The Dynamic Connectedness of Clean Energy and Financial Markets

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ABSTRACT

This thesis primarily aims at analysing the dynamic connectedness of clean energy stocks and other financial markets such as cryptocurrency, Technology, Crude oil, and Stock markets. To this end, this thesis is divided into two different sections. Firstly, we investigate the connectedness of renewable energy, common stock, oil, and technology markets, using monthly data from September 2004 to February 2020. The time-domain Diebold and Yilmaz spillover index approach is used to analyse the volatility spillover between these four markets. The study's findings reveal that the oil and clean energy markets have bidirectional volatility spillover. The oil market has been found to be a net receiver of volatility. Furthermore, the study shows that volatility spillover is stronger in extremely positive and negative shock times than in medium shock periods. In addition, our findings show that during crisis periods, the volatility spillover index rises, while total connection reached its lowest point in 2015. Our findings suggest that policymakers should be informed that, as long as oil prices remain low, alternative energy-producing industries will not require specific policies to mitigate their vulnerability to crude oil price shocks.

Secondly, we investigate the connectedness among clean energy, Bitcoin, the stock market, and crude oil empirically. The high-energy consumption of cryptocurrency transactions has raised concerns about the environment and sustainability among green investors and regulatory authorities. The time-varying parameter vector autoregression (TVP-VAR) is used to estimate the dynamics of connectedness in a daily dataset spanning the period November 11, 2013, to September 30, 2021. We find that the clean energy and traditional stock markets transmit shocks to Bitcoin and oil in terms of return, and they receive shocks in terms of volatility from Bitcoin and oil. Additionally, Bitcoin and other financial markets are only tenuously linked during non-crisis periods. Nonetheless, their connection strengthens substantially during times of crisis, such as the great cryptocurrency crash of 2018 and the COVID-19 pandemic of 2020. We believe that these findings can help explain how clean energy and cryptocurrency markets are linked during times of crisis.

Keywords: Clean Energy, Net Transmitter/Receiver, Cryptocurrency, TVP-VAR, Dynamic Connectedness, Realized Volatility.

ÖZ

Bu tez öncelikle temiz enerji hisse senetlerinin ve kripto para, teknoloji, ham petrol ve hisse senedi piyasaları gibi diğer finansal piyasaların dinamik bağlantılılarını analiz etmeyi amaçlamaktadır. Bu amaçla, bu tez iki farklı bölüme ayrılmıştır. İlk olarak, Eylül 2004 ile Şubat 2020 arasındaki aylık verileri kullanarak yenilenebilir enerji, hisse senedi, petrol ve teknoloji piyasalarının bağlantılıları incelenmektedir. Bu dört piyasa arasındaki oynaklık yayılımını analiz etmek için zaman boyutlu Diebold ve Yılmaz yayılma endeksi yaklaşımı kullanıldı. Çalışmanın bulguları, petrol ve temiz enerji piyasalarının çift yönlü oynaklık yayılımına sahip olduğunu ortaya koymaktadır. Petrol piyasasının net bir oynaklık alıcısı olduğu tespit edildi. Ayrıca, çalışma oynaklık yayılımının aşırı pozitif ve negatif şok zamanlarında orta şok dönemlerine göre daha güçlü olduğunu göstermektedir. Ayrıca bulgularımız, kriz dönemlerinde oynaklık yayılma endeksinin yükseldiğini, toplam bağlantının 2015 yılında en düşük noktasına ulaştığını gösteriyor. Bulgularımız, politika yapıcıların, petrol fiyatları düşük kaldığı sürece alternatif enerji üreten endüstriler konusunda bilgilendirilmeleri gerektiğini gösteriyor. Ham petrol fiyat şoklarına karşı kırılganlıklarını azaltmak için özel politikalar gerektirmeyecektir.

İkinci olarak, temiz enerji, Bitcoin, borsa ve ham petrol arasındaki bağlantıyı ampirik olarak araştırıyoruz. Kripto para işlemlerinin yüksek enerji tüketimi, yeşil yatırımcılar ve düzenleyici otoriteler arasında çevre ve sürdürülebilirliği ile ilgili endişeleri artırdı. Zamana göre değişen parametre vektör otoregresyon (TVP-VAR), modeli ile 11 Kasım 2013 ve 30 Eylül 2021 arasını kapsayan günlük bir veri setinde bağlantılılık dinamiklerini tahmin etmek için kullanılmıştır. Temiz enerji ve geleneksel borsaların şoklar ilettiğini görüyoruz. Getiri açısından Bitcoin ve petrole şok alıcısı, oynaklık açısından şok vericisi durumundadır. Ek olarak, Bitcoin ve diğer finansal piyasalar, kriz olmayan dönemlerde yalnızca zayıf bir şekilde bağlantılıdır. Bununla birlikte, 2018'deki büyük kripto para birimi çöküşü ve 2020'deki COVID-19 salgını gibi kriz zamanlarında bağlantıları önemli ölçüde güçleniyor. Bu bulguların, kriz zamanlarında temiz enerji ve kripto para piyasalarının nasıl bağlantılı olduğunu açıklamaya yardımcı olabileceğine inanıyoruz.

Anahtar Kelimeler: Temiz Enerji, Net Verici/Alıcı, Kripto Para, TVP-VAR, Dinamik Bağlantılılık, Gerçekleşen Oynaklık.

DEDICATION

To My Family.

