Volatility Spillovers among Energy Sector Stock Indices and Fossil Fuels in the Top Ten Energy Consuming Countries

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ABSTRACT

This study examines the volatility spillovers and the network connectedness among the energy sector stock indices and fossil fuels (Brent, Natural Gas, and Coal) in the top ten energy consuming countries. We apply the Diebold and Yilmaz (2012) spillovers approach, examining the period from June 1, 2009 to December 31, 2023. Our results reveal that the energy sector stock indices of USA, Canada, France, and the UK are net transmitters of volatility whereas the energy sector stock indices of China, India, Japan, Brazil, Indonesia, and Korea are net receivers. Fossil fuels are net receivers from the energy sector indices. Major global shocks are observed starting with the 2011-2012 Arab Spring pro-democracy protests followed by the 2014-2016 sharp decrease in oil prices by 70%, the COVID-19 pandemic in 2020 and the Russian-Ukrainian war in 2022. The volatility spillovers among the energy sector indices and the fossil fuels reach their peak points during these global shock periods. The peak periods are during the COVID-19 pandemic, the Russia-Ukraine war, and the Arab Spring protests. However, during the sharp decrease in oil prices (2014-2016), The Total Connectedness Index indicates a lower level of connection among energy sector stock indices and fossil fuels.

Keywords: Energy Stocks Indices, Fossil Fuels, Volatility Spillovers, Network Connectedness

ÖZ

Bu çalışma, en çok enerji tüketen on ülkenin enerji sektörü hisse senedi endeksleri ile fosil yakıtlar (Brent, Doğal Gaz ve Kömür) arasındaki volatilite bulaşıcılığını ve ağ bağlantılılığını incelemektedir. Diebold ve Yılmaz (2012) bulaşıcılık yaklaşımını uygulayarak 1 Haziran 2009 - 31 Aralık 2023 dönemini ele alıyoruz. Sonuçlarımız, ABD, Kanada, Fransa ve Birleşik Krallık'ın enerji sektörü hisse senedi endekslerinin net volatilite yayıcıları olduğunu, Çin, Hindistan, Japonya, Brezilya, Endonezya ve Kore'nin enerji sektörü hisse senedi endekslerinin ise net alıcılar olduğunu ortaya koymaktadır. Fosil yakıtlar, enerji sektörü endekslerinden net alıcı durumundadır. 2011-2012 yıllarındaki Arap Baharı demokrasi yanlısı protestoları, 2014-2016 yıllarındaki petrol fiyatlarında %70'lik keskin düşüş, 2020'deki COVID-19 pandemisi ve 2022'deki Rusya-Ukrayna savaşı ile başlayan büyük küresel şoklar gözlemlenmektedir. Enerji sektörü endeksleri ile fosil yakıtlar arasındaki volatilite bulaşıcılığı, bu küresel şok dönemlerinde en yüksek seviyelerine ulaşmaktadır. Zirve dönemleri COVID-19 pandemisi, Rusya-Ukrayna savaşı ve Arap Baharı protestoları sırasında gerçekleşmiştir. Ancak petrol fiyatlarındaki keskin düşüş döneminde (2014-2016), Toplam Bağlılık Endeksi enerji sektörü hisse senedi endeksleri ve fosil yakıtlar arasındaki bağlantının daha düşük olduğunu göstermektedir.

Anahtar Kelimeler: Enerji Hisse Senedi Endeksleri, Fosil Yakıtlar, Volatilite Bulaşıcılığı, Ağ Bağlılığı

DEDICATION

Dedicated to my beloved family and friends, whose support, encouragement and love been with me through this journey

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INTRODUCTION

1.1 Research Background

The energy sector plays an important role in the global economic dynamics. Crude oil, natural gas and coal are the most important fossil fuels for energy consumption and generating power (Chuliá, Furió, & Uribe, 2019). Crude oil is a fundamental resource in the global energy landscape, and its price greatly affects the economic conditions such as inflation, industrial production and overall economic movements (Lang & Auer, 2020). The fluctuations in oil prices are influenced by both demand/supply and geopolitical factors, and it provides valuable insights into the complex dynamics of the global economic landscape (Gong, Feng, Liu, & Xiong, 2023). Acknowledging the significant role of crude oil in economic analysis enhances our understanding of the interconnected forces shaping the contemporary global economy, as a result it serves as a valuable hedging tool and diversification asset (Hamilton, 1983; Barsky & Kilian, 2002).

Natural gas differs from oil in its consumption patterns and market dynamics. It provides better opportunities of diversification due to its lower connectedness with other energy commodities. Natural gas is used in both industrial and residential sectors, and moreover, it can be used as a hedge against specific economic conditions contributing to the overall risk mitigation within a portfolio (Baldacci, Golfarelli, Lombardi, & Sami, 2016).

Facing an increase in uncertainties from the environmentalists, coal is still a significant energy resource in certain regions. The inclusion of coal in investment portfolios reflects an acknowledgment of its market behavior, sensitivity to regulatory changes, and potential counterbalancing role during transitional events in the energy landscape (Apergis & Payne, 2014; Batten, Ciner, & Lucey, 2015). Understanding the volatility spillovers among the energy sector stock indices and the fossil fuels is crucial as the volatility spillover effects have major implications for investors. To properly manage investment portfolios, investors must comprehend the interconnectedness of various markets. The followings are some of the most important investment implications of these markets' volatility spillovers.

First, diversification is an important strategy for an efficient portfolio and for mitigating risk. The observed volatility spillovers and clustering in these markets have led to employ more complex portfolio management methods along with dynamic asset allocation strategies. Second, another significant approach for controlling portfolio risk is hedging strategies. Due to volatility spillover and clustering effects, investors require employ more than one hedging tool to successfully minimize risk such as the need to purchase oil, natural gas and coal futures at the same time. Last but not the least, investors must take into account the correlations across these markets when allocating their assets. For instance, to reduce the possibility of volatility transmission, investors may need to minimize their exposure to energy stocks when oil prices are high.

1.2 Aims of the Study

In this study, volatility spillovers are examined among energy sector stock indices of the top ten energy consuming countries and major fossil fuels. The top ten energy consuming countries are China, United States, India, Japan, Canada, Brazil, Turkey, United Kingdom, France and Indonesia (Energy Institute, 2023). Specifically, Brent crude oil, natural gas and coal are chosen as the major fossil fuels. In the literature, the focus has been on the spillover effects of crude oil and the volatility spillovers and interconnectedness of the major fossil fuel energy commodities, notably natural gas and coal, has not been examined extensively. To address this gap in the existing literature, this study conducts a comprehensive investigation into the volatility dynamics of three major fossil fuel commodities—crude oil, natural gas, and coal.

Energy commodities are directly connected to the financial market in various baths so in the light of the global economy. For instance, oil has a strategic importance towards the energy consumption bar that has a considerable implication towards the economy. It plays a crucial role in world economic growth and inflation and has an enormous contribution to the global Gross Domestic Product (GDP). contributing significantly to the global Gross Domestic Product (GDP), accounting for approximately 2.06% of the global GDP (Aguilera and Radetzki, 2017).

Acknowledging their correlation with broader macroeconomic factors, the aims of the study is to quantify the volatility transmission of these fossil fuels commodities and energy sector indices of the top ten energy consuming countries With the results of the study, the investors and policymakers will be provided with essential information for effective risk management and controlling their portfolio diversification in the present volatile structure of energy markets.

There are the following policy implications for both the investors and the policy makers. From the impact scores obtained for the energy stock sector indices, it is clear that diversification is crucial in the energy investment sector due to the uncertainties that might emanate. Energy stocks as well as in other energy-related sectors can be used in the diversification strategies. Given the importance of crude oil, natural gas and coal in the global energy markets, policymakers must keep an eye on movements in these commodities and their possible effects. Furthermore while constructing an efficient portfolio, investors and portfolio managers should consider the spillover effects of energy sector stock indices and the financial connectednesses between the energy indices and the fossil fuels returns. These considerations can result in better portfolio performance.

The study encompasses two primary objectives. First, the historical volatility patterns of the energy stock market indices and corresponding energy commodities (crude oil, natural gas, and coal) are examined over a specified period of 2009-2023. During this period, significant events had occurred and had resulted in market turmoils and spillovers. For instance, the European sovereign debt crisis (2010-2012) which had affected the Eurozone countries and had had implications for global markets (Alter & Beyer, 2014). The Arab Spring and geopolitical instability in the Middle East in 2011 had led to oil price spikes (Noguera-Santaella, 2016). The COVID-19 pandemic starting in 2020 had caused a global health crisis and had had severe economic disruptions between 2020-2022 (Ali, Bhuiyan, Zulkifli, & Hassan, 2022). The Russian-Ukraine war starting in 2022 had led to geopolitical instability in Europe that had caused oil, natural gas and coal price spikes (Szép, Jaber, & Kashour, 2022). Second, the role of volatility spillover in shaping risk management practices is investigated for investors with exposure to both fossil fuels energy commodities and energy sector market indices, and the potential impacts on portfolio risk, return and diversification implications are assessed.

1.3 Data and Methodology

This data period for the study is between 2009 and 2023. Daily data for energy sector indices are collected from the MSCI database for the following countries: China, United States, India, Japan, Canada, Brazil, Turkey, United Kingdom, Indonesia and France (www.msci.com). For the three major fossil fuels, namely Brent crude oil, natural gas and coal, daily price data is collected from Trading Economics (www.tradingeconomics.com).

Using the Diebold and Yilmaz (2012) spillover index method, the time invarying volatility spillovers among the energy sector market indices and energy commodities are examined. This methodology considers the important global economic and political events, and therefore, detects the spillovers among the indices and shows the spillover directions. The network connectedness visualization techniques is used to demonstrate the scale of connectedness.

1.4 Structure of the Study

This study contains five chapters. Chapter one introduces the study topic and the context of the study. Chapter two is the literature review where it demonstrates a deep understanding of the subject. Chapter three covers data and methodology. Chapter four contains the empirical results and their interpretations. Last, Chapter five has the conclusions, a summary of the findings and the implications for investors and policy makers.

Chapter 2

LITERATURE REVIEW

Most studies have investigated the volatility spillovers between energy and financial markets, particularly focusing on crude oil due to its pivotal role in the global economy. Zhang et al. (2021) employed a multivariate GARCH model to analyze the volatility transmission between crude oil prices and stock markets during geopolitical tensions and financial crises, they found significant oil price shocks have an impact on stock market volatility, especially in times of economic instability. Similar study, Mensi et al. (2022) used a quantile-based approach to reveal that negative shocks in oil markets have a more substantial impact on financial market volatility than positive shocks. The interactions of oil prices and financial markets are among the widely explored issues in current research. Filis and Chatziantoniou (2020) applied VAR-BEKK-GARCH model to capture simultaneous bi-directional volatility spillover between oil price and market uncertainty with reference to the various industrial sectors; where they found that the oil sector dominantly transmitted volatility to the industrial and consumer goods sectors. This means that oil price changes are particularly important in the determination of sectoral stock market risk. In line with these findings, Ji and Zhang (2021) established high volatility spillovers of oil and natural gas to equity in the prior decade, more so due to the geopolitical shocks and supply disruptions. But a number of other investigations have revealed a high degree of co-integration between oil prices and stock markets. For instance, Park and Ratti (2008) undertake a detailed empirical investigation of the relationship between oil price fluctuations and stock market returns across developing nations and discover the strange fact that in some nations, oil price volatility does not correlate with stock market volatility. Likewise, Miller and Ratti (2009) sought to establish a long-run link between oil prices and stock markets of the OECD countries and got rather weak results. Based on their study, they found out that actually, mutual fluctuations between short-term volatilities might occur but the impact of oil price changes on stock markets is less effective in the long-run.

