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MASTER’S THESIS

**EXAMINING RETURN AND VOLATILITY
CONNECTEDNESS BETWEEN GREEN AND FOSSIL
ENERGY MARKETS**

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MASTER THESIS
APPROVAL PAGE



DECLARATION

I hereby declare that this master's thesis titled as "Examining Return and Volatility Connectedness between Green and Fossil Energy Markets" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

Date

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ABSTRACT

Master's Thesis

Examining Return and Volatility Connectedness Between Green and Fossil Energy Markets

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This thesis aims to examine the return and volatility connectedness between green and fossil energy markets with an emphasis on green bonds, which play a vital role in financing green energy. To analyze the relationship, this study utilizes (sub)sectoral indices of green energy, including solar, wind, geothermal, bio/clean fuels, and water, along with fossil energy such as oil, natural gas, heating oil, and gasoline.

We employ time-varying parameter vector autoregression based frequency (TVP-VAR) approach by using daily price data for the period from November 1, 2012 to November 15, 2022. In addition, a portfolio analysis has been performed using the risk hedging effectiveness and the minimum connectedness portfolio.

Our results indicate a near-moderate level of connectedness, most of which is derived from short-term dynamics. The findings reveal that in terms of return connectedness, water and oil have a significant impact on the network, while other market factors affect green bonds and wind. Regarding volatility connectedness, oil and heating oil influence the market, while natural gas and green bonds are affected by other factors in the market.

A high level of connectedness across all series is observed during the COVID-19 pandemic and increase in connectedness is also observed following

Russia's invasion of Ukraine, indicating an intensification of connectedness during periods of uncertainty. Risk hedging effectiveness remains the same in the total and short term; however, changes are observed in the long term. The outcome of this study, which incorporates (sub)sectors and different energy types to examine the relationship between green and fossil energy markets, is expected to be valuable for investors, policymakers, and portfolio managers.

Keywords: Green Energy, Fossil Energy, TVP-VAR, Connectedness, Hedging Effectiveness



ÖZET

Yüksek Lisans Tezi

Yeşil ve Fosil Enerji Piyasaları Arasında Getiri ve Oynaklık Bağlantılılığının İncelenmesi

Birce TEDİK

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Bu tezde, yeşil ve fosil enerji piyasaları arasındaki bağlantılılığın getiri ve oynaklık yönünden incelenmesi amaçlanmıştır. Ayrıca yeşil enerji finansmanında önemli bir rolü olan yeşil tahvillere de yer verilmiştir. Bu ilişkiyi analiz etmek için, bu çalışma yeşil enerji (alt)sektörleri için güneş, rüzgâr, jeotermal, biyo/temiz yakıtlar ve su endeksleri kullanılmıştır. Fosil enerji için ise petrol, doğal gaz, kalorifer yakıtı ve gazolin kullanılmıştır.

1 Kasım 2012'den 15 Kasım 2022'ye kadar olan dönem için günlük fiyat verilerini kullanarak zamana göre değişen parametre vektör otoregresif (TVP-VAR) tabanlı frekans yaklaşımını kullandık. Ayrıca, riskten korunma etkinliği ve minimum bağlantılılık yaklaşımı kullanılarak portföy analizi yapılmıştır.

Sonuçlarımız, çoğu kısa vadeli dinamiklerden kaynaklanan orta düzeye yakın bir bağlantılılık olduğunu gösteriyor. Getiri bağlantılılığı bulgularına göre su ve petrol ağ üzerinde önemli bir etkiye sahipken, diğer piyasa faktörleri, yeşil tahvilleri ve rüzgârı etkilemektedir. Oynaklık bağlantılılığı bulgularına göre ise petrol ve kalorifer yakıtı piyasayı etkilerken, doğal gaz ve yeşil tahviller piyasadaki diğer faktörlerden etkilenmektedir.

COVID-19 pandemi döneminde tüm serilerde yüksek düzeyde bağlantılılık gözlenmiştir. Ayrıca, Rusya'nın Ukrayna'yı işgalinden sonra

bařlantılılıkta artış görölmüş, böylece belirsizlik dönemlerinde bařlantılılığın arttığı bulunmuştur. Riskten korunma etkinliğı açısından toplam ve kısa vade için önemli bir deęişiklik görölmezken, uzun vadede deęişiklikler gözlemlenmiştir. Yeşil ve fosil enerji piyasaları arasındaki ilişkiyi incelemek için (alt)sektörleri ve farklı enerji türlerini dahil eden bu çalışmanın sonuçlarının, yatırımcılar, politika yapıcılar ve portföy yöneticileri için faydalı olması beklenmektedir.

Anahtar Kelimeler: Yeşil Enerji, Fosil Enerji, TVP-VAR, Bařlantılılık, Riskten Korunma Etkinliğı



EXAMINING RETURN AND VOLATILITY CONNECTEDNESS BETWEEN GREEN AND FOSSIL ENERGY MARKETS

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ABBREVIATIONS

ARDL	Autoregressive Distributed Lag
BEKK	Baba, Engle, Kraft and Kroner
BIO	Bio/Clean Fuels
BND	Green Bond
BNEF	Bloomberg New Energy Finance
CAPM	Capital Asset Pricing Model
CoVaR	Conditional Value at Risk
COVID-19	Coronavirus
DCC	Dynamic Conditional Correlation
EIB	European Investment Bank
EMH	Efficient Market Hypothesis
EU	European Union
EUR	Euro
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GAS	Gasoline
GEO	Geothermal
GFEVD	Generalized Forecast Error Variance Decomposition
HE	Hedging Effectiveness
HOI	Heating Oil
ICC	International Chamber of Commerce
IEA	International Energy Agency
MCoP	Minimum Connectedness Portfolio
MCP	Minimum Correlation Portfolio
MPT	Modern Portfolio Theory
MVP	Minimum Variance Portfolio
NGS	Natural Gas

NPDC	Net Pairwise Directional Connectedness
OIL	Crude Oil
PCI	Pairwise Connectedness Index
SIC	Schwarz Information Criterion
SOL	Solar
TCI	Total Connectedness Index
TDIC	Time-dependent Intrinsic Correlation Method
TVP-VAR	Time Varying Parameter Vector Auto-Regression
USD	United States Dollar
VAR	Vector Autoregressive
WAT	Water
WHO	World Health Organization
WND	Wind

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INTRODUCTION

In recent years, as a part of the commodity market, fossil energy is a concern for investors and policymakers. Fluctuations in fossil energy prices, climate change, global events that affect daily life (e.g., COVID-19, Russia's invasion of Ukraine), and the preference toward green markets can all be described as some reasons for this concern.

Additionally, globalization, *“the fact that different cultures and economic systems around the world are becoming connected and similar to each other...”*¹, has made financial markets integrated thus, making them more vulnerable to shocks. These aforementioned factors have changed the market dynamics and balances.

The COVID-19 pandemic, which broke out between the end of 2019 and the beginning of 2020 is one of the global events that change the dynamics and create uncertainty in financial markets. Due to the pandemic, both energy investment and demand have declined. The supply chains were disrupted. Consequently, energy-related carbon dioxide (CO_2) emission decreased in this period. Roughly two years later, Ukraine was invaded by Russia in February 2022, which resulted in an energy crisis since Russia is known as the main exporter of oil and natural gas according to the report of International Energy Agency (IEA, 2022a).

Although Russia's critical position in energy supply, the European Union (EU) and its members have imposed individual and economic sanctions on Russia, including but not limited to the fields of energy, transportation, and finance². After Russia-Ukraine conflict, EU published policy to decrease dependency to natural gas in the name of a European Gas Demand Reduction Plan³. In addition, mild winter season helped reduce European natural gas demand by 8% (World Bank Group, 2023: 13). In a similar vein, due to concerns about energy security and uncertainties, high and volatile prices are observed in natural gas (IEA, 2022b: 24). Eventually, an ambiguous

¹Globalization (2023). Oxford Learner's Dictionary, Retrieved April 24, 2023, from <https://www.oxfordlearnersdictionaries.com/definition/english/globalization?q=globalisation>

²Council of the European Union (2023). Retrieved April 15, 2023, from <https://www.consilium.europa.eu/en/infographics/eu-sanctions-russia-ukraine-invasion/>

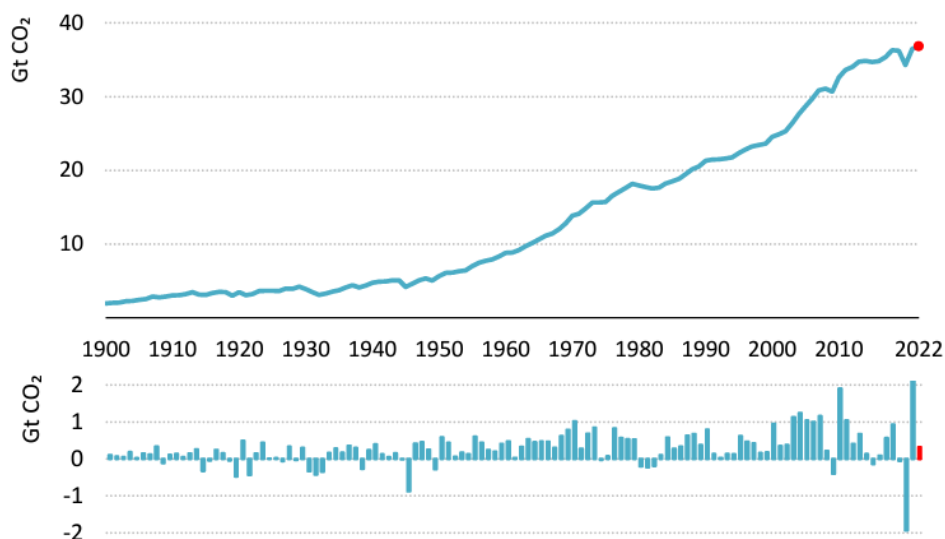
³Retrieved June 2, 2023, from https://ec.europa.eu/commission/presscorner/api/files/attachment/873148/Factsheet_European%20Gas%20Demand%20Reduction.pdf.pdf

environment and high prices will foster the energy transition for companies whose production depends on fossil products due to the increasing cost of production.

Fossil fuels consist of oil (petroleum), gas, and coal but also include derived products such as gasoline, heating oil, and so on. According to the Statistical Review of World Energy of British Petroleum (BP, 2022: 10), the largest consumption in 2021 is oil with around 32%, followed by coal and natural gas. Due to the non-renewable nature of fossil fuels, they will sooner or later be depleted in the future. Additionally, the instruments in the fossil energy market are often referred to as “dirty” by many researchers due to their polluting characteristics, especially to the atmosphere (see e.g., Saeed et al., 2021; Gargallo et al., 2022; Farid et al., 2023).

Figure 1 depicts the global CO_2 emission level that stems from energy and industry. As a result of the increasing consumption and demand for fossil fuels, the majority of carbon dioxide (CO_2) emission has become energy related. Nowadays, we testify to the highest level of energy-related CO_2 (IEA, 2023: 5). In addition, by sectors, the biggest contribution to CO_2 emissions come from energy and transport sectors (IEA, 2023: 6).

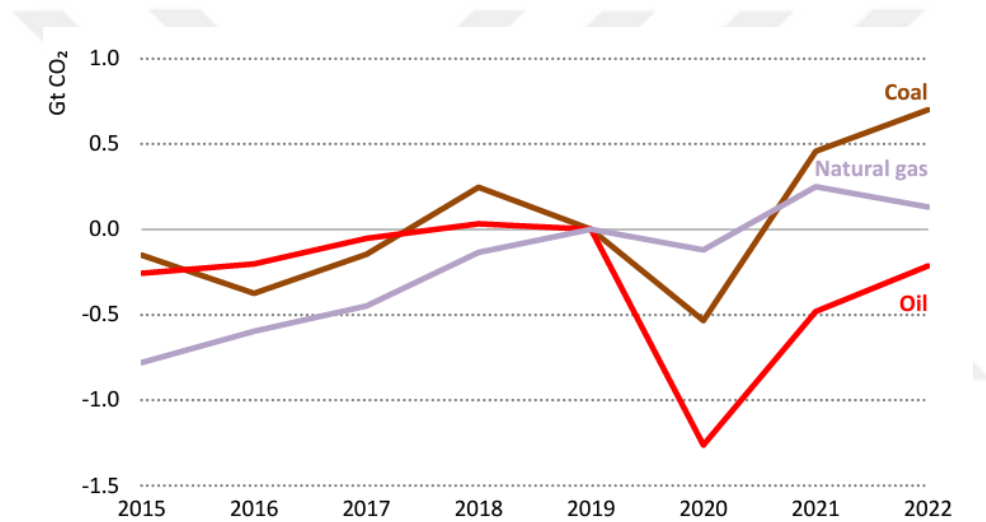
Figure 1: Global Energy and Industry Related CO_2 Emissions



Source: CO_2 Emissions in 2022 Report - IEA, 2023: 5. Notes: Gt = unit measure for emissions in gigatons

Figure 2 shows the contribution of each fossil energy type to CO_2 emissions. It is remarkable that during the Russia-Ukraine war, natural gas emissions experienced a significant decrease. However, in contrast, the contribution of coal to CO_2 emissions increased noticeably. A similar pattern can be observed for oil, where its contribution to CO_2 emissions also exhibited an upward trend. These findings highlight the varying impacts of different fossil fuels on CO_2 emissions and underline the need for green⁴ alternatives in the energy sector. To foster decarbonization is to decrease fossil fuels, progressively, in contrast to the tendency shown below.

Figure 2: Change in Fossil Energy Contribution to CO_2 Emission



Source: CO_2 Emissions in 2022 Report - IEA, 2023: 6.

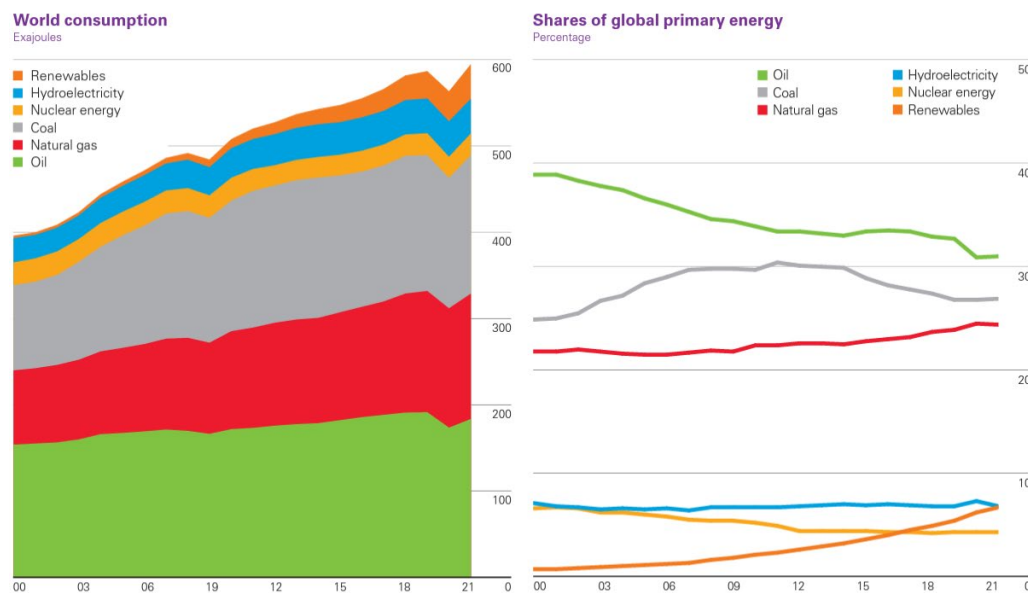
The transmission from fossil to green energy can be achieved through green finance, which is generally used to define the investment that supports environmental benefits (International Finance Corporation, 2017). But, besides capital, it needs time and technology. For instance, the infrastructural costs are high in renewable energy. However, fossil energy markets instruments have been used for several decades, therefore the infrastructure and extraction costs are low. Also, these fuels provide high energy density when burned. Another drawback related to renewable energy is the issue of storage, battery, supply, and other factors, which are interconnected with technological advancements. Consequently, technological progress is closely

⁴ The terms “green”, “clean”, and “renewable” are used interchangeably throughout this study.

associated with the renewable energy, so the literature explores this relationship using various technology stock and renewable energy indices (see e.g., Maghyereh et al., 2019; Kocaarslan and Soytaş, 2019).

Coherently, according to the report of International Renewable Energy Agency and Climate Policy Initiative, energy investments are dominantly made in fossil fuels (IRENA and CPI, 2023: 13). Figure 3 depicts the changes in consumption of global energy sources. The main sources of energy consumption are oil, followed by coal, and natural gas for fossil fuel side. The decrease in oil consumption is observed due to the increased uncertainties.

Figure 3: Global Energy Consumption

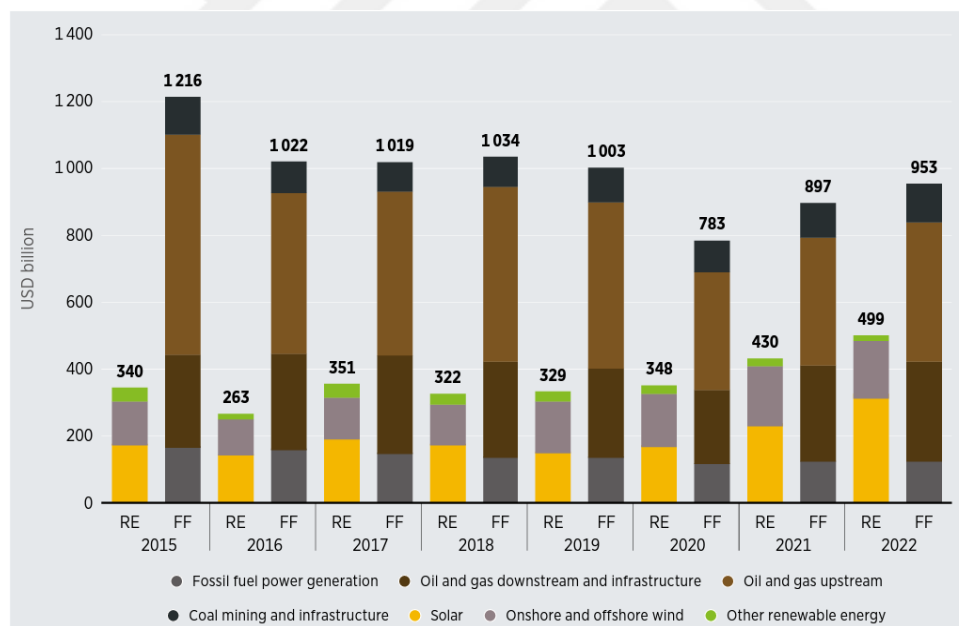


Source: BP Statistical Review of World Energy, 2022: 10.

Renewable energy varies depending on its source, such as solar, wind, geothermal, biofuels, etc. The upward trend in consumption of renewable energy can be seen in Figure 3. Rising and volatile fossil energy prices, incentives for energy transition, efforts to catch net zero emission targets, and energy security issues accelerate the investment in renewables. According to the report by Bloomberg New Energy Finance (BNEF), in terms of US dollar investment in renewables, China is ranked first, followed by the United States (BNEF, 2023: 10).

Solar and wind sectors have the largest portion among renewable energy investments. Figure 4 shows the fossil energy and renewable energy investment amounts. Despite the polluting nature, fossil fuel investments still dominate the energy market compared to renewables. Investments in oil and gas are leading to the growth of the fossil energy market. On the other hand, while fossil energy investments were around four times the green energy investments in 2015, it is less than double in 2022. The gap in terms of investment may stem from factors such as infrastructure costs, energy storage, and so on. The reliance on fossil fuel energy is the primary obstacle to achieving a transition towards a low carbon economy. Nevertheless, the depletion and unstable prices of fossil energy resources, environmental awareness and technological progress are expected to hasten the transition from fossil to green energy through green investment and green finance.

Figure 4: Investment in Energy Markets (USD billion)



Source: IRENA and CPI, 2023: 11.

The growing preference towards green markets and government policies, regulations, and incentives (e.g., credit, tax) accelerates this shift. This growing interest is also reflected in the decisions of investors and firms to invest in and finance green projects and products.

In this context, this thesis aims to examine the interrelationship among green energy (solar, wind, geothermal, bio/clean fuels, and water), green bonds, and fossil energy (oil, natural gas, heating oil, and gasoline) markets. The time-varying parameter-based vector autoregressive model (TVP-VAR) frequency connectedness approach is employed for the period from November 1, 2012, to November 15, 2022. In addition, portfolio and hedging effectiveness techniques are employed for portfolio managers and investors. Data period consists of major global events such as COVID-19 pandemic and the Russian-Ukraine conflict during which major fluctuations in energy prices were observed. We expect return and volatility transmission between fossil and green energy markets and the connectedness between them is expected to be time and frequency dependent. In addition, we expect an increasing connectedness especially during high uncertainty periods. Our results may be helpful for policymakers and investors in developing strategies and making decisions considering the fluctuations in energy prices.

This thesis contributes to literature in many aspects. First, besides crude oil prices, which are frequently discussed in the literature, we consider natural gas, gasoline, and heating oil prices, which are rarely discussed. Second, while a large extent of studies considers green markets on an aggregate or global level, we extend our data by considering a sectoral level and examining a large scale of green energy markets such as wind, solar, water, geothermal, and bio-clean markets. Third, we add green bonds into our analysis as an important part of the green market. Fourth, this study differs from the related literature regarding the methodology used. Unlike the studies investigating the relationship between these fossil energy and green markets, a time-varying parameter vector autoregressive (TVP-VAR) based frequency connectedness approach is used. Since this method does not follow the sliding windows procedure according to standard models, there is no observation loss, and it makes robust parameter estimation even in the presence of outliers. Another different aspect of the method to be used from the standard models in the literature is that by calculating the frequency connectivity approach criteria on the TVP-VAR model, more inferences can be made by determining the short- and long-term status of connectivity and which period is more dominant in influencing total connectivity. In addition, robustness controls can be made by using joint and extended joint criteria. Fifth, this

thesis consists of the analysis of the hedging effectiveness and portfolio strategies which have been mostly disregarded in several research studies.