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LIST OF ABBREVIATIONS

ARDL	Autoregressive Distributed Lag
BK	Barunik-Krehlik
BTC	Bitcoin
CE	Clean Energy
CO2	Carbon Dioxide
DCC	Dynamic Conditional Correlation
ECO	Wilder Hill Clean Energy Index
EIA	Energy Information Administration
ETF	Exchange-Traded Funds
FDI	Foreign Direct Investment
FEVD	Forecast Error Variance Decomposition
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GFEVD	Generalized Forecast Error Variance Decomposition
GLS-ADF	Generalized Least Squares Dickey-Fuller
GMM	Generalized Panel Method Of Moments
IAEA	International Atomic Energy Agency
JB	Jarque-Berra
NPDC	Net Pairwise Directional Connectedness
NYMEX	New York Mercantile Exchange
NYSX	New York Stock Exchange
OPEC	Organization Of The Petroleum Exporting Countries
PSE	Arca Tech 100 Index

QVAR	Quantile Vector Auto Regression
RW-VAR	Rolling Window Vector Auto Regression
S&P 500	Standard And Poor's 500
SD	Standard Deviation
TCI	Total Connectedness Index
TE	Technology
TVP-VAR	Time-Varying Parameter Vector Auto Regression
USO	United States Oil Fund
VAR	Vector Auto Regression
WTI	West Texas Intermediate

Chapter 1

INTRODUCTION

Political and economic crises have caused changes in prices in various markets. The energy market is one of the most influential markets in the financial markets. Any fluctuation in the energy markets, especially oil, has significantly impacted other markets. Therefore, policymakers closely monitor any changes in the energy markets and are looking for alternative ways to supply energy. The larger the country's economy, the greater the spillover effects and its transfer to other countries in the world. Since the U.S has the biggest economy in the world, any crisis in the U.S leads to internal turmoil in other economies.

In this dissertation, we use the concept of variance decomposition in vector autoregression. Our calculation methods for spillovers have useful details in transmitting important information. We frequently look for linkages between various assets, portfolios, and other concepts in the financial markets. Usually, returns or return volatilities are related objects. We go into further detail about the value of connectivity in financial contexts in this section, emphasizing the role of connectivity among distinct financial hazards.

We move forward for the time being on a verbal intuitive level, saving the strict definition of connection for other sections. We draw attention to the many fields in which connection difficulties arise, and we establish the notion of connectedness measurement for real-time crisis tracking, a notion that recurs throughout the dissertation. A crucial component of effective risk assessment is risk estimation. As a result, a lot of time and money is spent measuring different financial concerns. Economic exposure, or the risk of changes in portfolio value as a result of changes in the value of its underlying components, is one of the most fundamental. Since connectedness isolates the risk of a portfolio from the volatility of its underlying components, it is likely included in any thorough assessment of market risk. Because of this, a portfolio's risk is not just the weighted average of the hazards of its components. The interaction of the parts—including whether and how they are connected—determines the overall portfolio risk. It relies on connection whether there will be extreme market fluctuations, which are often characterized by all or most assets moving in the same direction.

The connectivity that distinguishes portfolio risk from the sum of component risks has been underlined as a key factor in our discussion of risk assessment concerns thus far. However, as portfolio allocation is all about reducing portfolio risk, connectivity must be recognized and measured for effective portfolio allocation. In other words, "portfolio concentration risk," which establishes the range of viable diversification opportunities, must be governed by connection.

If measuring connectivity is helpful in different conditions, it may also be helpful in a less evident but crucial mode, crisis tracking, because connectedness tends to surge rapidly during crises, as we shall see. As a result, a real-time dynamic crisis assessment sub-theme permeates this thesis. In this part, we have decided to discuss connectivity in relation to risk and how connectedness affects risk in multivariate settings. One would assume that connectivity is inherently undesirable since risk is occasionally seen as undesirable. We hasten to add that these conclusions are false for at least two different reasons.

First off, the danger is obviously not something that should be avoided at all costs. Because risk is the key to return, literally millions of people and businesses frequently and deliberately opt to incur financial risks of various forms. No risk, no return, as they say. The aim is to precisely analyze risks, including connectedness-related risk components, in order to accurately assess the required return.

Secondly, connectivity in financial circumstances goes beyond risk factors, at least in the way that it has historically been conceived, and some forms of connection may even be explicitly beneficial. For instance, connectedness can develop and change as a result of risk-sharing through insurance, connections between the sources and uses of money as savings are channeled into investments, comparative advantage patterns that lead to international trade, global capital market integration, and improved coordination of international financial regulation and accounting standards. In the end, trying to categorize various forms of connectivity as "good" or "bad" is useless. Instead, connectivity is just essential, making it useful to be able to measure it precisely.

Y frequently contains returns in the financial markets. Return connectivity follows expectational linkages if returns follow changes in investor sentiment. Returns typically exhibit weak conditional heteroscedasticity but low auto - correlation, especially when measured with a high frequency. Similar to the Gaussian distribution, they frequently have symmetric distributions but larger tails. Usually, large sets of disaggregated returns show factor structure.

Volatilities must be assessed since they are latent, unlike returns. Numerous methods of estimating volatility have drawn interest, including realized volatility and implied volatility as well as observation-driven GARCH type models and parameter-driven stochastic volatility models. Particularly when detected at relatively high frequency, volatilities have a propensity to be substantially serially correlated (far more so than returns). They also frequently have a right skew in their distribution, and natural logarithms are frequently used to create an approximation of normalcy. Factor structure is often seen in large sets of disaggregated return volatilities. Volatility connectivity measurements do not exhibit a long-term rising trend. When there is a lot of uncertainty or a financial crisis, volatility connectedness indicators drastically surge instead of moving upward. They remain high as long as the data relevant to the financial meltdown are included in the selection windows. Therefore, this section will deal with some relevant literature on spillover effects in different markets.

