol{\phi}) & \boldsymbol{0} \\ \nabla_{\phi\psi} L_c(\boldsymbol{\phi}, \boldsymbol{\psi}) & \nabla_{\psi\psi} L_c(\boldsymbol{\phi}, \boldsymbol{\psi}) \end{bmatrix}$$

and

$$\boldsymbol{B} = Var\left(\sum_{t=1}^{T} \frac{1}{\sqrt{T}} \begin{pmatrix} \nabla_{\phi} L_v(\boldsymbol{r}_t, \boldsymbol{\phi}_0) \\ \nabla_{\psi} L_c(\boldsymbol{r}_t, \boldsymbol{\phi}_0, \boldsymbol{\psi}_0) \end{pmatrix}\right)$$

being both square matrices with the dimension equal to the total number of estimated parameters in the model. For more detail including the necessary proofs, we refer the reader to the source material. The estimate of the asymptotic variance of $\hat{\boldsymbol{\theta}}_T$ is a *sandwich estimator* given by

$$\widehat{avar\left(\hat{\boldsymbol{\theta}}_T\right)} = \frac{1}{T} \widehat{\boldsymbol{A}}^{-1} \widehat{\boldsymbol{B}} \widehat{\boldsymbol{A}'}^{-1},$$

where

$$\widehat{\boldsymbol{A}} = \frac{1}{T} \sum_{t=1}^{T} \begin{bmatrix} \nabla_{\phi\phi} L_v(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}) & 0 \\ \nabla_{\phi\psi} L_c(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\psi}}) & \nabla_{\psi\psi} L_c(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\psi}}) \end{bmatrix}$$

and

$$\widehat{\boldsymbol{B}} = \frac{1}{T} \sum_{t=1}^{T} \begin{pmatrix} \nabla_{\phi} L_v(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}) \\ \nabla_{\psi} L_c(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\psi}}) \end{pmatrix} \begin{pmatrix} \nabla_{\phi} L_v(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}) \\ \nabla_{\psi} L_c(\boldsymbol{r}_t, \hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\psi}}) \end{pmatrix}'.$$

The calculation of derivatives will be done numerically by applying the Richardson's extrapolation method. For further details, we refer the reader to the work by Lindfield & Penny (1989) or Fornberg & Sloan (1994)[7].

Furthermore, according to Schopen (2012), this limited information estimator is consistent, but not fully efficient and consequently, the standard errors should to be corrected to account for the weak efficiency. However, in our analysis, we have opted for leaving the standard errors uncorrected.

The main limitation of the above defined framework is the necessity of the assumptions about the distribution of standard errors. In contrast to the ADCCX model introduced by Vargas (2008), ADCCE model by Li (2011) and ADCCEX model by Kleinbrod & Li (2017), the GDCCX model does not allow for asymmetry, which is another significant limitation that calls for further extension of the model. Moreover, the estimation process is extremely time-demanding and necessitates significant computational resources. As a result, analyzing vari-

[7] The method is implemented in the `numDeriv` R package by Gilbert & Varadhan (2019).

ous scenarios and market pairs is not as flexible as it would be when employing the co-exceedance measures within the quantile regression framework. Naturally, the validity of any statements regarding the effects of geopolitical risk measures on the pair correlations will depend on the accuracy of model specification, therefore, this limitations poses a formidable problem. An alternative approach could be for instance following the Antonakakis *et al.* (2017b) and using the bivariate VAR unrestricted BEKK-GARCH(1,1) model including the geopolitical risk index in the construction of the mean, variances and covariance matrices, or using any type of a simple multivariate GARCH model and then regressing the estimated conditional correlations on the geopolitical risk measures as in Narayan *et al.* (2018a). However, these approaches do not precisely correspond to what we wanted to achieve with our model and we harbor some reservations about their theoretical foundation.

4.3 Return Co-Exceedances and Quantile Regression

The co-exceedance measure by Baur & Schulze (2005) has emerged as a valuable tool for measuring financial contagion and has become a well established framework in both applied financial econometric work and statistical theory. By capturing the joint occurrence of extreme events, it provides insights into the interdependence and co-movements among financial assets during times of market stress and offers a quantitative framework to assess the dynamics of spillover effects. This way, it can help to identify potential sources of systemic risk and provide insight into the nature and magnitude of financial contagion. This section therefore aims to introduce the co-exceedance measure and establish the quantile regression framework, which will serve for its further analysis.

We will construct the co-exceedances measure according to the specification by Baur & Schulze (2005) as

$$C_{i,j;t} = C_t(\boldsymbol{r}_i, \boldsymbol{r}_j) = \begin{cases} \min(r_{i,t}, r_{j,t}) & \text{if } r_{i,t} > 0 \wedge r_{j,t} > 0 \\ \max(r_{i,t}, r_{j,t}) & \text{if } r_{i,t} < 0 \wedge r_{j,t} < 0 \\ 0 & \text{otherwise,} \end{cases} \tag{4.10}$$

where $r_{j,t}$ is a return in the originator's of contagion market and $r_{i,t}$ is a return in another given market i on a day t. The co-exceedances will be computed for all possible market pairs by using the unfiltered standardized returns and could be interpreted as extreme movements shared by markets i and j. If for example $C_t(\boldsymbol{r}_i, \boldsymbol{r}_j) = 5\%$, rates of returns for markets i and j at time t are at least 5 standard deviations above their mean. Since our dataset contains 10 different stock markets and 6 different foreign exchange markets, we will compute co-exceedance measures for 45 stock market pairs and 15 foreign exchange market pairs.

As it follows from the equation 4.10, if the returns are independently and identically distributed, zero return co-exceedances are expected to occur in about 50% of cases. This could lead to convergence problems during the estimation procedure, therefore, we will follow the approach of Lyócsa & Horvath (2018) and replace 0 value with a random number taken from a uniform distribution between -0.0001 and 0.0001.

Furthermore, we will follow the approach by Baur & Schulze (2005) and Lyócsa & Horvath (2018) and study the market return co-exceedances within the quantile regression framework. This choice of framework allows us to analyze the occurrence, the degree and the evolution of return co-exceedances over time. In addition, since it has essentially a non-parametric specification, it does not require any ex-ante specification of the distribution of co-exceedances or their conditional variance. Lastly, one of its notable advantages is its flexibility. While a quantile regression model is naturally very sensitive to the choice of control variables, it can be easily modified to accommodate different needs and specifications compared to other econometric approaches.

Let $\mathbf{C}(\boldsymbol{r}_i, \boldsymbol{r}_j)$ denote the vector of co-exceedances of length T, $\mathbf{X}$ a $T \times k$ matrix of exogenous variables and a constant, $\boldsymbol{\beta}(\tau)$ the vector of unknown parameters and finally $\boldsymbol{\epsilon}(\tau)$ the vector of disturbances. Consequently, the τ-th conditional linear quantile regression model can be specified as

$$\mathbf{C}_{i,j} = \mathbf{C}(\boldsymbol{r}_i, \boldsymbol{r}_j) = \mathbf{X}^T \boldsymbol{\beta}(\tau) + \boldsymbol{\epsilon}(\tau) \tag{4.11}$$

and assuming $Q_{\boldsymbol{\epsilon}(\tau)}(\tau|\boldsymbol{X}) = 0$, the conditional quantile of $\mathbf{C}(\boldsymbol{r}_i, \boldsymbol{r}_j)$ as

$$Q_{\mathbf{C}_{i,j}}(\tau|\boldsymbol{X}) = \mathbf{X}^T \boldsymbol{\beta}(\tau). \tag{4.12}$$

Taking all values of $\tau \in [0, 1]$ allows for obtaining the entire distribution of $\mathbf{C}_{i,j}$ given $\boldsymbol{X}$.

Our model specification for stock market and foreign exchange market return co-exceedances builds on that of Baur & Schulze (2005) and Lyócsa & Horvath (2018) and is defined as

$$\begin{aligned} Q_{\mathbf{C}_{i,j}}(\tau|\boldsymbol{X}) = \beta_0(\tau) &+ \beta_1(\tau)\Delta\log(GPR_t) + \beta_2(\tau)r_{MSCI,t} \\ &+ \beta_3(\tau)\Delta US10_t + \beta_4(\tau)r_{OIL,t} + \beta_5(\tau)r_{GOLD,t} \\ &+ \beta_6(\tau)\Delta VIX_t + \beta_7(\tau)C_{t-1}(\boldsymbol{r}_i,\boldsymbol{r}_j), \end{aligned} \tag{4.13}$$

where $r_{MSCI,t}, r_{OIL,t}, r_{GOLD,t}$ are respectively the daily continuous returns computed from MSCI World index prices, oil ICE Brent Crude prices and gold XAU prices. Moreover, $\Delta US10_t$ are daily changes in market yields on 10Y US treasury securities and ΔVIX_t are daily changes in the VIX index. In addition, $\Delta\log(GPR_t)$ are the 1-day lagged daily changes in the logged geopolitical risk index or an alternative geopolitical risk measure[8] and $C_{t-1}(\boldsymbol{r}_i,\boldsymbol{r}_j)$ is the lagged co-exceedance measure between stocks i and j to account for the persistence of co-exceedances.

The control variables $r_{MSCI,t}, \Delta US10_t, r_{OIL,t}, r_{GOLD,t}$ and ΔVIX_t have been selected to represent the main global factors that can potentially influence the structure and degree of co-exceedances between stock markets. This choice aligns with the previous research employing the quantile regression framework on return co-exceedances, such as Baur & Schulze (2005) and Lyócsa & Horvath (2018) and is more thoroughly described and explained in Chapter 3. Moreover, we have decided to employ the same global factors as key drivers also for return co-exceedances between the regional foreign exchange markets. While acknowledging the potential benefit of incorporating local control variables, for the sake of simplicity, we assume that the CEE countries are significantly impacted by global trends and have experienced the effects of globalization. This decision is based on the premise that the CEE countries are relatively integrated into the global economy, and the impact of global events and trends on their financial markets is substantial. Nonetheless, future research could explore the inclusion of local control variables to further refine and enhance the understanding of the unique regional dynamics in response to geopolitical risk.

The coefficient β_1 for changes in geopolitical risk gives information about the changes in the dependence during increased geopolitical risk. Since the re-

[8]the 1-day lagged daily changes in the logged geopolitical acts index $\Delta\log(GPA_t)$ or the logged geopolitical threats index $\Delta\log(GPT_t)$

sults of these previous studies suggest that contagion is primarily a left-tail-specific event, we would expect to detect contagion when the coefficient β_1 is significantly negative at lower quantiles, after controlling for these fundamental control variables that explain stock or foreign exchange market co-movements. This would imply that heightened geopolitical risk is amplifying the occurrence of extreme negative co-movements between these markets, potentially causing a contagion effect. This concept is also in line with the definitions of financial contagion by Forbes & Rigobon (2002), Bae *et al.* (2003) and Baur & Schulze (2005).

As proposed by Koenker & Bassett Jr (1978), the quantile regression coefficients, alternatively the estimator $\boldsymbol{b}(\tau)$ of $\boldsymbol{\beta}(\tau)$, can be obtained by minimizing the weighted absolute deviations between co-exceedances and a liner combination of exogenous variables as

$$\boldsymbol{b}(\tau) = \underset{\beta(\tau)\in\mathbb{R}^k}{\arg\min}\left\{ \sum_{t:C_{i,j;t}\geq \boldsymbol{x}_t^T\boldsymbol{\beta}(\tau)} \tau|C_{i,j;t} - \boldsymbol{x}_t^T\boldsymbol{\beta}(\tau)| + \sum_{t:C_{i,j;t}< \boldsymbol{x}_t^T\boldsymbol{\beta}(\tau)} (1-\tau)|C_{i,j;t} - \boldsymbol{x}_t^T\boldsymbol{\beta}(\tau)| \right\}, \tag{4.14}$$

where $\boldsymbol{x}_t^T$ for $t = 1, 2, \ldots, T$ denotes a vector of k exogenous variables.

The solution of the minimization problem requires an iterative estimator, transforming it into a linear programming problem, which can be solved by algorithm described in Koenker & D'Orey (1987) and Koenker & d'Orey (1994). To derive estimates of the standard errors of the quantile regression coefficients, we will employ bootstrapping with 500 replications, which is a widely recognized technique in the literature. Bootstrapping is performed using the Markov chain marginal bootstrap by He & Hu (2002) and Kocherginsky *et al.* (2005). Nevertheless, we have experimented with different bootstrapping methods and the results were largely identical. Moreover, under a set of regularity conditions, Buchinsky (1998) demonstrates that the quantile regression estimator $\boldsymbol{b}(\tau)$ is consistent and asymptotically normally distributed

$$\sqrt{T}\Big(\boldsymbol{b}(\tau) - \boldsymbol{\beta}(\tau)\Big) \overset{as.}{\sim} N\Big(0, \boldsymbol{H}^{-1}\boldsymbol{G}\boldsymbol{H}^{-1}\Big),$$

with $\boldsymbol{H} = E[f_\tau(0|\boldsymbol{x}_t)\boldsymbol{x}_t\boldsymbol{x}_t']$, $\boldsymbol{G} = \tau(1-\tau)E[\boldsymbol{x}_t\boldsymbol{x}_t']$ and f_τ being the density of disturbances $\epsilon(\tau)$. However, since quantile regression is among the most well-established econometric frameworks and is extensively covered in the literature, we refer the reader to the work by Buchinsky (1998) for further details.

4.4 Wavelet coherence

In order to compare our results with the burgeoning literature that applies the wavelet coherence analysis to examine the impacts of geopolitical risk measures on different types of investments, we will also incorporate this framework into our analysis[9]. Such studies include for instance Bhuiyan *et al.* (2018), Al-Yahyaee *et al.* (2019), Aloui & Hamida (2021), Su *et al.* (2019), Będowska-Sójka *et al.* (2022), Singh *et al.* (2022b) or Cheng *et al.* (2022). The main advantage of using this type of framework is that it offers a flexible and comprehensive approach to explore the time-frequency relationship and detect co-movements between two time series and hence, provides valuable insights into their dynamics and interactions. In addition, as highlighted by Roueff & Von Sachs (2011) and Su *et al.* (2019), it permits the examination of non-stationary series, so certain data transformations can be omitted. Therefore, to facilitate a more straightforward interpretation of our results, we will apply the wavelets directly on the oil, gold, the ECO index and the GPR index prices. This section aims to briefly explain the theoretical concepts of wavelet coherence framework. For more detailed theoretical explanation, we refer the reader to Farge (1992), Hudgins *et al.* (1993), Torrence & Compo (1998) and Aguiar-Conraria & Soares (2014) among others.

The application of continuous wavelet transforms to time series is used to achieve data similarity and divide them into wavelets.

Definition 4.1. A function $\psi(t) \in L^2(\mathbb{R})$ is called a *mother wavelet* (*admissible* or *analyzing*) if it satisfies the *admissibility condition*

$$0 < C_\psi := \int_{-\infty}^{\infty} \frac{|\psi(\omega)|}{|\omega|} d\omega < \infty, \tag{4.15}$$

where C_ψ is a constant called the *admissibility constant*, Farge (1992).

This condition ensures that the energy of the origin function $x(t)$ is preserved by the wavelet transform and it can be always recovered. Moreover, in our analysis, we will always consider ϕ being a *Morlet* mother wavelet that

[9] The analysis will be conducted using the `biwavelet` `R` package by Gouhier *et al.* (2021).

uses a Gaussian-modulated plane wave and is given by

$$\psi_{\omega_0}(t) = Ke^{i\omega_0 t}e^{-\frac{t^2}{2}},$$

where ω_0 is a non-dimensional frequency that satisfies the admissibility condition defined in 4.1.

By scaling and translating the mother wavelet function $\psi(t)$, we can obtain a family of wavelet daughters $\psi_{\tau,s}$ as

$$\psi_{\tau,s} := \frac{1}{\sqrt{|s|}}\psi\Big(\frac{t-\tau}{s}\Big), \quad \tau, s \in \mathbb{R}, s \neq 0, \tag{4.16}$$

where s is a scaling factor controlling the width of the wavelet and τ is a translation parameter that shifts the wavelet's position in time.

Finally, let $x(t) \in L^2(\mathbb{R})$ be a time series of interest. Then according to Aguiar-Conraria & Soares (2014), its continuous wavelet transform with respect to the wavelet ψ is given by

$$W_{x,\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\Big(\frac{t-\tau}{s}\Big)dt, \quad \tau, s \in \mathrm{R}, s \neq 0, \tag{4.17}$$

where τ, s denote time and scale respectively that specify the position of the wavelet W_x in the time and frequency domains.

As we will always consider two time series, one of the asset i and the second of a geopolitical risk measure, the corresponding *cross-wavelet transform* of time series $x(t)$ and $y(t)$ can be defined as

$$W_{xy,\psi}(\tau, s) = W_{x,\psi}(\tau, s)W^*_{y,\psi}(\tau, s) \tag{4.18}$$

and can be interpreted similarly to the local covariance measure as it identifies areas in specific time and frequency domains, where series exhibit co-movement. The definition was first introduced by Hudgins *et al.* (1993) and has been since widely applied by the academics.

Furthermore, the relative strength of the dependency can be expressed by computing the *wavelet coherence* as

$$R_{xy}(\tau, s) = \frac{|S\Big(W_{xy,\psi}(\tau, s)\Big)|}{\sqrt{S\Big(|W_{x,\psi}(\tau, s)|^2\Big)S\Big(|W_{y,\psi}(\tau, s)|^2\Big)}} \in [0, 1], \tag{4.19}$$

where $S(\cdot)$ denotes a smoothing operator in both time τ and scale s.

Since the wavelet function $\psi(t)$ and hence the continuous wavelet transform $W_{xy,\psi}(\tau, s)$ are complex functions, the cross-wavelet transform can be divided into the real part $Re(\cdot)$ and imaginary part $Im(\cdot)$. Following Farge (1992), the *phase-differences* can be then defined as

$$\phi(x, y) = \tan^{-1} \frac{Im(W_{xy,\psi}(\tau, s))}{Re(W_{xy,\psi}(\tau, s))} \in [-\pi, \pi]. \tag{4.20}$$

As described in Aguiar-Conraria & Soares (2014), $\phi(x, y) = 0$ indicates a perfect co-movement of time series x and y at the specific time-frequency. Moreover, for a specific time-frequency, we can distinguish 4 other cases:

- $\phi(x, y) \in \Big(-\pi, -\frac{\pi}{2}\Big)$: the series move out-of-phase, with x leading,
- $\phi(x, y) \in \Big(-\frac{\pi}{2}, 0\Big)$: the series move in-phase, with y leading,
- $\phi(x, y) \in \Big(0, \frac{\pi}{2}\Big)$: the series move in-phase, with x leading,
- $\phi(x, y) \in \Big(\frac{\pi}{2}, \pi\Big)$: the series move out-of-phase, with y leading.

In our analysis, we will use the above outline framework to study the relationship between geopolitical risk measures and gold, oil and the ECO index prices, as well as the connection between the GPR and VIX indices.

Chapter 5

Results

5.1 Effects of geopolitical risk on different financial assets

This section presents the main findings from univariate GARCH models and wavelet coherence analyses that were used to study the effects of geopolitical risk measures on oil, gold and the clean energy ECO index returns.

5.1.1 Univariate GARCH

Table 5.1 presents the estimation results of univariate GARCH models for gold, oil and the ECO index returns based on the model specification and selection process proposed in Chapter 4.1. We should highlight that to provide more detailed insights, all estimates of the δ or ζ coefficients for geopolitical risk measures have been scaled by a factor of 1,000. To examine the potential difference of effects that each of these three geopolitical risk measures (GPR, GPA and GPT) have on the mean return and volatility of each of the three assets, we have constructed a separate model for each of the measures.