This study consists of four chapters. Chapter 1 introduces the relevant background of the theory and some related concepts. Chapter 2 includes the literature review part that is divided into three main strands. In addition, it includes the development of the hypothesis. The methodology and data are presented in Chapter 3. The empirical results considering connectedness, minimum portfolio connectedness, and hedging effectiveness are given in Chapter 4.



CHAPTER ONE

THEORETICAL BACKGROUND AND RELATED CONCEPTS

This chapter presents an overview of the relevant theories. Initially, the study explains the concept of risk and return concept and portfolio theory. Later, diversification, hedging concepts, and capital asset pricing model (CAPM) are introduced. Following part discusses the efficient market hypothesis (EMH). Finally, the concepts on fossil energy and green energy markets are given.

1.1. RISK, RETURN AND MODERN PORTFOLIO THEORY

Risk and return are interrelated concepts in the field of finance. Historical (realized) return is related to the gain/loss of an investment in a given period (Zutter and Smart, 2019: 396). The return on investment is calculated as:

$$R_t = \frac{P_t - P_{t-1} + C_t}{P_{t-1}} \quad \text{Eq. 1}$$

where R_t is return at time t , P_t is the price of an asset at time t , and C_t is cash flow received from the asset (e.g., dividend payment). Other than historical return, the expected/anticipated return is related to future expectations about an asset. The future is not certain; therefore, it contains some risks.

Risk is defined as a measure of uncertainty (Zutter and Smart, 2019: 394). In the literature, the notion of “variance of returns” is mentioned by Markowitz (1952), he used “variance of returns” instead of risk. It represents the squared deviation from the mean (average). Similar to the variance (σ^2), the standard deviation (σ) is the square root of the variance and is calculated as:

$$\bar{r} = \sum_{t=1}^n \frac{r_t}{n} \quad \text{Eq. 2}$$

$$\sigma = \sqrt{\frac{\sum_{t=1}^n (r_t - \bar{r})^2}{n-1}} \quad \text{Eq. 3}$$

where $\bar{r}$ is the average return, n is the total number of observations.

Instead of an individual asset, investors can create a portfolio(s) with financial assets such as stocks, bonds, funds, options, commodities and so on. In addition to the standard deviation of an asset, the weights of each asset and the correlation between asset pairs must be known to calculate the portfolio's standard deviation. The portfolio return and standard deviation can be calculated as follows:

$$r_p = \sum_{j=1}^n w_j * r_j \quad \text{Eq. 4}$$

$$\sigma_p = \sqrt{\sum_{i=1}^n \sum_{j=1}^n w_i w_j \text{cov}(ij)} \quad \text{Eq. 5}$$

$$\text{cov}(ij) = \sigma_i \sigma_j \delta_{ij} \quad \text{Eq. 6}$$

where σ_p is the standard deviation of a portfolio, w is the assets weight in the portfolio, $\text{cov}(ij)$ is covariance between assets, δ_{ij} ⁵ denotes the correlation coefficient between assets. The sum of the weights of all assets must be equal to 1.

Markowitz (1952: 77) developed the process of portfolio selection in two distinct steps. The initial one involves shaping future expectations and beliefs, while the second step entails the selection of a portfolio based on these beliefs. Markowitz's approach to portfolio selection led to the establishment of the Modern Portfolio Theory (MPT) in the field of finance.

This theory is helpful for investors because it gives them valuable information about the risk and efficiency of a portfolio. The portfolio risk is lower compared to the

⁵ It takes a value between -1 and +1. Signs show the movements, while the range shows the strength.

risk associated with individual investments (Civelek and Durukan, 2011: 273). According to this framework, investors are seeking portfolios under some constraints: either maximizing expected/average return with given risk or minimizing risk with given expected/average return (Markowitz H. M., 1959: 129). Considering the risk preferences, investors are those who are risk averse and willing to get more returns with low risk.

In portfolio construction, the first concept is related to the minimum variance that Markowitz mentioned in his studies. This portfolio is known as the minimum variance portfolio (MVP) which aims to reduce portfolio variance with a given level of expected return. The other technique was developed by Christoffersen et al. (2014) and considers the correlation between variables and is known as the minimum correlation portfolio (MCP). Lastly, the minimum connectedness portfolio (MCoP) proposed by Broadstock et al. (2020). The purpose of this portfolio is to reduce interconnectedness by using the pairwise connectedness index. If there is a network shock, assets do not severely affect each other or be affected by the others (Broadstock et al., 2020: 14). Therefore, the portfolio is protected from network shocks.

1.2. DIVERSIFICATION AND HEDGING

MPT assumes that investors are risk-averse. Therefore, the portfolio should consist of financial instruments with low correlation to reduce risk (Zutter and Smart, 2019: 409). For instance, investing in similar products/industries cannot protect you from various risks. Investors should consider different securities, sectors, and markets to decrease their exposure to unsystematic risk. That's why investors should prefer different sectors/regions/securities when it comes to diversification.

There are numerous types of financial risks that securities may face. Some of them can be diversifiable while others are non-diversifiable. Therefore, security risk consists of unsystematic (diversifiable/firm) and systematic (non-diversifiable/market) risks.

Unsystematic risk refers to a type of risk that is unique. Since it is unrelated to the overall market conditions, its impact is limited and does not affect the broader market. For instance, this risk may arise from a variety of factors, such as legal issues,

managerial failures, and other problems. In contrast, systematic risk affects the overall market. For example, changes in interest rates, inflation, recession, wars, etc. impact all markets. Consequently, investors cannot run from systematic risks, and these risks cannot be eliminated through diversification, while unsystematic risks can be minimized through diversification.

Rather than investing solely in one country's market, the investor should invest in other countries to avoid country-specific risks. For each country, securities are inclined to move in the same direction. Thus, investing in more than one country's markets helps to reduce portfolio risks, and this is known as international diversification which has also been mentioned in Grubel's (1968) and Solnik's (1974) articles. This is another path which can help to reduce portfolio risk by reducing dependence on a single country's market.

Several studies have discovered various aspects of diversification, including portfolio size, correlation, and so on. Some articles examine the relationship between the quantity of securities, diversification, and its effect on portfolios. Among them Evans and Archer (1968: 767) found that after a certain number of assets, the marginal benefit of adding additional assets to a portfolio turns out to be limited. On the other hand, Elton and Gruber (1977: 426) found that the risk in a portfolio consisting of large number of instruments is lower than in a portfolio consisting of a small number. In addition, Longin and Solnik (1995) stated an increasing trend in the correlation in international markets. Solnik et al. (1996: 32) found that volatility spreads across markets.

In risk management, hedging is very crucial to protect investors against potential losses because of fluctuations in prices. Thus, investors use this strategy with instruments, frequently derivatives, such as options, futures, forwards, and swaps which will be detailed in the following parts.

To evaluate the effectiveness of portfolio strategy, investors may use hedging effectiveness. Hedging effectiveness allows an investor to compare the performance of a hedged position to an unhedged position (Ederington, 1979).

1.3. EFFICIENT FRONTIER AND THE CAPITAL ASSET PRICING MODEL

As part of the MPT, Markowitz presented the efficient frontier in “Portfolio Selection” (1952). It shows a possible set of optimal portfolios that offer the highest level of expected return with a given risk or the given expected return with the lowest risk. Also, adding risk-free investment makes the efficient frontier a straight line, and investors have the ability to select the portfolio that maximizes their utility function.

Another issue is related to the allocation of financial instruments. The same asset classes have similar risk-return characteristics. According to preferences, investors can create optimal portfolios with various asset classes to minimize risk.

CAPM, is an extension of MPT, and has been introduced by Sharpe (1964), Lintner (1965) and Mossin (1966). CAPM measures the expected return on investment with the help of a risk-free rate, beta and market risk premium. The linear relationship is given as follows:

$$E(R) = R_f + \beta[E(R_m) - R_f] \quad \text{Eq. 7}$$

where $E(R)$ is the expected return on the portfolio, R_f is the risk-free rate (e.g., treasury bills, government bonds), $E(R_m)$ is market return. $E(R_m) - R_f$ is known as the market risk premium. β reflects the systematic risk and which is a measure of the sensitivity of an asset to market volatility. The beta coefficient has a different meaning according to its thresholds:

- $\beta < 0$ The direction of the asset is opposite to the market direction.
- $\beta = 0$ This shows no systematic risk.
- $\beta = 1$ The systematic risk equals one show that the risk is in line with the market.
- $0 < \beta < 1$ It has less systematic risk compared to the market.
- $\beta > 1$ The systematic risk has higher than the market.

There are some assumptions about the CAPM. First, the market is assumed as perfect. It means that there is no transaction cost and taxes (Bodie et al., 2011: 309). The major criticism of this assumption is that the markets are imperfect, and investors may encounter related costs. Another assumption is that investors are rational and

therefore, avoid risks. Risk-free rates are applied for investors who want to borrow or lend (Alexander et al., 2000: 191). The investment horizons are the same for all investors. Investors' expectations are homogenous which means investors have the same risk and return expectations.

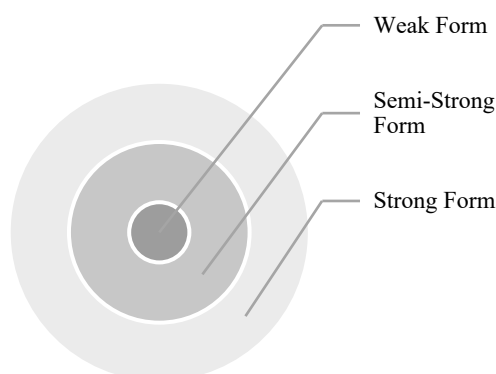
The CAPM examines the expected return and risk relationship, linearly. Under the abovementioned assumptions, this model is widely used although it does not fully overlap with the world in which we live (Karan, 2018: 209).

1.4. EFFICIENT MARKET HYPOTHESIS

The market “efficiency” is mentioned by Fama (1965: 90). EMH states that all available information is absorbed from the financial markets if the markets are “efficient” (Fama, 1970: 384). Informational efficiency means that prices in the market reflect all available information. Consequently, there can be no abnormal returns. All market participants are rational which means that participants' expectations are similar. If any transmission of return and/or volatility between markets is observed, it can be concluded that the markets are inefficient.

Fama (1970) divided market efficiency into three groups. Each form includes its predecessor form. These forms are weak form, semi-strong form, and strong form. Figure 5 depicts the forms of market efficiency.

Figure 5: Forms of Market Efficiency



In the weak form, investors know past prices. The weak form can be explained by a random walk. The random walk hypothesis says that price changes do not follow a pattern. Therefore, prices cannot be predicted earlier on, and investors can not earn an abnormal return by using past prices. The technical analysis, that is used by creating chart of past price movements to anticipate future price changes, is of no use. Past price changes cannot explain the changes in stock prices. Thus, the time series test is used to assess the weak form of market efficiency.

In the semi-strong form of market efficiency, the prices entirely reflect publicly available information. Publicly available information consists of financial statements, reports and so on which are presented to the community. This form contains historical data and public information. Accordingly, it is thought that no one can generate excess returns constantly (Civelek and Durukan, 2011: 267). The stock split and annual earnings announcement tests are used to assess the semi-strong form of market efficiency.

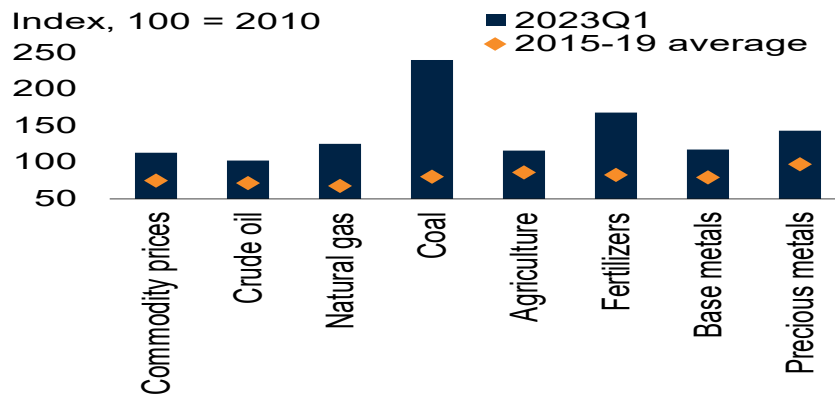
Besides historical data and public information, in the strong form efficiency, all information is available including confidential ones. Consequently, if the strong form endures, then no individual including insider trading, can outperform the market in any way. The test for insider trading is used to assess the strong form of market efficiency.

1.5. FOSSIL ENERGY MARKETS

Commodity markets consist of energy commodities (natural gas, oil, etc.), metals (gold, copper, etc.) and agriculture (wheat, sugar, coffee, etc.) commodities and etc. They are more vulnerable to various risks, which can be natural disasters, wars, and pandemics. Consequently, deterioration may occur on both the supply and demand sides, due to risks.

The commodity prices reached their peaks in 2022 increasing by 45% (World Bank Group, 2023: 2). Figure 6 shows commodity price changes. According to the Commodity Market Outlook report, the overall expectation is for price levels to decrease by 21% (World Bank Group, 2023: 5).

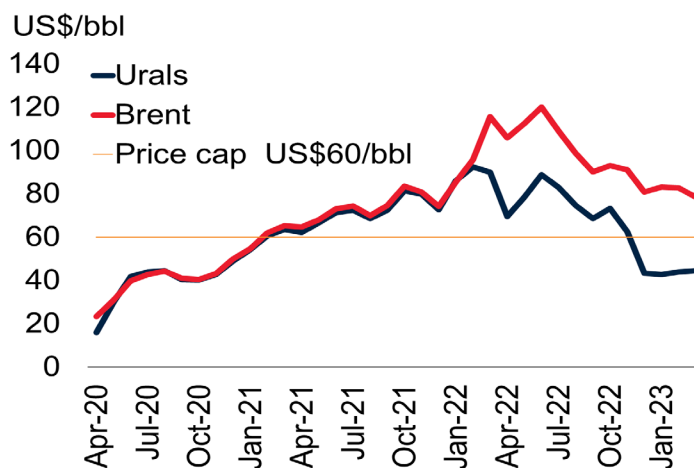
Figure 6: Commodity Price Indices



Source: World Bank Group, 2023: 2.

Energy commodities are the most important part of the commodity markets. Figure 7 shows the price changes in oil. Among the most commonly used fossil energy commodities, crude oil, has shown a decrease in price per barrel by 8% compared to last quarter of 2022, and its average price has become \$81 per barrel. The price per barrel is expected to decrease by 16% in 2023, and increase by 2.5% in 2024 (World Bank Group, 2023: 5).

Figure 7 : The Price Changes in Oil

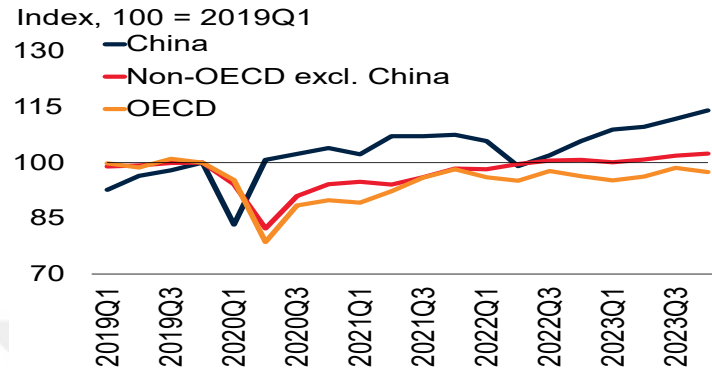


Source: World Bank Group, 2023: 10. Note: bbl = per barrel.

Figure 8 depicts the demand for oil and according to this figure the demand for oil has increased due to China's increased consumption amounts after loosening COVID-19 restrictions (World Bank Group, 2023: 9). Followed by China, non- OECD

countries are the second largest demander for oil. The consumption projected to increase in 2% during this year (World Bank Group, 2023: 11).

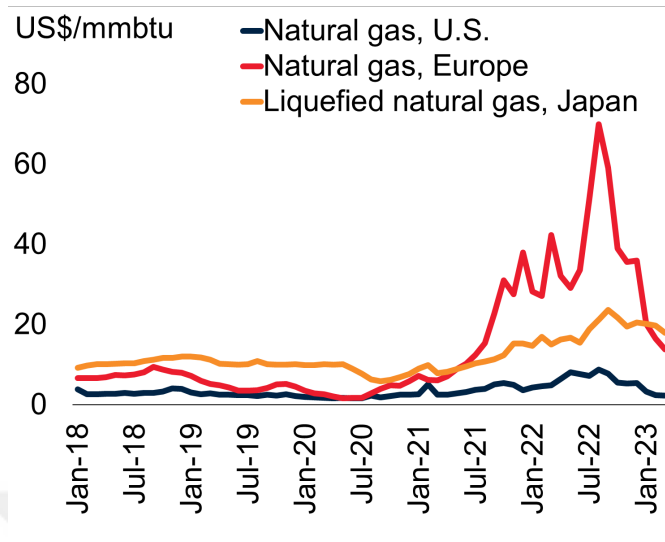
Figure 8: Demand for Oil



Source: World Bank Group, 2023: 10.

As another important fossil energy source, natural gas is essential for the companies in their production process. After Russia-Ukraine conflict, many countries applied some sanctions on it. As a result of limited natural gas flow to these countries, US production of natural gas has increased. Unlike the production, the demand for natural gas decreased by 2% globally in 2022 (World Bank Group, 2023: 13). Under the stress and uncertainties about economic and geographic events, natural gas price become volatile. The natural gas price fluctuations are given in Figure 9. Similar to forecasted price of oil, also, natural gas price (excluding liquefied natural gas) is expected to decrease by approximately between 50% - 60% band (World Bank Group, 2023: 14).

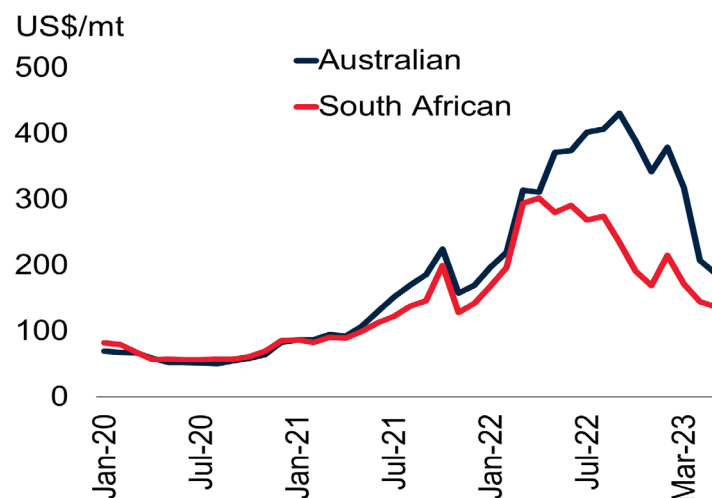
Figure 9: The Price Changes in Natural Gas



Source: World Bank Group, 2023: 14. Note: mmbtu = million British thermal units.

Lastly, coal price increased in Russia-Ukraine conflict in 2022, but it is decreased in the beginning 2023. The price movements are given Figure 10. Also, the coal price is expected to decrease by 42% in 2023 (World Bank Group, 2023: 17). According to the report by World Bank Group, the price decreased due to inconsistency between production and consumption. In addition, the world demand increased by 2% in last year (World Bank Group, 2023: 16).

Figure 10: The Price Changes in Coal



Source: World Bank Group, 2023: 14. Note: mt = metric tons.

1.6. GREEN MARKETS

This part provides information about the terms of green economy, green investment, green finance, and sustainability. This thesis focuses on green stocks and green bonds so that we will discuss them briefly in the following parts.

1.6.1. Green Finance and Sustainability

The concept of *green economy*, which originated in 1989, is a concept that aims to reduce environmental risks and ecological insufficiency (United Nations, 2015). Also, the International Chamber of Commerce (ICC) has published the Green Economy Roadmap which illustrates the concept of a green economy. This roadmap highlights the essential role of the corporate in explaining worldwide issues and lists ten conditions for the shift to the green economy. One of these conditions is green investment. *Green investment* includes investments in businesses that adopt environmentally friendly products, services, and sustainable practices (International Chamber of Commerce, 2012). It is a concept that includes investing in the firms/businesses that have an impact on nature through *green financing*. On the other hand, *sustainability finance* is the umbrella term that considers social, economic, environmental factors, unlike green finance, which only considers climate, excluding social and economic pillars (UNEP, 2016: 4).

Today, climate change is turning into a climate crisis. Due to increasing emissions, human beings are faced with rising temperatures and extreme weather conditions (drought, wildfires). To cope with the impacts of the climate crisis, some steps have been taken -to which the burning of fossil fuels is thought to be a major contributor - from the Kyoto Protocol to the Paris Agreement. On a national scale, some countries decided on Nationally Determined Contributions (NDCs) to reduce their gas emission, thus alleviating the effects of climate change. Also, the United Nations (UN) has taken some measures to cut back on the losses in the form of 17 Sustainable Development Goals (SDGs).

Among them, this thesis mainly related with Goal 7, affordable and clean energy and also Goal 13, climate action. With an increasing carbon dioxide emission,

the investment of clean energy is essential to achieve these goals by 2030. According to the Sustainable Development Goals Report 2022, committed climate finance investment fell below the \$100 billion threshold to \$79.6 billion (UN DESA, 2022: 20). Energy transmission from fossil to clean can be achieved through green economy, therefore green financing and green investing have crucial functions. In addition to Goal 7, this thesis indirectly related to Goal 6, 13, 14, 15⁶ because clean energy transformation has several effects on earth in terms of water, air, and land.