Oil and more recently natural gas are the fossil fuels that have attracted the most attention on how they interface with the financial markets. This was by measuring the degree of co–movements between oil price volatility as applied by Arouri et al., (2012) in their multivariate GARCH study on the European stock markets, the authors making a discovery of transmission effects. Also, Sadorsky (2014) analysed how increase in the oil prices have an impact on the stock prices of emerging markets and found that the stock prices of the emerging markets are more sensitive to oil price shocks. Similarly, Balcilar et al. (2015) looked into the causality between oil prices and stock returns employing bootstrap rolling-window approach. Based on their investigations, they came up with evidence that strongly pointed to the belief that oil prices bear a close influence to stock returns and that influence can only differ in light of time and market condition. Reboredo (2012) also established that the volatility spillovers between oil prices and stock returns are asymmetric – negative oil price shock have a stronger effect on the volatility of stock returns than positive shocks. Besides, in the study by Kang et al. (2015), the authors considered the effect of oil price shocks on the stock return and Shiller's volatility, they noted that oil prices affect the Shiller's volatility. The study by Liu et al. (2020) aimed at uncovering the interactions and volatility transmissions between oil and renewable energy stock markets. From their studies, they found out that movement towards the use of renewable energy sources affects volatility characteristics of the conventional energy resource – oil. Fresh and on-going research works carried out on the spillover effects of volatility in the oil prices and stock markets further enlighten the world on the general unprecedented effects that fluctuation in oil prices has on the financial market. For instance, Bilgin et al. (2024) looked at Kuwait and Qatar Islamic stock market indices and volatility spillover effects with energy commodities; crude oil and natural gas. They found significant bidirectional cross-market shock transmissions and volatility spillovers, highlighting the interconnectedness between Islamic financial markets and energy commodities during periods of market turbulence, although no spillover was found between Turkey's MSCI Islamic index and Brent crude oil (Bilgin et al., 2024). Similarly, Alzate-Ortega et al. (2024) explored the impacts of oil price fluctuations on emerging markets, highlighting medium- and long-term volatility spillovers during unpredicted periods such as the 2008 financial crisis, the 2015 oil price crash, and the COVID-19 pandemic. Further investigations into the interconnectedness of energy and financial markets, such as the study by Li et al. (2023), used the DY spillover index method to measure these effects. They found that the EU carbon market significantly influences cross-market volatility spillovers, particularly during extreme events like the COVID-19 pandemic. These findings are consistent with previous studies that have found significant volatility transmission between oil prices and stock markets during periods of economic stress (Ewing & Malik, 2010).

There is thus the link between taxes and volatility of the energy market, and it applies the interaction that is multiple. Studies reveal facts about the effect of price fluctuation in relation to taxes and its related factors in the energy market along with macroeconomic factors relevant to the field.

the effect of taxes as the factor influencing market stability of energy prices. Based on the results of an empirical analysis of the relationship between coal, natural gas and oil prices, the author determined that the fuel tax regime may not be appropriate, because the prices of the examined fuels behave in different ways. This implies that measures such as differential taxation policy may be more suitable in controlling fluctuations in energy prices and their impact on economic stability (The sources of diversification for firms and industries, 1994). Furthermore a study examines under what conditions energy taxes impact the burden on consumers or exporters in EU gas markets where it is established that tax-shifting dynamics are market structure and contract form contingency (Asche et al. , 2001). The second study looks into the consequential effect of transport fuel taxes with an assessment of the proportional share of expenditure on transport fuels in the lower income group indicating lesser proportions making such taxes less regressive in some countries (Flues & Thomas, 2015). A study examines how far energy taxes help in moderating the effect of change in oil prices on consumer prices, where they also argue that it is possible to lessen the effect by changing the Pigouvian component of taxes (Cremer et al. , 2015). Further, there exists a relationship between economic policy uncertainty and energy market volatility research has confirmed that policy uncertainty involving the taxation raises market volatility especially in energy market. Thus, different energy markets involve some risks that may be amplified, in case of liberalized access to competitive energy markets, and which taxation policies may either add to or offset depending on certain features of those polices (Scarcioffolo & Etienne, 2021).

The volatility spillover effects between natural gas, coal, and stock markets have gained a lot of attention in recent years. Chen et al. (2023) analyzed risk spillovers among clean energy markets, green bonds, and other financial assets in China, they found that during stable market conditions, green bonds experience fewer spillovers from clean energy markets, whereas in times of volatility, gold markets are subjected to fewer spillovers. Coskun (2023) further explored the dynamic correlations and volatility spillovers between subsectoral clean-energy stocks and commodity futures markets, highlighting that natural gas and coal as major transmitters of volatility to energy storage stocks. In Central-Eastern European markets, Jude et al (2023) investigated volatility and spillover effects during crisis periods, emphasizing significant correlations and shocks during the COVID-19 pandemic and the Ukrainian invasion. The study highlighted the urge for robust risk management strategies to mitigate the effect of such crises on financial and energy markets (Jude et al., 2023). Molina-Muñoz et al. (2023) found a shift in volatility transmission dynamics between energy and financial indices in emerging markets, noting a unidirectional pattern from energy to financial markets during the COVID-19 period.

Some studies have found minimal connectedness between natural gas prices and stock markets. For instance, while carrying out an examination of volatility spillovers between natural gas and stock market returns, Serletis and Xu (2020) provided rather limited evidence. According to their findings, they found that the relationship of natural gas prices to stock markets is less significant and have a great impact as compared to the impact of oil maybe because of the major structural and economic differences between these two commodities. Likewise, Manera et al. (2013) examined the volatility spillovers in both the USA and Europe applying the stock markets as well as natural gas prices and concluded that spillover effect was rather feeble and statistically insignificant. This suggests that natural gas markets could behave as quite distinct from stock markets, at least for some regional markets and for some conditions.

Recent studies also address the issues concerning the directional spillover effects from the markets of fossil fuels. Oviedo-Gómez et al. (2023) evaluated the spillover impacts between electricity spot prices and gas, coal, and crude oil prices in the Colombian market. They found that electricity spot prices are net shock receivers of volatility and are significantly influenced by fossil fuel price fluctuations (Oviedo-Gómez et al., 2023). Chen et al. (2023) emphasized the importance of coal, wind, and water energy markets in the volatility spillover network, contributing to market stability and identifying crucial energy markets for effective risk management post-COVID-19. Furthermore, Deng et al. (2022) examined the dynamic spillover effects and asymmetric connectedness between fossil energy and green financial markets in China. The study found that green bonds have the potential to act as safe-haven assets with low connectedness to energy markets, highlighting their role in mitigating risks in transitioning to a green economy. Xia (2022) provided a systematic literature review on the linkages and spillovers between clean energy and fossil fuel markets, pointing to the challenges of market integration in the context of transitioning to a green economy.

This research utilizes the time-in varying domain frameworks by Diebold and Yilmaz (2012) and Connectedness networks using GEPHI aproach to explore the spillover effects of volatility from fossil fuel (crude oil, natural gas and coal) and energy sector stock indices in the top ten energy consuming countries. Some studies have employed the Diebold–Yilmaz (2012) methodology. For example, Awartani and Maghyereh (2013) aimed at analysing the return and volatility spillovers between crude oil and stock market indices in the GCC countries based on the Diebold and Yilmaz (2009, 2012) method. Volatility spillovers were similarly looked at utilizing the same methodology by Mensi et al. (2018) on the S&P 500 index, STOXX Europe, 600 index, Dow Jones Asia/Pacific Index, MSCI world INDEX, and GIPSI stock markets. In the study done by Kang et al. (2017), the spillover effects were established between WTI crude oil and agricultural commodities: rice, wheat, corn and precious metals; gold and silver. Trabels (2018) used Diebold–Yilmaz approach (2012) and Barunik et al 2017 to examine the Connectedness of the cryptocurrency markets, the Bitcoin index, traditional currencies, stock markets, gold and the crude oil markets. Using the same methodologies, Liu et al. (2020) investigated the return and volatility spill over from the fossil fuel energies such as the crude oil, coal, Natural gas to the electricity spot and future markets in Europe. Tiwari et al. (2018) used Diebold Yilmaz (2012) and Barunik and Krehlik (2018) approaches to measure the volatility spillovers for a number of global assets including currency, credit default swaps, sovereign bonds, and stocks.

Recent studies have utilized econometric models and methodologies to investigate the volatility spillovers between energy markets and financial sectors. These methodological analysis have provided insights into how volatility in energy markets, particularly fossil fuels, have an impact on different financial sectors. The VAR-DCC-GARCH model analyzes the co-movements and volatility spillovers across different markets. For extant analysis on the fossil fuels, energy stock markets and the EU allowance, Gargallo et al. (2021) used the VAR-DCC-GARCH approach. The revealed results offered very valuable information about the possibility of integrating the sustainable assets into potential investment portfolios, and underlined the high level of volatility transmission across such markets (Gargallo et al. , 2021). Efremova et al., (2024) employed the similar method to analyse financial connectedness between oil and gas sector to Thai hospitality business during the energy crunch of 2021-2022. The study showed how econometric models can identify the transmission of shocks from energy markets to particular financial segments for future strategic planning for companies and policy makers (Efremova et al. , 2024). Some of the recent research in the stream of volatility spillover analysis has incorporated the machine learning approach. These methods have enhanced the accuracy of the analysis by integrating high-frequency data which in a way helps the researcher get actual dynamics and assess the probability of the spillover effects accurately. A research conducted by Jarboui et al in 2024 used the machine learning to establish relations between green FA, REMs, and Geopolitical risk index hence giving an indication on the part played by green FA and clean energy in managing geopolitical risks. Dynamic connectedness methods show how to look at the volatility spillovers in a sample, which involves multi-markets. It is through these analysis that total and directional spillovers can be measured and understood; the extent to which global financial and energy markets are connected. These method were used in a work of Gormus et al. (2023) to study the bidirectional price linkage between energy funds and oil market and deepen the analysis of the effect of the financialization of energy markets.

Some of the emerging research in volatility spillovers across oil markets and financial sub-markets demonstrate the intricacies of such structures and the two-way interactions in these markets. Based on the study done by Paientko and Amakude (2024), the volatility spillovers between energy markets and food commodity markets were examined though the application of BEKK-GARCH model. The findings were consistent with a time-varying bidirectional Granger causality test and also negated a lagged effect, but exhibited the complex interdependence on energy prices or agricultural computed from the evidence in Paientko and Amakude (2024). In addition, Alzate-Ortega et ‘, al., 2024) identified that supply oil price shocks cause volatility spillovers in the emerging oil markets, stocks and gold markets. The research established medium and long-term impact in periods of financial crisis including the global financial crisis of 2008, the 2015 oil price drop and the covid-19 health crisis (Alzate-Ortega et al. , 2024). Sánchez García and Cruz Rambaud (2023) looked at the transmission of volatility spillovers of oil and financial markets during the crises. The analysis highlighted the bidirectional relationships with significant net volatility shocks and spillovers from oil to stock markets, finding regional differences in response to crises, with the USA showing more reactivity compared to Europe (Sánchez García & Cruz Rambaud, 2023). Additionally, during the COVID-19 pandemic, the volatility transmission patterns between energy and financial stock indices in emerging markets changed to a unidirectional pattern from energy to financial markets. Hanif et al. (2023) studied the impact of COVID-19 on return and volatility spillovers between rare earth metals and renewable energy stock markets. They found a significant increase in spillovers during the pandemic, which affected cross-market hedge strategies.Some studies on volatility spillovers have provided a notable insights into the dynamics and interactions between different financial markets and commodities, shedding the light on the issues that been introduced by geopolitical risks and the financialization of oil markets. A study conducted by Gençyürek ey al. (2022) found that sector indices play a significant role in transmitting information to the oil market. This transmissions occurs during periods of positive time-varying conditional correlation between the oil market and S&P sector indices. . Similarly, a study by Ben Amar et al. (2023) investigated the interconnectedness of commodities and stock markets, particularly during Ramadan sub-periods, finding that gold act as a net volatility receiver compared to crude oil, suggesting greater diversification benefits from gold. Regional and sectoral analyses have proved that volatility spillovers can have big differences in the results depending on geographical and industrial contexts.

Additionally, Chirilă (2022) analyzed the Polish stock market, found that the banking sector is a primary transmitter of volatility spillover observing stronger connectedness during the COVID-19 crisis compared to pre-crisis levels. Furthermore, as study on the European travel and leisure sector emphasized the significant volatility spillover effects influenced by geopolitical and crude oil price uncertainties (Kumar, 2021).

The geopolitical risks are considered as a critical factors that have an influence on market volatility. An investigation conducted by Vuković et al. (2023) focused on the Asian OPEC+ member countries, pointing out that geopolitical events and natural disasters have a significant impact on oil stock returns, highlighting the necessity for investors to incorporate such risks into their decision-making processes. Additionally, Jarboui et al. (2024) employed a time-frequency connectedness approach to show how green financial assets and clean energy can mitigate geopolitical risks in financial markets. Smales (2019) found that increases in geopolitical risk are associated with positive oil returns and negative stock returns, with a more significant impact on oil prices the reason goes to the direct impacts on oil production. Furthermore, a study analyzed the volatility spillover impacts of oil, gold, and bulk shipping prices on financial markets, specifically in emerging markets in Eastern Europe, highlighting the significant risk transmission from these commodities (Pleșa, 2022).