Diebold & Yilmaz (2009) first effort looked at the spillover effect among 19 global equities, and they found that the spillover effects of returns and Volatility results were different. Returns spillover results were slow and continuous, and volatility results were clear bursts in major crises. Diebold & Yilmaz (2012) expand their methodology to measure total and directional spillovers. They investigate U.S stock market, FX (Foreign Exchange), bonds, and commodities. After 2008 crisis intensified, volatility spillovers raised and spillovers from stock markets to others. Studies related to the influence of spillover effects in return and realized volatility with VAR and QVAR methodologies are investigated by Balcilar et al. (2018). They investigate the spillover effect among gold, oil, and stock markets. Their results indicate bidirectional spillover across these three markets. In addition, they found that return results are higher with significant negative (positive) more considerable shocks than with moderate. Only large positive shocks cause more volatility spillover than average shocks.

Moreover, they investigate the position of gold and crude oil as secure investments across these three markets. Balcilar et al. (2021) introduce TVP-VAR methodology to investigate the connectedness between agricultural commodities and oil futures prices. They found that crude oil, as well as several commodities including livestock, sugar, and soybean, are transferring the shocks, and corn and some other commodities are net receivers of the shocks.

The sub-prime mortgage crisis that began in the United States in 2007 eventually developed into a serious worldwide financial catastrophe that affected all major developed and emerging economies. In fact, the industrialized nations went through their worst recession in years. As anticipated, the global recession stoked interest in business cycle studies among academics and decision-makers. The literature began to concentrate on the impact of globalization on international business cycles as the evidence about these cycles grew.

The uncertainty produced a spike in energy prices and a drop in stock market values during the 2008 economic catastrophe. The crisis rapidly expanded into a world economic shock, with financial institutions declaring bankruptcy. Throughout this time, international trade dropped. As housing markets collapsed and unemployment grew, evictions and foreclosures became more widespread. All of the factors mentioned above were sufficient to increase uncertainty in financial markets and cause price fluctuations.

In contrast, because of massive supply and demand shocks, the Coronavirus pandemic was accompanied by a substantial collapse in global energy markets. Due to mitigation efforts, stay-at-home orders, and travel prohibitions, the crude oil market was the most affected and saw the largest price drop (approximately -47$). In order to limit the pandemic's progress, the global outbreak of COVID-19 has forced a significant delay in key economic activity and a significant drop in global energy consumption. Since March 2020, the collapse of the OPEC+ output agreement has coincided with extraordinary negative demand and positive supply shocks, further depressing crude oil prices.

Crop prices have been affected by the increasing uncertainty in demand caused by transportation disruptions in several areas across the world. Green stock prices have fallen since January 2020, although the drop has already been less than that of the oil price. The current epidemic is having an impact on clean energy spending, which is necessary for continuing renewable energy development. Solar and biofuels are examples of alternative energy that are more sustainable. The worldwide renewable energy market has decreased growth rates since the COVID-19 virus emerged. In fact, country lockdowns have had an impact on global supply chains, slowing the delivery of crucial components and causing a manufacturing slowdown. Due to the pandemic's spread, all construction, installation, and manufacturing projects have been halted. Furthermore, the rapid drop in crude oil prices has considerably affected clean energy demand.

Climate change and rising Carbon emissions have sparked widespread interest in switching to renewable energy sources. The renewable and low-carbon energy sector has grown rapidly consequently of the expansion of alternative energy technology marketplaces, with decreased use and dependence on crude oil. For the formulation of a successful energy policy as well as the growth and development of clean energy production, the relationship between oil, clean energy, and technology is crucial. Furthermore, bitcoins have emerged as a viable investment choice. Cryptocurrency is a great alternative for risky investors, given the possibility of big earnings in a short period and a shift away from traditional assets. Cryptocurrencies are digital currency that is made out of binary data. Cryptocurrencies have gained a significant market share since 2009. According to the World Bank, cryptocurrencies would have a market share of US$364.5 billion in 2020. According to previous research, cryptocurrencies (bitcoins) have grown at an exponential rate over the last decade. One bitcoin has grown in value from $1 in 2009 to over $60,000 in 2021.

Aside from bitcoin's good potential as an alternative asset, its high energy consumption may be a red flag for policymakers and regulators. According to the BBC, Cambridge scholars estimate that Bitcoin uses about 121.36 terawatt-hours (TWh) of electricity every year, which is greater than Argentina's consumption with 46 million people. A single Bitcoin transaction consumes the equivalent of 53 days of electricity for an average American family, according to the Bitcoin Energy Consumption Index. Despite its high volatility and return, bitcoin's negative environmental impact may prompt authorities to impose rules or restrictions, leaving crypto investors with an uncertain future.

As a result, investors and policymakers should look into and evaluate the linkages among alternative stocks and other financial markets like technology stocks, traditional stocks, bitcoin, and energy markets. Any signs of significant volatility and return spillovers among Bitcoin and other types of assets might have an impact on asset allocation, risk assessment decisions, and regulatory actions aimed at securing global financial system stability. It is also essential for policymakers who are using crypto as part of their foreign reserves or experimenting with crypto-monetary equivalents.

Hence, this dissertation is divided into two main sections. The first part examines the dynamic connectedness among fossil fuel (WTI) and alternative energy, technology, and conventional stocks. In this part, we use two different methods, such as Rolling Window VAR and Quantile VAR. In the second part, we investigate the spillover effect among oil, cryptocurrencies, clean energy, and stock markets by TVP-VAR to estimate the total connectedness among these four markets.