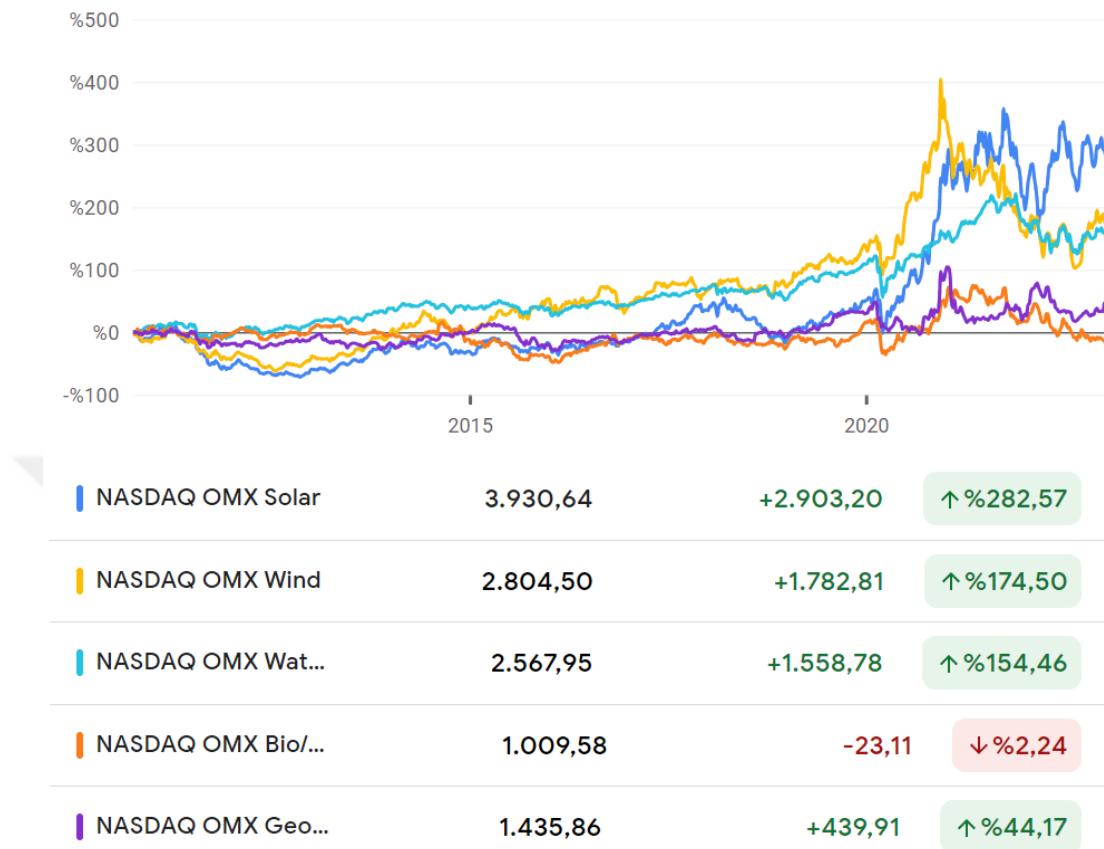
As determined at the 26th United Nations Climate Change Conference of the Parties (COP26), the Glasgow Climate Pact helps countries to act. Recently, COP 27 was completed, but the responsibilities seemed to be hanging in the air. Despite the fact that there are many definitions of green economy, this underlying concept which promotes a balanced relationship between the environment and human livelihood is still not fully comprehended. In the end, it should not be forgotten that the energy sector is one of the key areas that reduces emissions and limits global warming.

1.6.2. Green Stocks

Green stocks refer to the firms that operate/invest in an environmentally conscious manner. Rather than individual stocks, an aggregate index are used to track the companies in green sectors. Among them, we examine the green energy stocks. For instance, some of aggregate indices are S&P Global Clean Energy Index, European Renewable Energy Total Return Index, WilderHill New Energy Global Innovation Index, and so on. In this context, we focus on green energy stock indices that firms operate in renewable energy (sub)sectors such as wind, solar, geothermal, water and so on. The indices track firm performance of the specific (sub)sectors. For example, solar index tracks companies that generate power using solar energy. Figure 11 shows the changes in the price of the (sub)sectoral indices. Investors who give importance to environmentally responsible investments while supporting the transition from fossil to green are attracted by green stocks.

⁶ For further information please visit <https://sdgs.un.org/goals>.

Figure 11: Price Changes in Sub-sectoral Indices (NASDAQ OMX)



Source: Retrieved 2023, June 2 from <https://www.google.com/finance/>.

1.6.3. Green Bonds

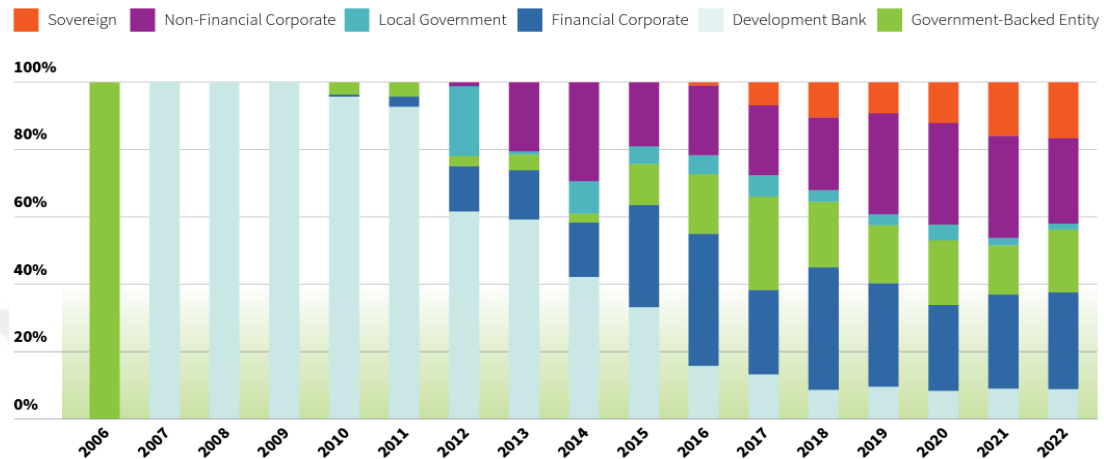
Green bonds are the debt or fixed income securities used to finance initiatives in renewable energy and other environmentally friendly fields. The European Investment Bank (EIB) issued the initial green bond in 2007 to finance environmental and sustainable investments⁷.

There are seven types of green bonds. These bonds are: (1) Corporate bond, (2) Project bond, (2) Asset backed security, (4) Supranational, sub-sovereign, and agency bond, (5) Municipal bond, (6) Sovereign bond, and (7) Financial sector bond (OECD, 2017: 34). Figure 12 gives the types of green bond issuers. In 2022, the major

⁷ For further information please visit <https://www.eib.org/en/investor-relations/cab/index.htm>

contribution in terms of issuance came from financial corporations with 29%, followed by non-financial corporations with 25% (Climate Bonds Initiative, 2023b: 9).

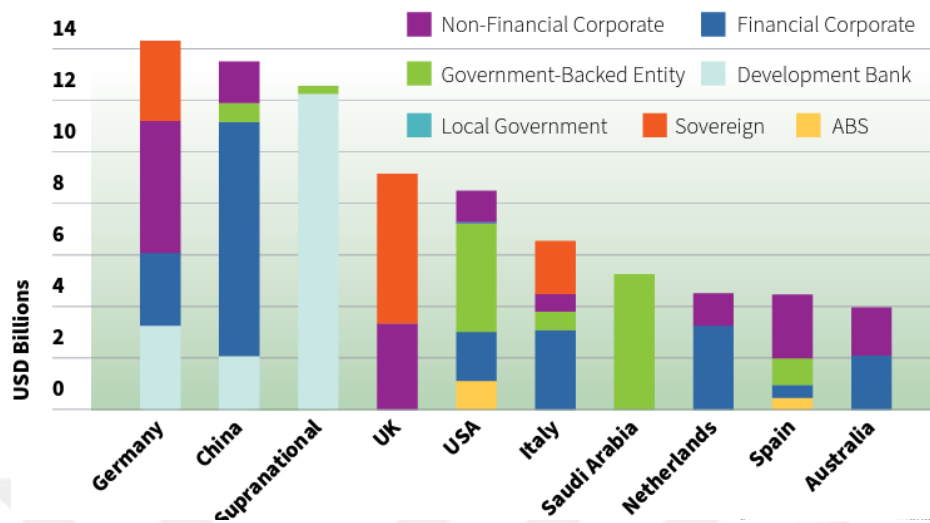
Figure 12: Types of Green Bonds Issuers



Source: Climate Bonds Initiative, 2023b: 9.

It is also vital to achieve sustainability goals and low carbon economy. As stated by the report of the Climate Bonds Initiative, green bond issuance exceeded \$2 trillion, cumulatively (Climate Bonds Initiative, 2022: 4). Figure 13 depicts the Country-Specific Green Bond Issuances and according to this figure, during the first quarter of 2023, Germany was the largest contributor with the majority of the contribution came from non-financial corporations (Climate Bonds Initiative, 2023a: 3). There has been a 17% increase compared to the previous quarter (Climate Bonds Initiative, 2023a: 1). Unlike Germany, China's largest contribution came from financial corporations. For the same period, the European Investment Bank (EIB) was the largest issuer with 11.8 billion USD. Moreover, Euro (EUR) is the most used hard currency in green bonds issuances (Climate Bonds Initiative, 2023b: 10). Also, different from green bond in terms of size and agreements/deals, another method for financing environmentally friendly projects by raising capital is called green loans, which constitutes 2% of the loan market in 2022 (Climate Bonds Initiative, 2023b: 7).

Figure 13: Country-Specific Green Bond Issuances



Source: Climate Bonds Initiative, 2023a: 3.

CHAPTER TWO

LITERATURE REVIEW

There have been many studies that examine the relationship between fossil energy and green markets. In recent years, green energy, and its relation to other energy groups (especially fossil energy) have been a vital subject for researchers due to the climate crisis, energy scarcity/dependency, incentives, and investors' preferences.

The literature can be categorized into three distinct aspects. The first strand centers on the relationship between oil and green energy. The second strand includes the literature chasing the relationship between other fossil energy types and green energy is presented. The third strand covers the literature that considers green bonds in addition to the abovementioned relationship.

2.1. THE RELATION BETWEEN OIL AND GREEN ENERGY

The first strand of literature consists of studies that investigate the relationship between the oil and green energy stock market at either the aggregate/global level (see e.g., Henriques and Sadorsky, 2008; Kumar et al., 2012; Managi and Okimoto, 2013; Inchauspe et al., 2015; Bondia et al., 2016; Ahmad, 2017; Dutta, 2017; Reboredo et al., 2017; Maghyereh et al., 2019; Kocaarslan and Soytas, 2019; Nasreen et al., 2020; Niu, 2021; Dawar et al., 2021; Attarzadeh and Balcilar, 2022; Xi et al., 2022) or sectoral/sub-sectoral levels (see e.g., Reboredo, 2015; Pham, 2019; Foglia and Angelini, 2020; Tan et al., 2021).

One of the pioneering studies in the literature explaining the relationship between alternative energy and oil prices was written by Henriques and Sadorsky (2008). The study examined the relationship between clean energy, oil price, interest rates, and the stock price of technology firms. The vector autoregression (VAR) method was used on the weekly data from 2001 to 2007. The results showed that the change in the oil price had a slight impact on the stock prices of clean energy. Sadorsky (2012: 254) used multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models to find volatility spillover between oil prices, the stock price of technology firms, and renewable energy. According to the results, there

was a weak association between oil prices and stock prices of renewable energy. Additionally, he found that oil might be used to hedge clean energy stocks. In addition, Kumar et al. (2012: 215) analyzed the connection between clean energy stocks, oil, and carbon prices by using the VAR method on the weekly data between 2005 and 2008. They found that the fluctuation in the stock price of clean energy was explained by historical movements in oil prices. Managi and Okimoto (2013) searched the link between oil price, technology, and clean energy stock prices by employing the Markov-switching vector autoregression (MSVAR) model from 2001 to 2010. Similar to Henriques and Sadorsky (2008) results, they pointed out that a shock to oil prices had an impact on stock price of clean energy.

Inchauspe et al. (2015) employed a different methodology to similar data used by Managi and Okimoto (2013). They searched for the relationship between oil, stock renewable energy, and technology stock prices by employing a state-space model from 2001 to 2014. Their study revealed that returns of renewable energy were affected by the technology index compared to oil. Other than that, the effect of oil prices on stock returns of renewable has increased after 2005. Alike to the previous study, Bondia et al. (2016: 558) used the cointegration method and Granger causality to observe the association among oil, clean energy and technology stock prices starting from January 2003 to June 2015. The findings presented that in the short run, the oil price affected the prices of clean energy stock. Ahmad (2017: 376) investigated the association between the oil, clean energy, and technology stocks prices by employing multivariate GARCH models and Diebold and Yilmaz's (2012) method covering the period from May 2005 to April 2015. The return spillover findings showed that while the clean energy and technology indices were net transmitters, oil was the net receiver. The volatility spillover results elicited that a significant volatility transmission from oil and technology index to clean energy index. Furthermore, he stated that hedging could be profitable if clean energy stocks and technology firms are paired with crude oil.

Dutta (2017: 1157) employed realized volatility (RV) model to examine the connection between volatility in the oil price and clean energy stocks covering the period from 2007 to 2016. The study showed that when the volatility in oil decreased, the price of oil increased. Therefore, rising oil prices pushed the market players to invest in stocks of clean energy. By using wavelet analysis, Reboredo et al. (2017: 241)

chased the relationship between oil prices and renewable energy stock prices. In the short term, dependency was weak between renewable energy and oil. Considering the long term, their relationship exhibited greater strength in contrast to the short term. Ferrer et al. (2018: 19-20) used Baruník and Křehlík's (2018) method to analyze the dynamic connectedness between prices of crude oil, renewable energy, technology stocks, and other variables. Contrary to the findings of other studies, the oil price was not the main driver of renewable energy stocks' price.

Kocaarslan and Soytas (2019) searched the oil price and renewable energy relationship using an autoregressive distributed lag (ARDL) and dynamic conditional correlation. They found that renewable energy and technology stocks were highly correlated. Therefore, the pair of renewable energy and oil gave more diversification chances. Maghyereh et al. (2019: 896) investigated the association between oil prices, stock prices of clean energy, and clean energy technology using multivariate GARCH models and, also wavelet analysis. The data consisted of two indices and crude oil prices from 2001 to 2018. An increasing return spillover over time was found from oil to clean energy. In addition, they revealed a positive relationship between clean energy and clean energy technology market. Nasreen et al. (2020) analyzed the dynamic connectedness between oil prices, stocks price of clean energy, and stock price of technology by employing wavelet analysis, Barunik and Krehlik's (2018) frequency domain, and Diebold and Yilmaz's (2012) time-domain approaches. They found that the oil price affected the returns of clean energy. Moreover, the hedging result showed that investors could use the clean energy index for oil. Niu (2021) analyzed the binary relationship between crude oil, clean energy, and technology in the short, medium, and long-term using the time-dependent intrinsic correlation method (TDIC). They found that the long-term positive correlation between the clean energy and technology index was higher than that of the short-term. In addition, a positive correlation was found between oil and the index of clean energy.

Dawar et al. (2021: 288) searched for the relationship between prices of oil and renewable energy employing quantile regression analysis to the weekly data spanning from 2015 to 2019. They showed that oil returns had an effect on returns of renewable energy under the bearish market. Xi et al. (2022) investigated the causal relationship between oil and stocks of renewable energy. They used the extreme Granger causality

and conventional tests for both frequency and time domains for the period from 2012 to 2021. Their findings showed that the extremely positive shocks of the selected renewable energy index affected the negative extreme shocks of oil. Also, the extreme positive shocks of oil affected the negative shocks of the selected renewable energy index. Attarzadeh and Balcilar (2022) used the spillover index to discover the total and directional connectedness among oil, technology, and clean energy by employing the VAR model. The study period covered monthly data from 2004 to 2020. Their findings showed a bidirectional volatility between oil and clean energy. Also, oil and clean energy were the net volatility receivers. In addition, their results indicated that oil was not a good hedge for clean energy, which was inconsistent with the results of Sadorsky (2012).

At the sectoral level, Reboredo (2015: 32) analyzed the relationship between prices of oil and renewable energy stocks. The conditional value at risk (CoVaR) was used to discover dependence structure and systematic risk. The findings elicited a strong dependency between oil prices and returns of renewable energy indices. Pham (2019: 373-374) investigated the relationship between oil and clean energy with sub-sectors such as solar, wind, geothermal, and fuel cell by combining Diebold and Yilmaz's (2012, 2014) methods and the VAR. The research concluded that biofuel was the clean energy subsector that was the most dependent on the price of oil. The price of oil had the least effect on the clean energy sub-sectors of wind, geothermal, and fuel cells. On the hedging side, active portfolio management was recommended due to the effect of the oil prices on the subsectors of clean energy being different. Foglia and Angelini (2020) conducted research that examined the association between prices of clean energy stock prices and price of oil. The study utilized data spanning from January 2011 to June 2020 and employed VAR and dynamic conditional correlation (DCC) methods. The result showed that these two markets' connectedness increased during the pandemic. Tan et al. (2021) searched for the risk relationship between oil and renewable energy by using the multivariate quantile methods and spillover index. They reported that oil acted as a risk and volatility receiver.

2.2. THE RELATION BETWEEN FOSSIL ENERGY AND GREEN ENERGY

The second strand of literature searches the relationship between various fossil energies and the green energy markets at either the aggregate/global level (such as Wen et al., 2014; Song et al., 2019; Xia et al., 2019; Jiang et al., 2021; Umar et al., 2022; Wang et al., 2022) or (sub)sectoral levels (such as Corbet et al., 2020; Zhou et al., 2022).

Among these studies, Wen et al. (2014: 63) used the asymmetric Baba, Engle, Kraft and Kroner (BEKK) model to investigate the volatility spillover of the Chinese renewable energy and fossil fuel markets. The period covered daily data from August 2006 to September 2012. The study revealed that there was a return spillover from historical returns of China's fossil fuel to renewable energy returns. Song et al. (2019) analyzed the association between investor sentiment, fossil, and renewable energy. They employed static and dynamic spillover for the period 2009-2018. They revealed that both renewable and fossil energy markets were linked. Xia et al. (2019) searched for the impact of fossil energy products' (oil, natural gas, electricity, coal, and carbon) price fluctuation on clean energy stock returns. They used a network approach with daily data from the period 2008-2019. They elicited that both markets were interrelated with each other. Similarly, Jiang et al. (2021) investigated the association between fossil energy and aggregate global renewable energy indices by using quantile on quantiles, and causality in quantiles analyses. The sample period covered daily data from July 2012 to December 2019. They found that fossil energy was positively influenced by renewable energy indices except for gas. Umar et al. (2022) used Baruník and Křehlík's (2018) and Diebold and Yilmaz's (2012) methods to investigate the connectedness between clean and fossil energy markets. They found a weak volatility connectedness between clean energy and fossil energy.

Considering some uncertainty indices such as Global Economic Policy Uncertainty Index and Geopolitical Risk, Wang et al. (2022) examined the relationship between natural gas and clean energy stock by employing the shrinkage method. They revealed that economic conditions and uncertainty indices could forecast the clean energy realized volatility. Corbet et al. (2020) analyzed the volatility relationship between renewable energy, oil, and coal by employing the spillover index approach.

Their study demonstrated that there was a spillover from oil prices to renewable energy and coal during the oil prices become negative. Moreover, Zhou et al. (2022) examined the relationship among energy markets such as natural gas, oil, and renewable energy subindices by employing the vine copula model and spillover network analysis. They found that the renewable energy market was highly impacted by extreme volatility spillover, especially in the condition of the bullish market.

2.3. THE RELATION BETWEEN GREEN, FOSSIL ENERGY, AND GREEN BOND

The third strand of literature considers the relationship between green and fossil energy, including the green bond markets. Among these studies, Reboredo (2018) examined the co-movement between energy commodity markets and green bonds by employing copula models from 2014 to 2017. The study revealed weak co-movement between green bonds and energy commodities. Similarly, employing VAR and wavelet methods, Reboredo et al. (2020) reported different and weak strengths between green bonds and energy in the period from 2014 to 2018. By extending the variables, Hammoudeh et al. (2020) investigated the relationship between the green bonds index, treasury bonds index, clean energy index, and carbon dioxide price from 2014 to 2020. They reported bounded causality from clean energy to green bonds. Using time and frequency-domain analyses, Naeem et al. (2021a) examined spillover between green bonds and commodities including but not limited to oil and natural gas. They documented the strong link between oil and green bonds. Naeem et al. (2021b) used time-varying optimal copula to find extreme tail dependence between heating oil, oil, natural gas, gasoline, coal, and green bonds. They reported extreme positive tail dependence between natural gas and green bonds, but extreme negative tail dependence between other energy commodities and green bonds. Nguyen et al. (2021) analyzed co-movements among indices of the green bond, treasury, clean energy, commodity, and stocks employing wavelet coherence. They found that green bonds had a negative or low correlation with commodities and stocks. Thus, diversification would be convenient.

Employing the quantile VAR, Saeed et al. (2021) investigated the connectedness among indices of green bonds, clean energy, oil, and energy ETFs. They revealed that return shocks were transmitted principally to oil from clean energy. Among all variables, green bonds were the least receiver and contributor in the return connectedness system. In lower quantiles, Lee et al. (2021) documented bi-directional causality moving from oil to green bond. Naeem et al. (2021c) found that bearish market conditions in energy commodities (oil, gasoline, and heating oil) resulted in a fall in return on green bonds. The hedging opportunity of green bonds against natural gas was brought to light because of the negative relationship between them. Mensi et al. (2022: 342-343) documented that oil and green bonds were the net receivers from the G7 stock markets except for Japan by using the time domain, frequency domain, and wavelets. Tiwari et al. (2022) investigated the spillover among the green bond index, renewable energy indices and carbon dioxide prices from 2015 to 2020. They found that the biggest transmitter of shocks to green bonds was renewable energy.