In their seminal study, Bhutto et al. (2023) focused on the causal relationship between the current and future Crude Oil Prices and the impact of Financialization and Geopolitical Risks as a guide to future energy policy and Risk Management.The effect of financialization of oil markets during the COVID-19 pandemic was also evident in a study by Foglia and Angelini (2020), which showed that clean energy firms experienced high volatility spillovers from crude oil markets, shifting the role of oil from a volatility transmitter to a volatility receiver during the pandemic. Several studies have investigated the role of oil as a transmitter affected by geopolitical risk. Lee and Kim (2022) demonstrated that oil prices spill the highest degree of volatility to other markets during crises, emphasizing that oil plays a critical role in financial market volatility dynamics. These findings been supported by Li and Su (2020), who found that the volatility spillovers between international crude oil markets and the commodity sectors of China are significantly impacted by extreme geopolitical or financial events, affecting various global events over time. As it has been explored by Ren et al. (2024) International shipping markets also shows significant volatility spillovers to other markets, including China's energy sector, with significant peaks that correlated with geopolitical tensions impacting oil and shipping industries.

The analysis of MENA financial markets, Elsayed and Helmi (2021) discussed that while geopolitical risk does not contribute to return spillovers, but it significantly have an impact on volatility spillover dynamics, pointing to the critical role of geopolitical risk in financial stability. The dynamic volatility connectedness of geopolitical risk, stocks, bonds, bitcoin, gold, and oil during global events, such as the COVID-19 pandemic and the Ukraine-Russian war, was analyzed by Shaik et al. (2024). The results indicated that oil acts as a net volatility receiver during global events period (Shaik et al., 2024). He and Hamori (2023) also spotted that significant spillovers, including geopolitical shocks like the 11/9 attacks and financial crises, have a huge impact on volatility spillovers among commodity markets, as crude oil is considered as a key transmitter of various risks.

The recent studies highlighted the influence of various risk on volatility spillovers across various financial and commodity markets especially energy sectors. The results highlights the necessity for risk management strategies and portfolio diversification as it shows that the markets are significantly interdependence.

Chapter 3

DATA AND METHODOLOGY

3.1 Data Description

In this study, we analyze daily price data starting on June 1, 2009, to December 31, 2023, focusing in the top ten energy consuming countries within the energy sector. Specifically, the countries under consideration are China, USA, India, Japan, Canada, Brazil, South Korea, Indonesia, France, and UK. Our investigation focuses on the primary fossil fuel futures markets, namely Brent crude oil, natural gas, and coal.

The variables for the study are presented in Table 3.1 providing comprehensive information of the variables for understanding the nature and goals of our analysis. The MSCI International China Energy Sector, it includes the large and mid market capitalization and the securities in the energy index are in order with the Global Industry Classification Standard (GICS). Moving to MSCI International USA Energy Sector, it was formed to segment the USA equity, it contains the large and mid market capitalization and the securities in the energy index are in order with the Global Industry Classification Standard (GICS) as well for the rest of the MSCI energy index variables in Table 3.1 as the MCSI energy index stand for a target which is capturing the large and mid market capitalization segments and those securities in the energy index are in order with the Global Industry Classification Standard (GICS). To calculate the return of the daily prices for each variable of the energy index we use the natural logarithm as in equation 1.

$$Rt = Ln\left(\frac{P1}{Pt-1}\right) * 100 \quad (1)$$

To measure volatility in each dataset, we calculated the absolute values of the return series. The data were obtained from the LSEG (Refinitiv) Datastream terminal for the energy sectors of the chosen countries and the EquityRT web platform (https://equityrt.com) for fossil fuel futures, covering Brent oil, natural gas, and coal. The dataset includes 3,412 observations. Brent Crude, US Natural Gas, and Newcastle Coal futures were chosen as benchmarks because of their global significance, liquidity, and representation of major players and regions in the energy markets. This strategic selection ensures a robust foundation for our analytical framework, contributing to a comprehensive understanding of energy futures dynamics.

Table 3.1: Data description

Variable Name	Data Description	Source	Symbol
China	MSCI International China Energy Sector	DataStream	.MICN0EN00PHK
USA	MSCI International USA Energy Sector	DataStream	.MIUS0EN00PUS
India	MSCI International India Energy Sector	DataStream	.MIIN0EN00PIN
Japan	MSCI International Japan Energy Sector	DataStream	.MIJP0EN00PJP
Canada	MSCI International Canada Energy Sector	DataStream	.MICA0EN00PCA
Brazil	MSCI International Brazil Energy Sector	DataStream	.MIBR0EN00PUS
Korea	MSCI International Korea Energy Sector	DataStream	.MIKR0EN00PKR
Indonesia	MSCI International Korea Energy Sector	DataStream	.MIID0EN00PID
France	MSCI International France Energy Sector	DataStream	.MIFR0EN00PEU
UK	MSCI International UK Energy Sector	DataStream	.MIGB0EN00PGB
Brent	Brent Crude Futures	EquityRT	LCO07:USC
Gas	Natural Gas Futures	EquityRT	NG07:USC
Coal	Coal Futures	EquityRT	UCXMC1:USC

The timeframe is determined based on data availability, ensuring that the analysis captured a range of significant economic events that had a major impact on global markets. We chose to focus on the energy sectors of countries included in the MSCI index, traded on the New York Stock Exchange (NYSE), was determined by their fossil fuel energy consumption, as outlined in Table 3.2. Selecting countries with the highest energy consumption allows us to investigate major shocks in the global energy market and look into the dynamics of global energy stocks. Taking a look at the below table we can see that China is the top country in energy consumption in 2022 by checking the total section and note that this energy consumption is by fuels not just fossils such as oil, natural gas and coal but considering also nuclear energy, hydro-electricity and Renewables, followed by USA, India, Japan, Canada, Brazil, Korea, Indonesia, France and UK respectively.

Table 3.2: Primary energy consumption worldwide in 2022, by fuel

Country	**Oil**	**Natural Gas**	**Coal**	**Nuclear energy**	**Hydro-electricity**	**Renewables**	**Total**
China	28.16	13.53	88.41	3.76	12.23	13.3	159.39
USA	36.15	31.72	9.87	7.31	2.43	8.43	95.91
India	10.05	2.09	20.09	0.42	1.64	2.15	36.44
Japan	6.61	3.62	4.92	0.47	0.7	1.53	17.84
Canada	4.27	4.38	0.39	0.78	3.74	0.59	14.14
Brazil	5.01	1.15	0.59	0.13	4.01	2.53	13.41
Korea	5.47	2.23	2.87	1.59	0.03	0.52	12.71
Indonesia	3.06	1.33	4.38	-	0.26	0.74	9.77
France	2.91	1.38	0.21	2.65	0.42	0.81	8.39
UK	2.67	2.59	0.21	0.43	0.05	1.36	7.31

Note: the measures in exajoules, A unit of energy in the international system (SI) corresponding to $1\cdot 10^{18}$ joules, 2.78 kWh or $2.39\cdot10^{14}$ kcal.

Brent oil, natural gas, and coal were chosen to represent the energy market in this study as they are the most consumed fossil fuels around the world. This approach provides an important understanding of market dynamics. The study is positioned to contribute valuable insights into the connectedness between global economic events and energy market performance.

As part of our energy futures benchmark selection, we chose Brent Crude energy futures, US Natural Gas futures, and Newcastle Coal futures, all traded on the New York Mercantile Exchange (NYMEX). First, we incorporate Brent Crude oil futures due to its status as a major benchmark for global oil transactions and it is derived from the North Sea, Brent Crude serves as a pricing reference for oil production in Europe, Africa, and the Middle East; Notably, it stands out as one of the most liquid markets globally, which make it a suitable benchmark index in this study (www.tradingeconomics.com). We also use WTI for robustness The reason behind choosing Brent oil index over WTI index it goes to some studies such as Fattouh, 2011 and Baumeister, and Kilian, 2016, suggest that after 2011, WTI stopped representing the global market after the increase of the shale oil production in the USA caused a huge surplus in the country; Thus, this shift implies that Brent crude as the more globally oriented commodity can serve as a more relevant benchmark for worldwide oil prices, and it is more appropriate to use it in studies focused on global energy economics or when building international models. The relatively recent separation of Brent and WTI prices is the necessity of a benchmark that reflects broader international market trends (Fattouh, 2011, Baumeister & Kilian, 2016).

Second, we use US Natural Gas futures, which are centered on delivery at the Henry Hub in Louisiana, USA. The Henry Hub serves as the focal point for 16 intra- and interstate natural gas pipeline systems, tapping into the regions abundant gas reservoirs (Mazighi, 2005). Given that the United States is a leading natural gas producer, these futures provide a comprehensive reflection of the market movements, especially in comparison to other major producers like Russia (Levi, 2013).Third, Newcastle Coal futures were chosen as a benchmark due to their widespread recognition as the global standard for coal pricing used in power generation, the standard GC Newcastle contract listed on ICE involves a weight of 1,000 metric tons, given that coal remains a predominant fuel for electricity generation worldwide, these futures offer valuable insights (www.tradingeconomics.com). Furthermore, according to the trading economics web (www.tradingeconomics.com), Newcastle Coal futures consider the significant role played by major coal producers and consumers such as China, the United States, India, Australia, Indonesia, Russia, South Africa, Germany, and Poland. Additionally, major coal exporters, including Indonesia, Australia, Russia, the United States, Colombia, South Africa, and Kazakhstan, contribute to the global coal market dynamics.

3.2 Methodology

Diebold and Yilmaz (2009) enhance the Volatility Spillover Index (SI) by providing a robust econometric tool for quantifying the spillover effects in financial markets, particularly in terms of volatility transmission across diverse assets or markets. This model addresses the necessity for a comprehensive measure capturing the interconnectedness and dynamics of volatility spillovers. The preliminary work for the Volatility Spillover Index originated from the earlier development of ARCH and GARCH models by Engle (2002), offering a framework for modeling time-varying volatility. The reason behind the development of the Volatility Spillover Index by Diebold and Yilmaz (2009) is to extend the understanding of volatility beyond individual assets. They aimed to identify and quantify how volatility in one asset spills over the other. Recognizing the potential implications of such spillover effects for risk management and portfolio diversification, the SI model emerged as a valuable contribution.

Utilizing the conditional variance decomposition concept, Diebold and Yilmaz (2009) broke down the total conditional variance of an asset into components attributed to its own past shocks and shocks from other assets in the system. This decomposition formed the foundation for the Spillover Index formula which computes total spillover effects between two assets by averaging the squared unexpected returns over time. Acknowledging the complexity and correlations within financial markets, Diebold and Yilmaz (2009) introduced a quantitative measure for the transmission of volatility shocks. The model adeptly addresses the complexity of interconnected markets, offering a major key role in sight for risk management, portfolio diversification, and systemic risk assessment. Moreover, it facilitates the assessment of systemic risk by pinpointing assets or markets contributing significantly to overall spillover effects. The model also allows for the examination of how spillover effects evolve over time, providing an important understanding of changing market dynamics.

In their 2009 study, Diebold and Yilmaz used a VAR-approximating model for variance decomposition, intentionally avoiding network theory or graphical representations. They based their analysis on a small dataset, using Cholesky factor identification. In their 2012 follow-up work, they advanced their methodology by employing a generalized VAR approach. This newer approach utilized forecast-error variance decompositions that do not depend on the ordering of variables, allowing them to quantify both total and directional volatility spillovers. This approach, as outlined in the Diebold and Yilmaz's (2012) study, proves advantageous for comprehensively assessing financial market interconnections. The Diebold–Yilmaz Spillover Index provides an extensive analysis of market interconnectedness, capturing both direct and indirect connections across asset classes, portfolios, and individual assets, both domestically and globally. It is instrumental in identifying shocks, influences, trends, and occurrences of contagion or herd behavior, offering valuable insights into how shocks transmit and propagate within a financial system.

Moreover, the generalized VAR approach introduced by Diebold and Yilmaz (2012) ensures that forecast-error variance decompositions are not influenced by the ordering of variables, specifically incorporating directional volatility spillovers. This aspect assists decision-makers in having enhanced insight of the risk that is attributed to the market. The spillover index method which is described in Diebold and Yilmaz (2009), which utilizes a conventional VAR model, only allows for the estimation of dynamic total spillover index allowing for no differentiation of directional spillover. Besides, the benchmarks realized from this model are subjected to the VAR lag orders chosen.