For gold, the best results were achieved by the choice of an asymmetric E-GARCH model with t-distributed innovations and by including the exogenous variable only in the mean equation. All the estimated coefficients are strongly statistically significant and the results of the diagnostic tests confirm the adequacy of the ARMA and the ARCH fit. Based on these results, we can observe that the estimates of the coefficient δ are positive and statistically significant. Therefore, the findings would suggest that regardless of a choice of a geopolitical risk measure, geopolitical risk has a positive impact on the mean gold returns, although the effect is very small in magnitude. These findings align with Baur & Smales (2018), who concluded that the GPR and GPT indices have a positive effect on gold returns and no significant impacts on their volatility. While their findings indicate that the GPA index does not significantly influence gold returns, our results do not support this conclusion. Nonetheless, it is evident that the coefficient δ for the GPA index returns is comparatively smaller when compared to estimated coefficients for the other two measures of geopolitical risk. The results further corroborate the findings by Baur & Smales (2020), Triki & Ben Maatoug (2021) and Będowska-Sójka *et al.* (2022) that gold exhibits a hedging or even a safe haven[1] property against geopolitical tensions. This property is in the literature often linked to the negative effects of increased geopolitical tensions on general financial uncertainty and oil prices volatility. As Triki & Ben Maatoug (2021) highlight, gold's tangibility and independence from counter-parties' debts and solvency provide reassurance to investors and make it a reliable hedge against stock market fluctuations. This concept, along with gold's safe-haven characteristic for stock markets, has been further explored in several other studies including Hillier *et al.* (2006), Baur & McDermott (2010) and Akbar *et al.* (2019). In addition, Tiwari *et al.* (2020) addresses and provides evidence for gold's safe haven status related to the oil market. As we have already explored, there is a consensus in the literature that oil volatility increases as a reaction to increased geopolitical risk, which could prompt investors to consider gold as a hedge. Additionally, the authors assert that geopolitical risk mostly has a negative effect on the dependence structure between gold and oil, which further supports this notion.

For oil, the best results were also achieved by the choice of an asymmetric E-GARCH model with t-distributed innovations and by including the exogenous variable again only in the mean equation. The estimated coefficients are mostly strongly statistically significant and the results of the diagnostic tests confirm the adequacy of the ARMA and the ARCH fit. Notably, the estimates of the coefficient δ showed consistently positive effect of geopolitical risk measures on the mean oil returns, regardless of the type of geopolitical risk measure. However, when considering the GPT index, the coefficient was statistically insignificant and we did not find any statistically significant effect on the volatility of oil prices or returns. These findings differ from the previ-

[1]Baur & Smales (2020) defines a *safe haven* asset as one whose returns exhibits either no or positive correlation with changes in geopolitical risk during extreme geopolitical crises, whereas a *hedge* asset is characterized by the lack of correlation or positive correlation of its returns with geopolitical risk on average.

ous literature, including Liu *et al.* (2019), Demirer *et al.* (2019), Cunado *et al.* (2020) or Smales (2021), that recognizes a substantial impact of heightened geopolitical risk on the volatility of oil returns, leading to an increase in their volatility. While we could argue that the difference in results stems from differences in econometric frameworks and sample periods, given the strong consensus in the literature on these effects, it is crucial to acknowledge that our model is considerably simplified compared to other models employed in the literature.

Lastly, for the clean energy ECO index, the best results were achieved by the choice of an asymmetric GJR-GARCH model with t-distributed innovation. Based on the results, we are unable to confirm any statistically significant effects of geopolitical risk measures on either returns or volatility of the clean energy index ECO. These findings are not in line with the theoretical reasoning by Yang *et al.* (2021), Sohag *et al.* (2022a) or Dutta & Dutta (2022) that since geopolitical risk can drive crude oil prices higher and crude oil and renewable energy exhibit characteristics of being close substitutes, their prices and hence returns should be increased as well. Conversely, negative impacts could be explained by the fact that the stock market for renewable energy can be affected by its connections to other financial markets like stocks, exchange rates, and commodities, which suffer drawbacks due to higher geopolitical risk and uncertainty[2]. However, the absence of statistically significant effects on the ECO returns and volatility and, consequently, the disparity from previous findings could be attributed to various factors, such as differences in the methodological approach or the sample used in the analysis. Furthermore, we argue that previous studies may have overlooked the fact that in addition to the observed increase in geopolitical risk in the recent period, it is crucial to consider the concurrent introduction of numerous environmental regulations and their critical role in shaping the renewable energy landscape. As a consequence, the prior literature might have quickly attributed certain observed trends to geopolitical risk rather than considering the potential influence of these regulations.

5.1.2 Wavelet coherence analysis

The contour plots of cross-wavelet coherences along with the corresponding phase differences between three different measures of geopolitical risk and three assets under consideration, are shown in Figure 5.1, 5.2 and 5.3. Each figure

[2]The dependency between these markets was examined for instance by Wu *et al.* (2020).

	Gold			Oil			Clean Energy		
	GPR	GPA	GPT	GPR	GPA	GPT	GPR	GPA	GPT
Model	eGARCH	eGARCH	eGARCH	eGARCH	eGARCH	eGARCH	gjrGARCH	gjrGARCH	gjrGARCH
Optimal parameter estimates									
μ	0.0002***	0.0003***	0.0003***	0.0005***	0.0006***	0.0005***	-	-	-
ar_1	-	-	-	-0.042***	-0.041***	-0.042***	0.414***	0.411***	0.418***
ma_1	-	-	-	-	-	-	-0.346**	-0.343**	-0.349**
$\boldsymbol{\delta}$	**0.755*** **	**0.386*** **	**0.510*** **	**1.505*** **	**0.921*** **	**0.634**	**-0.241**	**-0.072**	**-0.234**
ω	-0.095***	-0.093***	-0.095***	-0.092***	-0.091***	-0.092***	0.000005	0.000005***	0.000005***
α_1	0.036***	0.035***	0.036***	-0.043***	-0.043***	-0.043***	0.045***	0.045***	0.046***
β_1	0.990***	0.990***	0.990***	0.988***	0.988***	0.988***	0.914***	0.914***	0.914***
γ_1	0.113***	0.113***	0.114	0.134***	0.133***	0.134***	0.060***	0.060***	0.058***
$\boldsymbol{\zeta}$	-	-	-	-	-	-	-	-	-
shape	4.966***	4.968***	4.978***	6.344***	6.357***	6.340***	12.84***	12.82***	12.68***
Information Criteria									
AIC	-6.528	-6.527	-6.5274	-4.968	-4.968	-4.967	-5.151	-5.151	-5.151
BIC	-6.520	-6.520	-6.520	-4.959	-4.959	-4.958	-5.142	-5.142	-5.141

Table 5.1: **Univariate GARCH estimations**: The table presents the estimation results of Univariate GARCH models for gold, oil and ECO returns. The parameters $\boldsymbol{\delta}$ and $\boldsymbol{\zeta}$ represent the effects of the daily changes in a particular geopolitical risk measure and their estimates are multiplied by 1,000. Significance at 10%, 5% and 1% levels are denoted resp. by *, ** and *** superscripts. Type of a GARCH model is specified at the top and the AIC and BIC information criteria are presented at the bottom of the table.

corresponds to one of the assets - gold, oil and the clean energy ECO index. In the figures, warm, red colors with a black outline indicate statistical significance at 5%, while a lack of coherence is indicated by cold, blue colors.

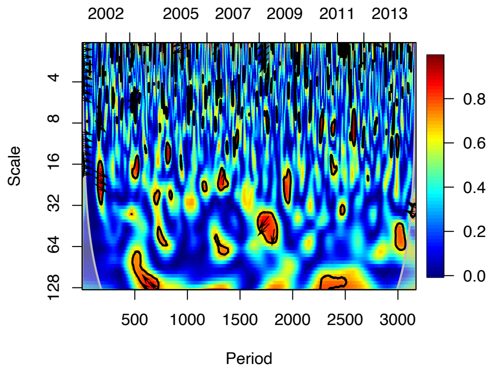
Furthermore, following the practical guide by Torrence & Compo (1998), when significant and substantial coherence is observed, the black arrows denote phase differences. Arrows oriented towards the left indicate negative correlation or *out-of-phase* relationship between the series, while right-oriented arrows signify a positive correlation or *in-phase* relationship. Additionally, downward-oriented arrows signify a temporal precedence of the second series over the first, while upward-oriented arrows indicate the opposite, suggesting that the first series leads the second. In our analysis, the first series consistently corresponds to the examined assets (gold, oil and the clean energy ECO index prices), while the second series corresponds to the geopolitical risk measures (the GPR, GPA and GPT indices). Lastly, the time dimension is represented along the horizontal axis and the frequency or scale dimension portrayed along the vertical axis, while the U-shaped grey curve and corresponding shaded areas show the *cone of influence*, where the edge effects are significant.

When examining the relationship between gold and the geopolitical risk measures using wavelet coherence analysis, our findings show that there are only a few specific small regions where the coherence is statistically significant. One notable region is detected in 2003, coinciding with the beginning of the Iraq war, specifically at higher frequencies around the 64-128 days band. This out-of-phase coherence with all three measures of geopolitical risk suggests that the gold-GPR, gold-GPA and gold-GPT pairs co-moved in opposite directions. This aligns with the market developments wherein gold prices experienced a sharp decline between February and April, followed by a subsequent rise, while geopolitical risk reached its peak in March following the invasion and then underwent a sharp decline. Another significant out-of-phase coherence is observed between gold and the GPR and GPT indices in early 2008. Based on the figure 5.1f, the relationship is stronger with GPT, even though the index remained relatively stable during this period. Conversely, gold prices exhibited a notable surge, followed by a sharp decline. In addition, a similar pattern can be observed around spring and summer of 2020. During this time, the GPT index experienced a decline from its peak in February 2020, while the gold prices were on the rise. In July, the situation reversed as the markets faced escalated risk associated with the threats of adverse geopolitical events, while gold prices began to fall. These findings also strongly support the use of wavelet analysis as an effective framework for capturing co-movement trends and presenting them in a visually appealing manner that can be easily interpreted. More recently, we can observe a short-term out-of-phase coherence with GPR and GPT measures in the 8-16 days band around the onset of 2022. This would indicate that gold prices experienced a declining trend following the increasing tensions between Russia and Ukraine, which continued even after the outburst of the Russian-Ukrainian war in March of 2022. On the other hand, shortly before the end of 2021, we can observe a short-term in-phase coherence. This occurrence can be attributed to the continuous upward trajectory of gold prices since 2018, despite the sudden and significant increase in the GPR index due to Ukrainian-Russian tensions. Consequently, it highlights the potential advantages of including gold in investment portfolios, as it demonstrated resilience to recent geopolitical tensions. Furthermore, for the majority of the time and frequency intervals analyzed, the coherence between gold and the geopolitical risk measures is not statistically significant, suggesting that their relationship is relatively weak or nonexistent in those regions and emphasizes the importance of gold as an asset protector. Overall, the presented findings also indicate that the GPA index generally lacks a strong relationship with gold prices, and heightened geopolitical threats are effectively incorporated into the GPT index. As a result, this underlines the importance of analyzing and utilizing the components of geopolitical risk separately for a more comprehensive understanding. Importantly, the findings mostly align with the previous literature like Będowska-Sójka *et al.* (2022), Baur & Smales (2020), Triki & Ben Maatoug (2021), offering supportive evidence that gold can serve as an effective hedging and diversifying tool against geopolitical risk for short-term investors. However, it is worth noting that during periods of extreme geopolitical tensions, gold may not always shield long-term investors from potential losses.

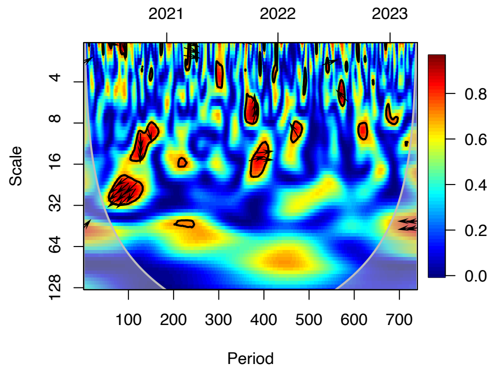
For oil, a significant in-phase coherence is observed with the GPA index in the 8-32 days band around the end of 2021, coinciding with the escalation of tensions between Ukraine and Russia. This indicates a rise in oil prices with an increasing GPA index, which aligns with the observed market behaviour and is in line with the prevailing consensus in the literature (see, *inter alia*, Bouoiyour *et al.* (2019), Su *et al.* (2019), Lee *et al.* (2021), Smales (2021) and Będowska-Sójka *et al.* (2022)). Following the outbreak of the war in early 2022, we can see a weakly significant coherence between oil prices and all measures of geopolitical risk across the 16-128 days band. Nevertheless, based exclusively on the figure 5.2b, we are unable to determine the direction of the effect, so we can only assume that it would follow a similar trend. In addition, on the figure 5.2e, we can see that there is a significant in-phase coherence with the GPT index around 64-128 days band and the beginning of 2003 when the Iraq war began. Moreover, the upward pointing arrows indicate that oil prices was the leading time series and we know that before the war, there has been a persistent increasing trend in oil prices since 2001. However, even though some studies, including Escribano & Valdes (2017), examine the perspective that governments often view crude oil as a political tool and in the particular case of the Iraq war, Iraq's vast oil reserves are one of the factors often cited as a motivating factor for the invasion, we will definitely refrain from drawing such strong conclusions solely based on the observed co-movements. Right after the invasion, there was a strong out-of-phase coherence in middle frequencies around 8-32 days band which can be attributed to the significant decrease in oil prices between February and April when the market was concerned that the invasion could potentially lead to a global conflict and disrupt oil supply chains. Subsequently, as oil prices returned to an increasing trend, this contributed to the observed co-movement pattern in the high frequency. Lastly, figures 5.2a, 5.2c and 5.2e show also a significant in-phase coherence in 2008 and in the 32-128 days band. As mentioned by Joo *et al.* (2020), prior to the Global financial crises of 2008, oil prices experienced a sharp increase driven by China's growing demand and then since July 2008, witnessed a dramatic decline. Given that the GFC did not trigger a substantial increase in the geopolitical risk, as it primarily led to heightened financial uncertainty not geopolitical, we cannot offer an economic rationale for this observation. In general, the presented results of wavelet coherence analysis between the oil prices and geopolitical risk indices strongly align with the previous literature, which has consistently shown that geopolitical risk significantly affects oil market and has the ability to drive oil prices higher. Unlike Bouoiyour *et al.* (2019), we discover a relationship between oil prices and the GPA index, however, we acknowledge that the relationship between oil and geopolitical risk is contingent on the specific categories involved.

For the clean energy ECO index prices, we can observe a strong in-phase coherence with all three geopolitical risk indices around the 32 days band in the beginning of 2014, when the Russian military invasion and annexation of the Crimean Peninsula occurred. Since both Russia and Ukraine are important oil producers, his event had profound implications on the crude oil market and consequently, through the substitution channel, clean energy equity prices might have increased as a result. The downward-pointing arrows in sub-figure 5.3c support this reasoning and indicate that GPA was leading, hence the effect was indeed created by the actual realization of adverse geopolitical events. This finding also aligns with the previous literature such as Yang *et al.* (2021), Rasoulinezhad *et al.* (2020), Lee *et al.* (2021) and Song *et al.* (2019) that this is likely driven by the effects on the crude oil supply chain and the subsequent rise in prices. In addition, we see a strong out-of-phase coherence with the GPA index surrounding the end of 2016 around the 32 band. This observation indicates that the geopolitical risk indices and the ECO prices moved in reverse directions and could be connected to an increased volatility in the GPA index due to geopolitical events such as the Russian interference in the U.S. Presidential Election and election of Donald Trump, the Brexit Referendum, North Korea's several missile and nuclear tests or the ongoing Syrian and Russo-Ukrainian conflicts. There were no significant spikes in the ECO prices during this period, despite an observed increase in their volatility. Nonetheless, the effect is generally small and since none of the previous studies specifically focused on their time-frequency relationship during this particular period of time, it cannot be conclusively considered in direct contrast to any previous conclusions. In regards to the most recent period, our findings, shown on figures 5.3b, 5.3d and 5.3f, replicate those of Będowska-Sójka *et al.* (2022) and indicate a quick out-of-phase coherence by the end of the first half of 2021. In addition, the results are expanded to the subsequent period, revealing a comparable coherence following the beginning of the war in 2022. However, this finding appears to be driven mostly by the increased geopolitical risk and subsequent short-term decline in the ECO prices. In general, across the majority of the time and frequency intervals analyzed, the coherence between ECO and the geopolitical risk measures lacks statistical significance, indicating a relatively weak or nonexistent relationship in those regions. This supports our findings from the univariate GARCH model and the conclusion of Będowska-Sójka *et al.* (2022) about the resilience of green investments to geopolitical tensions.

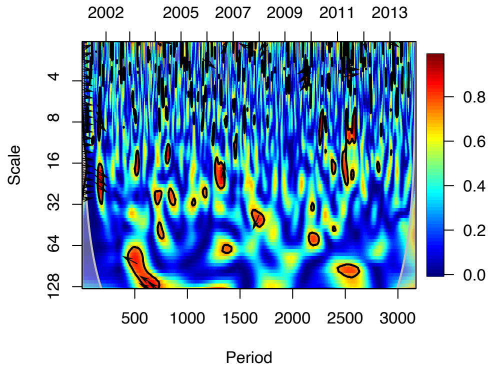
Overall, the results show that the examined coherences are rather short-lived and their phase tends to change over time and across frequencies, indicating both fast and long-term the responses. It is also interesting to observe how the coherences differ when considering various measures of geopolitical risk and the findings suggest that for effective risk management, it is essential to monitor all three measures to adequately address potential impacts of geopolitical risk. Although, major effects are visible also when solely focusing on the GPR index.



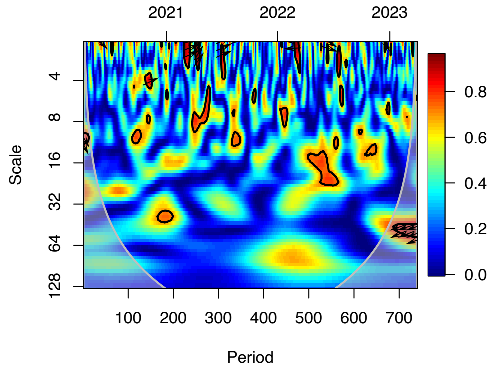
(a) Gold vs. GPR



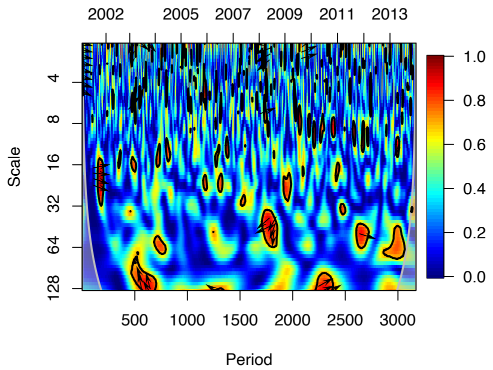
(b) Gold vs. GPR



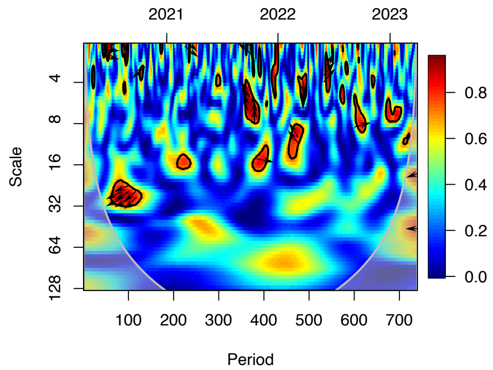
(c) Gold vs. GPA



(d) Gold vs. GPA

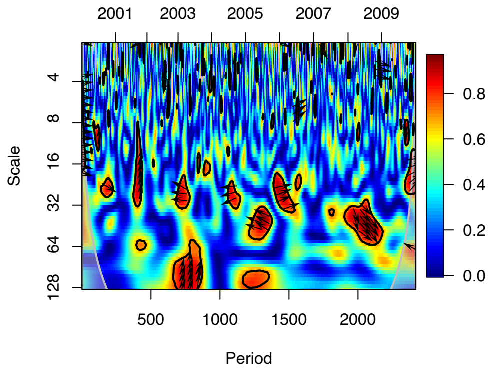


(e) Gold vs. GPT

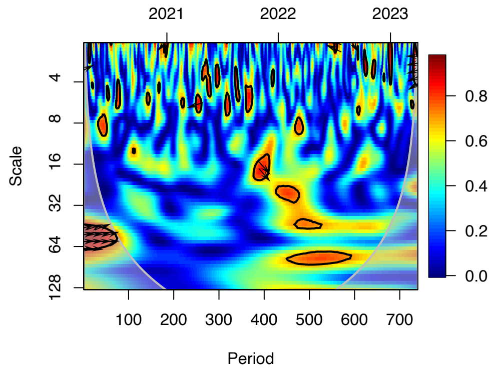


(f) Gold vs. GPT

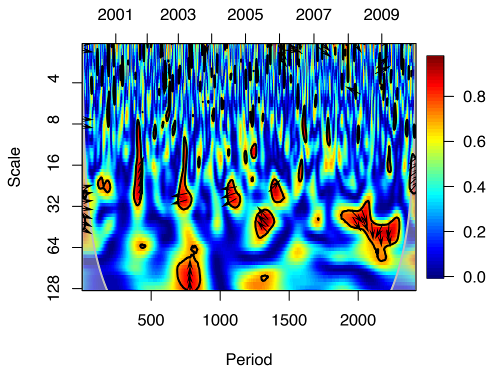
Figure 5.1: **Wavelet Coherence: Gold vs. Geopolitical Risk Indices**: The figure displays the results of wavelet coherence analysis between gold prices and the three geopolitical risk measures GPR, GPA and GPT. The analysis was made on two different samples, one covering the period between years 2001 and 2014 (on the left side) and the other between March, 2020 and March, 2023 (on the right).