The existing literature predominantly focuses on crude oil, while research involving other fossil fuel types, such as natural gas, coal, gasoline, and heating oil, is often neglected. Moreover, the prevalent use of global or aggregate green energy indices is evident, whereas sectoral or sub-sectoral indices have received less attention. Additionally, the hedging aspect has been largely overlooked in many studies.

Numerous methods have been employed in the literature, including vector autoregression, generalized autoregressive conditional heteroskedasticity, network analysis, connectedness approaches, intrinsic correlation, copula models, wavelet analysis, quantile regression, quantile on quantile, and cointegration, among others. Bearing in mind the previous studies and methods, the findings remain inconsistent and do not provide a comprehensive understanding.

Therefore, the purpose of this thesis is to contribute to the existing body of knowledge by examining sectoral and sub-sectoral levels of green energy, various types of fossil fuels - not limited to oil - and green bonds, offering a broader perspective on the subject matter. In addition, different from the related literature we calculated hedging effectiveness ratios to provide important insights for investors and portfolio managers. The hypothesizes of this thesis are given below.

H1: There is time-varying connectedness between fossil energy prices and green markets.

H2: There is frequency dominated connectedness between fossil energy prices and green markets.

H3: Time and frequency connectedness between fossil and green markets increase during uncertainty periods.



CHAPTER THREE

METHODOLOGY AND DATA

This part starts with the methodology employed in this thesis. It is followed by the data and the descriptive statistics. Lastly, the limitations of the study are provided.

3.1. METHODOLOGY

In this thesis, we employ the time-varying parameter vector autoregressive based frequency connectedness framework of Chatziantoniou et al. (2021) to calculate connectedness across variables. This approach is a combination of the studies of both Baruník and Křehlík (2018) and Antonakakis et al. (2020) by considering the frequency and time-varying parameter vector autoregressive (TVP-VAR) based connectedness, respectively. Koop and Korobilis's (2014) TVP-VAR method Diebold and Yilmaz's (2012, 2014) connectedness methods were combined in the work of Antonakakis et al. (2020).

The advantages of the TVP-VAR model are (i) preservation of observations, (ii) without arbitrarily selected rolling window sizes, and (iii) being resistant to outliers. The first one allows us to work with complete data without losing any observations. Secondly, the model eliminates arbitrarily selected rolling window sizes. Finally, the model is resistant to outliers, thus mitigating the effects of outliers.

The TVP-VAR based frequency connectedness enables us to investigate different frequency bands. The thesis examines the connectedness in short (1-5 days), and long (5-Inf) terms, respectively. The R programme is used for every output we have in this thesis.

3.1.1. Time-Varying Parameter Based Frequency Connectedness

This section introduces methodological background of TVP-VAR based frequency connectedness approach of Chatziantoniou et al. (2021) by analyzing connectedness both in time and frequency domains.

3.1.1.1. Connectedness in the Time Domain

The TVP-VAR(p) is given as follows:

$$x_t = \Phi_{1t}x_{t-1} + \Phi_{2t}x_{t-2} + \cdots + \Phi_{pt}x_{t-p} + \epsilon_t \quad \epsilon_t \sim N(0, \Sigma_t) \quad \text{Eq. 8}$$

where x_t and ϵ_t are $N \times 1$ dimensional vectors. The time-varying coefficients of the VAR and the time-varying variance-covariance matrix are denoted by Φ_{it} and Σ_t , respectively.

The generalized forecast error variance decomposition (GFEVD) (see, Koop et al., 1996; Pesaran and Shin, 1998) can be represented as:

$$\theta_{ijt}(H) = \frac{(\Sigma_t)_{jj}^{-1} \sum_{h=0}^H ((\Psi_h \Sigma_t)_{ijt})^2}{\sum_{h=0}^H (\Psi_h \Sigma_t \Psi_h')_{ii}} \quad \text{Eq. 9}$$

$$\tilde{\theta}_{ijt}(H) = \theta_{ijt}(H) / \sum_{k=1}^N \theta_{ikt}(H) \quad \text{Eq.10}$$

where $\tilde{\theta}_{ijt}(H)$ represents the contribution of variable j to the forecast error variance of variable i at the horizon H .

From now on, all connectedness measures can be calculated. Net pairwise directional connectedness (NPDC) can be formulated as follows:

$$NPDC_{ijt}(H) = \tilde{\theta}_{ijt}(H) - \tilde{\theta}_{jit}(H) \quad \text{Eq. 11}$$

$NPDC_{ijt}(H) > 0$ ($NPDC_{ijt}(H) < 0$) shows that variable j affects variable i more (less) than vice versa. Total directional connectedness TO others can be formulated as follows:

$$TO_{it}(H) = \sum_{i=1, i \neq j}^N \tilde{\theta}_{jit}(H) \quad \text{Eq. 12}$$

$TO_{it}(H)$ shows how much the shock in the variable i is transmitted to all other variables j . The total directional connectedness FROM others can be expressed as:

$$FROM_{it}(H) = \sum_{j=1, i \neq j}^N \tilde{\theta}_{ijt}(H) \quad \text{Eq. 13}$$

$FROM_{it}(H)$ shows directional total connectedness of variable i received from other variables j .

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \quad \text{Eq. 14}$$

NET shows net total directional connectedness. It derives from the difference between total directional connectedness TO others and FROM others. $NET_{it}(H) > 0$ ($NET_{it}(H) < 0$) indicates that variable i effects all others j more than being affected by them. If $NET_{it}(H) > (<) 0$ it is considered as a net transmitter (receiver) of shocks.

The degree of network interconnectedness as well as market risk can be expressed by the total connectedness index (TCI) and calculated as follows:

$$TCI_t(H) = N^{-1} \sum_{i=1}^N TO_{it}(H) = N^{-1} \sum_{i=1}^N FROM_{it}(H) \quad \text{Eq. 15}$$

TCI shows the average effect of the shock in one variable on the others.

3.1.1.2. Connectedness in the Frequency Domain

By using spectral decomposition of Stiasny (1996), the connectedness in the frequency domain can be examined. Using the frequency response function, $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h$, where $i = \sqrt{-1}$ and ω denotes the frequency to maintain the spectral density of x_t at a given frequency ω . This spectral density can be expressed as the Fourier transformation of the TVP-VMA (∞) model:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega h}) \Sigma_t \Psi'(e^{+i\omega h}) \quad \text{Eq. 16}$$

The frequency GFEVD is obtained by combining the GFEVD and the spectral density. By normalization, the frequency GFEVD is formulated as:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1} \left| \sum_{h=0}^{\infty} (\Psi(e^{-i\omega h}) \Sigma_t)_{ijt} \right|^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h}) \Sigma_t \Psi(e^{i\omega h}))_{ii}} \quad \text{Eq. 17}$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^N \theta_{ikt}(\omega)} \quad \text{Eq. 18}$$

where $\tilde{\theta}_{ijt}(\omega)$ denotes the fraction of the spectrum of the i th variable at frequency ω that can be ascribed to a shock in the j th variable.

The short-term and the long-term connectedness can be calculated by gathering all frequencies within a certain range.

$$\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega) d\omega \quad \text{Eq. 19}$$

where $d = (a, b): a, b \in (-\pi, \pi), a < b$. Frequency connectedness measures give spillover information in specific frequency band d :

$$NPDC_{ijt}(d) = \tilde{\theta}_{ijt}(d) - \tilde{\theta}_{jit}(d) \quad \text{Eq. 20}$$

$$TO_{it}(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{jit}(d) \quad \text{Eq. 21}$$

$$FROM_{it}(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ijt}(d) \quad \text{Eq. 22}$$

$$NET_{it}(d) = TO_{it}(d) - FROM_{it}(d) \quad \text{Eq. 23}$$

$$TCI_t(d) = N^{-1} \sum_{i=1}^N TO_{it}(d) = N^{-1} \sum_{i=1}^N FROM_{it}(d) \quad \text{Eq. 24}$$

However, in order to calculate the overall effect, Baruník and Křehlík (2018) proposed to weight all contribution measures of each frequency band d with respect to system by: $\sum_{i,j=1}^N \tilde{\theta}_{ijt}(d) / N$.

In the below, the association between all frequency (see Baruník and Křehlík, 2018) and time-domain (see Diebold and Yilmaz, 2012; Diebold and Yilmaz, 2014) connectedness measures are given.

$$NPDC_{ijt}(H) = \sum_d NPDC_{ijt}(d) \quad \text{Eq. 25}$$

$$TO_{it}(H) = \sum_d TO_{it}(d) \quad \text{Eq. 26}$$

$$FROM_{it}(H) = \sum_d FROM_{it}(d) \quad \text{Eq. 27}$$

$$NET_{it}(H) = \sum_d NET_{it}(d) \quad \text{Eq. 28}$$

$$TCI_t(H) = \sum_d TCI_t(d) \quad \text{Eq. 29}$$

3.1.2. Portfolio and Hedging Effectiveness

Minimum connectedness portfolio (MCoP) technique is proposed by Broadstock et al. (2020). The aim of this technique is to minimize bilateral connectedness, therefore pairwise connectedness indices are used (Broadstock et al., 2020: 14). The weight formula is given as follows:

$$w_{Rt} = PCI_t^{-1}I / IPCI_t^{-1}I \quad \text{Eq. 30}$$

where w denotes weight, PCI shows pairwise connectedness index matrix, and I denotes identity matrix. The higher weight of the variable in the portfolio is designed so that it does not affect others and is not affected by others too much. If there is a

network shock, assets do not severely impact each other or be impacted by the others. Thus, the portfolio is protected from shocks.

Hedging effectiveness (HE) was found by Ederington (1979). The ratio is used to evaluate the performance of the portfolio. There is a greater (smaller) reduction in risk as the HE ratio increases (decreases). HE is calculated as follows:

$$HE = 1 - \frac{Var(y_p)}{Var(y_{un})} \quad \text{Eq. 31}$$

where portfolio return variance is shown by $Var(y_p)$, and the unhedged variance is shown by $Var(y_{un})$.

3.2. DATA AND DESCRIPTIVE STATISTICS

In this section the data period, its source and processing will be explained. Table 1 depicts the data used in this thesis. All data is denominated in USD.

Table 1: Data Description

NASDAQ OMX Index	Abbreviation
Solar	<i>SOL</i>
Wind	<i>WND</i>
Geothermal	<i>GEO</i>
Bio/Clean Fuels	<i>BIO</i>
Water	<i>WAT</i>
S&P Dow Jones Index	
Green Bond	<i>BND</i>
Fossil Energy Futures	
Oil	<i>OIL</i>
Natural Gas	<i>NGS</i>
Heating Oil	<i>HOI</i>
Gasoline	<i>GAS</i>

The period spans from 01 November 2012 to 15 November 2022 and consists of 2529 observations. The daily frequency of data is used.

The data includes the daily closing price of five NASDAQ OMX indices, the S&P Green Bond Index, and four fossil energy futures. All data except the S&P Green

bond index is extracted from Thomson Reuters Datastream. S&P Green bond index is extracted from its website.⁸

3.2.1. Return Connectedness

Return connectedness refers to the degree to which changes in one asset's return affect the returns of other assets. It measures the extent to which shocks in one asset may influence the returns of other assets.

The first step is about turning the daily price series into a natural log return series. It is calculated as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \cdot 100 \quad \text{Eq. 32}$$

where R_t is the return at time t ; P_t and P_{t-1} are the price of the variable at time t and $t-1$, respectively. Figure 14 depicts the logarithmic return series. It is easy to see the effect of the COVID-19, declared as an emergency by the World Health Organization (WHO) in 2020⁹.

⁸ <https://www.spglobal.com/spdji/en/indices/esg/sp-green-bond-index/#overview>

⁹ See further: <https://www.who.int/europe/emergencies/situations/covid-19>

Figure 14: Return Series (2012-2022)

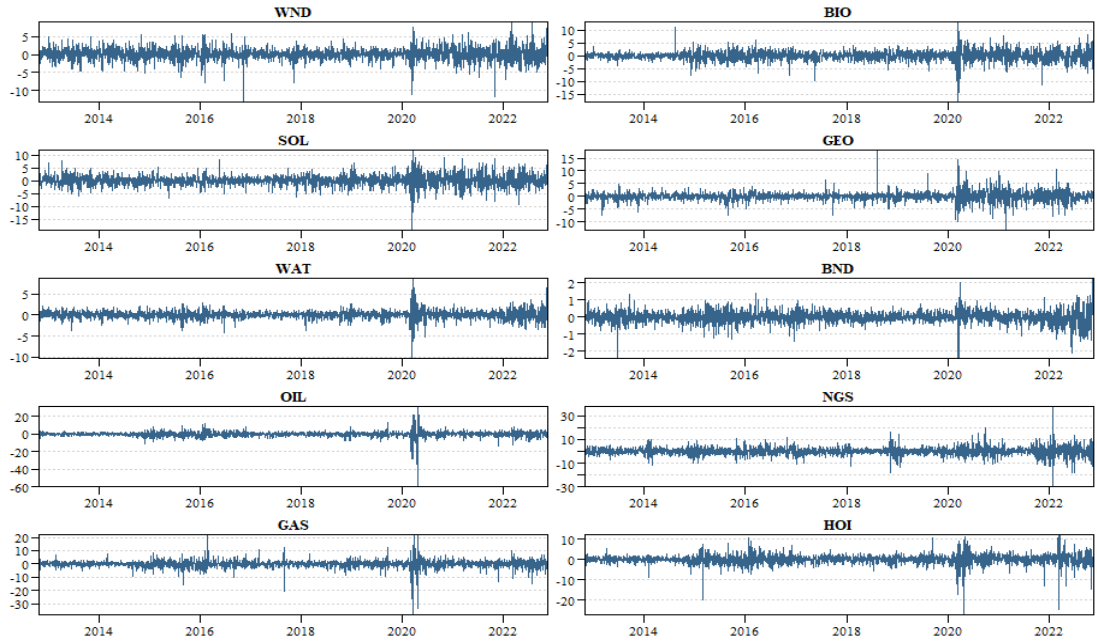


Table 2 shows the descriptive statistics of the log return series. According to Jarque and Bera (1980), hereinafter referred to as JB, the test results indicate that the null hypothesis is rejected at a 1% significance level for all series. Therefore, a normal distribution is not presented.

In order to assess the stationarity of the data, the unit root test proposed by Elliott et al. (1996), hereinafter referred to as ERS, is used. The result shows that the entire data set is stationary at the 1% significance level. Fisher and Gallagher (2012) developed the tests for the serial correlation, hereinafter referred to as Q and Q^2 . At a 1% significance level, the time series is autocorrelated up to 20 lags.

3.2.2. Volatility Connectedness

Volatility connectedness measures how much the volatility of one asset impacts the volatility of another assets.

In order to continue with volatility series, the calculation of absolute (ABS) return is performed. By taking absolute value of the returns, the measure of volatility is obtained. The details about R_t and its calculation can be found in the previous part.

$$ABS(R_t) = |R_t| \quad \text{Eq. 33}$$

Illustration of volatility series can be seen in Figure 15. Once again, the effect of the COVID-19 outbreak is observable, with a peak occurring in 2020. Additionally, some fluctuations can be observed during the period of Russian invasion of Ukraine.

Figure 15: Volatility Series (2012-2022)

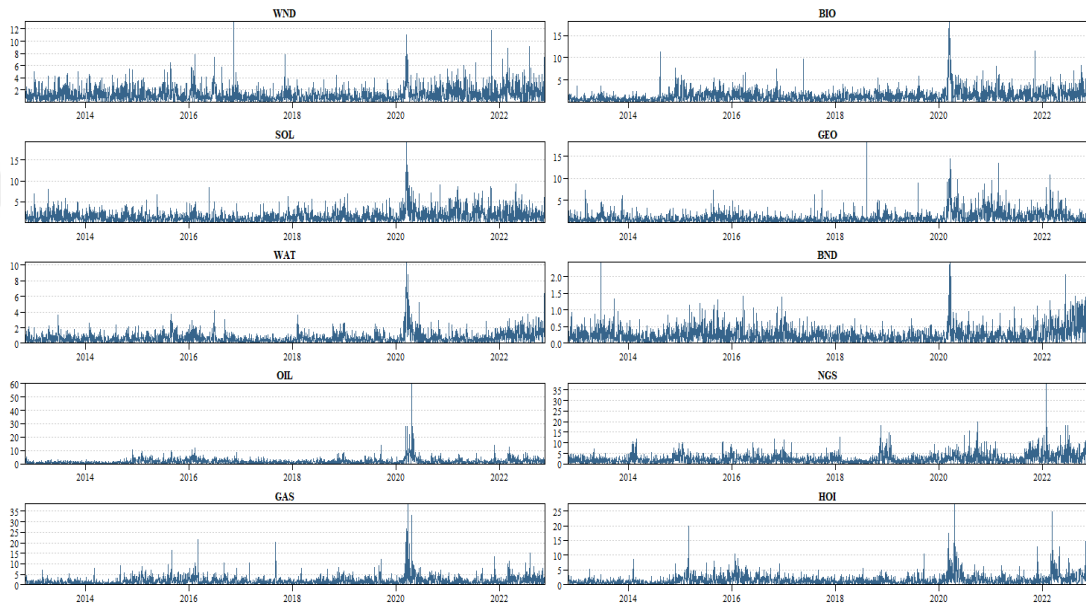


Table 3 reports the descriptive statistics of the volatility series. According to JB, the test results show that the null hypothesis is rejected at 1% significance level for all series. Hence, a normal distribution is not presented.

In order to assess the stationarity of the data, the unit root test proposed by Elliott et al. (1996) is employed. The result shows that the entire data set is stationary at 1% significance level. For the serial correlation, Q and Q^2 show that at 1% significance level, the time series is autocorrelated up to 20 lags.

Table 2: Descriptive Statistics of Return Series

	Mean	Variance	Skewness	Ex. Kurtosis	JB	ERS	$Q(20)$	$Q^2(20)$
WND	0.066*	2.913***	-0.331***	5.069***	2753.508***	-19.996***	25.164***	196.978***
BIO	-0.001	3.847***	-0.877***	10.801***	12616.501***	-15.792***	66.714***	2179.163***
SOL	0.015	4.506***	-0.498***	6.392***	4409.824***	-13.606***	58.391***	1368.219***
GEO	0.035*	3.123***	0.369***	12.231***	15821.411***	-12.479***	27.031***	339.160***
WAT	-0.005	1.019***	-0.587***	12.812***	17441.358***	-8.310***	138.967***	2681.710***
BND	0.000	0.124***	-0.505***	5.228***	2987.196***	-15.726***	51.968***	607.931***
OIL	0.019	9.472***	-2.857***	74.911***	594768.240***	-16.182***	108.499***	538.810***
NGS	-0.004	11.916***	0.234***	10.841***	12406.651***	-23.562***	41.718***	506.891***
GAS	0.007	8.219***	-1.884***	31.322***	104877.568***	-5.041***	25.140***	571.258***
HOI	0.015	5.628***	-1.458***	17.928***	34763.788***	-14.576***	22.300***	302.540***

Table 3: Descriptive Statistics of Volatility Series

	Mean	Variance	Skewness	Ex. Kurtosis	JB	ERS	$Q(20)$	$Q^2(20)$
WND	1.212***	1.447***	2.540***	12.148***	18271.543***	-9.838***	425.797***	196.978***
BIO	1.350***	2.023***	3.667***	26.756***	81106.721***	-10.350***	1557.106***	2179.163***
SOL	1.490***	2.295***	2.745***	15.336***	27961.154***	-14.545***	943.488***	1368.219***
GEO	1.146***	1.808***	3.732***	24.848***	70927.788***	-13.674***	1188.118***	339.160***
WAT	0.683***	0.553***	3.975***	30.045***	101778.913***	-9.069***	2457.898***	2681.710***
BND	0.250***	0.062***	2.660***	12.747***	20102.381***	-11.814***	806.183***	607.931***
OIL	1.803***	6.219***	8.825***	148.795***	2365835.194***	-12.056***	2152.981***	538.810***
NGS	2.392***	6.191***	3.561***	28.199***	89134.306***	-7.781***	907.520***	506.891***
GAS	1.788***	5.021***	6.079***	65.345***	465518.244***	-5.841***	1006.214***	571.258***
HOI	1.547***	3.233***	4.514***	39.820***	175675.986***	-12.756***	1431.205***	302.540***

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ denote significance levels at 1%, 5%, and 10%, respectively. JB stands for the Jarque and Bera (1980) normality test. ERS stands for the Elliot et al. (1996) unit root test. $Q(20)$ and $Q^2(20)$ are for the Fisher and Gallagher (2012) weighted portmanteau tests statistics.

3.3. LIMITATIONS OF THE STUDY

The first limitation of the study is associated with data period. The renewable energy indices are available from 2010 whereas the green bond index data is available from 2012. Since some data started in 2010 and others after 2012, we used the data from 2012 onwards by excluding the two-year data set. The second limitation is about volatility measure. We wanted to make volatility calculations using Parkinson's (1980) method, but due to absence of green bond index daily high and low prices, we did not continue with desired calculation method. We use absolute return for a measure of volatility for green bonds.



CHAPTER FOUR

EMPIRICAL FINDINGS

This section provides the empirical findings considering return and volatility connectedness. Subsequently, to pursue the portfolio analysis, minimum connectedness portfolio (MCoP) and hedging effectiveness results are given. This section offers valuable and detailed insights to portfolio management and risk management.

4.1. TIME-VARYING PARAMETER BASED FREQUENCY CONNECTEDNESS

This section presents return connectedness results. Then, volatility connectedness results will be given. Both connectedness results take into consideration on short-term (1-5 days) and long-term (5-Inf), respectively.

4.1.1. Return Connectedness

The TVP-VAR-based frequency connectedness framework of Chatziantoniou et al. (2021) is used to examine return connectedness. The time-varying parameter vector autoregression model's lag length is determined by the Schwarz information criterion (SIC). According to the results obtained, the lag length of our model is 1. The results are based on TVP-VAR (1) model with 10 days forecast horizon. As stated before, this thesis examines the return connectedness in terms of frequency in short (1-5 days) and long (5-Inf) terms, respectively.