To counter these restrictions, Diebold and Yilmaz (2012) extend a DY spillover index model to decrease VAR lag orders' influence and provide a way to capture one-way spillovers from one market to another. They use the generalized VAR outlined by Koop, Pesaran and Potter (1996), and Pesaran and Shin (1998) whose abbreviation is KPPS. This methodology calculates the degree of forecast error variation in one variable, say, x arising from shocks in a different variable, y, where $x \neq y$, also termed as spillover effect. In addition, the Diebold–Yilmas approach makes it possible introducing rolling windows, thereby enabling examination temporal dynamics of spillovers with regard to their size and signs. This makes it possible to define the transmission and reception of spillovers for each of the variables over different intervals of time. We employ the generalized VAR (q) method presented by Diebold and Yilmaz (2012) to evaluate directional spillovers in our dataset. Equation 2 illustrate a vector of disturbances that are independently and identically distributed.

$$Z_t = \sum_{i=0}^{q} \psi_i Z_{t-i} + u_t \text{ where } \varepsilon \sim (0, \Sigma) \quad (2)$$

Consider a stable variance characterized by N variables, denoted as VAR (q), where Z_t represents a vector comprising N variables at time t. In this context, ψ_i signifies an $N \times N$ autoregressive coefficient matrix, and u_t stands for the error term. By utilizing the VAR (q) model outlined in Equation (2), we can construct an infinite moving-average representation which can be expressed as follows:

$$Z_t = \sum_{n=0}^{\infty} L_n \varepsilon_{t-n} \quad (3)$$

where L_n is calculated by the following equation for the $N \times N$ coefficient matrix corresponding to the sequence of operations:

$$L_n = \psi_1 L_{n-1} + \psi_2 L_{n-2} + \ldots.. + \psi_q L_{n-q} \quad (4)$$

where L_0 is the $N \times N$ identity matrix, and $L_n = 0$ if $n < 0$.

According to Diebold and Yilmaz (2012), the system's dynamics depend on elements such as moving-average coefficients or transformations like variance decompositions and impulse-response transformations. For example, variance decompositions are used to identify the forecast-error variances for each variable, assigning them to different system shocks. Although VAR innovations are contemporaneously correlated, variance decompositions require orthogonal innovations. The modified VAR framework proposed by Koop et al. (1996) and Pesaran and Shin (1998) resolves this issue. The KPPS H-step forecast-error variance decompositions can be expressed as follows:

$$\sigma_{xy}^{g}(H) = \frac{\theta_{yy}^{-1} \sum_{h=0}^{H-1} (b_{x'} A_h \Sigma\, b_y)^2}{\sum_{h=0}^{H-1} (b_{x'} A_h \Sigma\, A_{h'} b_x)} \tag{5}$$

where θ_{yy}^{-1} denotes the error term for the standard deviation related to the y^{th} equation, and Σ represents the variance matrix for the error vector. The selection vector is b_x which is one for the y^{th} element and zero for others. However, it is important to note that the total number of components replaced in each row of the table, decomposing variance, does not add up to one. Consequently, each element in the variance decomposition matrix can be expressed as:

$$\widetilde{\sigma_{xy}^{g}}(H) = \frac{\sigma_{xy}^{g}(H)}{\sum_{y=1}^{N} \sigma_{xy}^{g}(H)} \tag{6}$$

The condition $\widetilde{\sigma_{xy}^{g}}(H) = 1$ indicates that the value of $\sigma_{xy}^{g}(H)$ is equal to 1. Additionally, the expression $\sum_{y=1}^{N} \sigma_{xy}^{g}(H)$ signifies that the sum of $\sigma_{xy}^{g}(H)$ for all values of *y* from 1 to *N* equals *N*.

Utilizing the KPPS variance decomposition, Diebold and Yilmaz (2012) formulated a comprehensive volatility spillover index, denoted as $S_g(H)$, as shows in the following equation:

$$S^{g}(H) = \frac{\sum_{xy(x\neq y)}^{N} \widetilde{\sigma_{xy}^{g}}(H)}{\sum_{xy}^{N} \widetilde{\sigma_{xy}^{g}}(H)} \times 100 = \frac{\sum_{xy(x\neq y)}^{N} \widetilde{\sigma_{xy}^{g}}(H)}{N} \times 100 \tag{7}$$

Total volatility index can be used to assist in the evaluation of shocks as a way of determining the volatility spillover of the energy sector stock indices and fossil fuel commodities. This helps us understand the contribution of various shocks to forecast error variance in the overall system. Essentially, the total volatility index allows for an examination of the comprehensive dynamics of volatility spillover within this set of variables and countries.

To determine the volatility spillovers from one market (*x*) to another market (*y*), we can employ the directional volatility spillover defined as follows:

$$S_{x.}^{i}(H) = \frac{\sum_{y=1}^{N}(y \neq x)\ \widetilde{\sigma_{xy}^{g}}(H)}{\sum_{x,y=1}^{N} \widetilde{\sigma_{xy}^{g}}(H)} \times 100 = \frac{\sum_{y=1}^{N}(y \neq x)\ \widetilde{\sigma_{xy}^{g}}(H)}{N} \times 100 \tag{8}$$

This equation calculates the directional volatility spillover index $S_{x.}^{i}(H)$ by summing the elements of the variance decomposition matrix for all pairs of variables *x* and *y* where $y \neq x$, normalizing the result by N (the total number of variables), and multiplying by 100 for percentage representation. The index quantifies the extent to which shocks from other markets contribute to the forecast error variance in the volatility of market *x*.

We also identify volatility spillovers transmitted from market *x* to other markets, the directional volatility spillover can be found as follows:

$$S_{.x}^{i}(H) = \frac{\sum_{y=1}^{N}(y \neq x)\ \widetilde{\sigma_{xy}^{g}}(H)}{\sum_{x,y=1}^{N} \widetilde{\sigma_{xy}^{g}}(H)} \times 100 = \frac{\sum_{y=1}^{N}(y \neq x)\ \widetilde{\sigma_{xy}^{g}}(H)}{N} \times 100 \tag{9}$$

This formula computes the directional volatility spillover index $S_{.x}^{i}(H)$ by summing the elements of the variance decomposition matrix for all pairs of variables *x* and *y* where $y \neq x$, normalizing the result by N (the total number of variables), and multiplying by 100 for percentage representation. The index quantifies the impact of shocks from market *x* on the forecast error variance in the volatility of other markets.

To conduct net volatility spillover analysis from one market to all other markets, the overall shock of volatility transmitted and received by all other markets in the sample are computed as shown in the equation 10:

$$S_x^g(H) = S_{.x}^g(H) - S_{x.}^g(H) \tag{10}$$

This equation computes the net volatility spillover index $S_x^g(H)$ by subtracting the directional volatility spillover from other markets to market x $S_{x.}^g(H)$ from the directional volatility spillover from market x to other markets $S_{.x}^g(H)$. The result provides insights into the overall impact of market *x* on the volatility of other markets, accounting for both sent and received volatility shocks.

Chapter 4

EMPIRICAL FINDINGS

4.1 Descriptive Statistics Results

Table 4.1 provides a comprehensive overview of the descriptive statistics for all return series. Our analysis indicates noteworthy findings, starting with mean and median, the mean return for China energy index is positive at 0.6%, indicating a positive performance. Moreover, the median return is -0.3% it can be explained that more than half of the returns are below the mean, with a significant observation of negative returns. Moving to the USA energy index, the mean return is 1.2%, while the median return is higher at 4.7%. This suggests that while the average returns are positive, the median of the returns are higher than the mean. Both mean and median returns are close and positive, at 5.2% and 4.9%, respectively for India energy index and it indicate a good performance with a relatively symmetric distribution of returns around the mean. Japan's energy index mean return is 1.3%, and the median return is at 0.8%. This suggests a modestly positive performance with a slight skew towards lower returns. The mean return for Canada energy index is nearly neutral at 0.2%, while the median return is higher at 4.3% than the mean. This indicates that the majority of the returns are positive, but there are some significant negative returns pulling down the mean. Brazil energy index have an average return of -1.0%, indicating a negative performance but the median return is positive at 3.8%, suggesting that while most returns are positive, there are significant negative outliers affecting the mean. Korea's energy index mean return is positive at 1.3%, but the median return is -3.8% and it indicates that when the mean performance is positive, the majority of returns are negative, with some high positive returns influencing the mean. Indonesia's energy index mean return is positive at 0.9%, but the median return is -6.3%. This suggests that most returns are negative, with a few high positive returns pulling the mean up. The mean return for France is 1.1%, while the median return is higher at 6.5%. This indicates that the majority of returns are positive. The mean return for the UK energy index is 0.4%, and the median return is 3.8% it suggests that while the average performance is positive, most returns are more positive, with some negative returns affecting the mean. The Brent crude oil, mean return is 1.4%, with a median return of 7.6% this indicates that while the average performance is positive, most returns are more positive, suggesting a right-skewed distribution. For natural gas, both mean and median returns are negative, at 3.3% and 8.1%, respectively and it indicate an overall negative performance, with the majority of returns being significantly negative. The mean return for coal is positive at 1.3%, while the median return is neutral at 0.0% so it suggests a balanced performance over the period, with an equal number of observations positive and negative returns, giving a neutral median and a positive mean due to a few positive outliers.

Moving to standard deviation we use it as a measurement of risk, we can notice three trends. First, the low to moderate risk are India energy index, Canada energy index, France energy index and UK energy index with a standard deviation rate of 1.627, 1.631, 1.743 and 1.761 respectively. Second, the moderate risks are: China energy index, USA energy index, Japan energy index and Korea energy index with a standard deviation of 1.828, 1.852, 1.854 and 2.249 respectively. Third, the high risk are Coal, Brent and Indonesia energy index with a standard deviation rate of 2.411, 2.563 and 2.593 respectively and not forgetting Brazil energy index and gas they are the highest risk of returns compare to the other variables in our sample with a standard deviation rate of 3.114 and 3.875 respectively.

In terms of skewness; Specifically, several variables, namely China energy Index, India energy index, Korea energy index, Indonesia energy index, Brent, Natural Gas, and Coal, exhibit positive skewness, indicative of a right-skewed distribution. Conversely, the remaining variables, including USA energy index, Japan energy index, Canada energy index, Brazil energy index, France energy index, and the UK energy index, display negative skewness, suggesting a left-skewed distribution. These skewness patterns shed light on the asymmetry in the return distributions of the respective variables, considering the observed positive skewness, the skewness of the Coal return series is the most skewed followed by Natural Gas. This observation means that these two energy commodities tend to have a positive skewness, or depressively move in tails to a great extent, which indicate that there are many large positive deviations, or movements, in the return distribution. In other words, the highest realized volatility which in other words is the highest number of such upward movements or the highest volatilities are those of Coal and Natural Gas. Taking a look at the negative skewness instances, we find that the skewness of the Canada energy index return series is the highest followed by Brazil energy index. This negative skewness signifies a left-skewed distribution indicating a tendency toward large negative deviations or extreme movements in the return distributions of Canada energy index and Brazil energy index. It can be implied that the most substantial realized volatility or notable downward price fluctuations are associated with Canada energy index followed by Brazil energy index. These observations contribute valuable insights into the asymmetry and the volatility movements of the respective countries' energy sectors, providing an important perspective on their market volatility movements.

Examining the kurtosis values, all return series' kurtosis values are more than 3 indicating a leptokurtic distribution with fat tails, and it is peaked compared to a normal distribution. Notably, the return series for coal also shows the highest kurtosis. Furthermore, the Jarque-Bera normality test results reject of the null hypothesis of normal distribution for all return series.

Table 4.1: Descriptive Statistics Results of the Return Series

	China	USA	India	Japan	Canada	Brazil	Korea	Indonesia	France	UK	Brent	Gas	Coal
Mean	0.006	0.012	0.052	0.013	0.002	-0.010	0.013	0.009	0.011	0.004	0.014	-0.033	0.013
Median	-0.003	0.047	0.049	0.008	0.043	0.038	-0.038	-0.063	0.065	0.038	0.076	-0.081	0.000
Maximum	10.003	15.014	18.136	9.868	14.845	21.832	17.633	16.117	16.366	19.521	41.455	44.715	51.500
Minimum	-10.680	-22.704	-10.734	-14.131	-21.200	-34.564	-16.716	-13.349	-18.164	-20.470	-30.796	-44.155	-39.855
Standard-Deviation	1.828	1.852	1.627	1.854	1.631	3.114	2.249	2.593	1.743	1.761	2.563	3.875	2.411
Skweness	0.002	-0.732	0.134	-0.162	-1.321	-0.912	0.313	0.338	-0.366	-0.423	0.189	0.393	0.815
Kurtosis	5.787	17.249	11.503	6.289	26.921	13.955	8.887	7.031	16.371	19.330	37.035	23.534	101.885
Jarque-Berra	1104.29*	29170.76*	10288.93*	1553.23*	82341.44*	17534.98*	4982.31*	2374.74*	25491.37*	38014.48*	164703.90*	60030.22*	1390509.00*

Notes: *statistically significant at 1% level; the return series of the energy sector index for the top ten energy consuming

4.2 Diebold and Yilmaz (2012) Results

4.2.1 Static Analysis

A static analysis has been done to examine the transmission in volatility over time among energy sector stock indices in the top ten fossil fuel consuming countries (China, USA, India, Japan, Canada, Brazil, South Korea, Indonesia, France, and UK), and three primary energy commodities: oil, natural gas, and coal. The relevant findings from the static analysis are presented in Table 4.2.