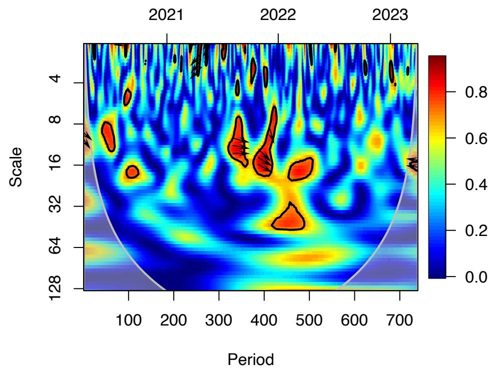
(a) Oil vs. GPR



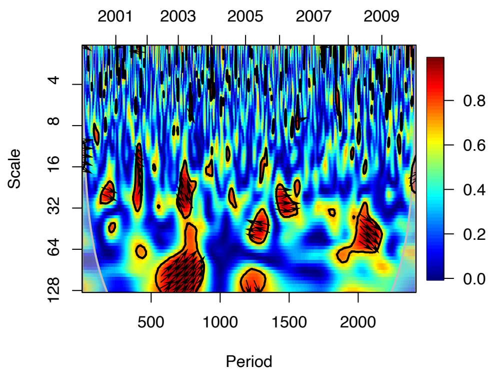
(b) Oil vs. GPR



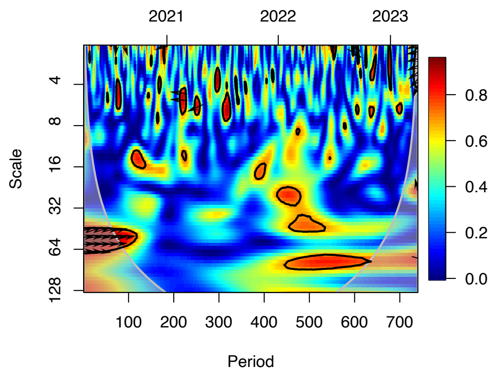
(c) Oil vs. GPA



(d) Oil vs. GPA

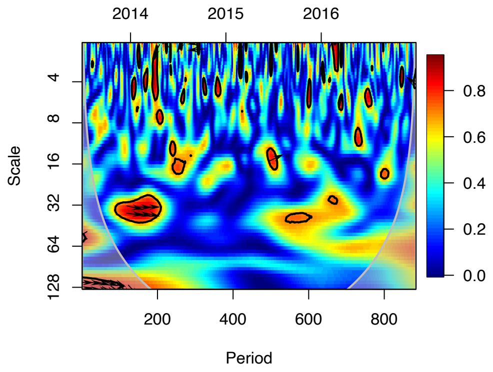


(e) Oil vs. GPT

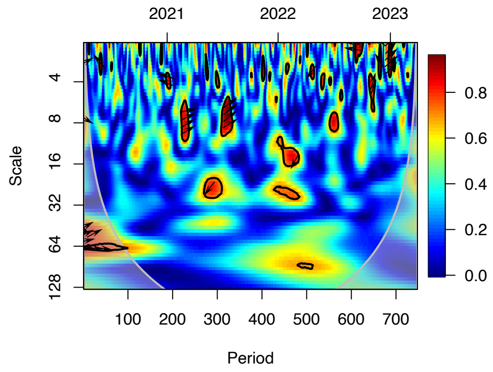


(f) Oil vs. GPT

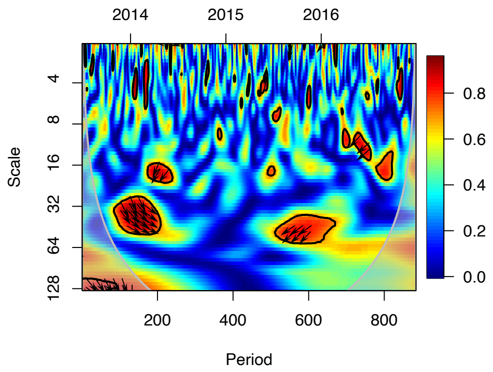
Figure 5.2: **Wavelet Coherence: Oil vs Geopolitical Risk Indices**: The figure displays the results of wavelet coherence analysis between times series of oil prices and the time series of three geopolitical risk measures GPR, GPA and GPT. The analysis was made on two different samples, one covering the period between years 2000 and 2009 (on the left side) and the other between March, 2020 and March, 2023 (on the right).



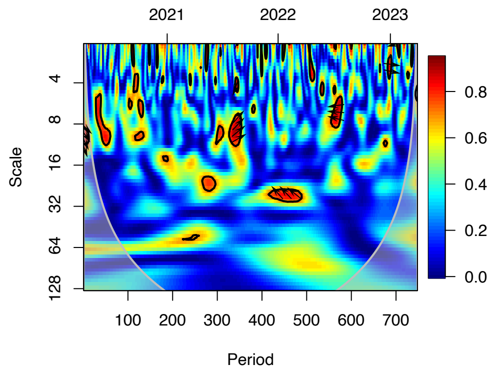
(a) Clean Energy vs. GPR



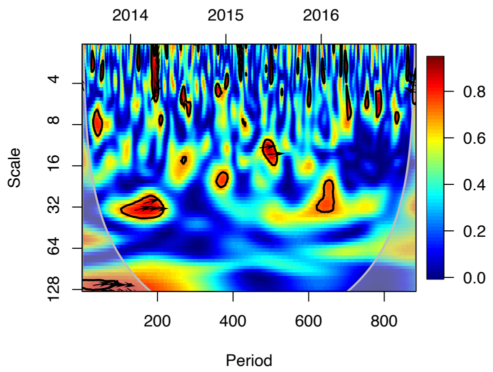
(b) Clean Energy vs. GPR



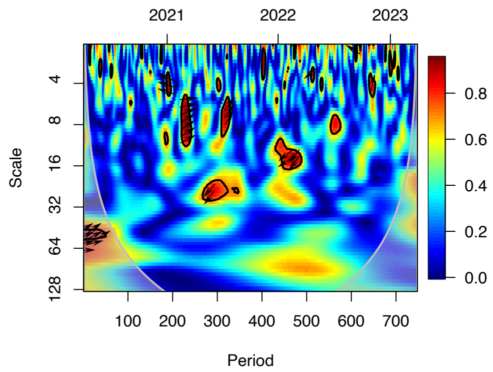
(c) Clean Energy vs. GPA



(d) Clean Energy vs. GPA



(e) Clean Energy vs. GPT



(f) Clean Energy vs. GPT

Figure 5.3: **Wavelet Coherence: Clean Energy Index vs. Geopolitical Risk Indices**: The figure displays the results of wavelet coherence analysis between times series of ECO prices and the time series of three daily geopolitical risk measures GPR, GPA and GPT. The analysis was made on two different samples, one covering the period between June 2013 and December 2016 (on the left side) and the other between March 2020 and March 2023 (on the right).

5.2 Effects on return co-movements

This section presents the main results of quantile regressions for return co-exceedances based on standardized returns and the GDCCX-GARCH models for selected stock and foreign exchange market pairs.

5.2.1 Return Co-Exceedances and Quantile Regression

Tables 5.2 and 5.3 present the descriptive statistics for return co-exceedances of stock market pairs and foreign market pairs respectively. As can be seen, the computed stock market return co-exceedances exhibit the same typical characteristics as their underlying continuous returns, specifically, negative skewness and high excess kurtosis. This implies that there is a higher occurrence of joint extreme negative shocks within the examined time period than extreme positive shocks. On the other hand, return co-exceedances for several foreign exchange pairs did not preserve the typical positive skewness observed for foreign exchange returns, and exhibit negative skewness. To name a few, USD/CZK-USD/BGN, USD/CZK-USD/EUR, USD/HUF-USD/BGN, USD/HUF-USD/EUR and USD/BGN-USD/EUR among others share this property. Unsurprisingly, the highest positive and negative joint co-movement occurred between the country pairs that exhibit the highest unconditional correlation such as the US-DE, US-UK, US-CA, DE-UK and UK-CA pairs.

Stock market pairs

Table 5.4 presents the estimates of $\beta_1(\tau)$ coefficient for logarithmic returns of the geopolitical risk index $\Delta\log(\text{GPR})$ for selected quantiles τ, multiplied by 10, using the quantile regressions based on the computed stock market return co-exceedances. The table does not contain results for all 45 stock market pairs, rather for a selected sample, where the coefficient for $\Delta\log(\text{GPR})$ was statistically and economically significant at least for one quantile[3].

As can be seen, for a number of stock market pairs, including for instance US-DE, US-UK, US-SA, CN-JP, CN-DE, CN-IN, CN-UK, CN-CA, DE-UK, DE-MX, DE-IL, UK-CA, UK-MX, UK-IL and IL-SA, the coefficient $\beta_1(\tau)$ is statistically significant primarily within the upper quantiles and mostly negative. With the exception of the DE-UK and CN-JP pairs, the common characteristic between these coun-

[3]For the purposes of transparency, the results of the QR models for all stock market and foreign exchange market pairs are included in supplementary data file for this thesis.

Pair	Mean	SD	Skew	Kurt	Min	Max	**Pair**	Mean	SD	Skew	Kurt	Min	Max
US-CN	-0.01	0.32	-1.25	21.08	-3.65	2.62	DE-IN	0.00	0.50	-1.19	18.01	-6.06	4.13
US-JP	-0.01	0.46	-0.52	20.59	-4.74	4.65	DE-UK	-0.02	0.79	-0.78	15.25	-9.32	7.40
US-DE	0.00	0.70	-0.67	25.13	-9.32	7.59	DE-CA	-0.01	0.66	-1.09	28.28	-9.32	7.40
US-IN	0.00	0.46	-1.49	24.78	-6.06	4.13	DE-MX	-0.02	0.58	-0.42	17.04	-4.73	7.01
US-UK	-0.02	0.69	-1.42	27.82	-9.42	7.84	DE-IL	-0.01	0.57	-0.62	12.82	-5.32	5.34
US-CA	-0.03	0.80	-1.52	25.90	-9.42	8.52	DE-SA	0.01	0.39	-1.68	37.18	-5.91	3.87
US-MX	-0.02	0.64	-0.73	16.87	-6.09	7.01	IN-UK	-0.01	0.51	-1.32	18.73	-6.06	3.78
US-IL	-0.01	0.52	-1.00	19.01	-5.45	5.34	IN-CA	0.00	0.50	-1.54	24.08	-6.06	4.13
US-SA	0.01	0.39	-2.53	42.10	-6.09	3.87	IN-MX	-0.01	0.47	-0.87	15.91	-3.95	4.13
CN-JP	-0.01	0.36	-0.99	16.40	-3.47	3.21	IN-IL	-0.01	0.45	-0.96	13.31	-4.19	2.81
CN-DE	0.00	0.33	-0.72	16.44	-3.45	2.71	IN-SA	0.01	0.38	-1.92	30.77	-4.75	3.87
CN-IN	-0.01	0.35	-0.99	19.14	-4.10	3.21	UK-CA	-0.02	0.67	-1.92	35.65	-10.44	7.84
CN-UK	-0.01	0.33	-0.76	17.89	-4.10	2.71	UK-MX	-0.03	0.57	-0.86	12.21	-4.73	3.33
CN-CA	-0.01	0.33	-1.18	17.57	-3.16	2.37	UK-IL	-0.02	0.56	-0.60	13.17	-5.32	5.34
CN-MX	-0.01	0.32	-1.02	18.62	-4.26	2.71	UK-SA	0.01	0.40	-3.14	57.52	-7.42	3.13
CN-IL	-0.01	0.30	-0.77	13.54	-2.84	1.89	CA-MX	-0.02	0.64	-0.71	17.62	-6.32	6.85
CN-SA	0.00	0.31	-2.72	35.67	-4.10	2.19	CA-IL	-0.02	0.52	-0.91	19.01	-5.45	5.34
JP-DE	-0.01	0.50	-0.39	13.46	-3.51	4.65	CA-SA	0.01	0.39	-2.62	42.05	-6.09	3.87
JP-IN	0.00	0.49	-0.66	15.13	-4.47	4.13	MX-IL	-0.02	0.48	-0.92	13.99	-4.73	3.33
JP-UK	-0.02	0.50	-0.12	16.35	-4.15	5.03	MX-SA	0.01	0.36	-1.34	27.87	-4.73	3.87
JP-CA	0.00	0.48	-0.35	21.08	-4.74	4.65	IL-SA	0.01	0.36	-1.58	25.63	-5.32	2.49
JP-MX	-0.01	0.45	-0.62	15.99	-4.74	4.19							
JP-IL	-0.02	0.45	-0.32	14.60	-3.51	4.65							
JP-SA	0.01	0.38	-1.32	22.15	-3.92	3.87							

Table 5.2: **Descriptive statistics for stock market return pair co-exceedances**: The table summarizes the descriptive statistics of the daily standardized continuous returns for stock markets in Exhibit A and for foreign exchange markets in Exhibit B. SD denotes standard deviation of the returns, Skew skewness and Kurt kurtosis.

try pairs is that although they have very strong trade and financial linkages, they are neither neighbouring countries nor located within the same geographic region. It is therefore unlikely that the geopolitical risk has increased equally in both markets within a pair. The reduced extreme positive return co-exceedances during favourable global market conditions may indicate a *flight-to-safety* ef-

Co-exceedance pair	Mean	SD	Skew	Kurt	Min	Max
USD/CZK-USD/HUF	-0.01	0.78	0.05	7.69	-5.60	5.28
USD/CZK-USD/PLN	-0.01	0.76	0.12	8.71	-5.56	5.53
USD/CZK-USD/BGN	-0.03	0.41	-0.12	5.72	-2.64	1.95
USD/CZK-USD/RON	-0.03	0.27	-0.11	8.82	-2.26	1.78
USD/CZK-USD/EUR	0.00	0.80	-0.02	5.54	-4.77	4.00
USD/HUF-USD/PLN	-0.01	0.80	0.22	9.27	-6.74	6.02
USD/HUF-USD/BGN	-0.03	0.40	-0.20	6.64	-3.36	1.95
USD/HUF-USD/RON	-0.03	0.26	-0.02	8.82	-2.26	1.78
USD/HUF-USD/EUR	-0.01	0.75	-0.03	6.29	-4.77	4.10
USD/PLN-USD/BGN	-0.03	0.39	-0.05	6.13	-2.52	2.30
USD/PLN-USD/RON	-0.03	0.27	-0.01	8.74	-2.26	1.78
USD/PLN-USD/EUR	-0.01	0.71	0.08	6.85	-4.64	4.10
USD/BGN-USD/RON	-0.03	0.26	1.02	24.50	-2.26	4.56
USD/BGN-USD/EUR	-0.03	0.43	-0.16	5.98	-3.36	1.95
USD/RON-USD/EUR	-0.03	0.27	0.01	8.58	-2.26	1.78

Table 5.3: **Descriptive statistics for foreign exchange market return co-exceedances**: The table summarizes the descriptive statistics of the daily standardized continuous returns for stock markets in Exhibit A and for foreign exchange markets in Exhibit B. SD denotes standard deviation of the returns, Skew skewness and Kurt kurtosis.

fect, where investors shift their focus to safe-haven assets and regions during times of geopolitical instability. The heightened geopolitical risk may have also led to disruptions in market connectedness, thereby suggesting that geopolitical risk has a tendency to undermine stock market integration between the mentioned market pairs. Taking an alternative perspective, numerous authors, including Greenwood-Nimmo *et al.* (2015), Antonakakis *et al.* (2017a) and Hedström *et al.* (2020), suggest the inherent sensitivity of oil-importing countries, such as China, to oil prices and the profound impacts associated with oil market spillover. As geopolitical risk affects oil volatility and increases oil prices, these markets may experience more severe effects of geopolitical risk than oil-exporting countries. Consequently, this could be another potential explanation for the decreased extreme positive co-exceedances observed between market pairs such as CN-CA, US-SA, DE-MX, UK-MX, and IL-SA. In addition, the observed decrease in extreme co-exceedances among the mentioned pairs may be attributed to heterogeneous impacts of heightened geopolitical risk on various stock markets. Drawing on the findings by Balcilar *et al.* (2018), it was found that China experiences substantial risk exposure to geopolitical risk, while India displays greater resilience to such shocks. Consequently, the decrease in their extreme positive co-exceedance aligns logically with these disparities.

In addition, for other market pairs such as US-JP, US-CA, US-MX, CN-MX, JP-CA, JP-MX, JP-SA and CA-MX, the $\beta_1(\tau)$ coefficient is positive and statistically significant in the lower quantiles, thus, increased GPR index returns decrease the size of extreme negative market co-movement. These results indicate that during adverse global market conditions, geopolitical risk does not contribute to increased financial integration or promote a contagion effect between these markets. Instead, the dominance of country-specific information allows one market within each pair to relatively outperform the other. This can indicate that during periods of heightened geopolitical risk, market behavior is influenced more by internal factors specific to each country than by the broader global geopolitical climate. These findings are in line with the results presented by Frijns *et al.* (2012), who concluded that political crises have an adverse impact on the level of financial integration. Using a different methodological framework, Sohag *et al.* (2022b) came to the same conclusion also when considering the connectedness between the US, Russia and Chinese markets. However, in our analysis, the coefficient for geopolitical risk indices for the US-CN country pair was not statistically significant at any quantile. This outcome may be attributed to several factors, such as differences in methodological approach, measure of geopolitical risk and the examination period.

Interestingly, the negative coefficient in lower $\tau = 0.05$ quantile for the IN-UK country pair implies that geopolitical risk exacerbates unfavorable market conditions in these countries. It may indicate a potential spillover or contagion effect between these highly connected financial markets since negative geopolitical shocks seem to transmit between the UK and India, amplifying the adverse market conditions in both countries. A similar effect can be observed also for the CN-UK, pair when using the GPT returns and the IN-SA, UK-IL, CA-IL and IL-SA pairs when using the GPA returns instead of GPR returns. Further investigation into the underlying mechanisms and dynamics of these spillover effects could provide valuable insights into the overall resilience and stability of their financial systems.

On the other hand, the US-MX market pair exhibits positive sensitivity to returns of all three geopolitical measures in some of the higher quantiles, implying that the extreme positive co-movement between these markets strengthens as geopolitical risk increases. This finding supports the common view that investors tend to lump countries within a particular geographic region together and perceive them as similar, regardless of potential disparities in their economic fundamentals. Although, the effect is not consistent across all higher quantiles and we do not observe the same effect on a the UK-DE pair, where the impact of increased geopolitical risk on the return co-exceedances is opposite to that of the US-MX pair. As a result, we strongly recommend conducting further investigations into the dynamics of this market pair and we will delve into studying their conditional correlations using a GDCCX GARCH model later in this chapter.

In addition, Tables 5.5 and 5.6 present the same results as Table 5.4, but taking into consideration changes in logged geopolitical acts index $\Delta \log(\text{GPA})$ or in logged geopolitical threats index $\Delta \log(\text{GPT})$ instead of $\Delta \log(\text{GPR})$. The results indicate that the effects of geopolitical risk are mostly consistent regardless of the choice of a geopolitical risk measure.

However, for a number of market pairs, the effects of geopolitical risk index on their return co-exceedances remain statistically insignificant. Furthermore, with a few exceptions, neither market pair shows a positive sensitivity to GPR returns at higher quantiles or a a negative sensitivity to GPR returns at lower quantiles. Consequently, geopolitical risk does not generally enhance financial integration between examined market pairs. These findings complement the results of Balcilar *et al.* (2016), who did not find any substantial evidence supporting significant cross-border effects of terror attacks on stock-market volatility and Hedström *et al.* (2020), who found no significant impact of geopolitical risk index on return or volatility spillovers among the examined markets that include also the Czech Republic, China, US, Japan and Europe.