The following structure will be used to organize this thesis: The dynamic connectedness of the stock, oil, clean energy, and technology markets is discussed in Chapter 2. The dynamic return and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets is discussed in Chapter 3. The conclusion and summary will be presented in the final chapter.

Chapter 2

ON THE DYNAMIC CONNECTEDNESS OF THE STOCK, OIL, CLEAN ENERGY, AND TECHNOLOGY MARKETS

2.1 Introduction

Economists have been urging policymakers to establish sustainable energy sectors in recent years to mitigate air pollution and balance the negative effects of oil price volatility, taking population growth and demand for fossil fuels into account. Furthermore, oil is a global commodity whose price is governed by supply and demand conditions. As a result, rising demand for oil from emerging economies combined with a supply constraint would drive up oil prices and push investors to switch to renewable energy.

Furthermore, the prospects for oil are complex over the near-medium term since the most significant oil users are not the nations with the largest crude oil reserves. Besides, Such concerns about future crude oil shortages, according to Reuters (2019), derive from current forecasts that world oil demand will peak in 2040, according to Hubbert Peak Theory (Tao & Li, 2007). Furthermore, estimates from 2004 expected a peak in production between 2016 and 2040 (Crampton, 2015).

According to Maji (2015), most industrialized countries working with the International Atomic Energy Agency (IAEA) have a coherent strategy to expand their use of renewable energy sources. In addition, several research projects have attempted to find the connection among financial variables and alternative energy in the last decade. Economic actions, such as pandemic diseases, wars, and terrorist attacks, have caused unprecedented fluctuations in oil prices, affecting countries directly and leading to increases in investment in alternative energy in both emerging and developed countries. However, technological developments and capital markets also play a crucial role in increasing or discounting renewable sector investment.

The effects mentioned above would convince oil exporters to reduce their reliance on oil revenues through investments in renewable energy sources, which could occur through declining demand from developing countries and falling oil prices. However, it is generally accepted that higher fossil fuel prices are good for an alternate energy company's financial performance. Rising oil prices are supposed to stimulate increased demand for alternative energy supplies. The fact is, we are not sure. Indeed, relatively little statistical work has been done to assess the delicacy of alternative energy firms' financial performances against oil prices. Nevertheless, it is possible to expect that higher oil prices might provide a strong stimulus to replace the oil-based generation of energy and move on to renewable energy sources.

To the best of our knowledge, there has been a little empirical study on the volatility spillovers from the fossil fuel to technology industries and alternative energy, such as Reboredo & Ugolini (2018) and Bondia et al. (2016), and the findings are inconclusive. For example, Bondia et al. (2016) found that alternative energy companies' returns have only S-T effect on oil prices, and there are no L-T diversification options when investing in oil prices and alternative energy stock returns.

Against this background, measured by volatility spillovers, the intermarket connectivity is a substantial component of international finance, with significant consequences for portfolio and hedging decisions. This study fills the gap by using the rolling window vector autoregressive (VAR) model of total connectedness in volatility among clean energy, technology, stock prices, and fossil fuels. Firstly, the time domain Diebold & Yilmaz (2012) (DY) spillover index is used to detect the total connectedness across the markets. Secondly, we estimate net pairwise spillovers among the markets to understand the structure of interconnectedness of these markets. Finally, we applied the quantile VAR (QVAR) method to discover the dynamic interaction between the behaviors of the asset prices, which can be distinctive in some quantiles compared to others. The chosen approaches will help us assess the direction of volatility spillovers between markets.

In three ways, our research adds to the existing empirical literature. First, in this thesis, the time domain DY spillover technique is utilized to examine the mechanisms of information transmission and the direction of spillovers among markets. Second, we use the QVAR model that permits model parameters to depend on how far the clean energy, stock index, technology, and oil deviate from means. As a result, the QVAR model can be utilized to investigate spillover dynamics in the tails. Thirdly, the clean energy and technology indexes we use in our study cover a majority of the market. They are also traded on the market through exchange-traded funds that mimic their performance, harmonizing them with the underlying stock and oil market indices. As a result, estimated models can more accurately capture risk spillover between these markets.

Methods used in our study allow us to quantify the intensity of cross-market spillovers as well as the direction of spillover impact among the assets in question. Decision-makers must understand the dynamic interconnection and directional spillover impacts among oil price, conventional, alternative energy, and technology stocks. This provides guidance on the optimal time and economic policy for encouraging investment in green energy and technologies. Additionally, unlike previous research, our findings are applicable to hedging and portfolio diversification strategies across the four financial markets we study. During times of uncertainty, investors may mitigate risk and adopt the best asset allocation strategy by understanding the direction and dynamic behavior of volatility spillovers.

This study aims to examine the time-varying volatility spillover across the stock, oil, renewable energy, and technology stock index. Our data suggest that these four economies experience large bidirectional spillovers. These, on the other hand, exhibit significant temporal fluctuation with sparse spillover. Additionally, the alternative energy index and oil price are the shocks' net recipients. By comparison, the traditional stock market and technology indices serve as net transmitters. The QVAR results indicate that large positive shocks generate stronger spillover than average shocks. Additionally, large negative volatility does not result in major spillovers to the clean energy, oil, technology, and conventional stock index.

The rest of this chapter is laid out as follows: First, a brief review of the existing literature is presented in Section 2. Next, the study's empirical methodology is described in Section 3. Next, the data is presented in section 4, while Section 5 contains the results and discussion. Lastly, section 6 closes the chapter by discussing policy implications and conclusions.