Each row in the table signifies the transfer of volatility spillovers to other markets, denoted as "TO". Conversely, each column represents the receipt of volatility spillovers from other markets, designated as "FROM." To compute the net volatility spillovers, we calculated the differences between the "FROM" and "TO" values. Additionally, the total spillover index, indicated as 43.70% in the lower right corner, facilitates a conclusive summary of all given (TO) and (FROM) among the markets. This index is calculated by finding the total of the received values where the total is divided by the total number of the markets in the sample that is 13 Markets X 100% =1300%.

The level of directional spillovers observed throughout the entire period under study is moderate by 43.70% out of 100%. This suggests that a significant portion of the forecast-error variance of volatility in all the energy indices and fossil fuel commodities in our sample is attributed to spillovers, suggesting a significant interdependence among volatilities.

Table 4.2: Volatility Spillover among Energy Sector Stock Indices and Fossil Fuels in the Top Ten Energy Consuming Countries Based on Full Sample Estimation

	China	USA	India	Japan	Canada	Brazil	Korea	Indonesia	France	UK	Brent	Gas	Coal	*From*	*Net*
China	54.59	6.69	2.77	4.93	6.43	3.26	2.71	4.06	5.58	5.49	2.99	0.26	0.26	45.40	-14.40
USA	2.10	32.47	1.98	0.98	19.97	6.88	1.57	1.34	11.42	12.57	8.08	0.24	0.40	67.50	28.00
India	3.05	4.11	64.88	1.51	5.48	2.42	1.25	3.65	4.90	5.16	3.00	0.17	0.43	35.10	-11.90
Japan	5.83	5.24	1.48	62.66	5.55	1.98	1.59	2.15	4.86	4.71	3.25	0.10	0.59	37.30	-19.50
Canada	2.06	19.49	2.46	1.33	33.49	7.70	1.42	1.87	10.66	11.61	7.50	0.23	0.18	66.50	29.20
Brazil	2.21	10.70	1.76	0.86	11.69	49.50	1.06	1.15	8.37	8.02	4.50	0.13	0.06	50.50	-7.90
Korea	3.38	6.18	1.64	1.63	5.71	2.54	63.79	1.49	5.22	5.81	2.12	0.27	0.19	36.20	-20.30
Indonesia	4.87	3.43	3.83	1.98	4.67	2.08	1.30	67.59	3.80	3.20	2.85	0.06	0.33	32.40	-11.70
France	2.64	12.10	2.26	1.22	11.32	5.72	1.62	1.72	35.68	20.14	5.21	0.18	0.19	64.30	16.90
UK	2.27	13.15	2.33	1.26	11.89	5.25	1.87	1.38	19.21	34.01	6.48	0.32	0.59	66.00	21.10
Brent	1.70	12.38	1.70	1.31	11.69	4.47	1.19	1.50	6.37	9.00	47.26	0.45	0.99	52.70	-4.10
Gas	0.44	0.77	0.15	0.02	0.72	0.21	0.15	0.22	0.37	0.47	0.44	94.98	1.06	5.00	-1.10
Coal	0.42	1.30	0.79	0.77	0.54	0.12	0.20	0.16	0.39	0.90	2.14	1.52	90.75	9.20	-3.90
To	31.00	95.50	23.20	17.80	95.70	42.60	15.90	20.70	81.20	87.10	48.60	3.90	5.30	568.30	*TCI=43.70%*

On average, approximately 43.70% of the variance in volatility forecast errors across these thirteen markets can be attributed to spillovers, with the remaining 56.3% likely reflecting external shocks. In Table 4.2, the directional net volatility spillovers reveal that the Canadian energy sector index has the most significant impact on other indices (TO Canada – FROM Others), showing a net spillover effect of 29.20% (95.70 – 66.50= 29.20%). The influence of Canada energy index is followed in magnitude by the index energy sectors of USA, UK, and France, respectively.

Focusing on energy commodities, crude oil stands out for its considerable volatility spillover to the United States, marked at about 8.08%. This observation aligns with the findings of studies by Bouri et al. (2022), Coskun and Taspinar (2022), and Ahmed and Huo (2021) conduct an extensive examination of the complex spillover effects between the volatility patterns of the crude oil market and the fluctuations occurring in the stock market. Their research explores the interrelationships and transmission mechanisms that connect these two markets. Given that the United States is considered as one of the biggest global oil importers, relying on Canada as its foremost supplier for both total petroleum and crude oil (accounting for 52% and 60% of U.S. petroleum and crude oil imports, respectively, in 2022, according to the U.S. Energy Information Administration, 2024), the USA energy market is particularly sensitive to shifts in crude oil volatility as well for volatility spillovers as we can notice from the static analysis results in table 4.2 USA receive spillover shocks by 67.50% from other energy markets. Such volatility spillovers can be explained to geopolitical tensions, sanctions on oil-producing countries, and the supply strategies of the Organization of the Petroleum Exporting Countries (OPEC).

Moreover, coal's volatility spillover is most pronounced in Japan and UK, having the highest 0.59% volatility transmission rate from coal to these two countries. For instance, in 2022, Japan was the top global coal importer by value, bringing in nearly $60 billion worth of coal, with India following as the second-largest importer, this highlights Japan's significant reliance on coal imports to fulfill its energy needs (Statista, 2023; U.S. Energy Information Administration, 2019). The case of UK, the demand of coal fell to 14% in 2022 compare to 2021, followed by the consumption of coal that fell in 2022 by 15% compare to 2021 and the production of coal fell to 38% in 2022 from the previous year 2021, but in 2022 UK imports coal from USA, when the import prices increased to 38% in 2022 compare to 2021, USA now becomes the largest coal exporter to UK with 39% share after UK’s decision to stop importing coal from Russia on august 2022 after the Russia-Ukraine war (Michaels, 2023).

Similarly, natural gas volatility significantly affects the UK having the highest 0.32% spillover rate. The UK's primary natural gas supplier is Norway, which provided over 341 terawatt hours of natural gas in 2022, followed by the United States coming in as the second-largest supplier (Statista, 2024). The dependence on these imports’ underscores how geopolitical events and global market shifts, such as supply constraints or price hikes, can lead countries to adjust their energy consumption patterns, increasingly turning to renewable energy sources. Furthermore, countries that heavily rely on imported energy sources are more affected by the volatility in these energy commodities. Our findings indicate that major energy commodities generally act as net receivers, with natural gas having the lowest rate as a net receiver from other markets at -1.10% (3.90-5= -1.10). However, Brent oil with - 4.10% net receiver rate (48.60 – 52.70= - 4.10%) and coal with a net receiver rate of - 3.90% (5.3 – 9.20 = -

3.90%) are considered the highest net receivers compared to the natural gas future market in the fossil fuels markets.

Our sample contains developed and developing countries, the results align with the findings of Jebabli et al. (2022), In specific, they analyzed volatility spillovers between market stocks and energy markets during the Global and Financial Crisis of year 2008 and the COVID-19 pandemic crises. The authors also discovered that in terms of volatility transmission, developed stock markets countries are net transmitters to crude oil. This aligns with Coskun and Taspinar (2022), who also investigated the dynamics between energy industry stock markets and energy markets. Our results further support these findings, demonstrating that developed countries in our sample exhibit similar volatility transmission patterns to energy markets, particularly crude oil as the net transmission is -4.10%, when natural gas is -1.10% and coal is -3.90% as the net receivers are negatives so this shows that the fossil fuels are net receivers. Nevertheless, such research is needed to estimate this relationship in the context of time varying data, adjusting for the roles of cyclical and other extraordinary factors which change over time. This is done in the coming section.

4.2.2 Dynamic Analysis

Figure 4.1 illustrates the dynamics of total volatility connectedness between 2009 to 2023 between energy indices of the highest fossil fuel consumption countries and energy markets, specifically crude oil, natural gas, and coal.

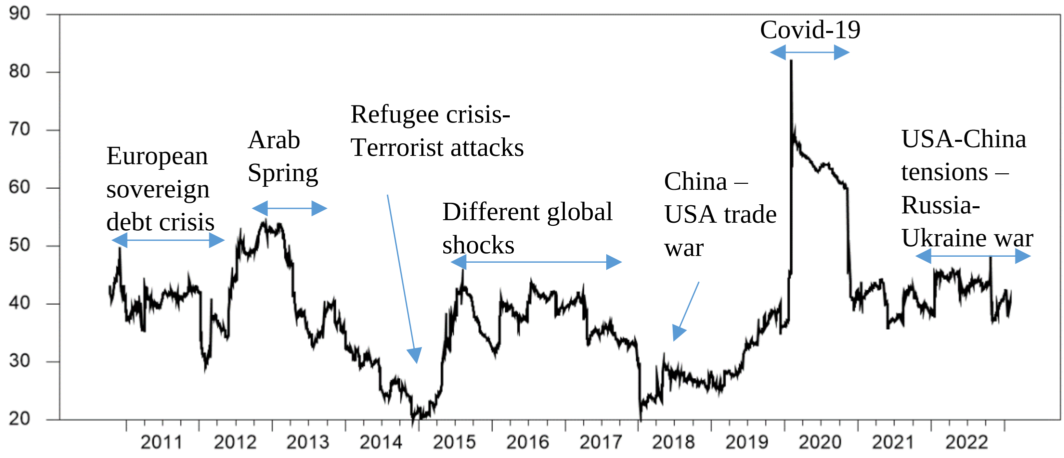

Figure 4.1: Total Volatility Spillovers Based on DY (2012)

The total volatility spillovers range from 20% to 85% over time, with the static total spillover index estimating them at 43.70%. Thus, this finding indicates that the time-varying approach offers a more comprehensive insight into the interdependence of volatility in energy sector stocks and energy markets compared to a static analysis. We observe numerous fluctuations and sudden spikes as a result of extreme events occurring throughout the world. There are clear oscillations seen in the early 2010s, which might potentially be linked to the European Sovereign Debt Crisis and the Arab Spring. These events may have led to a rise in volatility transmission across the energy markets, as seen by the fluctuating TCI values. The European nations encountered substantial fiscal deficits and debt levels, resulting in a crisis of trust between the European markets and economy. The crisis would have probably heightened the instability in the energy sectors, especially among European nations like France and the UK. Nevertheless, the figure 4.1 first period in 2011 demonstrates a state of relative stability before the beginning of fluctuations in the TCI. This suggests that although there was an impact, the spillover of volatility in the energy sector was not as significant as one would anticipate during a crisis. The decrease in demand for energy caused by cuts to spending and recession likely contributed to the reduction in volatility spillovers within the energy markets of the affected countries. As countries adopted these policies and markets adapted to the new financial conditions, the interrelated instability across these markets probably decreased, which helped to explain the decreasing trend seen in the figure. The Arab Spring, which started in late 2010, encompassed a sequence of anti-government demonstrations and revolts across the Arab world, comprising notable oil-exporting countries. This time frame may be linked to increased volatility in the energy sectors, since geopolitical instability in these regions may directly affect oil supply and pricing. This is why there were significant increases in the TCI during 2011-2012, as seen in figure 4.1 after 2015 up to late 2019, there appears to be a stability in the TCI between 20% and 45% on average, highlighting various indicators. Crisis recovery and stability it is usually the case for markets to stabilize and have reduced volatility over time after a major economic event, such as the European Sovereign Debt Crisis or the Arab Spring. As markets adjust to changing economic conditions and concerns are resolved, volatility often decreases. In addition, although markets are interconnected, there are times when local variables have a stronger influence than international causes, resulting in a reduction in the overall volatility spillover index. Moreover, the results referring to Figure 4.1 indicate that the COVID-19 pandemic is characterized by the most significant volatility spillovers between energy assets and fossil fuel energy markets. Put simply, the degree of interconnectedness in volatility among these markets amidst the COVID-19 pandemic in 2020 surpassed all other worldwide occurrence from 2009 to 2023 (as measured by the volatility spillover index, which peaked at around 85%). Recent studies as (Alamaren, Gokmenoglu, & Taspinar, 2024), (Coskun, & Taspinar, 2022) and (Bouri, Cepni, Gabauer, & Gupta, 2021) suggest that the coronavirus pandemic, which not only caused record levels of uncertainty and a decline in investor sentiment but also high volatility spillovers between markets, triggered an unexpected drop in real activities in the majority of economies and been mentioned earlier Following the World Health Organization's release of the vaccine, the market experienced less tension and increased stability.