τ	0.01	0.05	0.1	0.25	0.75	0.9	0.95	0.99
US-JP	-0.88	**0.76***	**0.58*****	**0.24****	0.22	0.24	-0.06	-1.53
US-DE	1.34	0.09	-0.01	0.08	0.17	-0.30	**-0.75****	**-1.78****
US-UK	-1.38	0.03	-0.21	0.13	-0.08	**-0.60****	-0.56	**-2.17****
US-CA	**2.94***	0.46	0.17	-0.00	0.02	-0.03	-0.24	-0.13
US-MX	-0.28	-0.28	**0.48***	**0.39****	**0.30***	0.28	0.19	2.26
US-SA	-0.78	0.22	0.05	0.03	-0.01	**-0.50****	**-0.82****	-0.27
CN-JP	0.46	0.71	0.31	0.11	**-0.16***	**-0.45****	-0.47	-0.81
CN-DE	-1.03	0.05	0.01	0.03	**-0.19****	-0.04	-0.03	**2.10***
CN-IN	0.67	-0.07	-0.14	0.03	-0.15	**-0.50***	-0.28	-0.35
CN-UK	0.86	-0.31	0.06	-0.07	**-0.19****	-0.25	-0.48	1.07
CN-CA	-0.73	-0.03	-0.04	-0.06	**-0.19***	**-0.43****	-0.08	0.58
CN-MX	**1.62****	0.41	0.32	0.06	-0.05	0.29	0.15	-0.89
JP-CA	-0.69	0.50	**0.66*****	**0.23***	0.06	-0.14	0.37	**1.87***
JP-MX	-1.22	0.02	0.21	**0.19***	0.24	-0.05	-0.05	0.60
JP-SA	-0.02	0.03	-0.10	**0.13***	0.21	-0.14	0.00	2.19
DE-UK	-1.52	-0.35	0.14	**-0.41****	-0.23	**-0.66***	**-1.34*****	-1.57
DE-MX	-0.80	-0.45	0.15	**0.31****	0.05	**-0.44****	**-0.73****	-1.39
DE-IL	-1.32	0.27	-0.38	-0.04	**-0.28***	-0.43	**-1.05****	**-3.53****
IN-UK	-0.57	**-0.88****	-0.22	-0.18	-0.10	-0.35	-0.67	-0.93
UK-CA	-1.96	0.07	0.05	-0.20	-0.06	-0.07	**-0.55***	**-1.55***
UK-MX	-0.31	-0.14	-0.09	0.05	-0.16	**-0.50****	**-1.39*****	**-2.08****
UK-IL	-0.62	-0.08	-0.28	-0.24	**-0.35****	-0.43	-0.68	**-3.84*****
UK-SA	0.18	0.32	-0.01	0.05	-0.07	-0.37	**-0.70****	-1.81
CA-MX	1.34	0.10	**0.70*****	**0.34****	0.01	-0.11	-0.24	0.82
IL-SA	0.50	0.12	0.07	-0.04	-0.12	-0.29	**-0.70***	**-1.58***

Table 5.4: **Quantile regression estimates for $\Delta \log(GPR)$ coefficient**: The table presents the estimates of $\beta_1(\tau)$ coefficient for changes in the logged geopolitical risk index $\Delta \log(GPR)$ in a model for stock market co-exceedances defined in equation 4.13 for selected quantiles τ, multiplied by 10. Significance at 10%, 5% and 1% levels are denoted by *, ** and *** superscripts, respectively.

τ	0.01	0.05	0.1	0.25	0.75	0.9	0.95	0.99
US-CN	-0.16	0.04	-0.05	-0.00	**-0.11***	-0.06	-0.37	-0.67
US-JP	-0.54	0.36	**0.36****	**0.18****	**0.16***	0.07	-0.18	-0.96
US-IN	-0.63	-0.07	-0.02	0.04	**-0.16***	-0.10	-0.13	-0.99
US-MX	1.38	0.11	**0.35****	**0.21****	0.14	-0.05	-0.03	**1.68***
US-IL	-0.49	-0.30	-0.00	-0.08	**-0.16***	**-0.26***	-0.25	-0.50
US-SA	-1.08	-0.16	-0.14	-0.06	-0.04	**-0.30***	**-0.46****	-0.91
CN-JP	-0.59	**0.48***	**0.38***	**0.11****	0.01	-0.09	-0.24	0.18
CN-DE	-0.01	**0.36***	0.21	0.05	**-0.10***	-0.14	-0.33	-0.28
CN-CA	-1.09	-0.05	-0.03	-0.03	**-0.11***	-0.24	-0.20	-0.15
CN-MX	0.04	0.08	**0.32****	0.02	-0.04	0.11	-0.00	-0.81
CN-SA	0.56	-0.31	-0.14	-0.00	-0.02	**-0.22***	-0.28	0.61
JP-DE	0.66	0.09	0.22	**0.24*****	0.11	-0.22	-0.14	-0.80
JP-MX	-0.59	0.23	**0.33****	**0.22*****	**0.20***	0.03	0.03	-1.09
JP-IL	0.73	0.34	0.23	**0.19****	0.01	0.14	-0.14	-0.16
JP-SA	-0.01	-0.12	-0.00	0.07	**0.15****	0.06	0.09	1.32
DE-IN	-0.77	-0.05	-0.18	0.04	0.01	-0.14	-0.26	**-1.56****
DE-CA	-0.66	0.11	0.02	0.05	0.01	-0.14	**-0.52****	-0.91
DE-MX	0.57	0.02	0.17	**0.23****	0.07	-0.12	-0.49	-0.28
DE-IL	-0.95	0.24	-0.14	0.01	-0.10	-0.19	**-0.73****	**-2.15****
IN-CA	-1.20	-0.20	-0.10	-0.06	-0.01	-0.08	-0.12	**-1.87****
IN-SA	**-2.20*****	-0.38	-0.19	0.05	-0.03	-0.15	-0.23	-1.40
UK-CA	-1.98	0.00	0.10	-0.10	0.06	-0.04	-0.28	**-1.34***
UK-MX	0.07	0.10	0.01	0.11	-0.10	-0.08	**-0.64****	-1.11
UK-IL	**-1.63***	-0.14	-0.29	-0.07	-0.06	-0.00	0.00	-1.91
UK-SA	-0.39	0.07	0.02	-0.00	-0.01	-0.25	-0.32	**-2.30****
CA-MX	0.34	-0.10	**0.34***	0.16	0.04	-0.02	-0.12	0.83
CA-IL	-0.68	**-0.53****	-0.20	-0.12	**-0.19****	-0.21	0.05	**-1.66***
CA-SA	-1.18	-0.17	-0.05	-0.08	-0.01	-0.17	**-0.48****	-0.08
IL-SA	**-2.04***	-0.04	0.06	-0.06	-0.06	-0.20	**-0.46***	**-1.88****

Table 5.5: **Quantile regression estimates for $\Delta \log(GPA)$ coefficient**: The table presents the estimates of $\beta_1(\tau)$ coefficient for changes in the logged geopolitical acts index $\Delta \log(GPA)$ in a model for stock market co-exceedances defined in equation 4.13 for selected quantiles τ, multiplied by 10. Significance at 10%, 5% and 1% levels are denoted by *, ** and *** superscripts, respectively.

τ	0.01	0.05	0.1	0.25	0.75	0.9	0.95	0.99
US-JP	-0.37	**0.57***	**0.52*****	**0.23****	0.07	0.02	-0.07	**-1.59***
US-DE	1.37	0.05	-0.06	0.01	0.15	-0.16	-0.36	**-1.23****
US-UK	-0.45	0.17	-0.07	0.18	-0.02	-0.28	-0.44	**-1.89*****
US-MX	-0.34	-0.31	0.30	**0.26****	0.14	**0.39***	0.43	0.57
US-IL	0.78	0.04	0.25	0.09	-0.00	-0.25	-0.46	**-1.48***
US-SA	0.92	0.43	0.23	0.08	0.03	**-0.45****	-0.37	0.51
CN-JP	1.23	0.41	-0.06	0.05	**-0.15***	**-0.47****	**-0.59****	-0.48
CN-DE	0.50	-0.20	-0.12	-0.02	**-0.13***	-0.14	0.06	**1.16***
CN-IN	0.93	-0.17	-0.22	0.04	-0.11	**-0.46****	-0.50	-0.23
CN-UK	1.14	**-0.50***	-0.12	-0.05	-0.08	-0.20	-0.42	0.70
CN-CA	-0.68	-0.34	-0.19	0.01	-0.08	**-0.33****	-0.31	1.06
CN-MX	**1.67****	0.30	0.03	0.06	-0.01	0.04	0.28	0.00
JP-DE	-0.57	0.03	0.19	-0.04	**-0.18***	-0.14	-0.05	0.00
JP-UK	-0.09	-0.56	-0.05	-0.06	-0.14	-0.20	**-0.80****	-0.23
JP-CA	-0.73	0.13	**0.57*****	**0.21****	-0.01	-0.07	0.08	0.89
JP-IL	-0.12	0.14	0.15	**0.17***	-0.09	-0.01	-0.52	-0.39
JP-SA	0.68	0.30	0.00	0.08	0.06	**-0.36***	-0.39	**2.39***
DE-UK	-0.08	0.37	0.29	-0.14	-0.14	**-0.48***	**-0.88****	**-1.81***
DE-MX	-0.01	-0.29	0.29	0.19	0.09	**-0.32***	-0.52	-1.01
DE-IL	-1.06	0.45	-0.19	0.04	-0.20	**-0.36****	-0.56	-1.35
IN-UK	-0.34	**-0.65****	-0.00	-0.07	0.01	-0.22	-0.44	-0.32
IN-SA	2.30	**0.83****	**0.51****	**0.10****	-0.08	0.01	-0.06	0.06
UK-CA	-0.92	**0.41***	0.18	-0.09	-0.03	-0.04	**-0.47***	-0.86
UK-MX	-0.28	-0.01	0.11	-0.03	0.02	-0.29	**-0.57***	**-1.53***
UK-IL	-0.08	0.42	0.11	-0.09	-0.18	**-0.47****	**-0.63***	**-2.28****
CA-MX	0.51	0.19	**0.58*****	**0.28***	0.03	-0.03	-0.07	0.48
CA-IL	0.02	0.43	0.28	0.11	0.03	-0.15	0.09	**-1.67***
CA-SA	1.02	**0.50***	0.22	0.09	0.08	-0.17	-0.18	0.41
MX-SA	1.84	0.21	0.23	0.06	0.05	-0.06	**0.55***	0.39
IL-SA	**2.11****	0.17	0.06	-0.01	-0.04	-0.22	-0.38	-0.16

Table 5.6: **Quantile regression estimates for $\Delta \log(GPT)$ coefficient**: The table presents the estimates of $\beta_1(\tau)$ coefficient for changes in the logged geopolitical threats index $\Delta \log(GPT)$ in a model for stock market return co-exceedances defined in equation 4.13 for selected quantiles τ, multiplied by 10. Significance at 10%, 5% and 1% levels are denoted by *, ** and *** superscripts, respectively.

Foreign exchange market pairs

The estimates of $\beta_1(\tau)$ coefficient for logarithmic returns of the geopolitical risk index $\Delta\log(\text{GPR})$ in the quantile regression model for foreign exchange return co-exceedances are presented in Table 5.7. The estimates are again multiplied by 10 and presented for 8 selected quantiles τ. As it becomes evident from the results, changes in geopolitical risk index do not, in general, significantly influence the foreign exchange co-exceedances in the CEE region. The statistically significant positive coefficients in the lowest quantile $\tau = 0.01$ for a number of pairs suggest that during unfavorable market conditions, geopolitical risk does not enhance financial integration between these markets. On the contrary,

τ	0.01	0.05	0.1	0.25	0.75	0.9	0.95	0.99
USD/CZK-USD/HUF	1.33	**0.83***	0.21	0.20	-0.13	-0.18	-0.36	-2.12
USD/CZK-USD/PLN	1.18	0.09	0.06	0.05	-0.17	0.30	0.38	-1.44
USD/CZK-USD/BGN	**1.81*****	0.30	0.31	0.10	0.09	-0.05	0.30	-0.40
USD/CZK-USD/RON	0.61	0.17	0.16	0.02	-0.01	0.15	-0.01	0.66
USD/CZK-USD/EUR	**3.58*****	0.43	0.02	0.27	-0.16	0.59	-0.07	1.09
USD/HUF-USD/PLN	1.77	**0.77***	0.41	0.15	-0.04	0.06	0.30	-1.74
USD/HUF-USD/BGN	**2.04*****	**0.49***	0.23	0.11	-0.07	-0.03	-0.09	-0.14
USD/HUF-USD/RON	**0.96*****	0.32	0.20	0.06	-0.01	0.06	-0.10	0.39
USD/HUF-USD/EUR	**3.03*****	0.79	**0.59***	0.27	0.01	0.24	-0.49	-0.75
USD/PLN-USD/BGN	**1.89*****	**0.53****	0.13	-0.09	-0.05	-0.19	0.05	0.29
USD/PLN-USD/RON	**0.84*****	0.19	0.02	0.00	-0.04	0.08	-0.02	0.83
USD/PLN-USD/EUR	**2.04*****	0.30	0.11	-0.08	0.00	0.08	0.41	-0.42
USD/BGN-USD/RON	**0.75*****	0.23	0.16	-0.02	-0.01	0.05	-0.06	0.66
USD/BGN-USD/EUR	**1.97*****	**0.76****	**0.43****	-0.03	0.14	-0.02	0.28	-0.19
USD/RON-USD/EUR	0.63	**0.38****	0.11	-0.01	0.01	-0.00	-0.16	0.83

Table 5.7: **Quantile regression estimates for $\Delta\log(GPR)$ coefficient**: The table presents the estimates of $\beta_1(\tau)$ coefficient for changes in the logged geopolitical risk index $\Delta\log(\text{GPR})$ in a model for foreign exchange return co-exceedances defined in equation 4.13, for selected quantiles τ, multiplied by 10. Significance at 10%, 5% and 1% levels are denoted by *, ** and *** superscripts, respectively.

it appears that when geopolitical risk is heightened, one of the markets in the pair is often gaining relative to the second one.

The effects of geopolitical risk are driven mostly by threats of adverse geopolitical events, since the results remain consistent when using the GPT index instead of the GPR index. However, when considering changes in GPA index instead, the coefficients $\beta_1(\tau)$ become statistically insignificant for all quantiles except $\tau = 0.25$, which becomes consequently more challenging to generally interpret from an economic standpoint. Nevertheless, based on our findings, we can conclude that the positive effect in lower quantiles is the most significant for the USD/CZK-USD/RON, USD/HUF-USD/BGN, USD/HUF-USD/EUR

τ	0.01	0.05	0.1	0.25	0.75	0.9	0.95	0.99
USD/CZK-USD/HUF	0.38	-0.03	-0.10	0.16	0.09	-0.08	0.06	-1.06
USD/CZK-USD/PLN	-0.63	-0.35	-0.15	0.16	-0.08	-0.14	0.26	-1.28
USD/CZK-USD/BGN	0.73	-0.07	0.12	**0.18****	0.05	-0.19	0.06	-0.04
USD/CZK-USD/RON	-0.22	-0.06	0.13	0.08	0.02	0.11	0.15	0.33
USD/CZK-USD/EUR	1.01	-0.46	-0.24	0.24	0.01	0.29	0.07	0.94
USD/HUF-USD/PLN	0.03	0.11	0.16	0.11	0.09	-0.03	0.28	-0.23
USD/HUF-USD/BGN	0.70	0.08	-0.01	**0.17***	0.04	-0.06	-0.06	-0.05
USD/HUF-USD/RON	0.04	0.06	0.18	0.07	0.05	0.09	0.14	0.48
USD/HUF-USD/EUR	0.71	0.01	0.25	**0.32***	0.16	-0.24	-0.29	-0.01
USD/PLN-USD/BGN	0.28	-0.02	-0.05	0.07	-0.02	-0.07	-0.00	0.58
USD/PLN-USD/RON	0.14	0.02	0.06	0.06	0.02	0.08	0.08	0.62
USD/PLN-USD/EUR	-0.25	-0.11	0.02	0.09	0.00	-0.15	0.29	0.14
USD/BGN-USD/RON	0.16	0.01	0.08	0.06	0.02	0.08	0.05	0.36
USD/BGN-USD/EUR	0.63	0.00	0.10	0.06	0.07	-0.08	0.15	0.20
USD/RON-USD/EUR	0.02	0.10	0.09	0.08	0.01	0.07	0.14	0.47

Table 5.8: **Quantile regression estimates for $\Delta \log(GPA)$ coefficient**: The table presents the estimates of $\beta_1(\tau)$ coefficient for changes in the logged geopolitical acts index $\Delta \log(GPA)$ in a model for foreign exchange market return co-exceedances for selected quantiles τ, multiplied by 10. The corresponding model is defined in equation 4.13. Significance at 10%, 5% and 1% levels are denoted by *, ** and *** superscripts, respectively.

pairs, which could indicate that country-specific information holds considerable influence in shaping market behavior in these countries. The presence of strong internal factors suggests that investors in these markets are more responsive to local monetary policy, market conditions and events, rather than solely reacting to changes in the geopolitical risk environment. These findings also suggest that global investors do not homogenize the considered markets simply because they belong to the same geographic region. Instead, they seem to acknowledge and recognize the distinct characteristics and differences among these countries.

τ	0.01	0.05	0.1	0.25	0.75	0.9	0.95	0.99
USD/CZK-USD/HUF	1.33	**0.83***	0.21	0.20	-0.13	-0.18	-0.36	-2.12
USD/CZK-USD/PLN	1.18	0.09	0.06	0.05	-0.17	0.30	0.38	-1.44
USD/CZK-USD/BGN	**1.81*****	0.30	0.31	0.10	0.09	-0.05	0.30	-0.40
USD/CZK-USD/RON	0.61	0.17	0.16	0.02	-0.01	0.15	-0.01	0.66
USD/CZK-USD/EUR	**3.58*****	0.43	0.02	0.27	-0.16	0.59	-0.07	1.09
USD/HUF-USD/PLN	1.77	0.77	0.41	0.15	-0.04	0.06	0.30	-1.74
USD/HUF-USD/BGN	**2.04*****	**0.49***	0.23	0.11	-0.07	-0.03	-0.09	-0.14
USD/HUF-USD/RON	**0.96*****	**0.32***	0.20	0.06	-0.01	0.06	-0.10	0.39
USD/HUF-USD/EUR	**3.03*****	0.79	**0.59***	0.27	0.01	0.24	-0.49	-0.75
USD/PLN-USD/BGN	**1.89*****	**0.53****	0.13	-0.09	-0.05	-0.19	0.05	0.29
USD/PLN-USD/RON	**0.84*****	0.19	0.02	0.00	-0.04	0.08	-0.02	0.83
USD/PLN-USD/EUR	2.04	0.30	0.11	-0.08	0.00	0.08	0.41	-0.42
USD/BGN-USD/RON	**0.75*****	0.23	0.16	-0.02	-0.01	0.05	-0.06	0.66
USD/BGN-USD/EUR	**1.97*****	**0.76****	**0.43****	-0.03	0.14	-0.02	0.28	-0.19
USD/RON-USD/EUR	0.63	**0.38****	0.11	-0.01	0.01	-0.00	-0.16	0.83

Table 5.9: **Quantile regression estimates for $\Delta\log(GPT)$ coefficient**: The table presents the estimates of $\beta_1(\tau)$ coefficient for changes in the logged geopolitical threats index $\Delta\log(GPT)$ in a model for foreign exchange market return co-exceedances for selected quantiles τ, multiplied by 10. The corresponding model is defined in equation 4.13. Significance at 10%, 5% and 1% levels are denoted by *, ** and *** superscripts, respectively.

5.2.2 GDCCX-GARCH model

This section presents results of GDCCX-GARCH models for selected stock market pairs pairs, where the effects of geopolitical risk measures on return co-exceedances were the most significant. To be specific, these pairs include US-MX, US-SA, US-JP, CN-DE, CN-JP, DE-UK, DE-IL, IL-SA, CN-CA and DE-MX and the estimation results are presented in Table 5.11. Additionally, the test of non-constant correlation by Engle & Sheppard (2001) rejects the null hypothesis of constant correlations for the CN-JP, DE-UK and DE-MX pairs. This indicates that these market pairs exhibit varying correlations over time, raising the need for further investigation and analysis and emphasizes the relevance of including them in this supplementary analysis.

In the table, the exhibit A presents the estimated coefficients of univariate GARCH models for all stock market series. Acknowledging that it possibly might lead to some minor losses of accuracy, we have decided to employ the same simplified univariate model specification for all ten markets. The model specification assumes normally distributed innovations $\epsilon_{i,t}$ and utilized an ARMA(0,0,0) model with zero mean, combined with either a GJR-GARCH(1,1) or a E-GARCH(1,1). Nevertheless, based on BIC, this model specification proves even to be optimal for the majority of markets series, except Canada and Mexico, where a higher-order ARMA model would be more suitable.