2.2 Review of Existing Studies

Renewable energy investments have developed steadily in the post-2004 period. The renewable energy industry has become a rapidly expanding energy sector in the last ten years, mainly because of carbon emission concerns, energy safety, oil spikes, new technology, and environmentally friendly customers. In 2019, global new renewable energy investment totaled approximately $302 billion. In the last two decades, funding for renewable energy worldwide has gradually increased. In 2004, investment in renewable energy amounted to almost US $37 billion, and in 2017, it rose to a total of US $331 billion.

The large increase in investment funding demonstrates that the sector has substantially matured. China and the United States are the most investment-paying countries in renewable energy, with the former's US $90 billion investment in 2019 Ajadi et al., (2020). However, this slightly decreased from the previous year, while US investment increased by 25%.

Kumar et al. (2012) and Henriques & Sadorsky (2008) reported that green energy investment needs well-developed financing structures. The stock markets are one way of funding investment in renewable energy. In an ideal portfolio, the allocation of renewable energy inventories depends on the complex relationship between these reserves and some other properties. An increase in oil prices could also lead to better prospects for investments in renewable energy because of substitution motives, Kumar et al., (2012) and Henriques & Sadorsky, (2008).

As stated by Karanfil (2009), indexes of financial market growth are one of the variables of concern for energy studies economists. This is because the development of the financial market can influence energy demand by influencing economic growth and reducing domestic constraints. In other words, the development of the financial market can boost energy usage through reduced financial risk and lending costs and improved access to advanced technology.

In line with Sadorsky (2010), stocks are generally seen as a critical financial indicator, and the rise in share prices is a sign of an economic boost in the future. Growth in share prices is especially attractive for companies because it gives business owners access through stock markets to extra funds and thus expands their company. Furthermore, Sadorsky (2011) concludes that the financial market's development can also lower risks for consumers and businesses, thus becoming a key factor contributing to economic wealth. Therefore, development in financial markets is regarded as a credible lever for consumers and businesses, increasing economic activity and demand for energy.

Investors can gain investment prospects through a diversified shelter of portfolios due to the volatility, correlations, and spillovers driving global markets. The advantages of diversification are achieved by incorporating low-correlation assets from global markets that decline the portfolio risk. While the advantages of investment are generally acknowledged globally, many investors appear to be unwilling to invest internationally. The volatility effects of renewable energy share and the potential connection among the share prices of green businesses and other markets, such as oil or technology share, are not well known. It is anticipated that future energy demands will involve alternative and renewable energy resources, which could change the role of the oil market. Many factors, including technical innovations, public recognition, and economic viability, play a vital role.

Furthermore, concerns about the affordability of the global energy system's sustainability and reliability frequently result in investments being asked for. Will market conditions, much affected by the policy, provide ample investment opportunities in the sectors and regions required? Will the funding available be adequate to realize these opportunities? Will investment be realized in areas that boost and solve the future fossil fuel shortage and climate change? It is important to research the global alternative energy market dynamics by evaluating whether they are driven more by the price of oil changes or the technology sector in terms of volatility spillovers. While the literature does not yet provide a theoretical account of the nature of these relationships, their expanding empirical aspect has facilitated establish them as one of the boundary fields of energy finance science.

Several studies have been conducted over the past two decades to determine the link among financial markets and the energy sector. To analyze the influence of financial expansion on energy consumption, Sadorsky (2010) used panel data from 22 developing countries. Using stock market indicators shows that stock market growth in developing markets has a statistically significant and optimistic effect on energy demand. Furthermore, Sadorsky (2011) uses the generalized panel method of moments (GMM) regression methodology to examine the influence of financial development on energy use in nine frontier economies of European countries. Study findings indicate that only the turnover on the stock exchange has a positive effect on energy consumption. Finally, Razmi et al. (2020), who used an ARDL technique, argue that in the LR, alternative energy could be influenced by the stock market and that green energy consumption could be increased in the long term.

The literature emphasizes the influence of oil prices on the stock index of emerging energies (mainly alternative energy). For example, Henriques & Sadorsky (2008) concluded that oil prices significantly influence the alternative energy stock market returns and that technology is correlated with renewable energy stock markets.

By analyzing a vector autoregression (VAR), Henriques & Sadorsky (2008) examine empirical connections between clean energy, technological stock prices, interest rates, and oil. The analysis shows that technology stock and oil prices are a granger causes of renewable stock. Although the traditional media is aware that oil is a major driver of changes in the stock prices of green energy firms, they conclude that technological shocks currently affect renewable energy companies' stock prices more than oil does. As a result, alternative energy firms own more stock of technology companies than fossil-fuel energy companies.

Based on the second major study, Sadorsky (2012) reviews the volatility spillovers in the US economy using GARCH models, using oil prices, technology, and clean energy business stock prices. He used BEKK, diagonal, constant conditional correlation, and DCC. The findings show that renewable energy companies' share prices are certainly more in line with the stock price of technology than oil.

By surveying long-term clean energy elasticity (FDI is considered a technology for clean energy), Paramati et al. (2016) note that economic output, FDI, and the stock market positively influence green energy consumption. Kumar et al. (2012) discuss the connection among green energy prices, the price of oil and technology, and interest rates and expand the study with carbon prices. A VAR model also examines the relationship of the variables. Their findings indicate that oil prices and technology impact renewable energy companies' stock prices separately. The writers, however, find no meaningful link between carbon prices and green energy. Inchauspe et al. (2015) find that the MSCI World Index and technology stocks have had a great impact during the sample era, and the effect of changes in the oil market is much less, while oil has become more relevant since 2007.