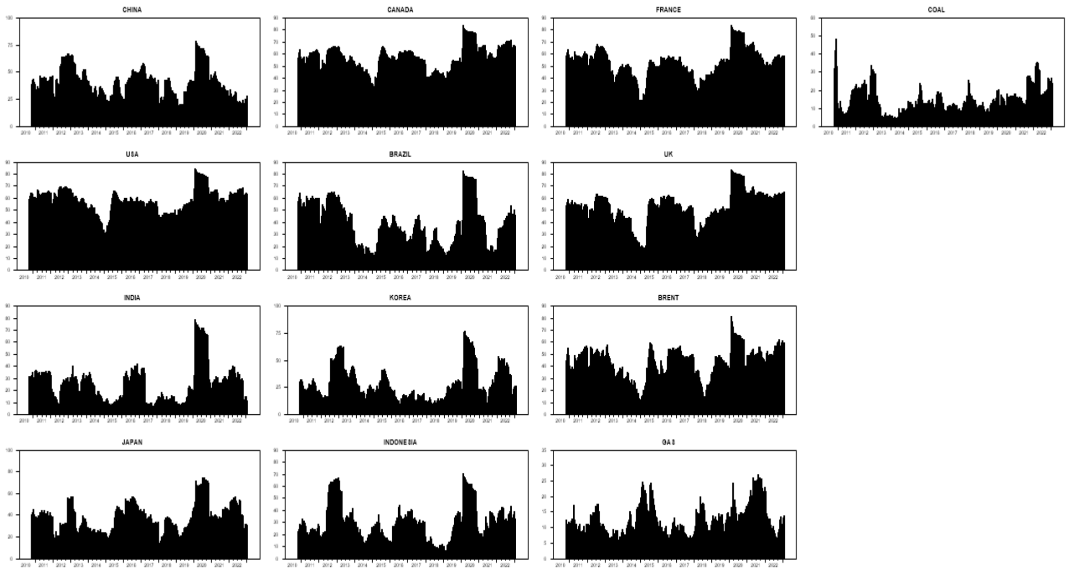

Figure 4.2: Directional Volatility Spillovers (FROM)

Our sample of energy indices and fossil fuels exhibits patterns of directional volatility spillovers, as seen in Figure 4.2. In 2020, during the COVID-19 era, volatility spillovers increased by almost 40%, which is in line with what Coskun and Taspinar, (2022) found. The transmission of volatility for fossil fuels has changed throughout time, as it did for Brent and natural gas during COVID-19. However, when it comes to coal, there isn't much transmission of volatility, unlike in 2009, which might be explained by the financial crisis of 2007–2008. Energy sector indexes in France, the United Kingdom, Canada, and the United States impart volatility to others in a way that varies with time. Similarly, when major shocks like COVID-19 hit, China, Japan, Brazil, and India transmitted their volatility to other countries. However, when it comes to India and Korea, this is not always the case. There was a brief period of lower volatility spillovers following the vaccination announcement, but they increased again in 2022 as a result of the Russian invasion of Ukraine, due to geopolitical tension and price inflation in line with the findings of Alamaren et al. (2024). When looking at fossil fuels, the average volatility of spillovers from crude oil to other markets was 55% during the Arab Spring and nearly 85% during the COVID-19 epidemic. Across the board, spillovers change as a result of global political and economic events. Thus, the variations in interconnectedness of natural gas and energy stocks seem to be chiefly driven by the time-varying transmission of volatility from all energy stocks. Figure 4.3 shows that volatility spillovers of gas peak in 2015, the same year that they do for both scenarios; when the net magnitude of transmission is taken into account, natural gas receives more than it transmits during this year. The transmission of directional volatility spillovers between coal and energy stock markets, as well as between energy stocks and coal, is substantial across the time frame of the sample. Figure 4.2 shows that during the 2009 the Global Financial Crisis, the transmission of coal volatility to other markets became more intense. Compared to other energy commodities, coal's volatility spillovers did not peak during the COVID-19 pandemic. Furthermore, as can be shown in figure 4.3, coal experiences market volatility, particularly between the 2009 and 2022 periods. This volatility might be attributed to factors such as the Russian-Ukrainian conflict, the reduction of natural gas supplies to EU nations, and a corresponding spike in demand for coal.

The sample of energy stock indices and fossil fuels are shown in Figure 4.3, which indicates the directional volatility spillovers all to one market.

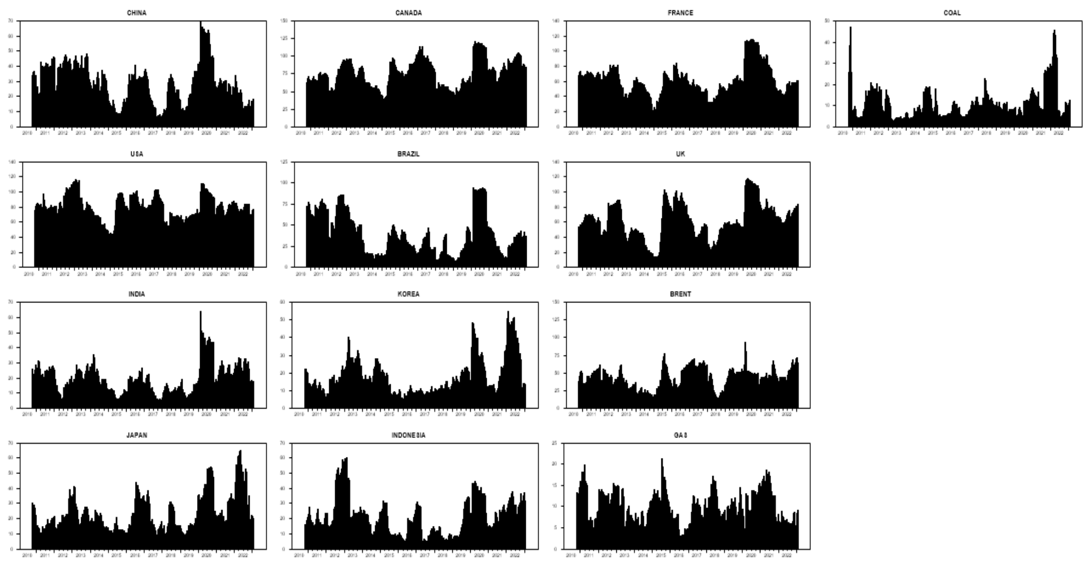

Figure 4.3: Directional Volatility Spillovers (TO)

There are observable changes in time in the transmission of impacts from other markets to one particular market. Compared to the rises in the direction of their volatility spillovers to different asset classes, the relative variation pattern is reversed. As a result, all energy indices experienced their peak volatility in 2020 during the COVID-19 period. However, in 2022, the Russian-Ukrainian war was more significant for Korea and Japan than the COVID-19 pandemic, and for Indonesia, the receiving shock was greatest from 2011 to 2012. Energy indices and fossil fuel prices had increased volatility spillovers. On average, throughout the COVID-19 period, developing countries like China, India, and Brazil observed time-variant volatility spillovers of 70%, 65%, and 85%, respectively. Canada, the United States, the United Kingdom, and France were the recipients of time-variant volatility spillovers from other developed nations' energy stock sectors, with average volatility spillovers reaching 120% throughout the COVID-19 period. When it comes to Indonesia, the most significant transmission of volatility from others was in the years 2011 and 2012. On average, volatility spillovers reached 65% during that time, which we attribute to internal political conflicts and environmental crises. After all, that was the year that Japan had its biggest earthquake, which caused a major economic crisis and a tsunami. When it comes to Japan and Korea, it's safe to assume that the Russian-Ukrainian war had an impact on both countries. In 2022, for example, the volatility spillovers to Japan and Korea were above 60% and 50%, respectively. As a result of the Russian invasion of Ukraine, Japan increased its military spending to 2% of its GDP, which could be traced back to the long-standing dispute between the two countries. We assume that the heightened volatility shock in Korea was caused by political tensions, since the relationship between Russia and Korea has grown increasingly heated following Korea's statement that it will help Ukraine with $100 million of aid.

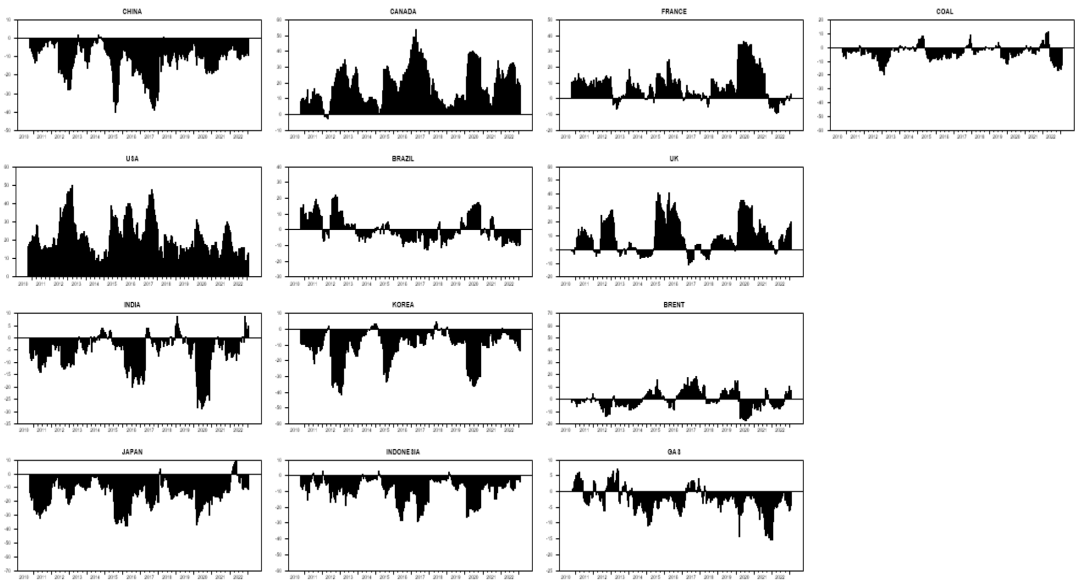

Figure 4.4: Net Volatility Spillovers Based on DY (2012)

To make it easy to comprehend, the energy stock indices contain ten countries of the most consuming of fossil fuels, developed countries, developing countries and the energy market (Brent oil, Natural gas and coal). Developed countries in our sample are Canada, USA, UK and France. Developing countries in the sample are China, Japan, Korea, Brazil, India and Indonesia. As we can see in the time variant from figure 4.4, we notice that the developed countries are net transmitters to other markets over time but on the other hand the developing countries are net receivers and this goes well with our static analysis in table 4.2. Looking at the energy market, starting with brent oil we can notice that it is fluctuating over time between transmitting and receiving to and from other markets but overall it is a receiver from all to brent by 52.70% check table 4.2, but looking at natural gas in the early time according to figure 4.4 we can see that it used to be net transmitter but then it changed to be a net receiver especially to itself by 94.98% as stated in table 4.2 and only 5% from others and it only transmit to other markets 3.40%, this might go to the increase demand on natural gas that led to an increase in its future prices as we can notice from figure 4.4 the most increase in net volatility was during 2022 the Russian Ukraine war followed by covid-19 in 2020. Nevertheless, for coal it is not different form natural gas as it receives from itself about 90.75% and from others 9.20% as it transmits to other markets only 5.30% and that make it as net receiver.

4.3 Volatility Spillover Network Results

Connectedness networks are used to illustrate directional volatility spillovers among variables, Figure 4.5 illustrates the movements of which shocks are transmitted FROM one market TO others. Additionally, Figure 4.6 displays the network of connectedness, showing the effects TO one market FROM others, a stronger influence is indicated by darker color and bolder lines and a lighter shade suggests a less influence during any global shock. Additionally, these volatility spillover networks are computed following the assessment of extreme volatility spillovers and using the connectedness network help to understand better the interconnectedness among the variables over time and help to make hedging and diversification strategies.