When we turn our attention to the GDCCX part of the results, all estimated parameters are statistically significant at 1% significance level except the persistence parameters a and b for the US-SA pair. Generally, the extremely significant persistence, as evident from the high estimates of the *dcc* b coefficients, aligns well with our theoretical expectations and overall, the estimates of the DCC parameters a and b, very close to the estimates obtained from the simple DCC model. Interestingly, the coefficient c for the changes in logged geopolitical risk index $\Delta \log(GPR_t)$ is positive for the US-SA, US-JP, IL-SA and CN-CA market pairs. This suggests that heightened geopolitical risk leads to and increase in the conditional correlations, and consequently, strengthens the cross-market linkages between these market pairs. These findings stand partially in contrast with the previously reported results from quantile regression for these pairs, which indicated that the GPR index returns decrease the absolute size of their co-exceedances and, thus, their extreme co-movements. Moreover, considering the US-SA and CN-CA pairs, the estimated time-varying conditional correlations $\rho_{ij,t}$ presented in Figure 5.5 suggest that this effect may be attributed to the continuously increasing conditional correlations between these markets over time, possibly suggesting progressing financial integration, and the fact that the GPR index has shown higher volatility and extreme levels in recent years. The economic explanation behind the observed positive effect for the IL-SA pair could be that the Middle East geographic region has frequently been the center of geopolitical tensions over the past two decades. As a result, these markets might share high sensitivity to geopolitical risk, as global markets often perceive them equally risky, irrespective of their individual country-specific characteristics. Consequently, when considering an extension of the definition of financial contagion by Forbes & Rigobon (2002), this observation may suggest the occurrence of a contagion effect. The positive effect of heightened geopolitical risk on their conditional correlations could imply that adverse events or shocks in one market lead to similar responses in the other, possibly amplifying the impact of geopolitical risk on both markets and heightened financial vulnerability in these markets during periods of geopolitical instability or uncertainty. In the context of the US-JP pair, the Figure 5.5 shows that their estimated dynamic conditional correlations exhibit significant volatility throughout the analyzed period. Therefore, it is challenging to link this effect directly to specific extreme peaks of geopolitical risk and a more in-depth investigation would be necessary to comprehensively understand the reasons behind this dynamic behavior. Overall, due to the scarcity of research on this topic, it is difficult to make comparisons of these findings with the existing literature.

On the other hand, the coefficient is negative for US-MX, CN-DE, CN-JP, DE-UK, DE-IL and DE-MX pairs, which would suggest that geopolitical risk weakens conditional correlations between these markets, allowing them to move in different directions. These results are consistent with the previously reported results from quantile regression for these pairs and align with the findings by Frijns *et al.* (2012) that political crises have negative effect on financial integration and Narayan *et al.* (2018b) that terrorist events lead to *flight-to-safety* effect. As mentioned before and taking into account the conclusions by Greenwood-Nimmo *et al.* (2015), Antonakakis *et al.* (2017a) and Hedström *et al.* (2020), the impacts of global geopolitical risk measures can vary depending on whether the markets operate in oil-importing or oil-exporting economies. Net oil-exporting countries benefit from higher oil prices whereas for oil-importing countries, higher oil prices imply raising domestic production costs, leading to higher prices and reduced consumption. Given that oil prices tend to rise with heightened geopolitical risk, the return co-movement between country pairs like US-

MX, DE-UK, DE-IL and DE-MX could potentially decrease. These insights underscore the importance of considering the oil-importing and oil-exporting statuses of countries when examining the effects of geopolitical risk on market co-movements and call for further research into the topic.

Observably, the estimated dynamic conditional correlations in the Figures 5.4, 5.5 and 5.6 suggest an opposite effect for the US-MX, DE-UK, DE-IL and DE-MX pairs, particularly evident in recent years. To further investigate this phenomenon, we have decided to re-examine the effect by focusing on a shorter period consisting of only the last 10 years. The results are presented in Table 5.10. Surprisingly, with the exception of the DE-UK pair, the coefficient for all the market pairs remain negative, failing to confirm our hypothesis. The US-MX pair's response is particularly interesting since our prior analysis showed some, albeit not robust, positive effect of geopolitical risk on their extreme positive co-exceedances. Instead, the evidence suggests that geopolitical risk has a dampening effect on the conditional correlations of these pairs. For the DE-UK pair, we can clearly observe an increase in their conditional correlations after the peaks of geopolitical risk index in January 2020 and February 2022. This observation indicates a notable connection between heightened geopolitical risk and stronger linkages between the German and UK markets during these specific periods. Moreover, the results consistently confirm the positive impact of geopolitical risk on the conditional correlations between Israel and Saudi Arabia, a relationship that persists even when analyzing the longer time period sample. Overall, in combination with the results of quantile regression that showed that the GPA index has the ability to magnify their extreme negative co-movements, we can conclude that this market pair is undoubtedly sensitive to geopolitical risk and their co-movements tend to intensify in face of heightened geopolitical risk. However, to gain a more comprehensive understanding of the interconnections between these markets, further investigation is warranted.

Nevertheless, it is also essential to address several concerns related to the model specification and estimation process. While our current analysis provides valuable insights, there are some potential limitations that warrant consideration. First of all, in order to estimate the asymptotic variance of the estimated parameters, we have computed the derivatives of the log-likelihood function $LL_c(\hat{\boldsymbol{\phi}}, \boldsymbol{\psi})$ numerically, which consequently introduces a bias to the estimation. Since we have not adopted the approach recommended by Schopen (2012) for correcting the standard errors, they do not account for the weak efficiency of the estimator and are generally underestimated. Furthermore, it should be emphasized that due to the model's demanding computational requirements and inefficiency of the solving algorithm, the adjustment of the model assumptions and parameters was limited and not flexible enough to ensure an optimal model setup. However, this approach serves primarily as a robustness check to validate our previous conclusions derived from the quantile regression estimation. Considering this, we approach the results with caution and refrain from making strong conclusions solely based on the outcomes of the GDCCX-GARCH model estimations. Moreover, by combining both approaches, we aim to mitigate any potential limitations or biases present in either model, enhancing the robustness and reliability of our analysis.

Country	US	CN	DE	UK	CA	MX	IL
Table A: Univariate GARCH estimations							
ω	0.04	0.002	-0.02	0.06	0.03	0.03	0.02
α_1	0.08	0.08	-0.18	0.01	0.03	0.07	0.09
β_1	0.78	0.93	0.94	0.77	0.78	0.82	0.83
γ_1	0.18	-0.02	0.15	0.29	0.27	0.11	0.08

Pair	US-MX	DE-UK	DE-IL	IL-SA	CN-CA	DE-MX
Table B: Multivariate GDCCX estimations						
dcc a	-0.018	-0.007	-0.006	-0.014	0.005	-0.013
dcc b	0.851	0.936	0.963	0.958	1.000	0.971
$\boldsymbol{\Delta \log(GPR_t)}$	**-0.044**	**0.047**	**-0.081**	**0.083**	**-0.076**	**-0.018**
Log likelihoods						
LL_v	-2984.8	-3321.0	-2935.7	-2746.0	-2534.3	-3048.8
LL_c	-1195.6	-833.5	-1158.8	-1382.2	-1412.4	-1298.1
Information Criteria						
AIC	1.685	1.176	1.633	1.947	1.989	1.829
BIC	1.696	1.187	1.644	1.958	2.000	1.840

Table 5.10: **Multivariate GDCCX-GARCH estimates using a sample of the last 10 years**: The table presents the estimation results for selected stock market pairs in the GDCCX model with $\Delta \log(GPR_t)$ as an exogenous variable, using a shorter sample of last 10 years. The upper Table A presents the estimates of univariate GARCH coefficients, whereas Table B in the middle part presents the dcc coefficient estimates. All coefficients are statistically significant at 1% level. Presented bellow are the computed final log likelihood functions and information criteria.

Country	US	CN	JP	DE	IN	UK	CA	MX	IL	SA
Table A: Univariate GARCH estimations										
ω	0.028	0.004	0.052	-0.003	-0.001	0.023	0.024	0.011	0.013	0.031
α_1	0.082	0.062	0.045	-0.104	-0.058	0.035	0.091	0.059	0.086	0.200
β_1	0.828	0.919	0.826	0.961	0.964	0.868	0.828	0.898	0.876	0.713
γ_1	0.120	0.037	0.145	0.193	0.258	0.138	0.117	0.068	0.049	0.173

Pair	US-MX	US-SA	US-JP	CN-DE	CN-JP	DE-UK	DE-IL	IL-SA	CN-CA	DE-MX
Table B: Multivariate GDCCX estimations										
dcc a	-0.004	-0.010	-0.012	0.011	0.010	-0.002	-0.006	-0.012	0.007	-0.006
dcc b	0.983	1.000	0.958	0.998	0.998	0.999	0.959	0.960	0.998	0.965
$\boldsymbol{\Delta} \log(\boldsymbol{GPR_t})$	**-0.033**	**0.099**	**0.072**	**-0.016**	**-0.014**	**-0.007**	**-0.019**	**0.134**	**0.024**	**-0.061**
Log likelihoods										
LL_v	-9404.0	-8430.3	-9506.3	-8688.2	-8742.3	-9612.6	-9267.3	-8245.3	-8485.9	-9668.7
LL_c	-3019.9	-3762.4	-3724.4	-3819.7	-3748.8	-2119.6	-3314.1	-3759.2	-3817.7	-3428.0
Information Criteria										
AIC	1.599	1.992	1.972	2.023	1.985	1.123	1.755	1.991	2.022	1.815
BIC	1.604	1.997	1.977	2.028	1.990	1.128	1.760	1.996	2.026	1.820

Table 5.11: **Multivariate GDCCX-GARCH estimates**: The table presents the estimation results for selected stock market pairs in the GDCCX model with $\Delta \log(GPR_t)$ as an ex. variable. The upper Table A presents the estimates of univariate GARCH coefficients, whereas Table B in the middle presents the dcc coefficient estimates. All coefficients are statistically significant at 1% level, except the *dcca* and *dccb* coefficients for the US-SA pair, which are statistically insignificant. Presented bellow are the computed final log likelihood functions and information criteria.

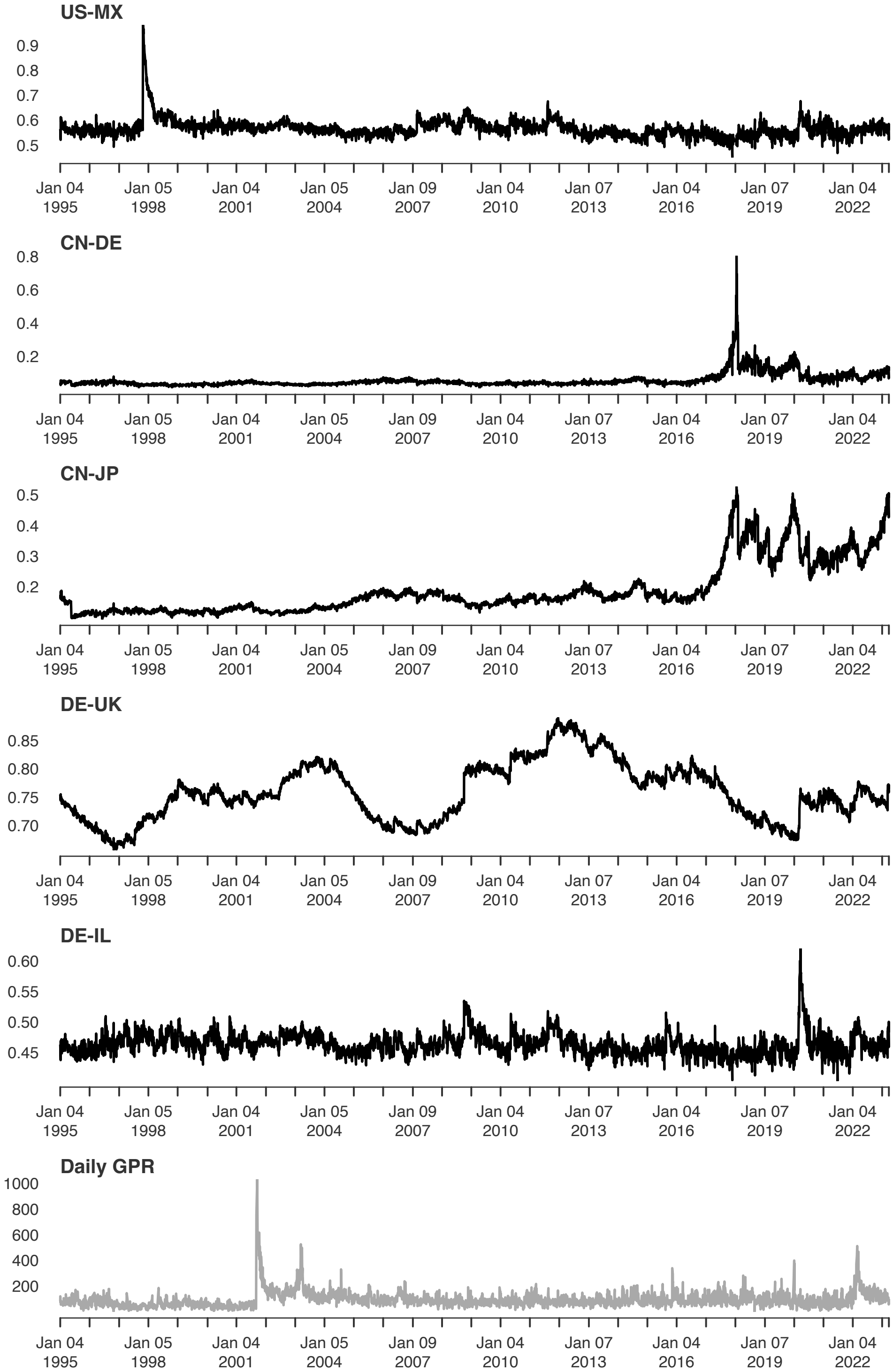


Figure 5.4: **GDCCX conditional correlations:** The figures present the first group of estimated conditional correlations from the GDCCX model specified in 4.7 and 4.8 between 5 selected country pairs, where the estimated coefficient for $\Delta \log(GPR_t)$ is positive. The last figure plots the 1-day lagged GPR index.

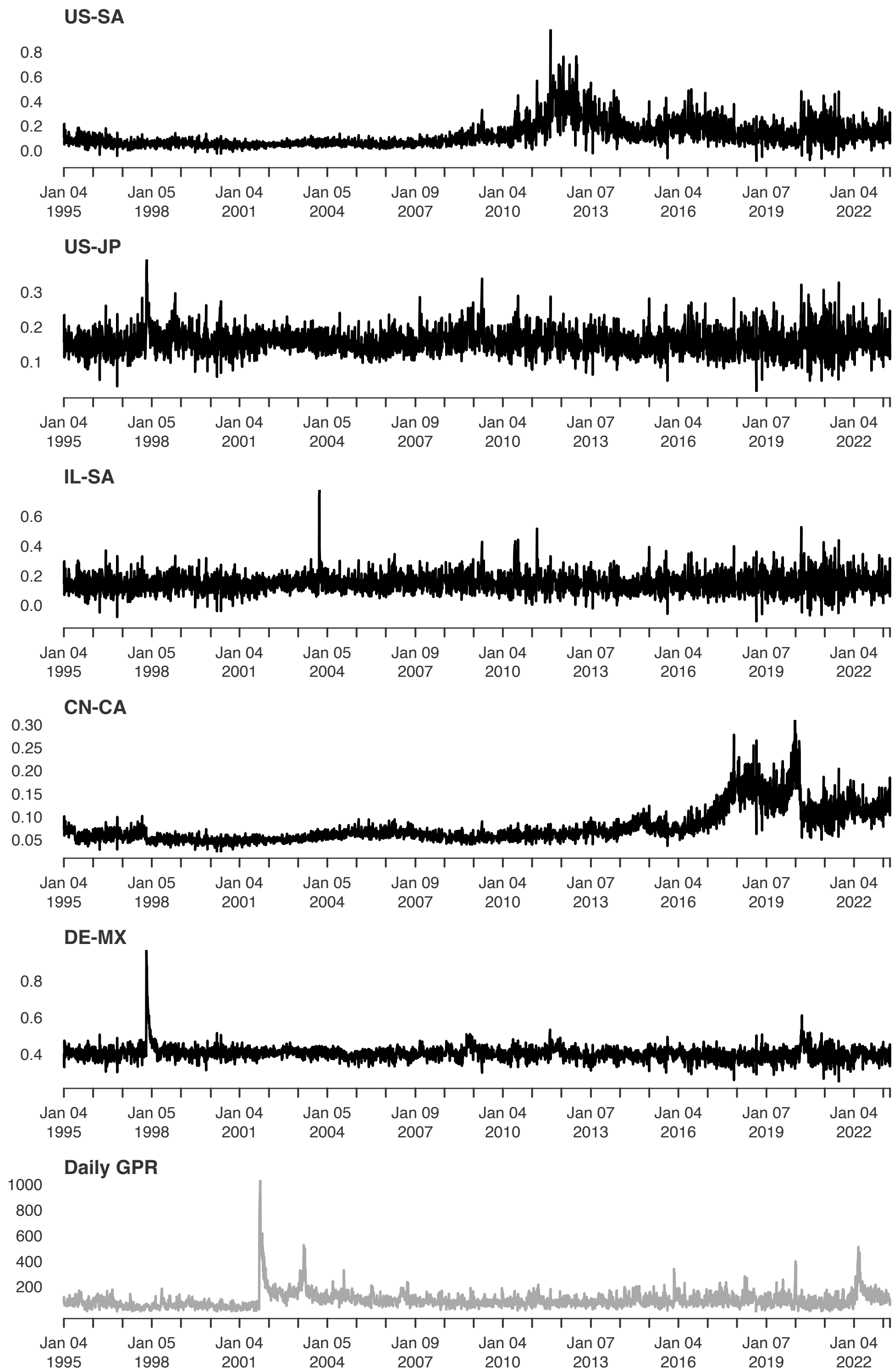


Figure 5.5: **GDCCX conditional correlations:** The figures present the second group of estimated conditional correlations from the GDCCX model specified in 4.7 and 4.8 between 4 selected country pairs, where the estimated coefficient for $\Delta\log(GPR_t)$ is negative and the DE-MX pair. The last figure plots the 1-day lagged GPR index.

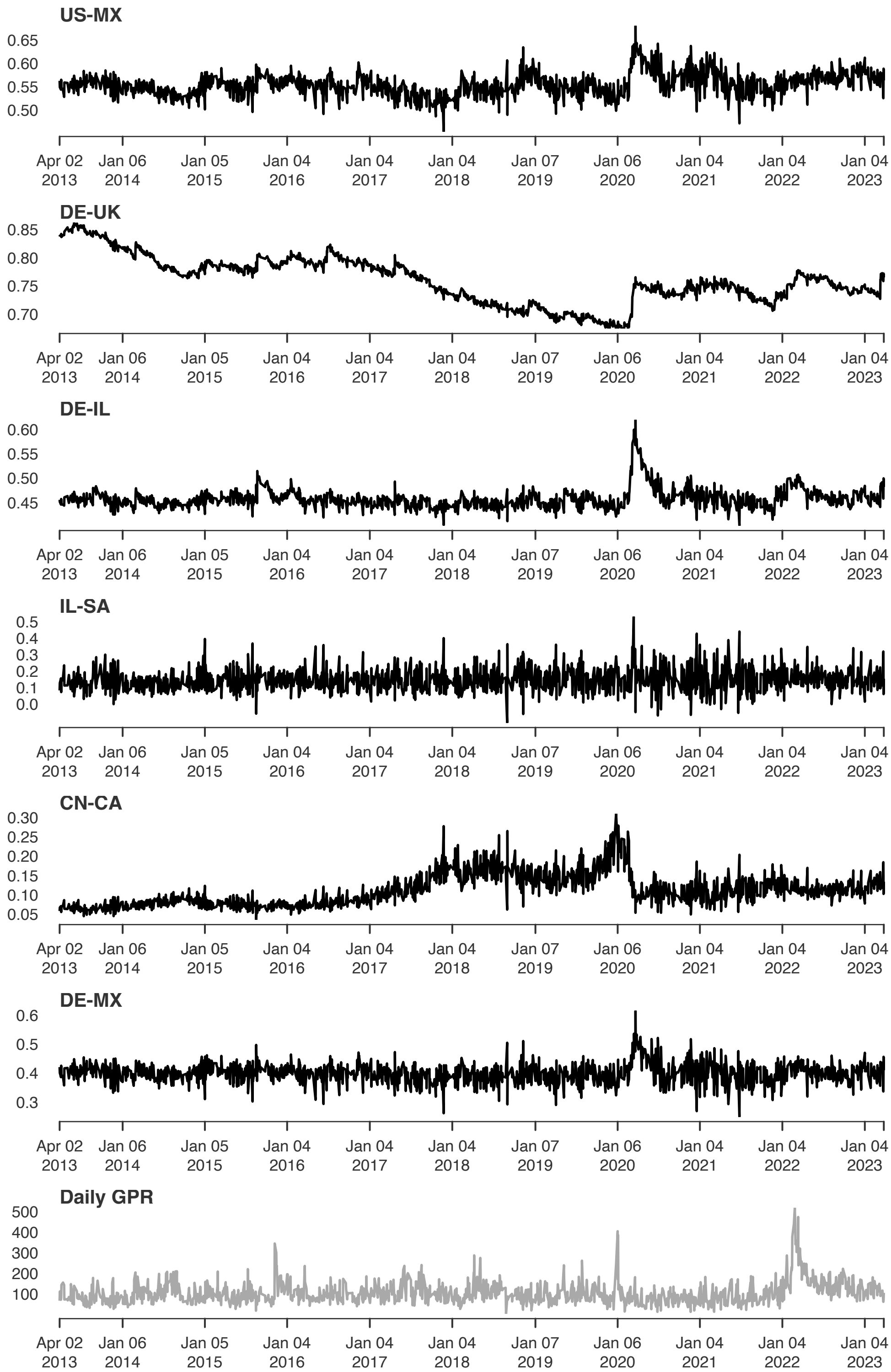


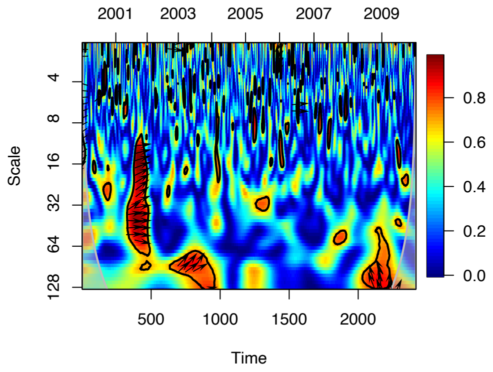
Figure 5.6: **GDCCX conditional correlations:** The figures present the estimated conditional correlations from the GDCCX model specified in 4.7 and 4.8 between 6 selected country pairs over the last 10 years. The last figure plots the 1-day lagged GPR index over the same period.