Finally, Ahmad (2017) examined the dynamic connection among oil, technology, and green energy stocks. The findings revealed that technology stock prices are important predictors of volatility spillovers in renewable energy companies and the price of oil. Moreover, technology and renewable energy companies are transferring the shocks to oil.

Nasreen et al. (2020) studied the dynamic connectedness of renewable energy, oil, and technology. They used the DY time domain and Barunik-Krehlik (BK) frequency domain approaches. Their finding indicates that shocks transmit from technology stocks to the stock price of clean energy, and oil is the receiver of the shocks from clean energy. In addition, Shocks in other markets have a significant influence on green energy companies, whereas shocks in the oil market have a minimal impact.

Managi & Okimoto (2013) use Markov-switching methodology to identify potential structural modifications in the studied relationship. The results showed that fossil fuel and green energy prices are linked to a shift from traditional to clean energy following the structural break in 2008, which contrasted with Henriques & Sadorsky (2008). Kocaarslan & Soytas (2019) used DCC model to analyze the essence of dynamic correlations among renewable energy and technology stocks and oil prices. Their investigations show that there are significant asymmetric influences on the DCCs.

Finally, according to the Batrancea et al. (2021) conclusion, the general public's growing awareness of natural resource scarcity and developing various clean energy projects by energy companies, convince us to investigate the role of renewable and nonrenewable energy is more significant.

The following explains how Diebold & Yilmaz (2009) applied the spillover index approach based on the seminal work on Sims' 1980 models of VAR and the popular concept of forecast error variance decomposition (FEVD). Researchers were especially interested in the risk spillovers through different markets. During 2008, seeing the expansion of the credit market crisis to other assets enabled the estimation of the contribution of shocks to parameters in the forecast error variances of the models, respectively. The evolution of spillover can be tracked over the period and demonstrated with spillover plots with rolling window estimates. In this analysis, the variant Diebold & Yilmaz (2012) of the spillover index is adopted to expand and generalize the Diebold & Yilmaz (2009) method in two ways. The first is the introduction of clarifying measures for directional spillover and net spillover, providing a decomposition 'input-output' of all spillovers from (or to) a specific source, and identifying key spillover receivers and transmitters. Secondly, by following Koop et al. (1996), Pesaran & Shin (1998), Diebold & Yilmaz (2012), and Balcilar et al. (2018), a generalized VAR framework is used. FEVDs are invariant for variable order in this case. This is notably relevant to the present analysis because of a specific positioning of variables in the future and spot volatility.

Finally, there is no compelling evidence of a linkage between clean energy and other assets. This thesis adds to the literature by analyzing the volatility spillover among clean energy, oil, stock index, and technology index by using DY time-domain spillover index and quantile VAR techniques.

2.3 Methodology

In this thesis, the analysis of the total and directional spillovers of volatilities among renewable energy, technology, and the stock market has been done by using the spillover index method of Diebold & Yilmaz (2012). The basic stationary VAR model of order p can be written as

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + e_t \tag{1}$$

where y_t is an N-vector of endogenous variables, Φ_i, $i = 1,2, \ldots p$ are $N \times N$ coefficient matrices, the constant term is c, the VAR model lag order is p, e_t is a zero-mean white noise vector of dimension $N \times 1$ with a variance matrix Σ. The generalized FEVD, presented by (Pesaran & Shin, 1998) and followed by Balcilar et al. (2018), is obtained using the moving average representation $y_t = \mu + \left(I - \Phi_1 L - \Phi_2 L^2 - \cdots - \Phi_p L^p\right)^{-1} e_t$ which can be shown as (Lütkepohl, 2005),

$$y_t = \mu + \sum_{i=0}^{\infty} \Psi_i e_{t-i} \tag{2}$$

In sum, generalized FEVD, based on equation (2), can be used to obtain directional, net, and total spillovers. The h-step FEVD can be written as,

$$\mathrm{j}_{ij}^{s}(h) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{h-1} \left(v_i' \Psi_h \Sigma v_j\right)^2}{\sum_{h=0}^{h-1} \left(v_i' \Psi_h \Sigma \Psi_h' v_i\right)^2} \tag{3}$$

Where σ_{jj} is the standard deviation of error terms for j-th equation, v_i is the selection vector with one on the i-th row and zero anywhere else. It is obvious that the sum of the own and cross-variance contributions is not unity under the generalized decomposition ($\sum_{j=1}^{N} j_{ij}^{s}(h) \neq 1$). Thus, we normalize each variance decomposition entry matrix as a row sum, equal to 100% (Balcilar et al., 2018).

$$\tilde{j}_{ij}^{s}(h) = \frac{j_{ij}^{s}(h)}{\sum_{j=1}^{N} j_{ij}^{s}(h)} \tag{4}$$

According to equation (4), we achieve $\sum_{j=1}^{N} j_{ij}^{s}(h) = 1$ and $\sum_{j=1}^{N} j_{ij}^{s}(h) = N$. By using volatility contributions, the TS index can be calculated as

$$TS(h) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{j}_{ij}^{s}(h)}{\sum_{i,j=1}^{N} \tilde{j}_{ij}^{s}(h)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{j}_{ij}^{s}(h)}{N} \times 100 \tag{5}$$