Table 4 shows the return connectedness results concerning both time and frequency domains. While Panel A shows time connectedness, Panels B and C depict frequency connectedness with both short (1-5) and long (5-Inf) terms, respectively.

According to this table, the average total connectedness index (TCI) is 43.68% indicating a moderate connectedness among fossil and green markets. On the other hand, we observe that the majority of total connectedness comes from short-term connectedness (39.06%) which is approximately eight times of long-term connectedness (4.61%) given in Panel B and C.

The diagonal amounts indicate idiosyncratic shocks. The remaining part of TCI which is 56.32% derived from own variable (idiosyncratic) shocks. Green markets show higher autocorrelation and thus lower cross correlation than fossil energy commodities other than natural gas. For instance, 76.28% and 88.57% of the future return shocks of green bonds and natural gas can be attributable to their own previous shocks. Thus, the future return shocks for them are less influenced by shocks in other markets. Despite the sizable levels of autocorrelation effects, the majority of the future return variances can be attributable to cross-correlation effects in the fossil energy commodity group except natural gas.

The pairwise spillover can be seen off-diagonally in Table 4. The pairwise spillovers among the fossil energy commodities are greater than those from green markets. For instance, the largest average pairwise spillover is found between the fossil energy futures; from OIL to HOI, with 25.36%. However, the lowest average pairwise spillover is found from NGS to WAT with 0.44%. The largest average pairwise spillover between greens; from WAT to SOL with 15.39%. Green bond market offers more diversification benefits within the green markets since its low connectedness with the others in the system. Similarly, natural gas provides more diversification opportunities because of its low connectedness with both green and fossil energy markets.

The net directional connectedness is shown at the bottom of each panel. It indicates that the positive (negative) value is the net shock transmitter (receiver). This means the transmitters influence other variables. Green variables, except for WND, GEO, and BND, are the net shock transmitter in the network. The main net transmitter among them is WAT (13.53%), followed by BIO (2.92%). The main net receiver among them is BND (-9.15), followed by WND (-8.13%).

Moreover, fossil energy variables except for NGS and GAS, are the net shock transmitter. The leading net transmitter is OIL (7.27%), followed by HOI (4.32%). The largest net receiver among fossil energy is NGS (-5.14%). Investors concerning portfolio optimization should hold financial assets that are net transmitters and avoid net receivers since net receivers are influenced by many risk sources.

Following WAT, it is obvious that OIL serves as the primary transmitter within the fossil energy sector with 7.27%. Regarding frequency bands, both WAT and OIL,

connectedness is driven by short-term with 11.31% and 6.04%, respectively. In addition, we observe that the heating oil is driven mostly by short-term effects. These findings highlight the significant role of the short term when it comes to market dynamics.



Table 4: Time and Frequency Connectedness

Total Panel A	<i>WND</i>	<i>BIO</i>	<i>SOL</i>	<i>GEO</i>	<i>WAT</i>	<i>BND</i>	<i>OIL</i>	<i>NGS</i>	<i>GAS</i>	<i>HOI</i>	<i>FROM</i>
<i>WND</i>	58.36	5.96	8.91	4.26	13.2	3.74	1.85	0.58	1.61	1.54	41.64
<i>BIO</i>	4.58	51.95	8.57	5.34	12.2	2.03	5.75	0.92	3.8	4.86	48.05
<i>SOL</i>	6.75	9.19	52.81	6.2	15.39	1.09	3.06	0.77	2.46	2.28	47.19
<i>GEO</i>	4.4	6.63	7.34	62.44	10.96	1.11	2.59	0.77	1.76	2	37.56
<i>WAT</i>	9.2	11.13	13.33	7.63	45.74	3.51	3.47	0.44	3.01	2.53	54.26
<i>BND</i>	4.98	3.76	2.03	1.62	6.09	76.28	1.99	0.52	1.43	1.32	23.72
<i>OIL</i>	0.95	4.68	2.74	1.75	3.2	1.06	40.58	0.72	19.39	24.92	59.42
<i>NGS</i>	0.72	1.75	1.16	1.13	1.02	0.58	1.69	88.57	1.65	1.72	11.43
<i>GAS</i>	1.1	3.68	2.66	1.33	3.21	0.64	20.93	0.75	44.53	21.18	55.47
<i>HOI</i>	0.82	4.21	2.21	1.41	2.52	0.81	25.36	0.81	19.88	41.97	58.03
<i>TO</i>	33.5	50.98	48.95	30.66	67.78	14.58	66.69	6.28	54.99	62.35	436.76
<i>Inc. Own</i>	91.87	102.92	101.75	93.1	113.53	90.85	107.27	94.86	99.53	104.32	cTCI/TCI
<i>Net</i>	-8.13	2.92	1.75	-6.9	13.53	-9.15	7.27	-5.14	-0.47	4.32	48.53/43.68
<i>NPDC</i>	3	5	5	2	7	1	9	0	5	8	
Short Term Panel B	<i>WND</i>	<i>BIO</i>	<i>SOL</i>	<i>GEO</i>	<i>WAT</i>	<i>BND</i>	<i>OIL</i>	<i>NGS</i>	<i>GAS</i>	<i>HOI</i>	<i>FROM</i>
<i>WND</i>	52.62	5	7.56	3.62	11.36	3.38	1.65	0.49	1.49	1.41	35.97
<i>BIO</i>	4.05	46.76	7.69	4.7	10.89	1.84	5.21	0.81	3.47	4.45	43.1
<i>SOL</i>	5.93	8.02	47.24	5.55	13.68	0.98	2.73	0.66	2.25	2.04	41.86
<i>GEO</i>	3.83	5.82	6.41	56.37	9.64	0.98	2.27	0.69	1.65	1.78	33.06
<i>WAT</i>	8.22	9.74	11.8	6.82	40.88	3.13	3.1	0.4	2.79	2.28	48.29
<i>BND</i>	4.34	3.09	1.66	1.4	5.07	68.75	1.75	0.46	1.21	1.15	20.14
<i>OIL</i>	0.88	4.22	2.53	1.57	2.93	1.01	37.33	0.65	17.86	22.93	54.6
<i>NGS</i>	0.66	1.57	1.05	1.02	0.93	0.53	1.57	81.07	1.51	1.58	10.42

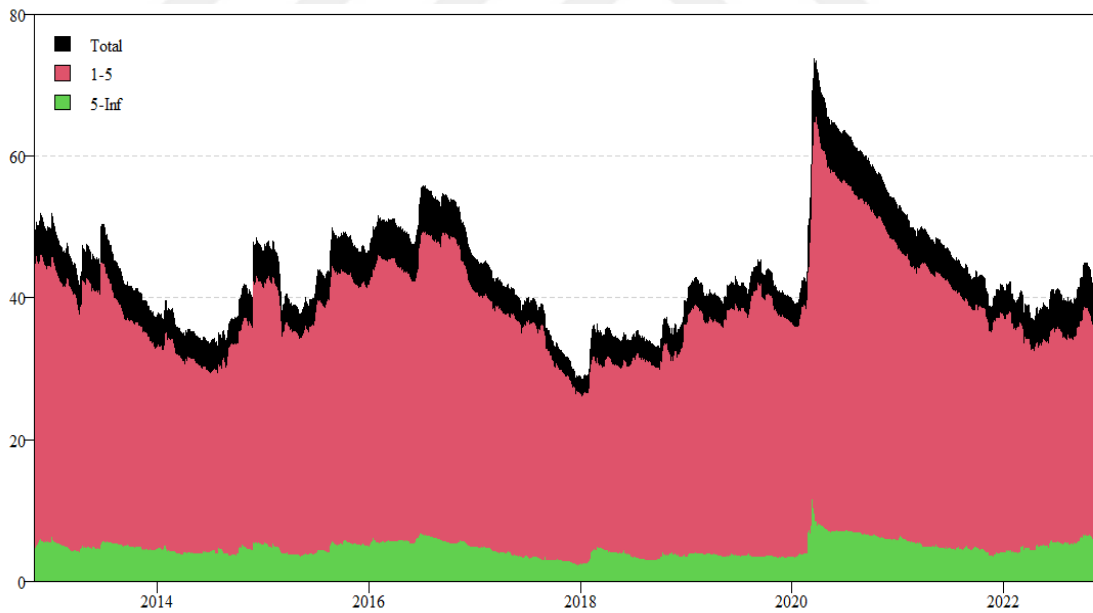
<i>GAS</i>	0.96	3.26	2.4	1.19	2.84	0.59	19.25	0.66	40.58	19.42	50.55
<i>HOI</i>	0.73	3.75	2	1.26	2.26	0.76	23.11	0.71	18.07	38.19	52.65
<i>TO</i>	29.61	44.48	43.09	27.14	59.59	13.19	60.64	5.54	50.32	57.04	390.64
<i>Inc.Own</i>	82.22	91.25	90.32	83.51	100.48	81.94	97.97	86.61	90.89	95.23	cTCI/TCI
<i>Net</i>	-6.36	1.39	1.23	-5.92	11.31	-6.96	6.04	-4.88	-0.24	4.39	43.40/39.06
<i>NPDC</i>	3	5	5	2	7	1	9	0	5	8	
Long Term Panel C											
<i>WND</i>	5.75	0.95	1.34	0.63	1.85	0.37	0.2	0.08	0.11	0.13	5.67
<i>BIO</i>	0.53	5.18	0.88	0.63	1.31	0.19	0.55	0.11	0.33	0.42	4.96
<i>SOL</i>	0.81	1.16	5.57	0.65	1.71	0.12	0.33	0.1	0.21	0.24	5.33
<i>GEO</i>	0.57	0.81	0.93	6.07	1.32	0.13	0.32	0.08	0.12	0.22	4.5
<i>WAT</i>	0.99	1.39	1.53	0.81	4.86	0.38	0.37	0.04	0.22	0.24	5.97
<i>BND</i>	0.63	0.67	0.37	0.21	1.02	7.53	0.23	0.06	0.22	0.17	3.58
<i>OIL</i>	0.07	0.45	0.21	0.18	0.26	0.05	3.25	0.07	1.53	1.99	4.82
<i>NGS</i>	0.06	0.18	0.11	0.11	0.09	0.05	0.12	7.51	0.14	0.14	1
<i>GAS</i>	0.15	0.42	0.27	0.14	0.37	0.05	1.68	0.09	3.96	1.76	4.91
<i>HOI</i>	0.09	0.46	0.21	0.15	0.26	0.05	2.24	0.11	1.81	3.77	5.38
<i>TO</i>	3.9	6.49	5.86	3.52	8.19	1.39	6.05	0.74	4.68	5.31	46.13
<i>Inc.Own</i>	9.64	11.68	11.43	9.59	13.05	8.92	9.3	8.25	8.63	9.08	cTCI/TCI
<i>Net</i>	-1.77	1.54	0.52	-0.98	2.22	-2.19	1.23	-0.26	-0.24	-0.07	5.13/4.61
<i>NPDC</i>	2	8	5	4	7	0	9	2	3	5	

Notes: The results are obtained from the model of TVP-VAR, one lag. TO denotes the transmission from a variable to others, excluding its shares. FROM shows, excluding own effects, the return spillover one variable receives from others. Net shows the difference between TO and FROM, which indicates net transmission. TCI denotes the total connectedness index. cTCI denotes corrected TCI. The net pairwise directional connectedness (NPDC) quantifies how many times particular variable dominates over other variables in terms of directional connectedness.

The visual representation of network can be seen in Figure 17. The upper-left network depicts the overall time connectedness (average). The upper-right and lower-left networks show short (1-5) and long (5-Inf) terms, respectively. The size of nodes represents to the magnitude of the degree of receiver/transmitter. Thicker arrows show the source base variable's effect on the target variable. In net terms, nodes displayed in blue represent that variables act as transmitters, while yellow ones show that variables act as receivers.

Figure 16 depicts the time and frequency connectedness indices. The time TCI is shown in the black-shaded area. The frequency part is shown in two ways: Short-term (1-5) frequency index (i.e., red shaded area) and long-term (5-Inf) frequency index (i.e., green shaded area). It is crystal clear that return connectedness is mostly driven by the short term. Therefore, network itself processes information rapidly. Our results support H1 and H2.

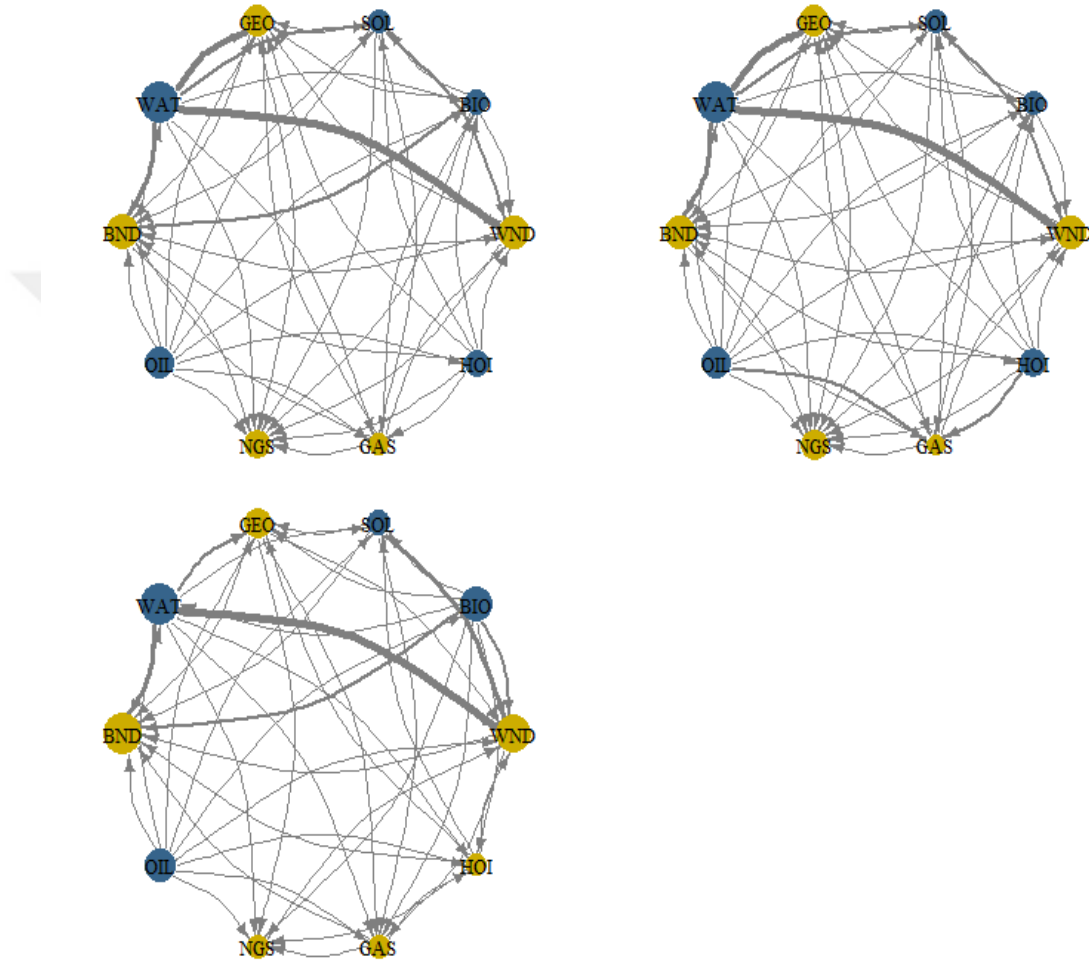
Figure 16: Dynamic Time and Frequency Connectedness



Notes: The results are obtained from the model of TVP-VAR, one lag. Lag is determined by the SIC. The black-shaded area shows the time TCI (Diebold and Yilmaz, 2012). The red and green shaded areas represent frequency connectedness indices (Baruník and Křehlík, 2018), both short (1-5) and long-term (5-Inf), respectively.

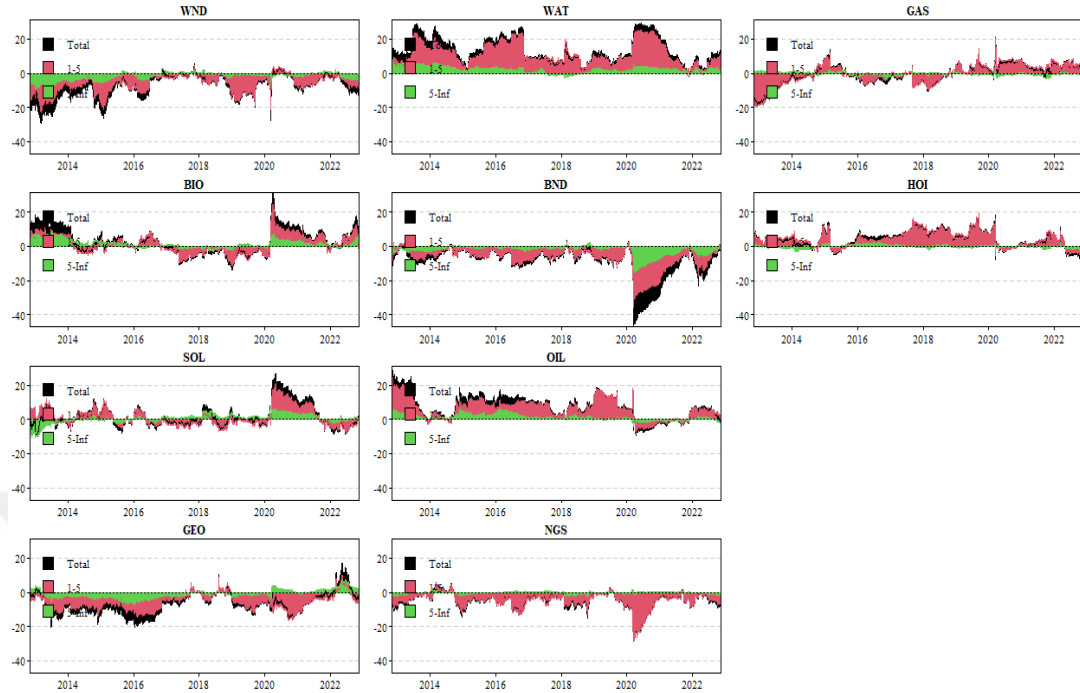
In Figure 16, the total connectedness fell gradually from 2020 to 2022. At the beginning of 2022, the Russia's invasion of Ukraine began; consequently, the total connectedness rose after 2022. This result supports H3.

Figure 17: Time and Frequency Connectedness Network



Notes: The results are obtained from the model of TVP-VAR, one lag. Lag is determined by the SIC. The upper-left network depicts the overall time connectedness (average). The upper-right and lower-left networks show short (1-5) and long (5-Inf) terms, respectively. The size of nodes represents to the magnitude of the degree of receiver/transmitter. Thicker arrows show the source base variable's effect on the target variable. In net terms, nodes displayed in blue represent that variables act as transmitters, while yellow ones show that variables act as receivers.

Figure 18: Net Directional Time and Frequency Connectedness

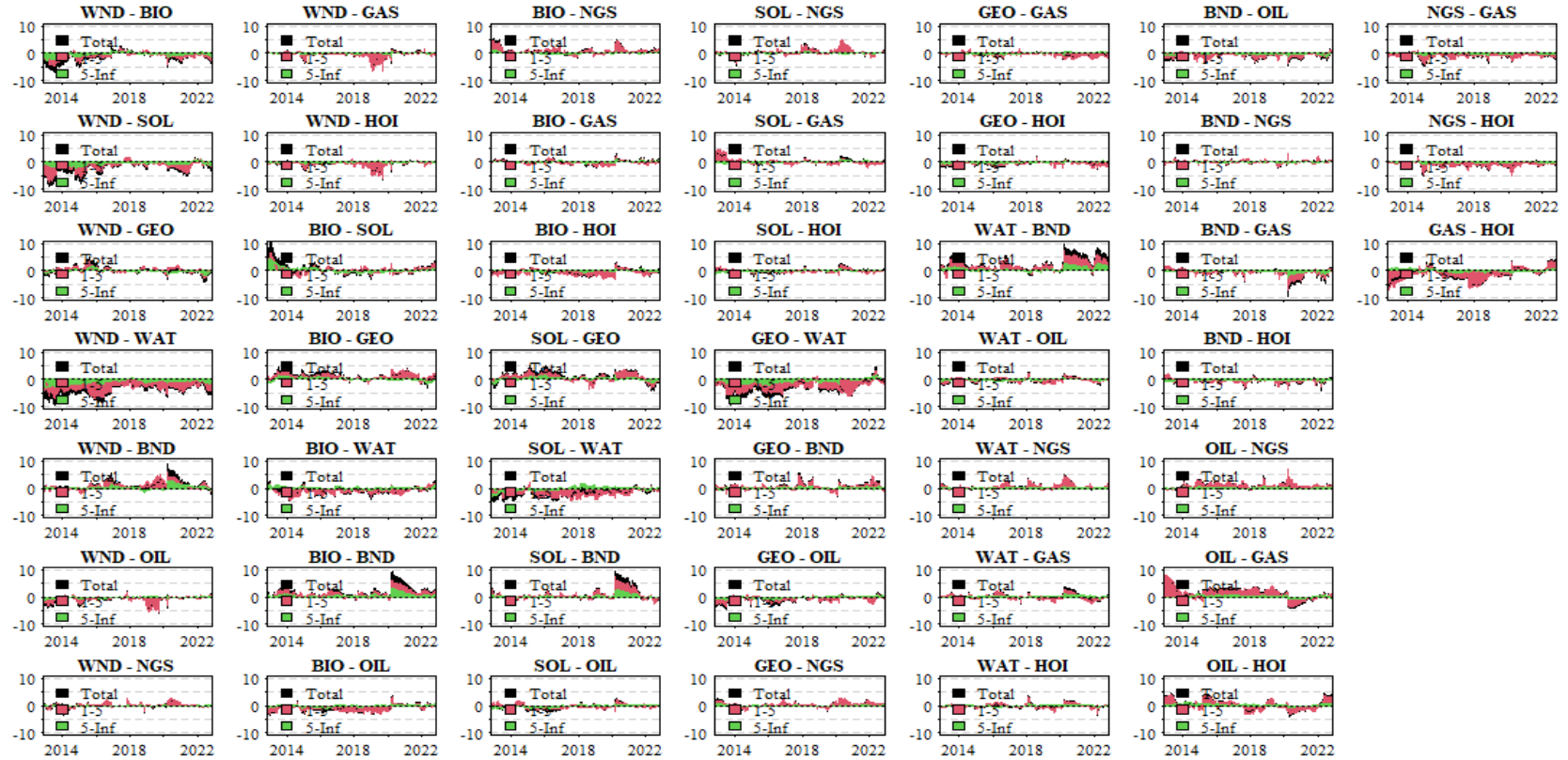


Notes: The results are obtained from the model of TVP-VAR, one lag. The black-shaded area shows the total net directional connectedness. The red and green-shaded areas represent both short (1-5) and long-term (5-Inf) frequency net directional connectedness, respectively.