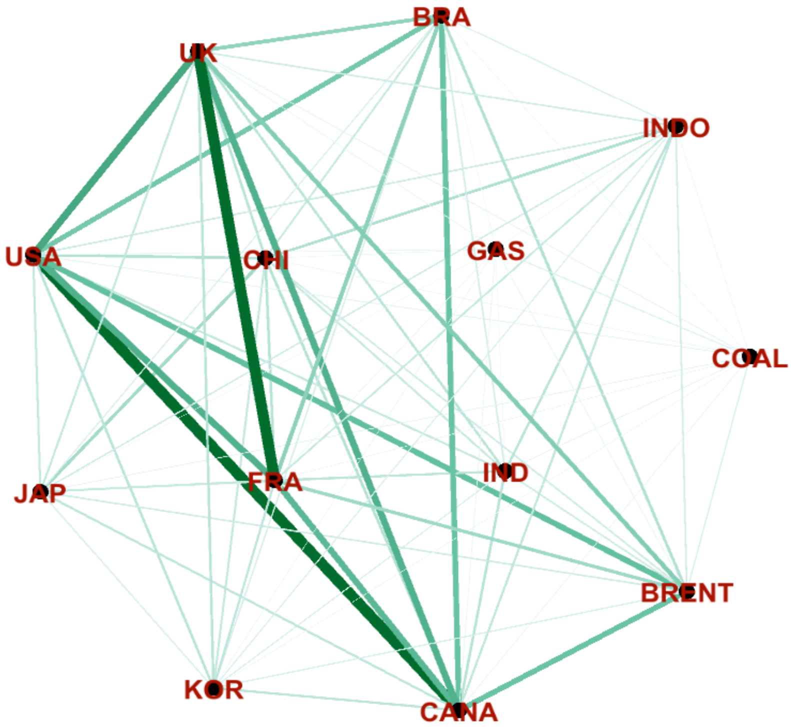

Figure 4.5: Connectedness Map FROM Others

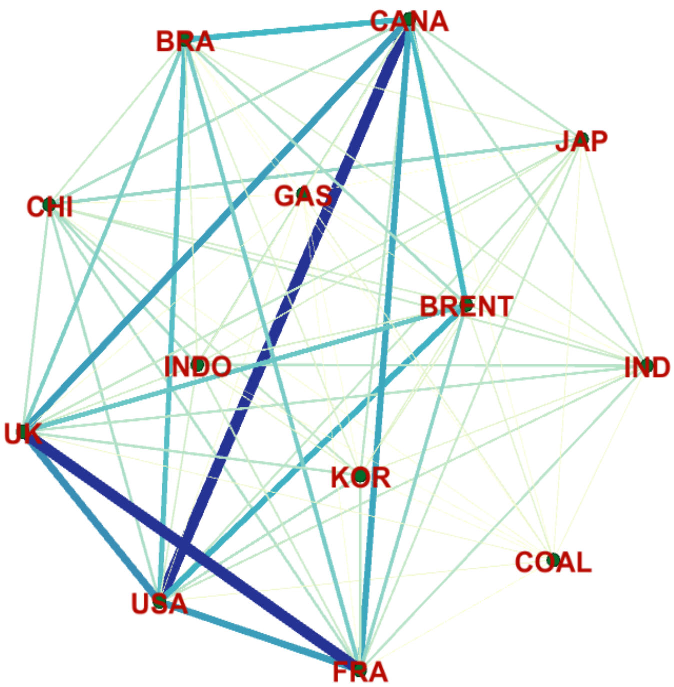

Figure 4.6: Connectedness Map TO Others

The energy market of China shows a clear 'From Others' value (45.40%) as shown in figure 4.6, so it receives a considerable amount of volatility from other markets. However, from its own contribution to itself ('Chi' to 'Chi') is (54.59%). This means that the Chinese energy market is influenced by external factors, and it is also impacted by self-influenced volatility and as we can look at figure 4.5 it is less connected with the other market as it only transmits (30%) to other energy markets.

Looking to the energy market of USA it is high 'To Others' value (95.50%), indicating a strong impact on other markets as we can see from figure 4.5 and it contributes volatility to itself by only (32.47%). However, USA is considered a transmitter country in the energy sector but it receives 'From Others' value (67.50%) as it is clear from figure 4.6 it is highly connected with Canada then UK, France and Brent.

India is no different from China as it is more of a volatility receiver, with its 'From Others' is (35.10%) value, as illustrated in figure 4.6. from table 4.2 we can notice that most of the volatility spillover from its own contribution to itself ('Ind' to 'Ind') is (64.88%). It explains why the Indian energy market is less connected as we can notice from figure 4.5 and figure 4.6 and it shows that it is less influenced by external factors, and it is much impacted by self-influenced volatility and as we can look at figure 4.5 it is less connected with the other market as it only transmits (23.20%) to other energy markets.

The energy market of Japan is like China and India as it is a net receiver 'From Others' by (37.30%) value, but from its own contribution to itself ('Jap' to 'Jap') is (62.66%). We may conclude that the internal influence is less than the external, indicating that it is more reactive to global energy market changes as we can see that from figure 4.6

that it is more connected to China mostly then Canada and we can look at figure 4.5 it is less connected with the other market as it is only transmit (17.80%) to other energy markets.

Canada’s energy market is the biggest transmitter to others with a value of (95.70%) and as we can see from figure 4.5 it is highly connected to other energy markets mostly to USA then UK, France, Brent and Brazil, and it contributes to its own volatility to a lesser extent with a value of (33.49%) moreover, as it is highly connected to others and transmit, it receive less compare to how much it transmit with a value of (66.50%) and it mostly receive from USA and UK followed by France, Brent and Brazil.

Brazil's energy market receives a good amount of volatility from others (50.50%) mostly from Canada, USA, France, UK and Brent respectively as shown in figure 4.6 and it contributes a lower amount of volatility to itself (49.50%), explaining its sensitivity to external factors, and it do transmit a fair amount of shock to others by (42.60%) especially to USA, Canada, UK and France respectively according to figure 4.5 this means that brazil’s energy market is connected to any global changes.

Korea has a moderate 'From Others' value (36.20%) mostly from china compare ‘To Others’ value (15.90%) this shows that Korea is less connected from the energy global market as it displayed on figure 4.6 (From Others) and figure 4.5 (To Others), suggesting that it is less influenced by other markets. Its own contribution to its volatility is also relatively high as it is transmitting to itself (63.79%).

The energy market of France is transmitter to others with a value of (81.20%) and as we can see from figure 4.5 it is highly connected to other energy markets mostly to

UK then USA, Canada, and Brent, and it contributes to its own volatility to a lesser extent with a value of (35.68%) moreover, as it is highly connected to others and transmit, it receive less compare to how much it transmit with a value of (64.30%) and it mostly receives from UK then followed by USA, Canada, Brazil and Brent.

Looking to the energy market of UK it is high 'To Others' value (87.10%), indicating a strong impact on other markets as we can see from figure 4.5 and it contributes volatility to itself by only (34.01%). However, USA is considered a transmitter country in the energy sector but it receives 'From Others' value (66.00%) as it is clear from figure 4.6 it is highly connected with France then USA, Canada, Brazil and Brent.

This show that the developed countries are more connected to any global events and shocks in the energy market over time than developing countries as we discussed in the dynamic analysis.

Brent crude is a major net receiver of volatility over time, with a 'From Others' value of (52.70%) and a lower volatility to itself with value of (47.26%), indicating that it's heavily influenced by global factors and it also transmit to other energy markets by (48.60%) value but according to figure 4.5 and figure 4.6 it highly connected with Canada the most followed with USA, UK, France, and Brazil respectively.

The natural gas future market receives less volatility from others with 5% value and it contributes shocks the biggest to its own volatility by 94.98%. This shows a degree of insulation from external shocks. As it also transmits only 3.90% which makes it the lowest net receiver compared to Brent and Coal and as shown in figures 4.5 and 4.6 it is has low connectedness in the energy market in our sample.

Coal has a high reception of volatility from itself by a shock transmission rate of 90.75% to itself, which its self-influenced volatility as natural gas market, and it receive from others 9.20% shocks and transmit to others 5.30% indicating a lower connectedness in the energy market in the sample as gas as we can look to figure 4.5 and 4.6. Coal is the second highest net receiver among the fossil fuels from our sample, who comes first is Brent oil and the lowest as a net receiver is natural gas.

4.4 Robustness Test

Verifying the empirical findings is essential to confirm their robustness and validity, especially considering the arbitrary selection of the oil index. The choice between the WTI futures energy index and the Brent futures energy index can notably influence the analysis of total connectedness. We utilized the WTI index as an alternative benchmark to assess the reliability of our empirical results. The analysis of the time-varying total spillovers presented in Table 4.3 indicates a lower connectedness of 41.10% for WTI compared to 43.70% for Brent. The variation in connectedness over time is relatively minor.

Table 4.3: Volatility Spillover Based on Full Sample Estimation Using WTI

	China	USA	India	Japan	Canada	Brazil	Korea	Indonesia	France	UK	WTI	Gas	Coal	*From*	*Net*
China	55.45	6.78	2.81	5.00	6.52	3.30	2.74	4.12	5.66	5.57	1.52	0.26	0.26	44.60	-13.70
USA	2.19	33.95	2.01	1.01	20.83	7.17	1.64	1.39	11.84	13.05	4.27	0.25	0.40	66.00	27.70
India	3.09	4.12	65.81	1.50	5.44	2.43	1.28	3.67	4.73	5.02	2.36	0.17	0.39	34.20	-11.80
Japan	5.96	5.32	1.49	64.15	5.64	2.01	1.60	2.20	4.95	4.78	1.19	0.11	0.60	35.90	-18.90
Canada	2.15	20.32	2.48	1.37	34.96	8.03	1.48	1.93	11.02	12.03	3.80	0.24	0.18	65.00	27.80
Brazil	2.27	10.99	1.78	0.88	12.00	50.98	1.09	1.18	8.58	8.22	1.85	0.13	0.06	49.00	-7.60
Korea	3.42	6.28	1.66	1.63	5.79	2.57	64.68	1.50	5.26	5.88	0.87	0.28	0.18	35.30	-19.80
Indonesia	4.94	3.45	3.83	2.01	4.70	2.09	1.30	68.57	3.81	3.20	1.71	0.07	0.32	31.40	-10.80
France	2.72	12.40	2.21	1.25	11.57	5.87	1.66	1.76	36.71	20.62	2.88	0.19	0.17	63.30	16.50
UK	2.36	13.59	2.31	1.30	12.25	5.43	1.94	1.42	19.81	35.24	3.45	0.33	0.57	64.80	19.90
WTI	0.98	8.41	0.98	0.30	6.79	2.21	0.46	1.12	3.42	5.01	68.93	0.66	0.74	31.10	-5.10
Gas	0.44	0.77	0.15	0.02	0.73	0.22	0.15	0.22	0.38	0.47	0.46	94.93	1.07	5.10	-0.90
Coal	0.42	1.28	0.71	0.76	0.51	0.11	0.20	0.15	0.33	0.83	1.63	1.55	91.50	8.50	-3.60
To	30.90	93.70	22.40	17.00	92.80	41.40	15.50	20.60	79.80	84.70	26.00	4.20	4.90	534.10	*TCI=41.10%*

This small difference suggests that WTI, despite its regional influences it is still maintains a significant degree of correlation with global oil market dynamics, similar to Brent, understanding that it might slightly understate the connectedness compared to Brent. As we can take a look at figure 4.7, we can see the movements over time.

Figure 4.7: Total Volatility Spillovers Based on DY (2012) Using WTI

Therefore, the results do not change by using Brent or WTI as a benchmark this result indicates a robust finding. Directional and net volatility figures are available in the appendix.

Chapter 5

CONCLUSIONS

In this study, volatility spillovers among energy sector stock indices and major fossil fuels (i.e., Brent crude oil, natural gas, and coal) in the top ten energy consuming countries are examined. The MSCI energy indices[1] are used for each country in the sample. By conducting time and transmission domain approaches, specifically the using Diebold and Yilmaz's (2012) index model, daily returns/prices/volatilities are examined for the period 01/06/2009 – 31/12/2023 which includes significant economic and political events such as the European sovereign debt crisis (2010-2012), the Arab spring (2011), the refugee crisis and ISIS attacks (2014–2015), the international crude oil crisis (2014), the increase in coal and natural gas prices (2016), the Canada's tug of war event (2016), the China–USA trade war (2018), the COVID-19 pandemic (2020), the USA-China tensions (2022), and the Russia-Ukraine war in 2022.