5.3 Comparison of geopolitical risk measures with general risk

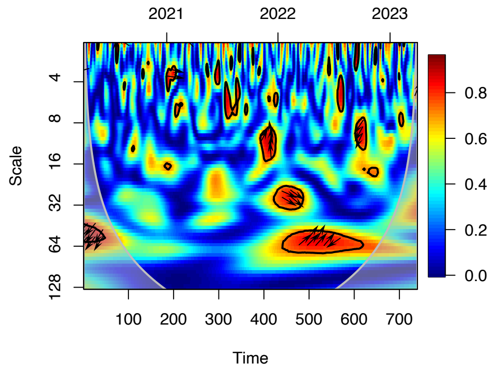
This section presents the results of the wavelet coherence analysis between the three geopolitical risk measures (GPR, GPA and GPT) and the VIX index, considering two different time periods: from January 4, 2000 until January 4, 2010 and from March 31, 2020 until March 31, 2023.

The plots of the resulting cross-wavelet coherences displayed in Figure 5.7 indicate that there are some short-lasting correlations between geopolitical risk and VIX, with varying phases and frequencies over time. However, generally, the prevailing direction of the arrows is upward, indicating the leading role of geopolitical risk measures. This observation aligns with our theoretical expectations and is consistent with the propositions put forth by Caldara & Iacoviello (2022). After the 9/11 terrorist attack in 2001 and subsequent invasion of Afghanistan and Iraq in 2003, there was a significant in-phase coherence between all three geopolitical risk measures and the VIX index across the 8-64 frequency band. This coherence was characterized by geopolitical risk measures consistently leading the VIX index and it remained consistent across all three measures of geopolitical risk, indicating a homogeneous relationship. Next, we can observe a negative out-of-phase coherence in the 32-128 band after the outburst of Global Financial Crisis in 2008, which aligns with the rationale that the financial risk, that was extremely high during this period, is only captured by the VIX index and that geopolitical risk was relatively minimal at the time. Turning our attention to the more recent period, a significant coherence can be observed in the 32-128 band following the start of the war in Ukraine. Among the three geopolitical risk measures, the coherence is the strongest between the GPT index and VIX index, while the weakest relationship is with the GPA index.

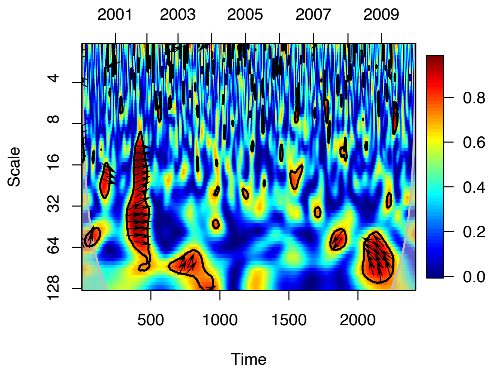
These findings shed light on the complex dynamics between geopolitical risk and the VIX index, underscoring the importance of considering different time periods and frequency bands to fully grasp their interconnections. Moreover, the results highlight the impact of geopolitical events on market volatility and risk perception, contributing to a deeper understanding financial and geopolitical interactions. Overall, the findings are consistent with Baur & Smales (2018) and Baur & Smales (2020), supporting the importance of the GPR index in providing additional information beyond the general measure of financial uncertainty captured by the VIX index.



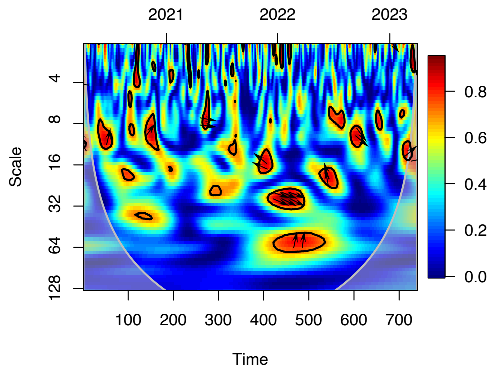
(a) VIX vs. GPR



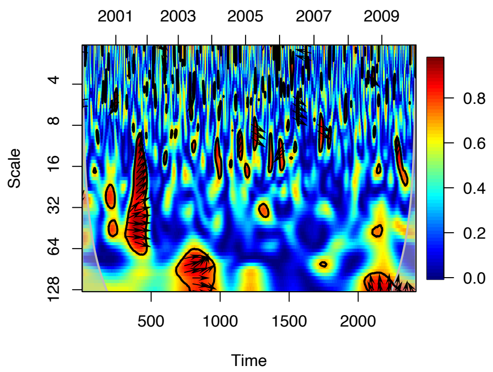
(b) VIX vs. GPR



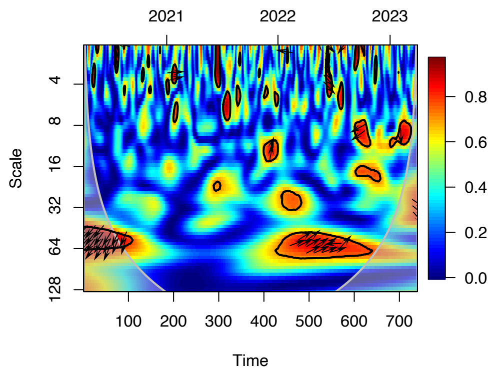
(c) VIX vs. GPA



(d) VIX vs. GPA



(e) VIX vs. GPT



(f) VIX vs. GPT

Figure 5.7: **Wavelet Coherence: VIX vs. Geopolitical Risk Indices**: The figure displays the results of wavelet coherence analysis between the VIX index and the three geopolitical risk measures GPR, GPA and GPT. Results for the 2000-2009 period are on the left, while results for the March 2020-2023 are on the right.

5.4 Further discussion and implications

In order to attain a more comprehensive and clearer understanding of the aforementioned relationships, this section presents the general interpretation of the previously reported results.

Overall, the findings obtained from univariate GARCH models and the wavelet coherence analysis lend support to the generally accepted conclusions on the effects of geopolitical risk on gold, oil and green clean energy investments, drawn by studies like Bouoiyour *et al.* (2019), Su *et al.* (2019), Baur & Smales (2020), Yang *et al.* (2021), Lee *et al.* (2021), Song *et al.* (2019), Triki & Ben Maatoug (2021) and Będowska-Sójka *et al.* (2022). Building upon these results, investors seeking to protect their portfolios during geopolitical uncertainties may consider allocating a portion of their assets to gold due to its hedging and safe haven characteristics, although gold may not always fully shield long-term investors from potential losses during extreme geopolitical crises, such as the invasion of Afghanistan. Additionally, clean energy investments could be strategically included to diversify and hedge against geopolitical risk due to their demonstrated resilience. This, in turn, can bolster efforts to promote clean energy adoption globally as policymakers and investors can leverage this attribute to encourage greater investments in renewable energy projects, enhancing energy security and sustainability. Moreover, policymakers and market participants should be aware of the impacts of geopolitical risk crude oil prices. Geopolitical crises can disrupt oil supplies and lead to price spikes, necessitating contingency plans to mitigate potential adverse effects on energy markets. Being proactive in understanding and addressing these implications can contribute to a more stable energy landscape. However, while this study establishes a connection between geopolitical risk and various investments, further research is encouraged to delve into the underlying mechanisms and reasons behind the observed relationships.

Secondly, if we attempt to make a broad generalization based on the presented findings from the quantile regression and multivariate GDCCX-GARCH models, we can emphasize the following key implications. In periods of heightened geopolitical uncertainties, we can observe a consistent decrease in extreme absolute return-co-exceedances and for specific market pairs, such as US-DE, US-UK, US-SA, CN-UK, CN-CA, DE-MX, UK-MX and UK-IL. Moreover, for the US-SA and DE-MX pairs, these findings are supported by the results of the multivariate GDCCX model that showed in such periods negative effects on their conditional correlations. This intriguing pattern may signify a *flight-to-safety* effect, wherein investors instinctively flock towards regions with lower geopolitical tensions, seeking to shield their portfolios during times of uncertainty. Another logical interpretation, supported by the findings of Balcilar *et al.* (2018), suggests that certain markets have the capacity to absorb the impacts of adverse geopolitical events better, possibly attributed to the effective response of supervising authorities or other country-specific information. Consequently, these observations potentially provide opportunities for investors to diversify their portfolios strategically and navigate turbulent periods with more stability. The results also show that heightened geopolitical risk has the potential to disrupt market connectedness and undermine stock market integration between various market pairs. These pairs extend beyond those previously mentioned, encompassing the US-JP, US-CA, US-MX, CN-MX, JP-CA, JP-MX, JP-SA and CA-MX pairs. Policymakers should be vigilant of such disconnections and consider appropriate measures to ensure the stability of global financial markets. In addition, our study implies that there might be support for the inherent sensitivity of oil-importing countries, like China, to oil prices, which are found to rise during periods of heightened geopolitical risks. This could be a potential explanation for the decreased market co-movements for pairs such as CN-CA, US-SA, DE-IL and DE-MX. Understanding the impact of geopolitical risk on oil-importing nations is crucial in making informed investment decisions, as these countries may face additional challenges and vulnerabilities stemming from their dependence on oil imports. Moreover, investors should be mindful of such influences on their investments and consider the oil-importing and oil-exporting statuses of countries when formulating their portfolios.

On the other hand, the observation of negative geopolitical shocks transmitting between markets, such as between the UK and Germany, the Israel and Saudi Arabia or the UK India, may indicate potential spillover or contagion effects between highly connected financial markets. As a result, policymakers and regulators should closely monitor such interconnectedness to prevent adverse consequences and mitigate risks during times of geopolitical instability or uncertainty.

Curiously, in general, geopolitical risk does not appear to promote contagion effects between other market pairs. Instead, market behavior seems to be influenced more by internal factors specific to each country, rather than by the broader global geopolitical climate. Interestingly, this holds particularly true for the regional foreign exchange market pairs, despite these countries being in the same geographic region, leading to the possibility of major global market players perceiving them as similarly affected by global geopolitical events. This intriguing insight can serve as a guiding compass for investors navigating through periods of heightened risk, prompting them to focus on country-specific information to make informed decisions that align with the unique characteristics of each market.

Overall, additional research is warranted to delve deeper into the complexities underlying the effects of geopolitical risk on return co-exceedances and fluctuations in conditional correlations among the examined markets concerning geopolitical risk.

Chapter 6

Conclusion

In conclusion, motivated to address the existing gaps in the literature and the recurrent backdrop of geopolitical events, this thesis has focused on examining the effects of geopolitical risk on three distinct investment types and co-movements among both global stock markets and regional foreign exchange markets.

In its first part, this analysis emphasized the importance of incorporating geopolitical risk in portfolio strategies. Overall, the findings derived from both univariate GARCH models and the supplementary methodology, the wavelet coherence analysis, aligned with the widely accepted conclusions concerning the effects of geopolitical risk. Notably, these results shed light on the gold's hedging properties, the positive relationship between geopolitical risk and oil prices, and the resilience of clean energy investments, along with offering some explanations for these observed effects. Building on these insights, investors seeking to safeguard their portfolios during periods of geopolitical uncertainties may strategically allocate a portion of their assets to gold and clean energy investments. Nevertheless, it is crucial to recognize that gold may not provide an absolute protection to long-term investors during extreme geopolitical crises, as demonstrated by the reaction of oil prices to the Iraq war. Similarly, short-term investors in clean energy investments can experience potential losses, as evidenced by the observed short-term decline in the ECO prices following the start of the Russian-Ukrainian war. Lastly, policymakers and market participants should remain vigilant about the significant impact of geopolitical risk on crude oil prices, as geopolitical crises can disrupt oil supplies and lead to price spikes. These findings represent the main conclusions from the first part of our analysis and offer valuable guidance and implications for investors and policymakers navigating an uncertain geopolitical environment.

Given that geopolitical risk introduces substantial uncertainties in financial markets, it has the potential to disrupt the global financial markets. As a result, the primary part of the thesis focused on the examination of return co-movements between 45 different stock market pairs and 15 foreign exchange markets from the CEE region in the context of heightened geopolitical risk. Addressing the limited and conflicting prior literature, we sought to enhance the reliability of our findings and gain a comprehensive understanding of the relationship between geopolitical risk and market co-movements. This was accomplished by strategically integrating two novel approaches, namely return co-exceedances using the quantile regression framework and dynamic conditional correlations. In general, we have consistently observed that geopolitical risk tends to weaken most market co-movements and does not cause contagion effects between major global stock markets or regional foreign exchange markets. This finding holds true even when considering the latest geopolitical events and markets within the same geographic regions. Throughout our analysis, we have discussed several reasons contributing to this phenomenon, including a flight-to-safety effect, diverse sensibilities of different markets to heightened geopolitical risk, effective responses of certain authorities to adverse geopolitical developments and the varying reactions of oil-importing and exporting countries to geopolitical events. In addition, we have provided evidence of some exceptions from this behaviour, such as the Israel-Saudi Arabia market pair or the United Kingdom and India market pair, which displayed a more interconnected relationship, warranting closer monitoring to manage risks during geopolitical instability. Moreover, our analysis expanded its scope to examine selected markets using a shorter sample period, providing crucial insights into their dynamics. For instance, the time-varying conditional correlations between the United Kingdom and Germany were found to increase under heightened geopolitical risk over the last 10 years, highlighting the importance of considering these trends.

Overall, by being the first to examine these relationships, this analysis has made significant strides in understanding the effects of geopolitical risk on return co-exceedances and dynamic conditional correlations between global stock markets as well as the regional foreign exchange markets. Apart from the presented findings, our primary contribution lies in the utilization and implementation of the multivariate GDCCX-GARCH model, effectively empowering other researchers to explore the impact of various exogenous factors on dynamic conditional correlations. Another crucial contribution of our research involves the examination of regional foreign exchange markets, which have been largely overlooked in prior studies, despite their potential vulnerability to geopolitical risk, especially in light of the ongoing Russian-Ukrainian war near their borders. By addressing this gap, our study provides valuable insights into the dynamics of these markets and their response to geopolitical events, contributing to a more comprehensive understanding of how their monetary policies and country-specific information can influence their reaction to such events. In addition, the reassessment of how geopolitical risk impacts gold, oil, and green investments expands the scope of insights garnered from our analysis and furnishes valuable guidance for investors in crafting their investment portfolio strategies. Through the examination of the dynamics between the geopolitical risk measures and the VIX index, our analysis yields valuable insights into the financial and geopolitical interactions and offers additional evidence of the significance of the GPR index in providing supplementary information. Furthermore, employing multiple frameworks to examine the aforementioned effects contributes to the better understanding by offering diverse viewpoints. It underscores the importance of corroborating findings through different methodologies, reinforcing the significance of thorough analysis and avoiding premature conclusions.

In terms of future research, it would be worthwhile to develop more structural approaches to assess the effects of geopolitical risk. Such approaches could be systematically employed in portfolio and risk management, as well as policy analysis across different institutions. Furthermore, since we have expanded the literature on the significance of geopolitical risk in financial markets, integrating the GPR index into prominent digital information sources within the financial industry, such as Reuters and Bloomberg, could prove immensely valuable. This would enable portfolio management analysts worldwide to directly access and utilize the geopolitical risk index in their decision-making processes, fostering a more informed and proactive approach to navigating geopolitical uncertainties and optimize their investment decisions on a global scale.

Bibliography

Abakah, E. J. A., A. K. Tiwari, I. P. Alagidede, & L. A. Gil-Alana (2022): "Re-examination of risk-return dynamics in international equity markets and the role of policy uncertainty, geopolitical risk and vix: Evidence using markov-switching copulas." *Finance Research Letters* **47**: p. 102535.

Adjaouté, K. & J.-P. Danthine (2003): "European financial integration and equity returns: A theory-based assessment." .

Aguiar-Conraria, L. & M. J. Soares (2014): "The continuous wavelet transform: Moving beyond uni-and bivariate analysis." *Journal of Economic Surveys* **28(2)**: pp. 344–375.

Akbar, M., F. Iqbal, & F. Noor (2019): "Bayesian analysis of dynamic linkages among gold price, stock prices, exchange rate and interest rate in pakistan." *Resources Policy* **62**: pp. 154–164.

Akbari, A. & L. Ng (2020): "International market integration: A survey." *Asia-Pacific Journal of Financial Studies* **49(2)**: pp. 161–185.

Al Mamun, M., G. S. Uddin, M. T. Suleman, & S. H. Kang (2020): "Geopolitical risk, uncertainty and bitcoin investment." *Physica A: Statistical Mechanics and its Applications* **540**: p. 123107.

Al-Yahyaee, K. H., M. U. Rehman, W. Mensi, & I. M. W. Al-Jarrah (2019): "Can uncertainty indices predict bitcoin prices? a revisited analysis using partial and multivariate wavelet approaches." *The North American Journal of Economics and Finance* **49**: pp. 47–56.

Aloui, C. & H. B. Hamida (2021): "Oil-stock nexus in an oil-rich country: does geopolitical risk matter in terms of investment horizons?" *Defence and Peace Economics* **32(4)**: pp. 468–488.

Antonakakis, N., I. Chatziantoniou, & G. Filis (2017a): "Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest." *International Review of Financial Analysis* **50**: pp. 1–26.

Antonakakis, N., R. Gupta, C. Kollias, & S. Papadamou (2017b): "Geopolitical risks and the oil-stock nexus over 1899–2016." *Finance Research Letters* **23**: pp. 165–173.

Arin, K. P., D. Ciferri, & N. Spagnolo (2008): "The price of terror: The effects of terrorism on stock market returns and volatility." *Economics Letters* **101(3)**: pp. 164–167.

Aysan, A. F., E. Demir, G. Gozgor, & C. K. M. Lau (2019): "Effects of the geopolitical risks on bitcoin returns and volatility." *Research in International Business and Finance* **47**: pp. 511–518.

Bae, K.-H., G. A. Karolyi, & R. M. Stulz (2003): "A new approach to measuring financial contagion." *The Review of Financial Studies* **16(3)**: pp. 717–763.

Baele, L., A. Ferrando, P. Hördahl, E. Krylova, & C. Monnet (2004a): "Measuring european financial integration." *Oxford review of economic policy* **20(4)**: pp. 509–530.

Baele, L., A. Ferrando, P. Hördahl, E. Krylova, & C. Monnet (2004b): "Measuring financial integration in the euro area." *Technical report*, ECB occasional paper.

Baker, S. R., N. Bloom, & S. J. Davis (2016): "Measuring economic policy uncertainty." *The quarterly journal of economics* **131(4)**: pp. 1593–1636.