Figure 18 illustrates the net directional time and frequency connectedness. Some of the variables act as net transmitters such as WAT, OIL, and HOI. Over time, changes are seen in terms of direction and magnitude. For instance, BIO and SOL are net receivers but they turn to net transmitters after 2020. By contrast, OIL was a net transmitter, but it changed to the net recipient for a while after 2020. For some of the variables, their magnitude increased such as WAT and BND.

The visualization of net pairwise directional connectedness is given in Figure 19. We observe that WND consistently receives transmission from WAT throughout the period of analysis. However, certain transmission patterns have changed after the pandemic. For instance, OIL is influenced by GAS for a while. Additionally, at the start of the 2020, BND acted as a receiver to BIO, SOL, WAT, and WND.

Figure 19: Net Pairwise Directional Connectedness



Notes: The results are obtained from the model of TVP-VAR, one lag. Black shaded areas show the total net pairwise directional connectedness, while red and green shaded areas denote short (1-5) and long (5-Inf) terms, respectively. The shaded area above (below) zero means that the first variable transmits (receives) the spillover to (from) the second variable.

4.1.2. Volatility Connectedness

Similar to the previous section, the TVP frequency connectedness framework of Chatziantoniou et al. (2021) is used. The lag length of the time-varying parameter vector autoregression model was determined as 1 by the Schwarz information criterion (SIC). The results are based on TVP-VAR (1) model with 10 days forecast horizon. We examine the frequency both in short (1-5) and long (5-Inf) terms, respectively.

Table 5 shows the volatility connectedness results concerning both time and frequency domains. The Panel A shows time connectedness while panels B and C depict frequency connectedness with both short (1-5) and long (5-Inf) terms.

According to Panel A of Table 5, the total connectedness index (TCI) is calculated as 37.38%. So, it explains 37.38 percent of variations in the network. The remaining part of TCI which is 62.62% derived from own variable (idiosyncratic) shocks. For instance, 82.04% and 74.73% of the future volatility shocks of natural gas and green bonds can be attributable to their own previous shocks. Thus, the future volatility shocks for them are less influenced by shocks in other markets. Other panels report that the majority of total connectedness comes from short-term connectedness (26.15%) which is approximately two times that of long-term connectedness (11.23%).

The diagonal amounts point to own-variable shocks. The pairwise spillover can be seen off-diagonally in Table 5. The largest average pairwise spillover is found between the fossil energy futures; from OIL to HOI, with 23.95%. The largest average pairwise spillover is driven by short term with 17.97%. However, the lowest average pairwise spillover is found from NGS to GEO with 0.72%. Among green variables, the largest average pairwise spillover is found from WAT to SOL, with 11.04%. Similar to OIL-HOI, this relationship is driven by short term with 8.56%. Similar to the result of return connectedness, green bond market offers more diversification benefits within the green markets due to its low connectedness with the others in the system. Likewise, natural gas provides more diversification opportunities because of its low connectedness with both green and fossil energy markets which consistent the findings of Umar et al. (2022).

Table 5: Time and Frequency Connectedness

<i>Total Panel A</i>	<i>WND</i>	<i>BIO</i>	<i>SOL</i>	<i>GEO</i>	<i>WAT</i>	<i>BND</i>	<i>OIL</i>	<i>NGS</i>	<i>GAS</i>	<i>HOI</i>	<i>FROM</i>
<i>WND</i>	70.19	2.79	4.71	4.09	7.85	4.29	1.37	1.36	1.48	1.85	29.81
<i>BIO</i>	2.62	63.92	4.77	3.52	8.02	2.04	6.17	1.80	3.01	4.13	36.08
<i>SOL</i>	4.07	5.31	66.25	4.71	11.04	1.78	1.87	1.12	1.66	2.20	33.75
<i>GEO</i>	3.52	4.31	5.17	69.51	7.18	1.76	2.37	0.72	3.12	2.34	30.49
<i>WAT</i>	5.79	7.56	9.01	5.68	55.64	3.24	4.44	1.34	3.53	3.78	44.36
<i>BND</i>	4.99	2.71	1.72	2.01	4.39	74.72	2.59	1.82	2.19	2.87	25.28
<i>OIL</i>	1.12	5.46	1.03	1.63	3.46	1.39	45.97	1.50	15.54	22.89	54.03
<i>NGS</i>	1.14	2.81	1.26	1.26	1.38	2.21	3.23	82.04	1.73	2.95	17.96
<i>GAS</i>	0.93	3.37	1.11	2.30	3.27	1.03	18.04	0.78	51.64	17.52	48.36
<i>HOI</i>	1.20	4.53	1.32	1.56	3.15	1.39	23.95	1.29	15.31	46.29	53.71
<i>TO</i>	25.38	38.85	30.09	26.77	49.74	19.14	64.03	11.73	47.57	60.54	373.83
<i>Inc. Own</i>	95.57	102.77	96.34	96.28	105.38	93.85	110.00	93.76	99.21	106.83	cTCI/TCI
<i>Net</i>	-4.43	2.77	-3.66	-3.72	5.38	-6.15	10.00	-6.24	-0.79	6.83	41.54/37.38
<i>NPDC</i>	1.00	7.00	3.00	3.00	6.00	2.00	9.00	1.00	6.00	7.00	

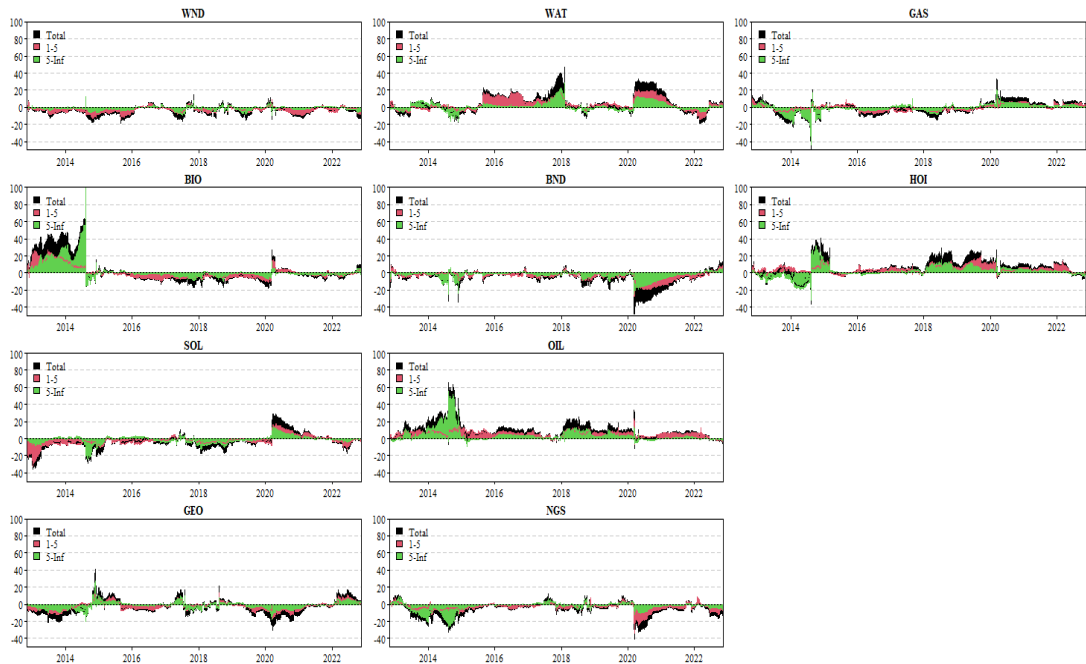
Notes: The results are obtained from the model of TVP-VAR, one lag. TO denotes the transmission from a variable to others, excluding its shares. FROM shows, excluding own effects, the return spillover one variable receives from others. Net shows the difference between TO and FROM, which indicates net transmission. TCI denotes the total connectedness index. cTCI denotes corrected TCI. The net pairwise directional connectedness (NPDC) quantifies how many times particular variable dominates over other variables in terms of directional connectedness.

Short Term Panel B	<i>WND</i>	<i>BIO</i>	<i>SOL</i>	<i>GEO</i>	<i>WAT</i>	<i>BND</i>	<i>OIL</i>	<i>NGS</i>	<i>GAS</i>	<i>HOI</i>	<i>FROM</i>
<i>WND</i>	60.83	2.10	3.60	2.94	6.05	3.30	0.94	0.91	1.06	1.28	22.17
<i>BIO</i>	1.94	52.72	3.66	2.28	5.94	1.48	2.93	1.03	1.59	2.10	22.94
<i>SOL</i>	3.14	4.05	57.32	3.26	8.56	1.32	1.18	0.82	1.19	1.51	25.03
<i>GEO</i>	2.58	2.69	3.64	57.57	5.11	1.20	1.18	0.49	2.03	1.27	20.19
<i>WAT</i>	4.56	5.52	7.06	4.03	46.73	2.37	2.77	0.88	2.47	2.41	32.07
<i>BND</i>	3.74	1.76	1.22	1.35	3.12	65.06	1.54	1.32	1.47	1.96	17.47
<i>OIL</i>	0.74	2.30	0.69	0.86	2.19	0.86	35.72	0.79	11.80	17.58	37.81
<i>NGS</i>	0.76	1.41	0.90	0.87	0.87	1.64	1.67	70.36	1.14	1.60	10.87
<i>GAS</i>	0.69	1.50	0.86	1.49	2.35	0.66	13.43	0.43	43.02	13.40	34.81
<i>HOI</i>	0.82	1.98	0.96	0.87	2.03	0.93	17.97	0.71	11.88	37.36	38.15
<i>TO</i>	18.98	23.28	22.59	17.94	36.23	13.76	43.61	7.37	34.62	43.13	261.52
<i>Inc.Own</i>	79.80	76.01	79.90	75.51	82.96	78.82	79.34	77.73	77.64	80.49	cTCI/TCI
<i>Net</i>	-3.20	0.34	-2.45	-2.24	4.16	-3.71	5.80	-3.50	-0.20	4.98	29.06/26.15
<i>NPDC</i>	1.00	5.00	3.00	3.00	5.00	2.00	9.00	2.00	7.00	8.00	
Long Term Panel C											
<i>WND</i>	9.36	0.69	1.11	1.16	1.80	1.00	0.43	0.45	0.42	0.57	7.63
<i>BIO</i>	0.68	11.20	1.12	1.25	2.07	0.57	3.24	0.77	1.41	2.03	13.13
<i>SOL</i>	0.93	1.26	8.93	1.45	2.48	0.46	0.69	0.30	0.47	0.69	8.72
<i>GEO</i>	0.94	1.62	1.52	11.94	2.07	0.56	1.19	0.24	1.10	1.07	10.30
<i>WAT</i>	1.24	2.04	1.95	1.65	8.91	0.87	1.66	0.45	1.07	1.36	12.29
<i>BND</i>	1.26	0.95	0.50	0.66	1.27	9.65	1.05	0.50	0.72	0.91	7.82
<i>OIL</i>	0.37	3.17	0.34	0.77	1.27	0.53	10.25	0.71	3.74	5.31	16.22
<i>NGS</i>	0.37	1.40	0.36	0.39	0.51	0.56	1.56	11.67	0.59	1.35	7.10
<i>GAS</i>	0.24	1.87	0.25	0.81	0.92	0.37	4.61	0.35	8.62	4.12	13.54
<i>HOI</i>	0.38	2.56	0.35	0.70	1.12	0.46	5.98	0.58	3.43	8.93	15.56
<i>TO</i>	6.40	15.56	7.50	8.83	13.51	5.38	20.42	4.36	12.95	17.41	112.31
<i>Inc.Own</i>	15.77	26.76	16.44	20.77	22.42	15.03	30.67	16.03	21.57	26.34	cTCI/TCI
<i>Net</i>	-1.23	2.43	-1.21	-1.48	1.22	-2.44	4.20	-2.74	-0.59	1.85	12.48/11.23
<i>NPDC</i>	1.00	7.00	4.00	3.00	6.00	1.00	9.00	1.00	6.00	7.00	

The net directional connectedness is reported at the bottom of each panel. It indicates that the positive (negative) value is the net shock transmitter (receiver). Among green variables, except for BIO and WAT, are the net shock receiver from the system. The most dominant net transmitter among them is WAT (5.38%). Furthermore, fossil energy variables except for NGS and GAS, are the net shock transmitter. In the fossil side, it is obvious that the leading transmitter is OIL (10%).

In Figure 20, we present an illustration of the net directional time and frequency connectedness. Over time, the overall TCI fluctuates in terms of both direction and magnitude. For example, prior to 2020, SOL and BIO were net recipients for a limited period, but later on, they became net transmitters. Throughout the sample period, OIL was mostly a net transmitter. In addition, certain variables experienced periods of increased magnitudes, including WAT, BND, BIO, OIL, NGS, and SOL.

Figure 20: Net Directional Time and Frequency Connectedness

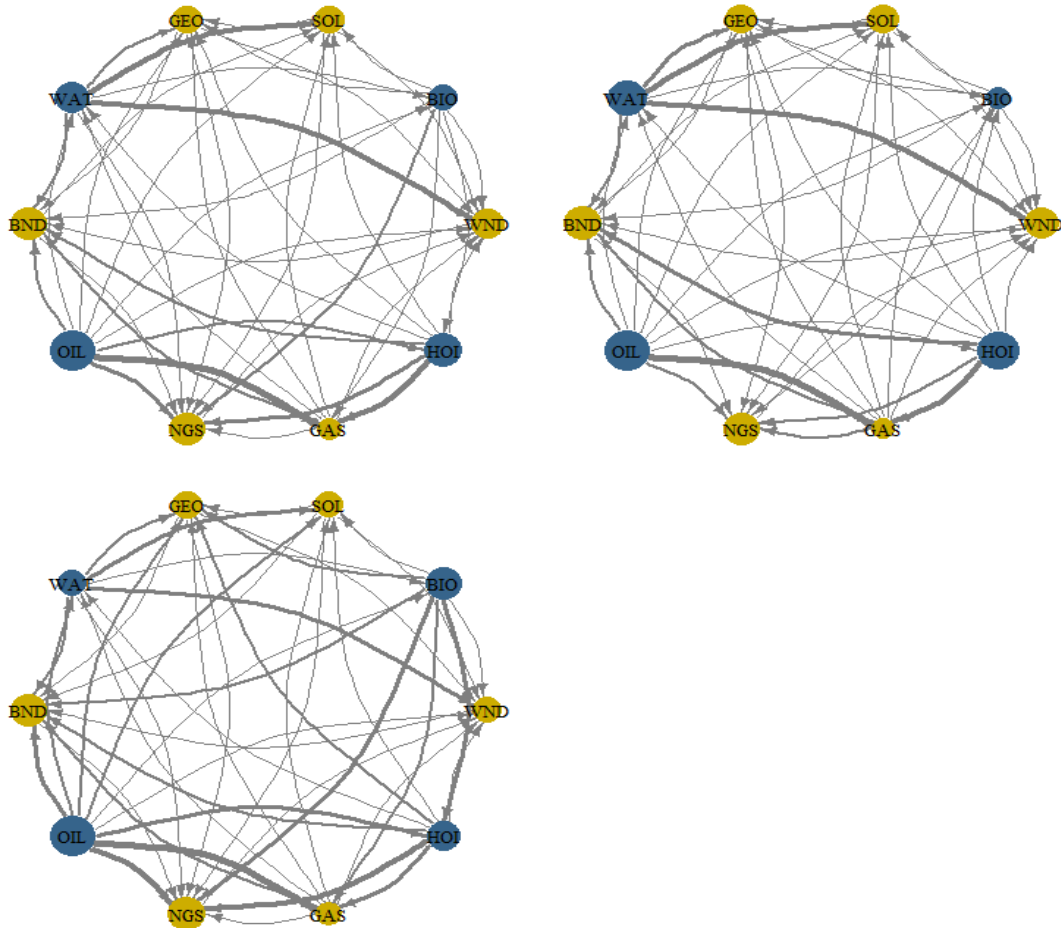


Notes: The results are obtained from the model of TVP-VAR, one lag. The black-shaded area shows the total net directional connectedness. The red and green-shaded areas represent both short (1-5) and long-term (5-Inf) frequency net directional connectedness, respectively.

The upper-left network depicts the overall time connectedness is depicted in Figure 21. The upper-left network depicts the overall time connectedness (average). The upper-right and lower-left networks show short (1-5) and long (5-Inf) terms, respectively. The size of nodes represents to the magnitude of the degree of receiver/transmitter. Thicker arrows show the source base variable's effect on the target variable. In net terms, nodes displayed in blue represent that variables act as transmitters, while yellow ones show that variables act as receivers.

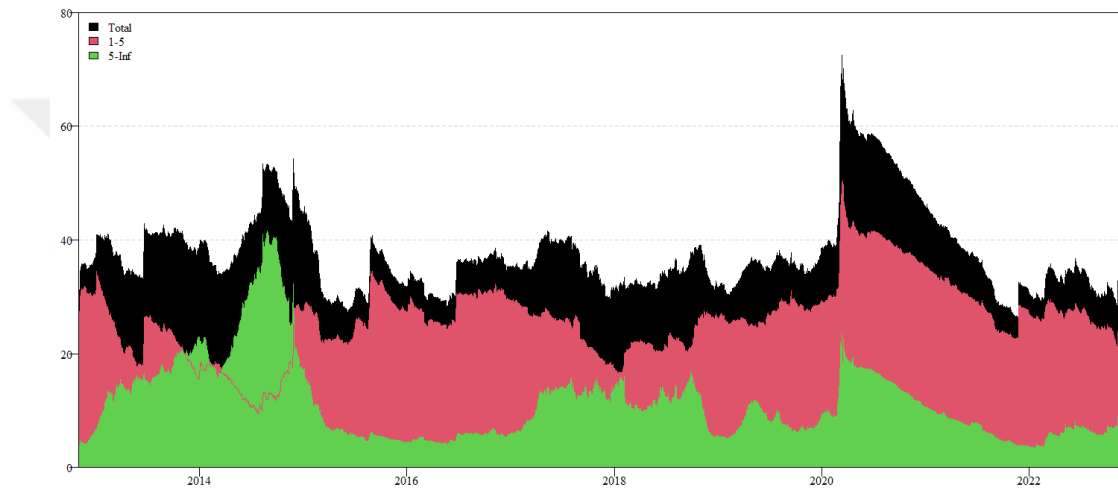
The visual presentation of net pairwise directional connectedness is given in Figure 23. Some transmission structure changed after the COVID-19 pandemic, this relationship caught between SOL-GEO, and WAT-BND.

Figure 21: Time and Frequency Connectedness Network



Notes: The results are obtained from the model of TVP-VAR, one lag. The SIC determines lag. The upper-left network depicts the overall time connectedness (average). The upper-right and lower-left networks show short (1-5) and long (5-Inf) terms, respectively. The size of nodes represents to the magnitude of the degree of receiver/transmitter. Thicker arrows show the source base variable's effect on the target variable. In net terms, nodes displayed in blue represent that variables act as transmitters, while yellow ones show that variables act as receivers.

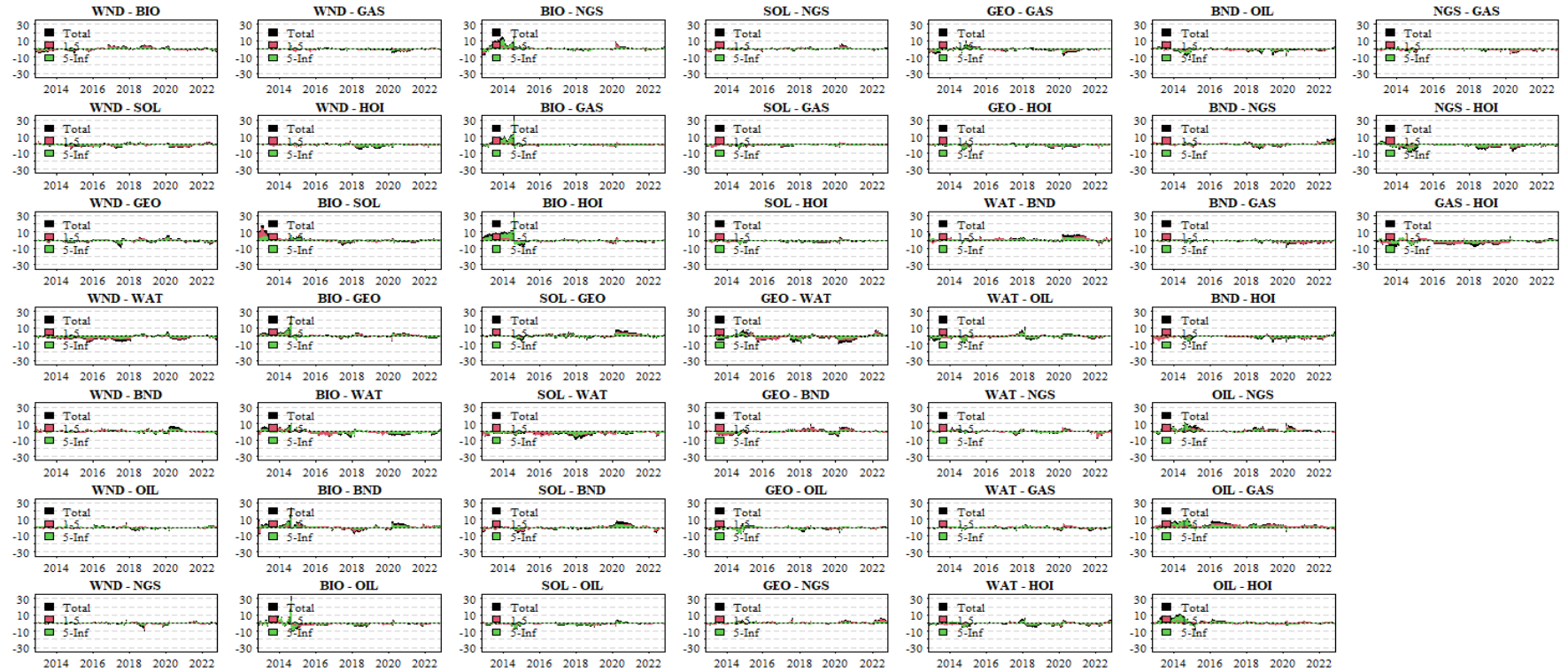
Figure 22: Dynamic Time and Frequency Connectedness



Notes: The results are obtained from the model of TVP-VAR, one lag. Lag is determined by the SIC. The black-shaded area shows the time TCI (Diebold and Yilmaz, 2012). The red and green shaded areas represent frequency connectedness indices (Baruník and Křehlík, 2018), both short (1-5) and long-term (5-Inf), respectively.