For examining the connectedness between fossil fuel commodities and energy stock indices, three main energy commodities are used to provide a comprehensive picture of how these energy markets are connected over time. In addition, investigating the energy stock index at country level allows to explore the volatility within the energy markets of that country. Analyzing the energy index of an individual country helps to

[1] MSCI International China Energy Sector, MSCI International USA Energy Sector, MSCI International India Energy Sector, MSCI International Japan Energy Sector, MSCI International Canada Energy Sector, MSCI International Brazil Energy Sector, MSCI International Korea Energy Sector, MSCI International Korea Energy Sector, MSCI International France Energy Sector, and MSCI International UK Energy Sector.

understand the relationship between the energy stock index and the fossil fuel energy markets. This approach provides a deep insight into understanding how global energy market movements have an impact on local energy stocks. It also reveals the interdependence between a country's energy sector and fossil fuel prices. To accomplish these objectives, the impacts of both static and time-varying factors on the interconnectedness of market volatilities are examined by using the Diebold and Yilmaz’s (2012) index model.

The most noteworthy results of this study are the followings: Primarily, the overall volatility spillover index of 43.70% in the static analysis suggests that volatilities are interdependent. The US energy index has the biggest volatility spillover of 12.38% to Brent crude oil followed by the Canada energy index having 11.69% volatility spillover to Brent crude oil. Natural gas has the highest level of volatility shocks from itself, accounting for 94.98% of its volatility and it receives only 5% of its volatility from other energy markets. Moreover, coal also receives most of its volatility from itself, with 90.75% of its volatility and only 9.20% transmitted from other energy markets. These results suggest that investors might be particularly sensitive to changes in crude oil prices. Natural gas and coal are different as there are no volatility impacts from other energy markets relative to Brent crude oil. Moreover, the US energy index has the highest volatility spillover of 67.50% from other energy markets followed by Canada energy index (66.50%), UK energy index (66.00%), France energy index (64.30%) and Brazil energy index (50.50%) in descending order.

USA energy index and Brazil energy index receive the highest volatility spillovers of 19.49 and 7.70% from Canada energy index respectively while Canada energy index receives the highest spillover of 19.97% from USA energy index. France energy index transfers the highest volatility of 20,14% to UK energy index while France energy index receives the highest volatility spillover of 19.21% from UK energy index.

Furthermore, the highest volatility spillover of 8.08% is from Brent crude oil to US energy index followed by the volatility spillover of 7.50% from Brent crude oil to Canada energy index. However, coal has the highest volatility spillovers of 0.59% and 0.59% to Japan energy index and UK energy index respectively. These observations could be attributed to the fact that countries may increase their demand for other energy commodities such as coal or natural gas in order to meet the energy necessities in face of supply constraints and steep prices in crude oil owing to economic and politically related issues. These energy indices and energy commodities' volatility spillovers are even more considerable for countries such as China, USA and Canada because these nations are the heaviest consumers of energy in the world.

Furthermore, the time varying volatility spillovers are examined in the study. Several oscillations and spikes are detected in the results of the dynamic volatility analyses. These extreme spillovers can be attributed to economic and political turmoil's. For instance, the COVID-19 pandemic has the greatest volatility spillovers among energy stock indices and fossil fuel energy commodities. Hence, during the COVID-19 pandemic starting in 2020, the interconnectedness of these markets' volatility is greater than the one during the global financial crisis in 2008. It is safe to say that catastrophic occurrences such as a financial collapse, a spike or a fall in the price of energy commodities can have major impacts on the interaction between the volatility of energy stock indices and fossil fuel energy markets. Extreme events like financial crisis and price changes of energy commodities have major influences on the overall volatility interaction between the energy stock indices of developed countries (i.e., USA energy index, Canada energy index, France energy index and UK energy index) and the fossil fuel energy markets. However, low volatility connectedness between fossil fuels and developing countries' energy indices (i.e., China, India, Brazil, Indonesia, Korea and Japan).

The examination of directional volatility spillovers within energy markets demonstrates that the most levels of spillovers from crude oil to other markets occurred during the COVID-19 pandemic. Additionally, the volatility of spillovers from other markets to crude oil has exhibited significant variations over time. Over time, the volatility of spillovers from other markets to crude oil varies greatly. During the 2014-2016 oil price collapse, natural gas has the most volatility transmission to other markets. During the Russia-Ukraine war starting in February 2022, coal's volatility transmission to other markets has become the highest. During the sample period, the highest volatility transmission peaks during the Russia-Ukraine war and the COVID-19 pandemic. Generally, it can also be observed that developed countries' energy stock indices convey significant volatility to Brent crude oil since a poor connection among developing energy stock indices are observed during the sample period. A probable reason for this is that developed countries that supply energy might have big impact on oil markets and potentially forecast future price movements. However, developing countries with energy market stock indices that rely on importing fossil fuels may not have an influence in the energy market movements.

In this study, the results show that the fossil fuel energy markets and energy stock indices are highly interdependent, and these are significantly influenced by global political, financial, and chaotic events. The countries must establish an energy policy roadmap that prioritizes the reduction of their dependence on imported oil, natural gas, and coal, as economic and political turmoil are unlikely to subside. To achieve this, alternative options such as renewable energy sources of solar, wind, and hydroelectric power. Additionally, encouraging the investment in bioenergy and geothermal energy might reduce the reliance on imported fossil fuels. An essential alternative for power generation may involve the enhancement and utilization of renewable energy sources. Therefore, investors and policymakers should be aware of the increased volatility transmission during turbulent periods, as this can cause oil prices to rise and adversely affect stock prices in the energy market sector. Furthermore, natural gas and coal may be used as substitute resources for crude oil, and their levels of volatility have a mutual impact on each other. Therefore, it is advisable for investors to closely observe and forecast for unexpected turmoil's and their effects on fossil fuel commodities to make informed decisions on portfolio diversification methods.

For policy decisions, uncertainties in regard to taxation rates and policies within the energy sector can be mitigated by the governments, which may in effect decrease volatility levels of retail energy prices. Moreover, they can also frame policy measures that will help stabilize domestic energy prices and by so doing control volatility in exchange rates within the country. Additionally, governments can support investments for renewable energy development through subsidies, tax credits, and grants. These motivations may increase the investment in solar, wind, and other renewable energy sources, helping to diversify the energy supply and reduce dependence on fossil fuels.

The limitations of this study is that the energy indices of the top ten energy consuming countries are used. As high energy consuming countries, Germany, Russia and Saudi Arabia are excluded as there is no data available for the period before 2009. Future studies might therefore enlarge the sample size. Since the market coverage of indices is limited, the study can be carried out at company level. Further studies could include renewable energy and green bonds, and incorporate Baruník and Křehlík's (2018) method to measure the frequency dynamics of financial connectedness and systemic risk for portfolio hedging strategies.

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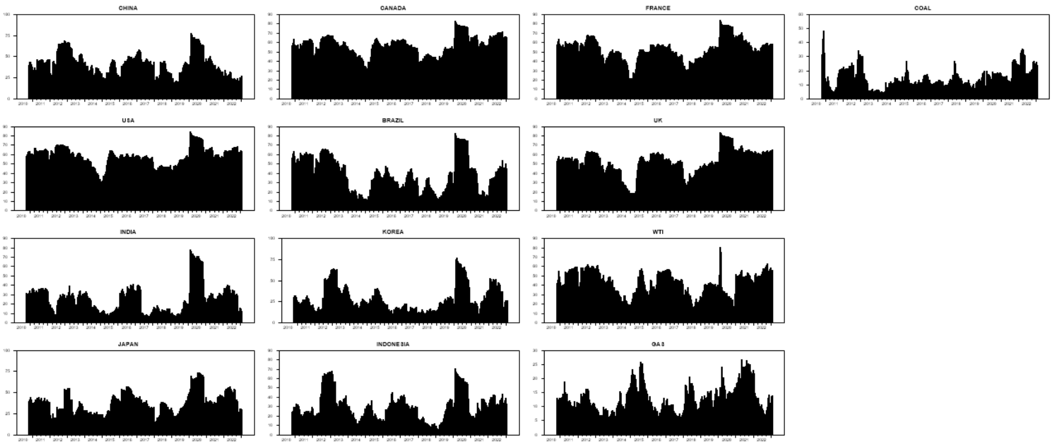
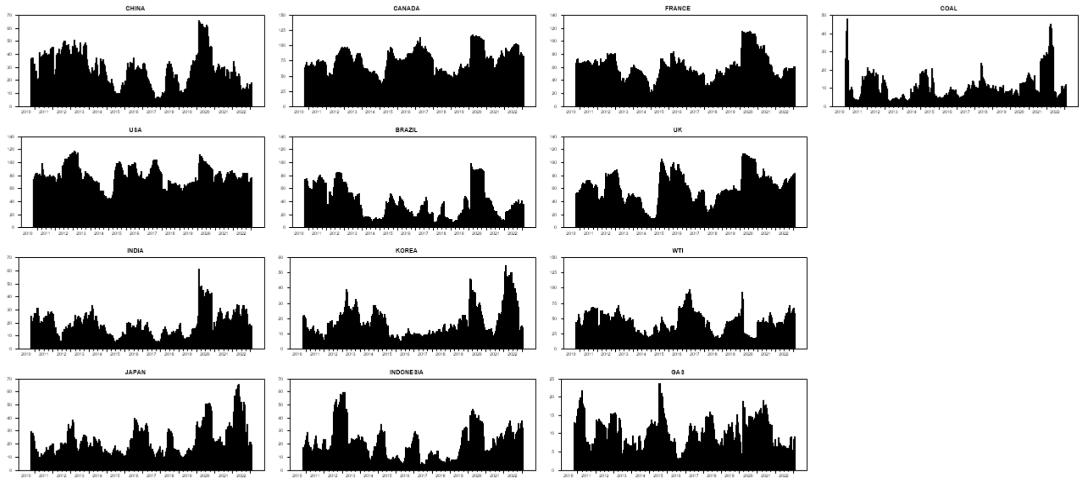
APPENDICES

Appendix A: Directional Volatility Spillovers (FROM), Robustness Check



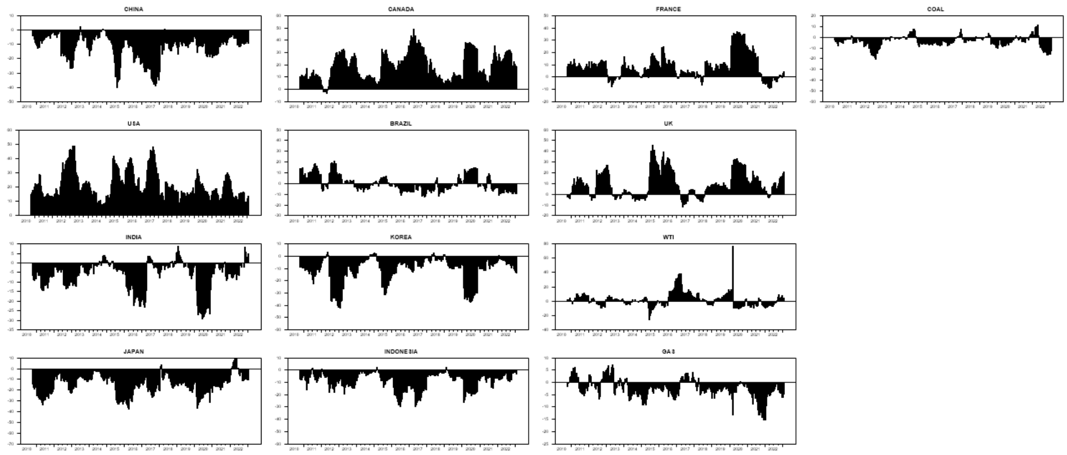
Directional volatility spillovers (from) one energy market (to) others using WTI index as a benchmark for a robustness check. As we can notice that there are no huge differences in the movements of shocks between the Brent crude oil index and WTI index. However, to compare between the indices WTI is more sensitive to the global events as it transmitted shocks to other markets compare to Brent index and especially during Covid-19 on 2022.

Appendix B: Directional Volatility Spillovers (TO), Robustness Check



Directional volatility spillovers (to) one energy index (from) others, using WTI index as a benchmark for a robustness check. As we can notice that there are no huge differences in the volatility transmissions between the Brent crude oil index and WTI index. Although we can note that WTI is less receiving of shocks compared to Brent index, which make WTI less sensitive to any changes from the other energy markets.

Appendix C: Net Volatility Spillovers Based on DY (2012) Using WTI Index, Robustness Check



Net volatility spillovers based on DY (2012) using WTI index as a benchmark for a robustness check. The WTI index is way more sensitive to global events compare to Brent index but the results of the sample from the study as almost the same with a little of differences depending on the connectedness of the sample index. WTI index is more transmitting of shocks compared to Brent index especially during Covid-19 on 2020 as we can see the highest peak of transmission of shocks were during that period, which make WTI more sensitive to any global events.