Balcilar, M., M. Bonato, R. Demirer, & R. Gupta (2018): "Geopolitical risks and stock market dynamics of the brics." *Economic Systems* **42(2)**: pp. 295–306.

Balcilar, M., R. Gupta, C. Kyei, & M. E. Wohar (2016): "Does economic policy uncertainty predict exchange rate returns and volatility? evidence from a nonparametric causality-in-quantiles test." *Open Economies Review* **27(2)**: pp. 229–250.

Baur, D. & N. Schulze (2005): "Coexceedances in financial markets—a quantile regression analysis of contagion." *Emerging Markets Review* **6(1)**: pp. 21–43.

Baur, D. & L. Smales (2018): "Gold and geopolitical risk." *SSRN Electronic Journal* .

Baur, D. G. & T. K. McDermott (2010): "Is gold a safe haven? international evidence." *Journal of Banking & Finance* **34(8)**: pp. 1886–1898.

Baur, D. G. & L. A. Smales (2020): "Hedging geopolitical risk with precious metals." *Journal of Banking & Finance* **117**: p. 105823.

Bekaert, G., C. R. Harvey, & A. Ng (2005): "Market integration and contagion." *The Journal of Business* **78(1)**: pp. 39–69.

Bhuiyan, R. A., M. P. Rahman, B. Saiti, & G. Mat Ghani (2018): "Financial integration between sukuk and bond indices of emerging markets: Insights from wavelet coherence and multivariate-garch analysis." *Borsa Istanbul Review* **18(3)**: pp. 218–230.

Bollerslev, T. (1986): "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics* **31(3)**: pp. 307–327.

Bollerslev, T. & J. M. Wooldridge (1992): "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances." *Econometric reviews* **11(2)**: pp. 143–172.

Bonga-Bonga, L. (2018): "Uncovering equity market contagion among brics countries: An application of the multivariate garch model." *The Quarterly Review of Economics and Finance* **67**: pp. 36–44.

Bouoiyour, J., R. Selmi, S. Hammoudeh, & M. E. Wohar (2019): "What are the categories of geopolitical risks that could drive oil prices higher? acts or threats?" *Energy Economics* **84**: p. 104523.

Bouras, C., C. Christou, R. Gupta, & T. Suleman (2019): "Geopolitical risks, returns, and volatility in emerging stock markets: Evidence from a panel garch model." *Emerging Markets Finance and Trade* **55(8)**: pp. 1841–1856.

Bouri, E., R. Gupta, & X. V. Vo (2022): "Jumps in geopolitical risk and the cryptocurrency market: The singularity of bitcoin." *Defence and Peace Economics* **33(2)**: pp. 150–161.

Boyer, B. H., T. Kumagai, & K. Yuan (2006): "How do crises spread? evidence from accessible and inaccessible stock indices." *The journal of finance* **61(2)**: pp. 957–1003.

Buchinsky, M. (1998): "Recent advances in quantile regression models: a practical guideline for empirical research." *Journal of human resources* pp. 88–126.

Będowska-Sójka, B., E. Demir, & A. Zaremba (2022): "Hedging geopolitical risks with different asset classes: A focus on the russian invasion of ukraine." *Finance Research Letters* **50**: p. 103192.

Caldara, D. & M. Iacoviello (2022): "Measuring geopolitical risk." *American Economic Review* **112(4)**: pp. 1194–1225.

Cappiello, L., R. F. Engle, & K. Sheppard (2006a): "Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns." *Journal of Financial Econometrics* **4(4)**: pp. 537–572.

Cappiello, L., A. Kadareja, B. Gerard, & S. Manganelli (2006b): "Financial integration of new eu member states." *European Central Bank* .

Carrieri, F., V. Errunza, & K. Hogan (2007): "Characterizing world market integration through time." *Journal of Financial and Quantitative Analysis* **42(4)**: pp. 915–940.

Cheng, S., Z. Zhang, & Y. Cao (2022): "Can precious metals hedge geopolitical risk? fresh sight using wavelet coherence analysis." *Resources Policy* **79**: p. 102972.

Chibane, M. & N. Janson (2020): "Do bitcoin stylized facts depend on geopolitical risk?" *Available at SSRN 3530020* .

Chittedi, K. R. (2015): "Financial crisis and contagion effects to indian stock market: 'dcc–garch' analysis." *Global Business Review* **16(1)**: pp. 50–60.

Chowdhury, M. A. F., M. S. Meo, & C. Aloui (2021): "How world uncertainties and global pandemics destabilized food, energy and stock markets? fresh evidence from quantile on quantile regressions." *International Review of Financial Analysis* **76**: p. 101759.

Christiansen, C. & A. Ranaldo (2009): "Extreme coexceedances in new eu member states' stock markets." *Journal of Banking & Finance* **33(6)**: pp. 1048–1057.

Corsetti, G., M. Pericoli, & M. Sbracia (2005): "'some contagion, some interdependence': More pitfalls in tests of financial contagion." *Journal of International Money and Finance* **24(8)**: pp. 1177–1199.

Cunado, J., R. Gupta, C. K. M. Lau, & X. Sheng (2020): "Time-varying impact of geopolitical risks on oil prices." *Defence and Peace Economics* **31(6)**: pp. 692–706.

Demirer, R., R. Gupta, Q. Ji, & A. K. Tiwari (2019): "Geopolitical risks and the predictability of regional oil returns and volatility." *OPEC Energy Review* **43(3)**: pp. 342–361.

Dumas, B., C. R. Harvey, & P. Ruiz (2003): "Are correlations of stock returns justified by subsequent changes in national outputs?" *Journal of international Money and Finance* **22(6)**: pp. 777–811.

Dungey, M. & R. Fry (2004): "Empirical modeling of contagion: a review of methodologies." .

Dutta, A. & P. Dutta (2022): "Geopolitical risk and renewable energy asset prices: Implications for sustainable development." *Renewable Energy* **196**: pp. 518–525.

Engle, R. (2002): "Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models." *Journal of Business & Economic Statistics* **20(3)**: pp. 339–350.

Engle, R. & K. Sheppard (2001): "Theoretical and empirical properties of dynamic conditional correlation multivariate garch." *University of california at san diego, economics working paper series*, Department of Economics, UC San Diego.

Engle, R. F., D. M. Lilien, & R. P. Robins (1987): "Estimating time varying risk premia in the term structure: The arch-m model." *Econometrica* **55(2)**: pp. 391–407.

Escribano, G. & J. Valdes (2017): "Oil prices: Governance failures and geopolitical consequences." *Geopolitics* **22(3)**: pp. 693–718.

Farge, M. (1992): "Wavelet transforms and their applications to turbulence." *Annual review of fluid mechanics* **24(1)**: pp. 395–458.

Fernandez, V. (2008): "The war on terror and its impact on the long-term volatility of financial markets." *International Review of Financial Analysis* **17(1)**: pp. 1–26.

Fisher, T. J. & C. M. Gallagher (2012): "New weighted portmanteau statistics for time series goodness of fit testing." *Journal of the American Statistical Association* **107(498)**: pp. 777–787.

Forbes, K. & R. Rigobon (2001): "Measuring contagion: conceptual and empirical issues." In "International financial contagion," pp. 43–66. Springer.

Forbes, K. J. & S. Claessens (2004): "International financial contagion: The theory, evidence and policy implications." In "conference" The IMF's role in emerging markets economies" in Amesterdam," p. 01.

Forbes, K. J. & R. Rigobon (2002): "No contagion, only interdependence: Measuring stock market comovements." *The Journal of Finance* **57(5)**: pp. 2223–2261.

Fornberg, B. & D. M. Sloan (1994): "A review of pseudospectral methods for solving partial differential equations." *Acta numerica* **3**: pp. 203–267.

Frijns, B., A. Tourani-Rad, & I. Indriawan (2012): "Political crises and the stock market integration of emerging markets." *Journal of Banking & Finance* **36(3)**: pp. 644–653.

Fur, E. L., H. B. Ameur, E. Braune, & B. Faye (2016): "Financial market contagion and fine wines: The evidence of the adcc garch model." *International Journal of Entrepreneurship and Small Business* **29(4)**: pp. 583–601.

Galanos, A. (2022): *rmgarch: Multivariate GARCH models.* R package version 1.3-9.

Ghalanos, A. & S. Theussl (2015): *Rsolnp: General Non-linear Optimization Using Augmented Lagrange Multiplier Method.* R package version 1.16.

Gilbert, P. & R. Varadhan (2019): *numDeriv: Accurate Numerical Derivatives.* R package version 2016.8-1.1.

Gkillas, K., R. Gupta, & C. Pierdzioch (2020): "Forecasting realized gold volatility: Is there a role of geopolitical risks?" *Finance Research Letters* **35**: p. 101280.

Gkillas, K., R. Gupta, & M. E. Wohar (2018): "Volatility jumps: The role of geopolitical risks." *Finance Research Letters* **27**: pp. 247–258.

Glosten, L. R., R. Jagannathan, & D. E. Runkle (1993): "On the relation between the expected value and the volatility of the nominal excess return on stocks." *The journal of finance* **48(5)**: pp. 1779–1801.

Gouhier, T. C., A. Grinsted, & V. Simko (2021): *R package biwavelet: Conduct Univariate and Bivariate Wavelet Analyses.* (Version 0.20.21).

Greenwood-Nimmo, M., V. H. Nguyen, & Y. Shin (2015): "Measuring the connectedness of the global economy." .

Gu, X., Z. Zhu, & M. Yu (2021): "The macro effects of gpr and epu indexes over the global oil market—are the two types of uncertainty shock alike?" *Energy Economics* **100**: p. 105394.

Gunay, S. & G. Can (2022): "The source of financial contagion and spillovers: An evaluation of the covid-19 pandemic and the global financial crisis." *Plos One* **17(1)**: p. e0261835.

Gupta, R., A. Majumdar, C. Pierdzioch, & M. E. Wohar (2017): "Do terror attacks predict gold returns? evidence from a quantile-predictive-regression approach." *The Quarterly Review of Economics and Finance* **65**: pp. 276–284.

He, X. & F. Hu (2002): "Markov chain marginal bootstrap." *Journal of the American Statistical Association* **97(459)**: pp. 783–795.

Hedström, A., N. Zelander, J. Junttila, & G. S. Uddin (2020): "Emerging market contagion under geopolitical uncertainty." *Emerging Markets Finance and Trade* **56(6)**: pp. 1377–1401.

Hillier, D., P. Draper, & R. Faff (2006): "Do precious metals shine? an investment perspective." *Financial analysts journal* **62(2)**: pp. 98–106.

Horváth, R., Š. Lyócsa, & E. Baumöhl (2018): "Stock market contagion in central and eastern europe: unexpected volatility and extreme co-exceedance." *The European Journal of Finance* **24(5)**: pp. 391–412.

Hudgins, L., C. A. Friehe, & M. E. Mayer (1993): "Wavelet transforms and atmopsheric turbulence." *Physical Review Letters* **71(20)**: p. 3279.

Hui, H. C. (2020): "Does geopolitical risk affect exchange rates? the case of indonesia." *The Case of Indonesia (June 26, 2020)* .

Hui, H. C. (2021): "The long-run effects of geopolitical risk on foreign exchange markets: evidence from some asean countries." *International Journal of Emerging Markets* .

Iyke, B. N., D. H. B. Phan, & P. K. Narayan (2022): "Exchange rate return predictability in times of geopolitical risk." *International Review of Financial Analysis* **81**: p. 102099.

Joo, K., J. H. Suh, D. Lee, & K. Ahn (2020): "Impact of the global financial crisis on the crude oil market." *Energy Strategy Reviews* **30**: p. 100516.

Karagozoglu, A. K., N. Wang, & T. Zhou (2022): "Comparing geopolitical risk measures." *The Journal of Portfolio Management* **48(10)**: pp. 226–257.

Kisswani, K. M. & M. I. Elian (2021): "Analyzing the (a)symmetric impacts of oil price, economic policy uncertainty, and global geopolitical risk on exchange rate." *The Journal of Economic Asymmetries* **24(C)**: p. S1703494921000098.

Kleinbrod, V. M. & X.-M. Li (2017): "Order flow and exchange rate comovement." *Journal of International Money and Finance* **77**: pp. 199–215.

Kocherginsky, M., X. He, & Y. Mu (2005): "Practical confidence intervals for regression quantiles." *Journal of Computational and Graphical Statistics* **14(1)**: pp. 41–55.

Koenker, R. & G. Bassett Jr (1978): "Regression quantiles." *Econometrica: journal of the Econometric Society* pp. 33–50.

Koenker, R. & V. d'Orey (1994): "Remark as r92: A remark on algorithm as 229: Computing dual regression quantiles and regression rank scores." *Journal of the Royal Statistical Society. Series C (Applied Statistics)* **43(2)**: pp. 410–414.

Koenker, R. W. & V. D'Orey (1987): "Algorithm as 229: Computing regression quantiles." *Journal of the Royal Statistical Society. Series C (Applied Statistics)* **36(3)**: pp. 383–393.

Kollias, C., C. Kyrtsou, & S. Papadamou (2013): "The effects of terrorism and war on the oil price–stock index relationship." *Energy Economics* **40**: pp. 743–752.

Kyriazis, N. A. (2021): "The effects of geopolitical uncertainty on cryptocurrencies and other financial assets." *SN Business & Economics* **1(1)**: pp. 1–14.

Laurent, S., L. Bauwens, & J. Rombouts (2006): "Multivariate garch models: a survey." *Journal of Applied Econometrics* **21(1)**: pp. 79–109.

Lee, C.-C., C.-C. Lee, & Y.-Y. Li (2021): "Oil price shocks, geopolitical risks, and green bond market dynamics." *The North American Journal of Economics and Finance* **55**: p. 101309.

Lee, C.-C., H. Tang, & D. Li (2022): "The roles of oil shocks and geopolitical uncertainties on china's green bond returns." *Economic Analysis and Policy* **74**: pp. 494–505.

Li, X.-M. (2011): "How do exchange rates co-move? a study on the currencies of five inflation-targeting countries." *Journal of Banking & Finance* **35(2)**: pp. 418–429.

Lindfield, G. R. & J. E. Penny (1989): *Microcomputers in numerical analysis.* Halsted Press.

Liu, J., F. Ma, Y. Tang, & Y. Zhang (2019): "Geopolitical risk and oil volatility: A new insight." *Energy Economics* **84(C)**.

Lv, X., X. Dong, & W. Dong (2021): "Oil prices and stock prices of clean energy: New evidence from chinese subsectoral data." *Emerging Markets Finance and Trade* **57(4)**: pp. 1088–1102.

Lyócsa, Š. & R. Horvath (2018): "Stock market contagion: a new approach." *Open Economies Review* **29(3)**: pp. 547–577.

Marques, A. C., J. A. Fuinhas, & D. A. Pereira (2018): "Have fossil fuels been substituted by renewables? an empirical assessment for 10 european countries." *Energy policy* **116**: pp. 257–265.

Moser, T. (2003): "What is international financial contagion?" *International Finance* **6(2)**: pp. 157–178.

Narayan, P. K., S. Narayan, S. Khademalomoom, & D. H. B. Phan (2018a): "Do terrorist attacks impact exchange rate behavior? new international evidence." *Economic Inquiry* **56(1)**: pp. 547–561.

Narayan, S., T.-H. Le, & S. Sriananthakumar (2018b): "The influence of terrorism risk on stock market integration: Evidence from eight oecd countries." *International Review of Financial Analysis* **58**: pp. 247–259.

Nelson, D. B. (1991): "Conditional heteroskedasticity in asset returns: A new approach." *Econometrica* **59(2)**: pp. 347–370.

Nguyen, T. N., T. K. H. Phan, & T. L. Nguyen (2022): "Financial contagion during global financial crisis and covid–19 pandemic: The evidence from dcc–garch model." *Cogent Economics & Finance* **10(1)**: p. 2051824.

Nyblom, J. (1989): "Testing for the constancy of parameters over time." *Journal of the American Statistical Association* **84(405)**: pp. 223–230.

Park, C. & S. Park (2020): "Rare disaster risk and exchange rates: An empirical investigation of south korean exchange rates under tension between the two koreas." *Finance Research Letters* **36**: p. 101314.

Patel, R., J. W. Goodell, M. E. Oriani, A. Paltrinieri, & L. Yarovaya (2022): "A bibliometric review of financial market integration literature." *International Review of Financial Analysis* **80**: p. 102035.

Pericoli, M. & M. Sbracia (2003): "A primer on financial contagion." *Journal of economic surveys* **17(4)**: pp. 571–608.

Pineda, J., L. M. Cortés, & J. Perote (2022): "Financial contagion drivers during recent global crises." *Economic Modelling* **117**: p. 106067.

Plakandaras, V., P. Gogas, & T. Papadimitriou (2018): "The effects of geopolitical uncertainty in forecasting financial markets: A machine learning approach." *Algorithms* **12(1)**: p. 1.

Plakandaras, V., R. Gupta, & W.-K. Wong (2019): "Point and density forecasts of oil returns: The role of geopolitical risks." *Resources Policy* **62**: pp. 580–587.

Pukthuanthong, K. & R. Roll (2009): "Global market integration: An alternative measure and its application." *Journal of Financial Economics* **94(2)**: pp. 214–232.

R Core Team (2023): *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria.

Rasoulinezhad, E., F. Taghizadeh-Hesary, J. Sung, & N. Panthamit (2020): "Geopolitical risk and energy transition in russia: Evidence from ardl bounds testing method." *Sustainability* **12(7)**: p. 2689.

Roueff, F. & R. Von Sachs (2011): "Locally stationary long memory estimation." *Stochastic Processes and their Applications* **121(4)**: pp. 813–844.

Samitas, A., E. Kampouris, & Z. Umar (2022): "Financial contagion in real economy: The key role of policy uncertainty." *International Journal of Finance & Economics* **27(2)**: pp. 1633–1682.

Schopen, J.-H. (2012): *Exogenous Variables in Dynamic Conditional Correlation Models for Financial Markets.* Ph.D. thesis, Universität Bremen.

Singh, S., P. Bansal, & N. Bhardwaj (2022a): "Correlation between geo political risk, economic policy uncertainty and exchange rates using partial and multiple wavelet coherence in p5 nations." *International Journal of Global Warming* **27(4)**: pp. 379–401.

Singh, S., P. Bansal, & N. Bhardwaj (2022b): "Correlation between geopolitical risk, economic policy uncertainty, and bitcoin using partial and multiple wavelet coherence in p5 + 1 nations." *Research in International Business and Finance* **63**: p. 101756.

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

Sohag, K., S. Hammoudeh, A. H. Elsayed, O. Mariev, & Y. Safonova (2022a): "Do geopolitical events transmit opportunity or threat to green markets? decomposed measures of geopolitical risks." *Energy Economics* **111**: p. 106068.

Sohag, K., R. Vasilyeva, A. Urazbaeva, & V. Voytenkov (2022b): "Stock market synchronization: The role of geopolitical risk." *Journal of Risk and Financial Management* **15(5)**.

Song, Y., Q. Ji, Y.-J. Du, & J.-B. Geng (2019): "The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets." *Energy Economics* **84**: p. 104564.

Su, C.-W., K. Khan, R. Tao, & M. Nicoleta-Claudia (2019): "Does geopolitical risk strengthen or depress oil prices and financial liquidity? evidence from saudi arabia." *Energy* **187**: p. 116003.

Tiwari, A. K., G. C. Aye, R. Gupta, & K. Gkillas (2020): "Gold-oil dependence dynamics and the role of geopolitical risks: Evidence from a markov-switching time-varying copula model." *Energy Economics* **88**: p. 104748.

Torrence, C. & G. P. Compo (1998): "A practical guide to wavelet analysis." *Bulletin of the American Meteorological society* **79(1)**: pp. 61–78.

Triki, M. B. & A. Ben Maatoug (2021): "The gold market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk." *Resources Policy* **70(C)**: p. S030142072030903X.

Vargas, G. A. (2008): "What drives the dynamic conditional correlation of foreign exchange and equity returns?" *Available at SSRN 1093286* .

Whaley, R. E. (2000): "The investor fear gauge." *The Journal of Portfolio Management* **26(3)**: pp. 12–17.

White, H. (1996): *Estimation, inference and specification analysis.* 22. Cambridge university press.

Wu, F., W.-L. Zhao, Q. Ji, & D. Zhang (2020): "Dependency, centrality and dynamic networks for international commodity futures prices." *International Review of Economics & Finance* **67**: pp. 118–132.

Yang, K., Y. Wei, S. Li, & J. He (2021): "Geopolitical risk and renewable energy stock markets: An insight from multiscale dynamic risk spillover." *Journal of Cleaner Production* **279**: p. 123429.