Figure 22 presents the time and frequency connectedness indices. The time TCI is shown in the black-shaded area. The frequency part is shown in two ways: Short-term (1-5) frequency index (i.e., red shaded area) and long-term (5-Inf) frequency index (i.e., green shaded area). The volatility connectedness is mostly driven by the short term. The total connectedness fell steadily. At the beginning of 2022, due to Russia's invasion of Ukraine began; we observed an increase in the total connectedness. Our results support all three hypotheses.

Figure 23: Net Pairwise Directional Connectedness



Notes: The results are obtained from the model of TVP-VAR, one lag. Black shaded areas show the total net pairwise directional connectedness, while red and green shaded areas denote short (1-5) and long (5-Inf) terms, respectively. The shaded area above (below) zero means that the first variable transmits (receives) the spillover to (from) the second variable.

4.2. MINIMUM CONNECTEDNESS PORTFOLIO AND HEDGING EFFECTIVENESS

In this section, we analyze the portfolio allocation under minimum connectedness approach outlined by Broadstock et al. (2020). To do so, we examine both return and volatility connectedness, considering the time and frequency domains. In order to evaluate portfolio, Ederington's (1979) hedging effectiveness (HE) used. The portfolio weights, considering total, short term, and long term, are provided in figures within Appendices 1 through 6.

MCoP approach centers around pairwise connectedness to minimize spillovers of shocks. Consequently, greater weight will be given to those less affected. Also, HE value is related with risk reduction. A higher value express the greater risk reduction.

4.2.1. Return and Hedging Effectiveness

The hedging effectiveness ratios are shown in Table 6. For minimum connectedness portfolio, the three substantial average weights in the portfolio are as follows: NGS with 17.7%, followed by BND with 16%, and GEO with 13.6%.

The total weight of renewable energy indices constitutes approximately 45%. As an important part of green market, if investors also invest in green bonds, the weight of greens increases approximately to 61%. The remaining weight of 39% comes from fossil energies.

If investors invest on average 12.3% in WND, 8.2% in BIO, 9.2% in SOL, 13.6% in GEO, 4.7% in OIL, 17.7% in NGS, 9.4% in GAS, and 6.9% in HOI, each asset's volatility will reduce by 56.7%, 67.2%, 72%, 59.6%, 86.7%, 89.4%, 84.6% and 77.6%, respectively. The asset volatility will increase by 23.9% and 9.15% if investors invest 1.9% in WAT and 16% in BND, respectively. The results are statistically significant at 1% significance level.

Table 6: Hedging Effectiveness (Return)

Total	<i>Mean</i>	<i>Std.Dev.</i>	<i>5%</i>	<i>95%</i>	<i>HE</i>	<i>p-value</i>
<i>WND</i>	0.123	0.018	0.097	0.155	0.567	0.000
<i>BIO</i>	0.082	0.027	0.033	0.118	0.672	0.000
<i>SOL</i>	0.092	0.034	0.013	0.136	0.720	0.000
<i>GEO</i>	0.136	0.023	0.097	0.176	0.596	0.000
<i>WAT</i>	0.019	0.025	0.000	0.069	-0.239	0.000
<i>BND</i>	0.160	0.019	0.130	0.199	-9.156	0.000
<i>OIL</i>	0.047	0.042	0.000	0.117	0.867	0.000
<i>NGS</i>	0.177	0.018	0.153	0.212	0.894	0.000
<i>GAS</i>	0.094	0.031	0.046	0.148	0.846	0.000
<i>HOI</i>	0.069	0.038	0.000	0.124	0.776	0.000

Short	<i>Mean</i>	<i>Std.Dev.</i>	<i>5%</i>	<i>95%</i>	<i>HE</i>	<i>p-value</i>
<i>WND</i>	0.123	0.017	0.099	0.152	0.577	0.000
<i>BIO</i>	0.084	0.028	0.032	0.119	0.680	0.000
<i>SOL</i>	0.094	0.034	0.011	0.137	0.727	0.000
<i>GEO</i>	0.136	0.022	0.094	0.168	0.606	0.000
<i>WAT</i>	0.021	0.026	0.000	0.073	-0.209	0.000
<i>BND</i>	0.161	0.023	0.130	0.208	-8.912	0.000
<i>OIL</i>	0.044	0.040	0.000	0.110	0.870	0.000
<i>NGS</i>	0.174	0.017	0.151	0.208	0.897	0.000
<i>GAS</i>	0.092	0.030	0.046	0.143	0.850	0.000
<i>HOI</i>	0.070	0.037	0.000	0.124	0.781	0.000

Long	<i>Mean</i>	<i>Std.Dev.</i>	<i>5%</i>	<i>95%</i>	<i>HE</i>	<i>p-value</i>
<i>WND</i>	0.117	0.045	0.055	0.201	0.447	0.000
<i>BIO</i>	0.070	0.041	0.000	0.132	0.581	0.000
<i>SOL</i>	0.086	0.043	0.001	0.144	0.643	0.000
<i>GEO</i>	0.128	0.043	0.068	0.207	0.484	0.000
<i>WAT</i>	0.013	0.023	0.000	0.069	-0.581	0.000
<i>BND</i>	0.153	0.052	0.080	0.235	-11.964	0.000
<i>OIL</i>	0.085	0.067	0.000	0.209	0.830	0.000
<i>NGS</i>	0.191	0.038	0.139	0.276	0.865	0.000
<i>GAS</i>	0.098	0.044	0.030	0.176	0.804	0.000
<i>HOI</i>	0.060	0.052	0.000	0.144	0.714	0.000

Regarding the terms, most of the weights are the same for short term (1-5). This means that the asset's role in portfolio remains consistent in the short term. The hedging results for short term are very similar to total results. On the other hand, the long term (5-Inf) results vary in terms of weights under MCoP and also, HE.

The total weight of renewable energy indices and green bond constitutes approximately 57% in long term. The remaining weight of 43% comes from fossil energies. Among green variables, the largest weight is BND with 15.3%. The largest weight in fossil energies is NGS with 19.1%.

In long term, if investors invest on average 11.7% in WND, 7% in BIO, 8.6% in SOL, 12.8% in GEO, 8.5% in OIL, 19.1% in NGS, 9.8% in GAS, and 6% in HOI, each asset's volatility will reduce by 44.7%, 58.1%, 64.3%, 48.4%, 83%, 86.5%, 80.4%, and 71.4%, respectively. The asset volatility will increase by 58.1% and 11.96% if investors invest 1.3% in WAT, and 15.3% in BND, respectively. The results are statistically significant at 1% significance level.

The figures for total, short term and long-term results in terms of portfolio weights are given in Appendix 1, 2 and 3 respectively.

4.2.2. Volatility and Hedging Effectiveness

Table 7 represents hedging effectiveness ratios. The three assets carrying the most substantial average weights in the portfolio are NGS, BND, and GEO, accounting for 15.6%, 13.2%, and 12.4% respectively.

The total weight of renewable energy indices constitutes approximately 50%. As an important part of the green market, if investors also invest in green bonds, the weight of greens increases approximately to 64%. The remaining weight of 36% comes from fossil energies.

If investors invest on average 12% in WND, 10.2% in BIO, 10.9% in SOL, 12.4% in GEO, 6.4% in OIL, 15.6% in NGS, 9.2% in GAS, and 5% in HOI, each asset's volatility will reduce by 52.2%, 65.8%, 69.9%, 61.8%, 88.9%, 88.8%, 86.2%, and 78.6%, respectively. The asset volatility will increase by 25% and 10.22% if investors invest 5.2% in WAT, and 13.2% in BND, respectively. The results are statistically significant at a 1% significance level.

Table 7: Hedging Effectiveness (Volatility)

Total	<i>Mean</i>	<i>Std.Dev.</i>	<i>5%</i>	<i>95%</i>	<i>HE</i>	<i>p-value</i>
<i>WND</i>	0.120	0.019	0.091	0.145	0.522	0.000
<i>BIO</i>	0.102	0.048	0.000	0.153	0.658	0.000
<i>SOL</i>	0.109	0.034	0.039	0.149	0.699	0.000
<i>GEO</i>	0.124	0.018	0.087	0.149	0.618	0.000
<i>WAT</i>	0.052	0.039	0.000	0.117	-0.250	0.000
<i>BND</i>	0.132	0.021	0.091	0.157	-10.227	0.000
<i>OIL</i>	0.064	0.032	0.004	0.134	0.889	0.000
<i>NGS</i>	0.156	0.025	0.120	0.209	0.888	0.000
<i>GAS</i>	0.092	0.029	0.049	0.135	0.862	0.000
<i>HOI</i>	0.050	0.034	0.000	0.110	0.786	0.000

Short	<i>Mean</i>	<i>Std.Dev.</i>	<i>5%</i>	<i>95%</i>	<i>HE</i>	<i>p-value</i>
<i>WND</i>	0.112	0.015	0.086	0.131	0.494	0.000
<i>BIO</i>	0.115	0.028	0.076	0.155	0.638	0.000
<i>SOL</i>	0.101	0.030	0.044	0.138	0.681	0.000
<i>GEO</i>	0.124	0.016	0.097	0.150	0.595	0.000
<i>WAT</i>	0.055	0.035	0.000	0.107	-0.323	0.000
<i>BND</i>	0.123	0.022	0.083	0.152	-10.880	0.000
<i>OIL</i>	0.085	0.038	0.039	0.162	0.882	0.000
<i>NGS</i>	0.145	0.025	0.105	0.191	0.882	0.000
<i>GAS</i>	0.084	0.027	0.047	0.128	0.854	0.000
<i>HOI</i>	0.057	0.034	0.007	0.124	0.774	0.000

Long	<i>Mean</i>	<i>Std.Dev.</i>	<i>5%</i>	<i>95%</i>	<i>HE</i>	<i>p-value</i>
<i>WND</i>	0.111	0.065	0.007	0.224	0.349	0.000
<i>BIO</i>	0.128	0.083	0.000	0.248	0.535	0.000
<i>SOL</i>	0.110	0.065	0.000	0.209	0.590	0.000
<i>GEO</i>	0.091	0.047	0.004	0.175	0.479	0.000
<i>WAT</i>	0.037	0.049	0.000	0.142	-0.702	0.000
<i>BND</i>	0.137	0.059	0.025	0.223	-14.285	0.000
<i>OIL</i>	0.046	0.071	0.000	0.188	0.849	0.000
<i>NGS</i>	0.165	0.077	0.034	0.286	0.848	0.000
<i>GAS</i>	0.113	0.068	0.000	0.246	0.813	0.000
<i>HOI</i>	0.060	0.056	0.000	0.168	0.709	0.000

Most of the weights are similar for short term (1-5). This shows that the asset's role in the portfolio remains the same in short term. The hedging results for the short term reflect total results. However, the long term (5-Inf) results differ in terms of weights under MCoP approach and also, HE ratios.

In the long term (5-Inf), the sum weight of fossil energies constitutes approximately 38%. The remaining weight originates from renewable energy indices and green bonds. Among green variables, the largest weight is attributed to BND with 13.7%, followed by BIO with 12.8%. The lowest weight in renewable energy is WAT with 3.7%. Within fossil energies, NGS has the highest weight with 16.5%, while OIL has the lowest with 4.6%.

In long term, if investors invest 11.1% in WND, 12.8% in BIO, 11% in SOL, 9.1% in GEO, 4.6% in OIL, 16.5% in NGS, 11.3% in GAS, and 6% in HOI, and each asset's volatility will reduce by 34.9%, 53.5%, 59%, 47.9%, 84.9%, 84.8%, 81.3%, 70.9%, respectively. The asset volatility will increase by 70.2% and 14.29% if investors invest 3.7% in WAT and 13.7% in BND, respectively. The results are statistically significant at 1% significance level.

The figures for total, short term and long term results in terms of portfolio weights are given in Appendix 4, 5 and 6 respectively.

CONCLUSION

This thesis investigates dynamic return and volatility connectedness among green energy (solar, wind, geothermal, bio/clean fuels, and water), green bonds, and fossil energy (oil, natural gas, heating oil, and gasoline) markets by employing a TVP-VAR frequency connectedness approach of Chatziantoniou et al. (2021) from November 1, 2012, to November 15, 2022. In addition, we employ Minimum connectedness portfolio (MCoP) technique that is proposed by Broadstock et al. (2020) and hedging effectiveness (HE) ratio developed by Ederington (1979) to determine the weights of minimum connectedness portfolio and hedging effectiveness ratios for the portfolios consisting of these assets respectively.

This study extends the related literature in terms of data and the methodology used. It is more comprehensive than the previous literature since it includes different types of fossil energy markets other than oil (such as natural gas, gasoline etc.) and sub-sectoral level green energy stock markets and green bonds. In addition, the technique used allows us to assess whether short or long term dynamics dominates the total connectedness. Moreover, minimum connectedness portfolio and hedging effectiveness analysis are firstly employed for the portfolios including a broad range of energy markets.

Our result indicates mediocre level of total return connectedness index with a level of 43.68% while the findings of Pham (2019) indicate a high (66.19%) and Song et al. a low (23.85%) connectedness between fossil and green energy markets. This might be result of using different data and techniques. According to return connectedness results, water, and oil impact the network, while green bonds and wind are influenced by the others in the market. Our result is inconsistent with the findings of Ahmad (2017) regarding oil and clean energy relationship. However, our result is in line with Pham (2019) who also found slight connection between oil and geothermal and wind. Our results are similar to the findings of Reboredo (2018) and Reboredo et al. (2020) in terms of the relationship between green bonds and energy stock, and also are in line with the finding of Tiwari et al. (2022) on the return transmissions from green energy stocks to green bonds are more than those from fossil energies. In addition, green bond's net receiver role is parallel with the findings of Saeed et al.

(2021). Investors who are concerned with optimal portfolio management should consider investing in net transmitters such as water and oil and avoid net receivers such as green bonds and wind since net shock receivers may be affected by many risks.

Moreover, we notice that all series demonstrate high connectedness (approximately 70%) during the COVID-19 pandemic. Additionally, connectedness tends to rise after the Russia's invasion of Ukraine, which indicates that connectedness increased during uncertainty periods. This result is in line with the findings of Pham (2019) and Foglia and Angelini (2020). In addition, we find that the majority part of the total return connectedness is derived from short-term dynamics. So that, diversification may be more beneficial for investors in the long-term. Considering frequency bands, both water and oil connectedness are driven by short-term with 11.31% and 6.04%, respectively. The short-term driven relationship is similar with the result of Ferrer et al. (2018) but in contrast to Reboredo et al. (2017). Under MCoP approach, the total average weight of greens constitutes approximately 61%. The remaining weight of 39% comes from fossil energies. The total three largest average weights are natural gas, green bond, and geothermal, respectively. The result obtained for diversification is consistent with the findings of Reboredo (2018), and Nguyen et al. (2021).

We find a relatively low volatility connectedness with a level of 37.38% that is almost similar to the finding of Song et al. (2019) with a level of 31.70%. In detail, findings demonstrate that oil and heating oil impact the market, while natural gas and green bond are influenced by the others in the market. Our result is contrary to the findings of Ahmad (2017) and Tan et al. (2021)'s findings that oil is net receiver from clean energy. The network dynamics may show that investors who are concerned with portfolio management should consider investing in net transmitters such as oil and heating oil and avoid net receivers such as green bonds and natural gas since net shock receivers may be affected by other variables. Our results demonstrate total volatility connectedness increases during uncertainty periods with a domination of short term dynamics. Considering frequency bands, both oil and heating oil connectedness are driven by short-term with 5.8% and 4.98%, respectively. This connectedness result is in line with Umar et al. (2022). Under MCoP approach, the total average weight of greens constitutes approximately 64%. The remaining weight of 36% comes from

fossil energies. The total largest average weights are exactly the same as the results in the return part. The existence of significant return and volatility connectedness among this market indicates that the markets are inefficient. In other words, our findings do not support EMH of Fama (1970).

Our results provide valuable insights to both investors and policymakers in terms of developing portfolio strategies and making decisions by considering the fluctuations in energy prices. The short-term driven relationship for return and volatility connectedness provides an important implication for the investors that diversification opportunities may be more beneficial in long-term investments. Investors concerning portfolio optimization should hold financial assets that are net transmitters and avoid net receivers since net receivers are influenced by many risks. The asset's role in portfolio remains consistent in the short term under MCoP approach. This may show that investors who prefer a portfolio considering minimum connectedness should invest twice as much in greens compared to fossils. The growing investors interest in renewable energy is crucial for decreasing dependence on fossil energy. The transition from fossil to green markets can make the overall system to be more stable. It is supported by noteworthy evidence of both connectedness, highlighting the role of water and bio/clean indices in transmitting shocks to the system. Investors and policymakers should consider both dynamics of short and long terms in order to develop strategies and make decisions. Short-term fluctuations can be influenced by shocks and uncertainties, however long-term dynamics provide more information about tendencies in the market.

Further research should be conducted to examine the relationship between the green and fossil energy markets in order to identify and compare other portfolio strategies, such as minimum variance portfolio (MVP), minimum correlation portfolio (MCP), and associated hedging rates. This thesis can be extended in terms of data and sample period. Moreover, countries and their development level can be taken into consideration. Additionally, other methodologies might be employed in further studies.

REFERENCES

- Ahmad, W. (2017). On the dynamic dependence and investment performance of crude oil and clean energy stocks. *Research in International Business and Finance*, 42, 376-389.
- Alexander, G. J., Sharpe, W. F., & Bailey, J. V. (2000). *Fundamentals of investments (3rd Edition)*. USA: Prentice Hall.
- Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84.
- Attarzadeh, A., & Balcilar, M. (2022). On the Dynamic Connectedness of the Stock, Oil, Clean Energy, and Technology Markets. *Energies*, 15(5), 1893. doi:<https://doi.org/10.3390/en15051893>
- Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271-296. doi:<https://doi.org/10.1093/jjfinec/nby001>
- BNEF. (2023). *Energy Transition Investment Trends 2023 (Summary Report)*. BNEF. Retrieved from <https://about.bnef.com/energy-transition-investment/#toc-report>, (01.05.2023)
- Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments and portfolio management (9th ed.)*. NY: McGraw-Hill.
- Bondia, R., Ghosh, S., & Kanjilal, K. (2016). International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. *Energy*, 101, 558-565. doi:<https://doi.org/10.1016/j.energy.2016.02.031>

BP. (2022). *Statistical Review of World Energy*. Retrieved from <https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2022-full-report.pdf>, (03.04.2023)

Broadstock, D. C., Chatziantoniou, I., & Gabauer, D. (2020). Minimum Connectedness Portfolios and the Market for Green Bonds: Advocating Socially Responsible Investment (SRI) Activity. *Available at SSRN 3793771*. doi:<http://dx.doi.org/10.2139/ssrn.3793771>, (03.01.2023)

Chatziantoniou, I., Gabauer, D., & Gupta, R. (2021). Integration and risk transmission in the market for crude oil: A time-varying parameter frequency connectedness approach. *Working Paper No. 202147*, University of Pretoria Department of Economics, available at: www.up.ac.za/media/shared/61/WP/wp_2021_47.zp209709.pdf, (03.01.2023)

Christoffersen, P., Errunza, V., Jacobs, K., & Jin, X. (2014). Correlation dynamics and international diversification benefits. *International Journal of Forecasting*, 30(3), 807-824.

Civelek, M. A., & Durukan, M. B. (2011). *Investments (3rd Edition)*. Ankara: Efil Publishing.

Climate Bonds Initiative. (2022). *Summary Q3*. CBI. Retrieved from <https://www.climatebonds.net/resources/reports/q3-2022-market-summary>, (23.04.2023)

Climate Bonds Initiative. (2023a). *Sustainable Debt Market Summary Q1*. CBI. Retrieved from [cbi_susdebt_q1_2023_01d.pdf](#), (02.06.2023)

Climate Bonds Initiative. (2023b). *Global State of the Market Report 2022*. CBI. Retrieved from https://www.climatebonds.net/files/reports/cbi_sotm_2022_03e.pdf, (02.06.2023)

Corbet, S., Goodell, J. W., & Günay, S. (2020). Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. *Energy Economics*, 92, 104978. doi:<https://doi.org/10.1016/j.eneco.2020.104978>

Dawar, I., Dutta, A., Bouri, E., & Saeed, T. (2021). Crude oil prices and clean energy stock indices: Lagged and asymmetric effects with quantile regression. *Renewable Energy*, 163, 288-299.

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

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182, 119–134.