Equation 5 can measure total spillover. The index is used to calculate the average spillover contributions from shocks through interest variables of total FEVD. Besides, this research focuses on two key dimensions to measure the directional spillover: the directional spillovers transmitted by a variable from all other variables and the directional spillovers received by a variable from all other variables. The former is determined as:

$$DS_{i\leftarrow j}(h) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{j}_{ij}^{s}(h)}{\sum_{i,j=1}^{N} \tilde{j}_{ij}^{s}(h)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{j}_{ij}^{s}(h)}{N} \times 100 \tag{6}$$

and

$$DS_{i\rightarrow j}(h) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{j}_{ji}^{s}(h)}{\sum_{i,j=1}^{N} \tilde{j}_{ji}^{s}(h)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{j}_{ji}^{s}(h)}{N} \times 100 \tag{7}$$

Net spillover can be calculated by equation (8);

$$NS_{i}(h) = DS_{i\rightarrow j}(h) - DS_{i\leftarrow j}(h) \tag{8}$$

Finally, we measure the net pairwise spillover by equation (9) to provide the contribution intensity of assets. It will estimate the net transmission volatility shocks from one market to the other

$$\mathrm{NP}_{ij}(h) = \left(\frac{\tilde{j}_{ji}^{s}(h)}{\sum_{i,m=1}^{N} \tilde{j}_{im}^{\delta}(h)} - \frac{\tilde{j}_{ij}^{s}(h)}{\sum_{j,m=1}^{N} \tilde{j}_{jm}^{s}(h)}\right) \times 100 = \left(\frac{\tilde{j}_{ji}^{s}(h) - \tilde{j}_{ij}^{s}(h)}{N}\right) \times 100 \tag{9}$$

2.4 Data

The performance of clean energy is measured through the WilderHill Clean Energy Index (ECO). For the technology, we use the Arca Tech 100 Index (PSE) maintained by the New York Stock Exchange. For the common stocks, we use the S&P 500 composite to represent the overall market performance. The ECO indicator includes companies that invest in renewable energy or contribute to sustainable energy (Ferrer et al., 2018) (Elie et al., 2019). The PSE index includes large technology companies from different industries. West Texas Intermediate (WTI) crude oil future prices are commonly regarded as proxies for volatilities in the oil market. We used Yahoo Finance for Arca Tech and S&P 500 and the Energy Information Administration (EIA) for the oil price (WTI). This thesis examines volatility spillovers among four assets. We converted daily data to realized monthly volatility from September 2004 until February 2020.

The choice of the four variables is based on the following considerations. Our primary goal is to examine how clean energy and technology markets move in relation to the common stock and oil markets over time. The S&P 500 and WTI indices cover the risks associated with common stocks and oil markets, respectively. Hedging the risks associated with these two large assets is a significant concern to investors. We consider the technology and clean energy sectors as potential hedge assets.

To determine their relationship to the S&P 500 and oil markets, we look at their spillover dynamics with the S&P 500 and oil markets. We use the WTI index for oil since it is the most widely traded crude oil product in the US market. The S&P 500 and WTI are both traded on major stock exchanges. Investors can invest in WTI in a variety of ways. One common option of investing in WTI is to purchase the United States Oil Fund (USO). USO targets a benchmark futures contract, namely the near-month WTI crude oil futures contract for light, sweet crude oil supplied to Cushing, Oklahoma, which is traded on the New York Mercantile Exchange (NYMEX).

USO invests in a variety of other oil-related contracts and may also participate in forwards and swaps. To reflect the dynamic relationship between the S&P 500 and WTI, the clean energy and technology series should also include market-traded assets. Additionally, they should represent the broad technological and clean energy sectors. The ECO Index we use is a global index of firms whose innovative technology and services focus on cleaner energy generation and usage, conservation, efficiency, and the advancement of renewable energy in general.

The New York Stock Exchange maintains the PSE Index. The index does, however, include stocks that trade on exchanges other than the NYSE. The index's goal is to serve as a standard for evaluating the performance of companies that use technology innovation across a wide range of industries. Leading firms in a variety of areas, including electronics, software, computer hardware, health care equipment, semiconductors, and biotechnology, are included in the index. Thus, both the ECO and PSE indices have broad coverage. Although these indices are not directly traded, they can be indirectly traded by investing in exchange-traded funds (ETF) that mirror the performance. The NYSE Arca Tech 100 Index Fund is an exchange-traded fund that mirrors the PSE index's performance. For ECO, there are two widely traded ETFs. In the US, the Invesco Global Clean Energy ETF seeks to mirror the performance of ECO. The Invesco Global Clean Energy ETF, which seeks to mirror the performance of ECO, is also available in Europe. We also avoid the curse of dimensionality issues by using indexes with broad coverage. The VAR models perform poorly when they are fitted to more than a few variables.

The evaluation of monthly data across the sample period is depicted in Figure one. As shown in Figure one, the dynamics of technology (TE) and the S&P500 (ST) index followed a similar uptrend pattern after the 2008 crisis, and they reached 2470 and 3450 points, respectively.

In contrast, the clean energy (CE) index and oil price (WTI) dropped sharply during the crisis and fluctuated until the end of our sample period. As we can see, oil prices increased until 2008 and reached their highest price (145 $), but after the economic crisis, oil prices dramatically decreased. As a result, the clean energy index, which reached the highest record of 297 points, declined after 2008, and it fluctuated in a range of 36 to110 points.