Ye, W., Y. Zhu, Y. Wu, & B. Miao (2016): "Markov regime-switching quantile regression models and financial contagion detection." *Insurance: Mathematics and Economics* **67**: pp. 21–26.

Ye, Y. (1987): *Interior Algorithms for Linear, Quadratic, and Linearly Constrained Non-Linear Programming.* Ph.D. thesis, Department of ESS, Stanford University.

Zhang, Y., L. Zhou, Y. Chen, & F. Liu (2022): "The contagion effect of jump risk across asian stock markets during the covid-19 pandemic." *The North American Journal of Economics and Finance* **61**: p. 101688.

Appendix A

Appendix

A.1 Code for the GDCCX model estimation

```
#### General parameters ####
m <- 2 # number of time series
n <- 11 # number of total parameters to be estimated
Xbar <- mean(GPR_d_diff_log_s) # mean of the exogenous variable
N <- length(stocks[,1]) # length of time series

#### UNIVARIATE MODELS ####
# ARIMA model based on BIC
mean_models_auto_bic <- lapply(stocks,function(y){auto.arima(y,
    max.p = 2, max.q = 2, ic = "bic")})
# computing E-GARCH and GJR-GARCH models for all time series
e_spec <- e_fit <- gjr_spec <- gjr_fit <- list()
for (i in 1:10){
  e_spec[[i]] <- ugarchspec(mean.model = list(armaOrder =
      arimaorder(mean_models_auto_bic[[i]]),include.mean = FALSE
      ),
                           variance.model = list(model = "
                              eGARCH",garchOrder = c(1, 1)),
                           distribution.model = "norm")
  e_fit[[i]] <- ugarchfit(e_spec[[i]], stocks[,i])
}
for (i in 1:10){
  gjr_spec[[i]] <- ugarchspec(mean.model = list(armaOrder =
      arimaorder(mean_models_auto_bic[[i]]),include.mean = FALSE
      ),
                             variance.model = list(model = "
                                gjrGARCH",garchOrder = c(1, 1)
                                ),
```

```
                                    distribution.model = "norm")
  gjr_fit[[i]] <- ugarchfit(gjr_spec[[i]], stocks[,i])
}

# best choice of GARCH model for each time series
garch_models <- c("gjrGARCH", "gjrGARCH", "gjrGARCH", "eGARCH",
    "eGARCH","gjrGARCH","gjrGARCH","gjrGARCH","gjrGARCH","
    gjrGARCH")

# fitting unigarch models
uspec <- ufit <- list()
for (i in 1:10){
  uspec[[i]] <- ugarchspec(mean.model = list(armaOrder = c(0,0)
      , include.mean = FALSE),
                                variance.model = list(model = garch_
                                    models[i], garchOrder = c(1, 1)),
                                distribution.model = "norm")
  ufit[[i]] <- ugarchfit(uspec[[i]], stocks[,i])
}

# combining disparate objects
gdccx_pairs <- c("US-MX","US-SA","US-JP","CN-DE","CN-JP","DE-UK
    ","DE-IL","IL-SA","CN-CA", "DE-MX")

i_s <- c(rep(1,3),rep(2,2),rep(4,2),9,2,4)
j_s <- c(8,10,3,4,3,6,9,10,7,8)

# specification of univariate models for selected market pairs
# saving data for selected market pairs in a list
nuspec <- data <- list()
for (i in 1:10){
  nuspec[[i]] <- multispec(list(uspec[[i_s[i]]],uspec[[j_s[i
      ]]]))
  data[[i]] <- stocks[,c(i_s[i],j_s[i])]
}

ncl <- makePSOCKcluster(2)

# fitting univariate models, computing standardized residuals
    and Q bar matrix
nunifit <- res <- sig <- stdresid <- Qbar <- list()
for (i in 1:10){
  nunifit[[i]] <- multifit(nuspec[[i]], data[[i]], cluster =
      ncl)
```

```
  res[[i]] <- residuals(nunifit[[i]])
  sig[[i]] <- sigma(nunifit[[i]])
  stdresid[[i]] <- res[[i]]/sig[[i]] # std residuals from the
     univariate fit
  Qbar[[i]] <- cov(stdresid[[i]])
}

#### DCC GARCH model ####
# DCC test
dcc_test <- list()
for (i in 1:9){
  dcc_test[[i]] <- list()
  for (j in ((i+1):10)){
    dcc_test[[i]][[j]] <- DCCtest(stocks[,c(i,j)], c(1,1))
  }
}
dcc_test

# fitting simple DCC-GARCH model for selected market pairs
dcc_fit_list <- dcc_spec <- dcc_cor <- list()
for (i in 1:10){
  dcc_spec[[i]] <- dccspec(uspec = nuspec[[i]],dccOrder = c(1,
     1),model = "DCC",distribution = 'mvnorm')
  dcc_fit_list[[i]] <- dccfit(dcc_spec[[i]], data[[i]], solver
     = "solnp")
  dcc_cor[[i]] <- rcor(dcc_fit_list[[i]], output = "matrix")
}

#### LL functions ####
# theta = parameters, phi parameters are for univariate part,
   psi for dcc part

LL <- function(theta, ipair){

  ispec <- list()
  ispec[[1]] <- ugarchspec(mean.model = list(armaOrder = c(0,
     0), include.mean = FALSE),
                           variance.model = list(model = "
                              gjrGARCH", garchOrder = c(1, 1)),
                           distribution.model = "norm",
                           start.pars = list(omega = theta[1],
                              alpha1 = theta[2], beta1 = theta
                              [3], gamma1 = theta[4]))
```

```
ispec[[2]] <- ugarchspec(mean.model = list(armaOrder = c(0,
   0), include.mean = FALSE),
                           variance.model = list(model = "
                              gjrGARCH", garchOrder = c(1, 1)),
                           distribution.model = "norm",
                           start.pars = list(omega = theta[5],
                              alpha1 = theta[6], beta1 = theta
                              [7], gamma1 = theta[8]))
# combining disparate objects
nispec <- multispec(ispec)
iunifit <- multifit(nispec, data[[ipair]])

ires <- residuals(iunifit)
isig <- sigma(iunifit)
istdresid <- ires/isig
iQbar <- cov(istdresid)

# DCC
C <- list()
c <- matrix(0, ncol = 2, nrow = 2)
c[1,m] <- theta[11]
c[m,1] <- theta[11]
C[[1]] <- c

I <-  matrix(1, 2, 2)
A <- diag(2) * theta[9] # dcc a
B <- diag(2) * theta[10] # dcc b

iQ <- iR <- ill <- list()
for(t in 1:N){
  if(t == 1){
    iQ[[t]] <- iQbar
  } else{
    iQ[[t]] <- iQbar * (I - A - B) - C[[1]]*Xbar +
      A * (istdresid[t-1,]%*%t(istdresid[t-1,])) + B*iQ[[t
         -1]] +
      C[[1]]*X[t-1,1]
  }

  if(min(eigen(iQ[[t]])$value) <= 0){
    ill[[t]] <- 1000000000
  } else {
    iR[[t]] <- diag(c(1/sqrt(diag(iQ[[t]])))) %*% iQ[[t]] %*%
        diag(c(1/sqrt(diag(iQ[[t]]))))
```

```
        ill[[t]] <- (1/2)* (log(det(iR[[t]])) + istdresid[t,]%*%
            MASS::ginv(iR[[t]])%*%istdresid[t,])
      }
    }

    LLH <- sum(unlist(ill))
    return(LLH)
}
LL_t <- function(theta, t0){
    data <- stocks[,c(1,10)] # can become a parameter

    uspec <- list()
    uspec[[1]] <- ugarchspec(mean.model = list(armaOrder = c(0,
        0), include.mean = FALSE),
                             variance.model = list(model = "
                                 gjrGARCH", garchOrder = c(1, 1)),
                             distribution.model = "norm",
                             start.pars = list(omega = theta[1],
                                 alpha1 = theta[2], beta1 = theta
                                 [3], gamma1 = theta[4]))

    uspec[[2]] <- ugarchspec(mean.model = list(armaOrder = c(0,
        0), include.mean = FALSE),
                             variance.model = list(model = "
                                 gjrGARCH", garchOrder = c(1, 1)),
                             distribution.model = "norm",
                             start.pars = list(omega = theta[5],
                                 alpha1 = theta[6], beta1 = theta
                                 [7], gamma1 = theta[8]))
    # combining disparate objects
    nuspec <- multispec(uspec)
    nunifit <- multifit(nuspec, data)

    res <- residuals(nunifit)
    sig <- sigma(nunifit)
    stdresid <- res/sig # standardized residuals from the
        univariate fit
    Qbar <- cov(stdresid)

    # DCC
    C <- list()
    c <- matrix(0, ncol = m, nrow = m)
    c[1,m] <- theta[length(theta)]
    c[m,1] <- theta[length(theta)]
```

```
  C[[1]] <- c

  I <-  matrix(1, m, m)
  A <- diag(m) * theta[length(theta)-2] # dcc a
  B <- diag(m) * theta[length(theta)-1] # dcc b

  Q <- list()
  for(t in 1:N){
    if(t == 1){
      Q[[t]] <- Qbar
    } else{
      Q[[t]] <- Qbar * (I - A - B) - C[[1]]*Xbar + A * (
          stdresid[t-1,]%*%t(stdresid[t-1,])) + B*Q[[t-1]] + C
          [[1]]*X[t-1,1]
    }
  }
  if(min(eigen(Q[[t0]])$value) <= 0){
    ll <- 1000000000
  } else {
    R <- diag(c(1/sqrt(diag(Q[[t0]])))) %*% Q[[t0]] %*% diag(c
        (1/sqrt(diag(Q[[t0]]))))
    ll <- (1/2)* (log(det(R)) + stdresid[t0,]%*%MASS::ginv(R)%*
        %stdresid[t0,])
  }

  return(ll)
}
LL_c <- function(psi,ipair){

  m <-2
  # DCC
  C <- list()
  c <- matrix(0, ncol = m, nrow = m)
  c[1,m] <- psi[3]
  c[m,1] <- psi[3]
  C[[1]] <- c

  I <-  matrix(1, m, m)
  A_dcc <- diag(m) * psi[1] # dcc a
  B_dcc <- diag(m) * psi[2] # dcc b

  Q <- R <- ll <- list()
  t <- 3
  for(t in 1:N){
```

```
    if(t == 1){
      Q[[t]] <- Qbar[[ipair]]
    } else{
      Q[[t]] <- Qbar[[ipair]] * (I - A_dcc - B_dcc) - C[[1]]*
          Xbar +  A_dcc * (stdresid[[ipair]][t-1,]%*%t(stdresid
          [[ipair]][t-1,])) +
        B_dcc*Q[[t-1]] + C[[1]]*X[t-1,1]
    }

    if(min(eigen(Q[[t]])$value) <= 0){
      ll[[t]] <- 100000000000
    } else {
      R[[t]] <- diag(c(1/sqrt(diag(Q[[t]])))) %*% Q[[t]] %*%
          diag(c(1/sqrt(diag(Q[[t]]))))
      if(min(eigen(R[[t]])$value) <= 0){
        ll[[t]] <- 100000000000
      } else {
        ll[[t]] <- (1/2)* (log(det(R[[t]])) + stdresid[[ipair
            ]][t,]%*%MASS::ginv(R[[t]])%*%stdresid[[ipair]][t,])
      }
    }
  }

  LLH <- sum(unlist(ll))
  return(LLH)
}
LL_c_t <- function(psi,t0,ipair){

  # DCC
  C <- list()
  c <- matrix(0, ncol = 2, nrow = 2)
  c[1,2] <- psi[3]
  c[2,1] <- psi[3]
  C[[1]] <- c

  I <-  matrix(1, 2, 2)
  A_dcc <- diag(2) * psi[1] # dcc a
  B_dcc <- diag(2) * psi[2] # dcc b

  Q <- list()
  for(t in 1:N){
    if(t == 1){
      Q[[t]] <- Qbar[[ipair]]
    } else{
```

```
      Q[[t]] <- Qbar[[ipair]] * (I - A_dcc - B_dcc) - C[[1]]*
         Xbar + A_dcc * (stdresid[[ipair]][t-1,]%*%t(stdresid[[
         ipair]][t-1,])) +
        B_dcc*Q[[t-1]] + C[[1]]*X[t-1,1]
    }
  }

  if(min(eigen(Q[[t0]])$value) <= 0){
    ll <- 1000000000
  } else {
    R <- diag(c(1/sqrt(diag(Q[[t0]])))) %*% Q[[t0]] %*% diag(c
       (1/sqrt(diag(Q[[t0]]))))
    ll <- (1/2)* (log(det(R)) +
          stdresid[[ipair]][t0,]%*%MASS::ginv(R)%*%stdresid[[
             ipair]][t0,])
  }

  return(ll)
}

#### ESTIMATION ####
# computing start parameters
unipars <- gdccx_ipars <- list()
for (i in 1:10){
  unipars[[i]] <- c(nunifit[[i]]@fit[[1]]@fit$coef,
                    nunifit[[i]]@fit[[2]]@fit$coef)
  gdccx_ipars[[i]] <- matrix(0, ncol = 3, nrow = 11)
  colnames(gdccx_ipars[[i]]) <- c("Level", "LB", "UB")
  rownames(gdccx_ipars[[i]]) <-  c("omega", "alpha1", "beta1",
     "gamma1", "omega", "alpha1", "beta1", "gamma1", "dcca", "
     dccb", "c1")
  gdccx_ipars[[i]][,1] <- c(unipars[[i]],dcc_fit_list[[i]]@mfit
     $coef[9:10],
                            0.05)
  gdccx_ipars[[i]][,2] <- c(rep(-1,9),0,-1)
  gdccx_ipars[[i]][,3] <- c(rep(1,11))
}

# MLE: finding the minimum (max) with solnp function
gdccx_sol_fin <- list()
for (i in c(1:10)){
  gdccx_sol_fin[[i]] <-  try(solnp(pars = gdccx_ipars[[i
     ]][9:11,1], fun = LL_c, LB = gdccx_ipars[[i]][9:11,2],
                                   UB = gdccx_ipars[[i
```

```
                                                    ]][9:11,3], ipair = i),
                                                    silent = FALSE)
}

# MLE: finding the minimum (max) with gosolnp function
gdccx_sol_fin_2 <- list()
for (i in c(1:10)){
  gdccx_sol_fin_2[[i]] <-  try(gosolnp(pars = gdccx_ipars[[i
     ]][9:11,1], fun = LL_c, LB = gdccx_ipars[[i]][9:11,2],
                                                     UB = gdccx_ipars[[i
                                                        ]][9:11,3], ipair = i
                                                        , n.restarts = 2, n.
                                                        sim = 700), silent =
                                                        FALSE)
}

# saving the estimated parameters
gdccx_pars <- list()
gdccx_pars_table <- matrix(NA, nrow = 3, ncol = 10)
for (i in 1:10){
  gdccx_pars[[i]] <- c(unipars[[i]], gdccx_sol_fin[[i]]$pars)
  gdccx_pars_table[,i] <- gdccx_sol_fin[[i]]$pars
}

#### A ####
gdccx_hess <- list()

for (i in c(1:10)){
  gdccx_hess[[i]] <- numDeriv::hessian(x = gdccx_pars[[i]],
     func = LL,
                                                     ipair = i)
}

A0 <- A1 <- list()
for (i in c(1:10)){
  A0[[i]] <- matrix(0, nrow = 11, ncol = 11)
  A0[[i]][1:4,1:4] <- nunifit[[i]]@fit[[1]]@fit$hessian
  A0[[i]][5:8,5:8] <- nunifit[[i]]@fit[[2]]@fit$hessian
  A0[[i]][9:11,1:8] <- gdccx_hess[[i]][9:11,1:8]
  A0[[i]][9:11,9:11] <-  gdccx_sol_fin[[i]]$hessian
  A0[[i]] <- -A0[[i]]/N
  A1[[i]] <- -gdccx_sol_fin[[i]]$hessian/N
}
```

```
#### B ####
gdccx_grad <- list()
for (i in c(1:10)){
  gdccx_grad[[i]] <- matrix(NA,nrow = N, ncol = 3)
  for (t in  1:N) {
    gdccx_grad[[i]][t,] <- numDeriv::grad(x = gdccx_pars[[i
        ]][9:11], func = LL_c_t, t0 = t, ipair = i)
  }
}

B0 <- B2 <- B3 <- B4 <- jointscores <- list()
for (i in c(1:10)){
  jointscores[[i]] <- matrix(0,nrow = N, ncol = 11)
  jointscores[[i]][,1:4] <- nunifit[[i]]@fit[[1]]@fit$scores
  jointscores[[i]][,5:8] <- nunifit[[i]]@fit[[2]]@fit$scores
  jointscores[[i]][,9:11] <- gdccx_grad[[i]]
  B0[[i]] <- cov(jointscores[[i]])
  B2[[i]] <- t(jointscores[[i]])%*%(jointscores[[i]])* (1/N)
}

#### RESULTS ####
# saving the estimated parameters with std. errors, t-value and
    p-value
res <- gdccx_cvar <- se.coef <- tval <- pval <- list()
for (i in c(1:10)){
  gdccx_cvar[[i]] <-(1/N)*ginv(A0[[i]])%*%B0[[i]]%*%ginv(A0[[i
     ]])

  se.coef[[i]] <- sqrt(diag(abs(gdccx_cvar[[i]]))) # robust
      standard errors
  tval[[i]] <- as.numeric(gdccx_pars[[i]]/se.coef[[i]]) # t-
      statistics
  pval[[i]] <- 2* ( 1 - pnorm(abs(tval[[i]]))) # p-values

  res[[i]] <- matrix(NA, 11, 4)
  rownames(res[[i]]) <- rownames(gdccx_ipars[[i]])
  colnames(res[[i]]) <- c("Estimate", "Std. Err.", "t-value", "
     p-value")

  res[[i]][,1] <- gdccx_pars[[i]]
  res[[i]][,2] <- se.coef[[i]]
  res[[i]][,3] <- tval[[i]]
  res[[i]][,4] <- pval[[i]]
}
```

```
# computing information criteria
InfoCrit <- function(fit){
  AIC <- (-2 * -fit$values[length(fit$values)])/N + 2 * 3/N
  BIC <- (-2 * -fit$values[length(fit$values)])/N + 3* log(N)/N
  SIC <- (-2 * -fit$values[length(fit$values)])/N + log((N + 2
     * 3)/N)
  HQIC <- (-2 * -fit$values[length(fit$values)])/N + (2 * 3 *
     log(log(N)))/N
  InfoCrit <- list(AIC = AIC, BIC = BIC)
  return(InfoCrit)
}

InfoCrit_table <- matrix(NA, nrow = 2, ncol = 10)
for (i in 1:10){
  InfoCrit_table[1,i] <- InfoCrit(gdccx_sol_fin[[i]])$AIC
  InfoCrit_table[2,i] <- InfoCrit(gdccx_sol_fin[[i]])$BIC
}

# extracting the LL values
LL_table <- matrix(NA, nrow = 2, ncol = 10)
for (i in 1:10){
  LL_table[1,i] <- nunifit[[i]]@fit[[1]]@fit$LLH + nunifit[[i]]
     @fit[[2]]@fit$LLH
  LL_table[2,i] <- -gdccx_sol_fin[[i]]$values[length(gdccx_sol_
     fin[[i]]$values)]
}

#### GDCCX COR ####
# computing the GDCCX conditional correlations
ComputeCor <- function(psi, ipair){

  m <- 2
  C <- list()
  c <- matrix(0, ncol = m, nrow = m)
  c[1,m] <- psi[3]
  c[m,1] <- psi[3]
  C[[1]] <- c

  I <-  matrix(1, m, m)
  A <- diag(m) * psi[1] # dcc a
  B <- diag(m) * psi[2] # dcc b

  Q <- list()
```

```
  rho <- c()
  for(t in 1:N){
    if(t == 1){
      Q[[t]] <- Qbar[[ipair]]
    } else{
      Q[[t]] <- Qbar[[ipair]] * (I - A - B) - C[[1]]*Xbar +
        A * (stdresid[[ipair]][t-1,]%*%t(stdresid[[ipair]][t
           -1,])) +
        B*Q[[t-1]] + C[[1]]*X[t-1,1]
    }

    rho[t] <- Q[[t]][1,2]/sqrt(Q[[t]][1,1]*Q[[t]][2,2])
  }

  return(rho)
}

gdccx_cor <- list()
for (i in c(1:10)){
  gdccx_cor[[i]] <- ComputeCor(gdccx_pars[[i]][9:11],i)
  gdccx_cor[[i]]  <- as.xts(gdccx_cor[[i]] , order.by = index(
      stocks[,1]))
}
```