Dutta, A. (2017). Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. *Journal of Cleaner Production*, 164, 1157-1166.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The journal of finance*, 34(1), 157-170.

Elliott, G., Rothenberg, T., & Stock, J. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, 64, 813-836.

Elton, E. J., & Gruber, M. J. (1977). Risk Reduction and Portfolio Size: An Analytical Solution. *The Journal of Business*, 50(4), 415–437.

Evans, J. L., & Archer, S. H. (1968). Diversification and the Reduction of Dispersion: An Empirical Analysis. *The Journal of Finance*, 23(5), 761–767.

Fabozzi, F. J., Modigliani, F., Jones, F. J., & Ferri, M. G. (2002). *Foundations of financial markets and institutions (International Edition-3rd Edition)*. New Jersey: Pearson Education .

Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business*, 38(1), 34–105.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417.

Ferrer, R., Shahzad, S. J., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics*, 76, 1-20.

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

Foglia, M., & Angelini, E. (2020). Volatility connectedness between clean energy firms and crude oil in the COVID-19 era. *Sustainability*, 12(23), 9863. doi:<https://doi.org/10.3390/su12239863>

Grubel, H. G. (1968). Internationally diversified portfolios: welfare gains and capital flows. *The American economic review*, 58(5), 1299-1314.

Hammoudeh, S., Ajmi, A. N., & Mokni, K. (2020). Relationship between green bonds and financial and environmental variables: A novel time-varying causality. *Energy Economics*, 92, 104941. doi:<https://doi.org/10.1016/j.eneco.2020.104941>

Henriques, I., & Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. *Energy Economics*, 30(3), 998-1010. doi:<https://doi.org/10.1016/j.eneco.2007.11.001>

Hull, J. (2012). *Risk Management and Financial Institutions (3rd Edition)*. New Jersey: John Wiley & Sons, Inc.

IEA. (2022a). *Oil Market and Russian Supply*. Paris: IEA. Retrieved from <https://www.iea.org/reports/russian-supplies-to-global-energy-markets>, (01.05.2023)

IEA. (2022b). *Gas Market Report, Q3-2022*. Paris: IEA. Retrieved from <https://www.iea.org/reports/gas-market-report-q3-2022>, (01.05.2023)

IEA. (2023). *CO2 Emissions in 2022*. Paris: IEA. Retrieved from <https://www.iea.org/reports/co2-emissions-in-2022>, (01.05.2023)

Inchauspe, J., Ripple, R. D., & Trück, S. (2015). The dynamics of returns on renewable energy companies: A state-space approach. *Energy Economics*, 48, 325-335. doi:<https://doi.org/10.1016/j.eneco.2014.11.013>

International Chamber of Commerce. (2012). *Green Economy Roadmap*. Retrieved from [https://icc-portugal.com/images/publicacoes/documentos_gratuitos/Ambiente_Energia/ICC_Green_Economy_Roadmap_-_best_practices_and_calls_for_collaborations_\(2012\).pdf](https://icc-portugal.com/images/publicacoes/documentos_gratuitos/Ambiente_Energia/ICC_Green_Economy_Roadmap_-_best_practices_and_calls_for_collaborations_(2012).pdf), (02.06.2023)

International Finance Corporation. (2017). *Green Finance: A Bottom-Up Approach to Track Existing Flows*. Washington, D.C: IFC. Retrieved from https://www.ifc.org/wps/wcm/connect/12ebe660-9cad-4946-825f-66ce1e0ce147/IFC_Green+Finance+-+A+Bottom-up+Approach+to+Track+Existing+Flows+2017.pdf?MOD=AJPERES&CVID=IKMn-t, (02.06.2023)

IRENA, & CPI. (2023). *Global landscape of renewable energy finance, 2023*. Abu Dhabi: International Renewable Energy Agency. Retrieved from <https://mc-cd8320d4-36a1-40ac-83cc-3389-cdn-endpoint.azureedge.net/->

/media/Files/IRENA/Agency/Publication/2023/Feb/IRENA_CPI_Global_RE_financ
e_2023.pdf?rev=8668440314f34e588647d3994d94a785, (23.04.2023)

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters*, 6(3), 255-259.

Jiang, Y., Wang, J., Lie, J., & Mo, B. (2021). Dynamic dependence nexus and causality of the renewable energy stock markets on the fossil energy markets. *Energy*, 233, 121191. doi:<https://doi.org/10.1016/j.energy.2021.121191>

Karan, M. (2018). *Yatırım analizi ve portföy yönetimi (5th Edition)*. Ankara: Gazi Kitabevi.

Kocaarslan, B., & Soytas, U. (2019). Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (US dollar). *Energy Economics*, 84, 104502. doi:<https://doi.org/10.1016/j.eneco.2019.104502>

Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, 71, 101-116.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, 74(1), 119-147.

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics*, 34(1), 215-226.

Lee, C. C., Lee, C. C., & Li, Y. Y. (2021). Oil price shocks, geopolitical risks, and green bond market dynamics. *The North American Journal of Economics and Finance*, 55, 101309. doi:<https://doi.org/10.1016/j.najef.2020.101309>

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1), 13–37.

Longin, F., & Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990? *Journal of international money and finance*, 14(1), 3-26.

Maghyreh, A. I., Awartani, B., & Abdoh, H. (2019). The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations. *Energy*, 169, 895-913.

Managi, S., & Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market? *Japan and the world economy*, 27, 1-9. doi:<https://doi.org/10.1016/j.japwor.2013.03.003>

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77–91.

Markowitz, H. M. (1959). *Portfolio Selection: Efficient Diversification of Investments*. John Wiley & Sons, Inc.

Mensi, W., Naeem, M. A., Vo, X. V., & Kang, S. H. (2022). Dynamic and frequency spillovers between green bonds, oil and G7 stock markets: Implications for risk management. *Economic Analysis and Policy*, 73, 331-344.

Mishkin, F. S., & Eakins, S. G. (2018). *Financial markets and institutions (Global Edition)*. Pearson Education Limited.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, 34(4), 768–783.

Naeem, M. A., Adekoya, O. B., & Oliyide, J. A. (2021b). Asymmetric spillovers between green bonds and commodities. *Journal of Cleaner Production*, 314, 128100. doi:<https://doi.org/10.1016/j.jclepro.2021.128100>

Naeem, M. A., Bouri, E., Costa, M. D., Naifar, N., & Shahzad, S. J. (2021a). Energy markets and green bonds: A tail dependence analysis with time-varying optimal copulas and portfolio implications. *Resources Policy*, 74, 102418. doi:<https://doi.org/10.1016/j.resourpol.2021.102418>

Naeem, M. A., Nguyen, T. T., Nepal, R., Ngo, Q. T., & Taghizadeh-Hesary, F. (2021c). Asymmetric relationship between green bonds and commodities: Evidence from extreme quantile approach. *Finance Research Letters*, 43, 101983. doi:<https://doi.org/10.1016/j.frl.2021.101983>

Nasreen, S., Tiwari, A. K., Eizaguirre, J. C., & Wohar, M. E. (2020). Dynamic connectedness between oil prices and stock returns of clean energy and technology companies. *Journal of Cleaner Production*, 260, 121015. doi:<https://doi.org/10.1016/j.jclepro.2020.121015>

Nguyen, T. T., Naeem, M. A., Balli, F., Balli, H. O., & Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters*, 40, 101739. doi:<https://doi.org/10.1016/j.frl.2020.101739>

Niu, H. (2021). Correlations between crude oil and stocks prices of renewable energy and technology companies: a multiscale time-dependent analysis. *Energy*, 221, 119800. doi:<https://doi.org/10.1016/j.energy.2021.119800>

OECD. (2017). *Mobilising Bond Markets for a Low-Carbon Transition, Green Finance and Investment*. Paris: OECD Publishing. doi:<https://doi.org/10.1787/9789264272323-en>, (02.06.2023)

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *The Journal of Business*, 61-65.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1), 17-29.

Pham, L. (2019). Do all clean energy stocks respond homogeneously to oil price? *Energy Economics*, 81, 355-379.

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics*, 48, 32-45.

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, 74, 38-50.

Reboredo, J. C., Rivera-Castro, M. A., & Ugolini, A. (2017). Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Economics*, 61, 241-252.

Reboredo, J. C., Ugolini, A., & Aiube, F. A. (2020). Network connectedness of green bonds and asset classes. *Energy Economics*, 86, 104629. doi:<https://doi.org/10.1016/j.eneco.2019.104629>

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics* 34(1), 248-255. doi:<https://doi.org/10.1016/j.eneco.2011.03.006>

Saeed, T., Bouri, E., & Alsulami, H. (2021). Extreme return connectedness and its determinants between clean/green and dirty energy investments. *Energy Economics*, 96, 105017. doi:<https://doi.org/10.1016/j.eneco.2020.105017>

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. . *The journal of finance*, 19(3), 425-442.

Solnik, B. H. (1974). Why Not Diversify Internationally Rather than Domestically? *Financial Analysts Journal*, 30(4), 48–54.

Solnik, B., Boucrelle, C., & Fur, Y. L. (1996). International Market Correlation and Volatility. *Financial Analysts Journal*, 52(5), 17–34.

Song, Y., Ji, Q., Du, Y. J., & Geng, J. B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energy Economics*, 84, 104564. doi:<https://doi.org/10.1016/j.eneco.2019.104564>

Stiassny, A. (1996). A spectral decomposition for structural VAR models. *Empirical Economics*, 21, 535-555.

Tan, X., Geng, Y., Vivian, A., & Wang, X. (2021). Measuring risk spillovers between oil and clean energy stocks: Evidence from a systematic framework. *Resources Policy*, 74, 102406. doi:<https://doi.org/10.1016/j.resourpol.2021.102406>

Tiwari, A. K., Abakah, E. J., Gabauer, D., & Dwumfour, R. A. (2022). Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. *Global Finance Journal*, 51, 100692. doi:<https://doi.org/10.1016/j.gfj.2021.100692>

Umar, M., Farid, S., & Naeem, M. A. (2022). Time-frequency connectedness among clean-energy stocks and fossil fuel markets: Comparison between financial, oil and pandemic crisis. *Energy*, 240, 122702. doi:<https://doi.org/10.1016/j.energy.2021.122702>

UN DESA. (2022). *The Sustainable Development Goals Report 2022*. New York, USA: UN DESA. Retrieved from <https://unstats.un.org/sdgs/report/2022/>, (02.06.2023)

UNEP. (2016). *Definitions and Concepts: Background Note. Inquiry Working Paper 16/13*. Retrieved from https://wedocs.unep.org/bitstream/handle/20.500.11822/10603/definitions_concept.pdf?sequence=1&%3BisAllowed=, (02.06.2023)

United Nations. (2015). “*United Nations sustainability goals: 8-green economy*”. Retrieved from <https://sustainabledevelopment.un.org/index.php?menu=1446,> (02.06.2023)

Wang, J., Ma, F., Bouri, E., & Zhong, J. (2022). Volatility of clean energy and natural gas, uncertainty indices, and global economic conditions. *Energy Economics*, 108, 105904. doi:<https://doi.org/10.1016/j.eneco.2022.105904>

Wen, X., Guo, Y., Wei, Y., & Huang, D. (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics*, 41, 63-75.

World Bank Group. (2023). *Commodity Markets Outlook*. Washington, DC.: World Bank. Retrieved from <https://openknowledge.worldbank.org/server/api/core/bitstreams/6864d537-d407-4cab-8ef1-868dbf7e07e2/content,> (02.06.2023)

Xi, Y., Zeng, Q., Lu, X., & Huynh, T. L. (2022). Oil and renewable energy stock markets: Unique role of extreme shocks. *Energy Economics*, 109, 105995. doi:<https://doi.org/10.1016/j.eneco.2022.105995>

Xia, T., Ji, Q., Zhang, D., & Han, J. (2019). Asymmetric and extreme influence of energy price changes on renewable energy stock performance. *Journal of Cleaner Production*, 241, 118338. doi:<https://doi.org/10.1016/j.jclepro.2019.118338>

Zhou, W., Chen, Y., & Chen, J. (2022). Risk spread in multiple energy markets: Extreme volatility spillover network analysis before and during the COVID-19 pandemic. *Energy*, 256, 124580. doi:<https://doi.org/10.1016/j.energy.2022.124580>

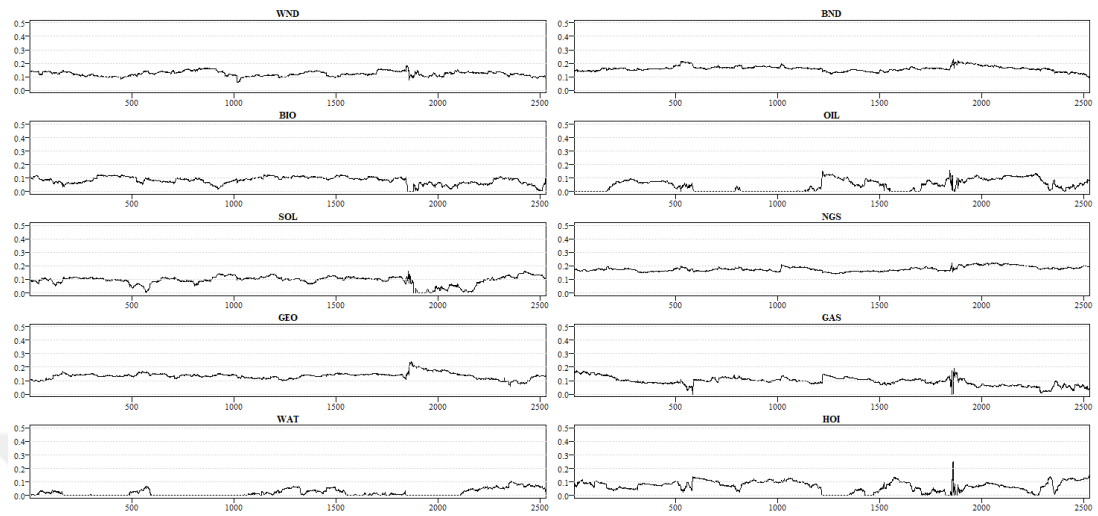
Zutter, C. J., & Smart, S. B. (2019). *Principles of Managerial Finance (15th Edition)*. Pearson Education.



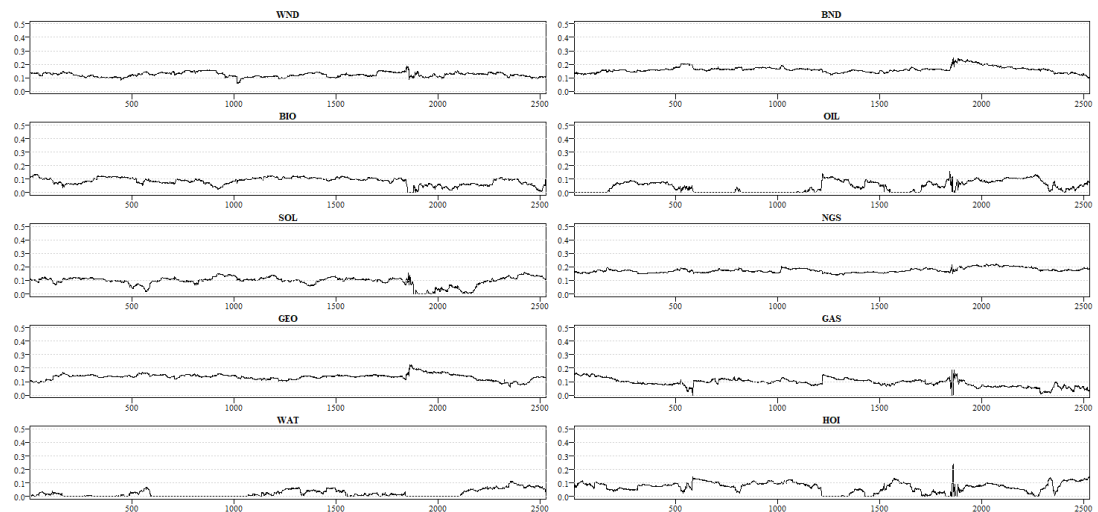


APPENDICES

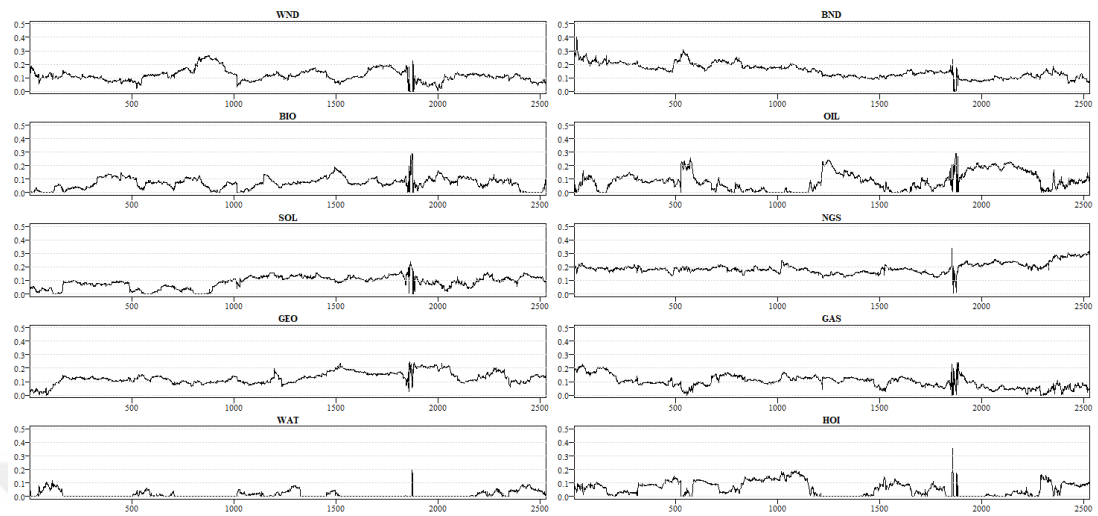
Appendix 1: MCoP - Portfolio Weights (Return - Total)



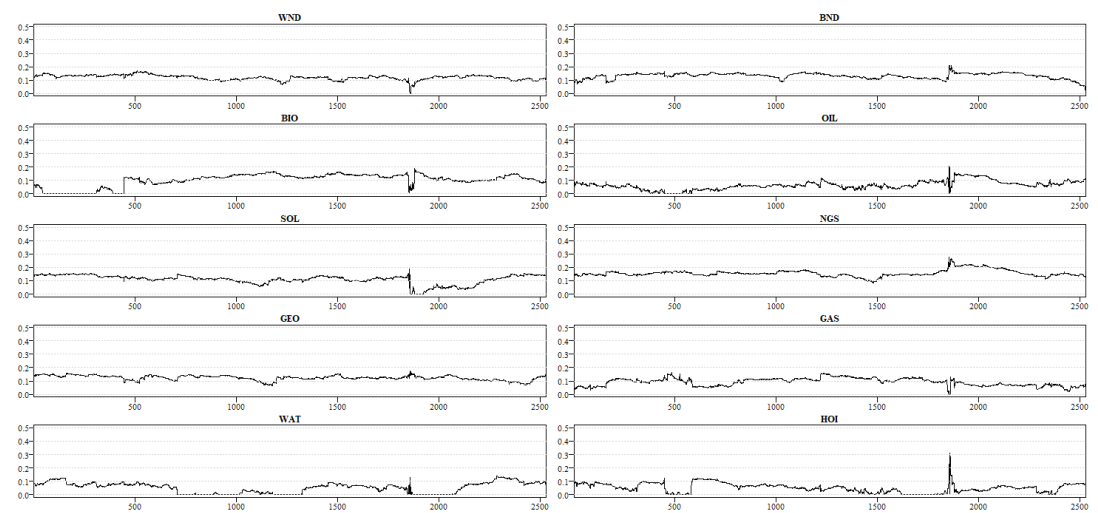
Appendix 2: MCoP - Portfolio Weights (Return – Short term)



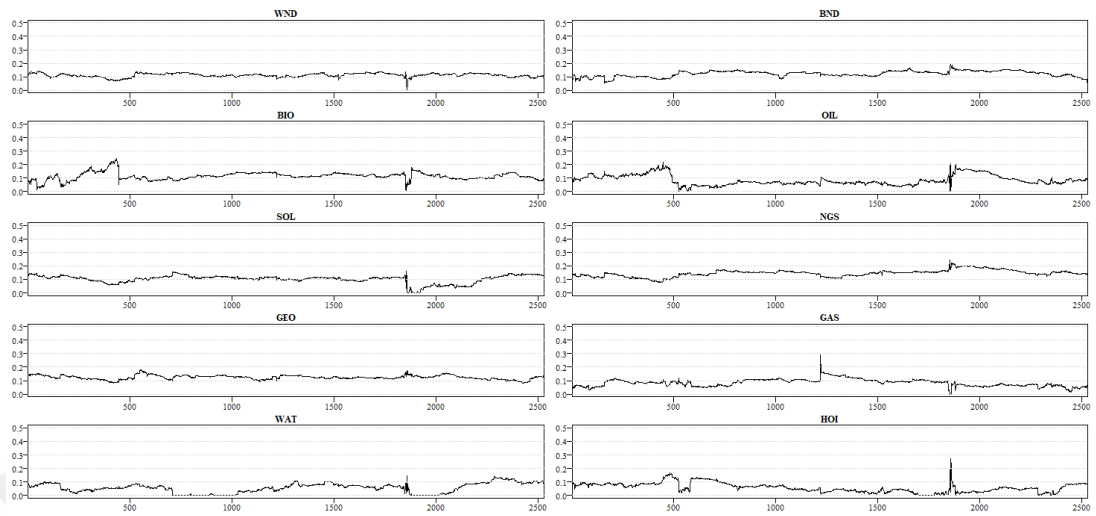
Appendix 3: MCoP - Portfolio Weights (Return – Long term)



Appendix 4: MCoP - Portfolio Weights (Volatility – Total)



Appendix 5: MCoP - Portfolio Weights (Volatility – Short term)



Appendix 6: MCoP - Portfolio Weights (Volatility – Long term)