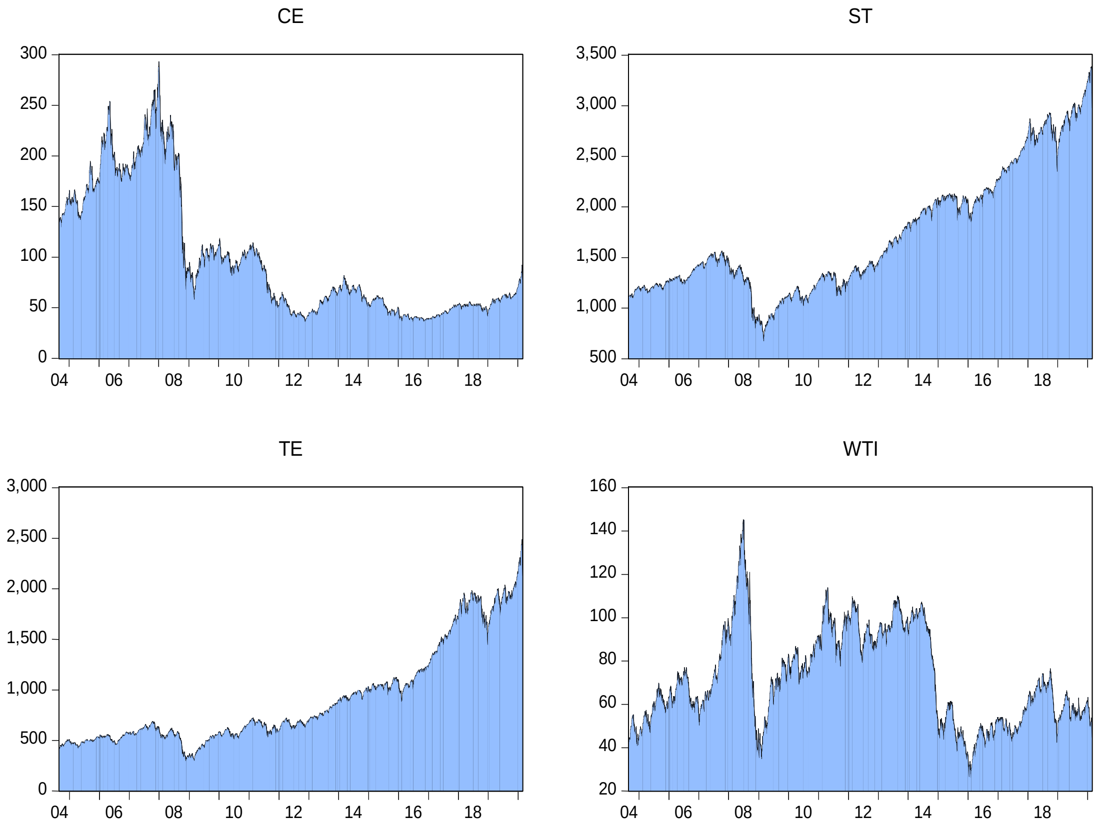


Figure 1: Time series plot of the clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series. The y-axis for WTI represents per barrel in the dollar, and the x-axis shows the sample period. All other three assets are indexes, with the y-axis denoting index value and the x-axis, the time (yearly)

We can calculate realized volatility in three steps; first, we find the percentage log return of daily data by $Lr_{j,t} = \log(P_{j,t}/P_{j,t-1}) \times 100$, where $Lr_{j,t}$ is percentage log return and $P_{j,t}$ is the price level. Secondly, to find a monthly realized variance, we use $rvar_{j,t} = \sum_{n=1}^{N} Lr_{j,t,n}^2/N$. Finally, we calculate the realized volatility as $rvol_{j,t} = \sqrt{rvar_{j,t}}$ (Barndorff-Nielsen & Shephard, 2002).

Table 1 provides summary statistics for the monthly-realized volatility of all four variables. According to the mean, oil has the highest positive value, followed by clean energy, technology, and the S&P 500. Considering the risk, the standard deviation (SD) of WTI's realized volatility is higher than that of other indexes, and the S&P 500 records the minimum monthly volatility. The positive skewness of all four variables indicates that the volatilities are symmetric, an expected property. Furthermore, all variables have positive kurtosis (greater than 3), but the S&P 500 has the highest likelihood of experiencing extreme realized volatility.

Table 1: Descriptive statistics for realized volatility

	CE	**S&P 500**	**TE**	**WTI**
Mean	0.034	0.018	0.024	0.041
Median	0.030	0.014	0.020	0.036
Maximum	0.155	0.103	0.104	0.152
Minimum	0.015	0.006	0.009	0.014
SD	0.018	0.013	0.013	0.020
Skewness	3.16	3.19	2.67	2.21

Kurtosis	17.29	17.30	13.34	9.90

2.5 Results and Discussion

Table 3 presents the static connectedness estimates of the whole sample. To represent the total, directional, and net spillover, we obtain the FEVDs in a similar manner to the method in Diebold & Yilmaz (2012). The optimal lag of the VAR model is one according to Schwarz information criterion (SC). Hence, the values in each row indicate the spillover transmitted to other markets. The values in each column indicate the spillover received from other markets and the own market. The label "Transmitted" denotes the spillover effect from one market to another, and the "Received" shows this effect from other markets. The sum of each row, except for its own effect in the market, represents the value of the "Received."

Similarly, the sum of each column without its own effect is denoted as "Transmitted" for each market. By subtracting the Transmitted value from the Received value, we find the net spillover effect for each market. As a result, this calculation is required to understand which market is a net transmitter or net receiver. Finally, the DY time-domain spillover index (61.530%) can be calculated by summing the value of the received (transmitted) and dividing it by 400% (four markets × 100%).

According to Table 3, the net spillover index is 61.530% among clean energy, the stock market, technology, and oil. It shows that the connectedness of shocks can explain around 61% of FEVDs, and 39% can be considered idiosyncratic shocks. The stock market index is the significant contributor element to the FEVD of the other markets with 87%, followed by technology, clean energy, and oil with 70%, 57%, and 30%, respectively. In terms of receivers, the largest one is clean energy (67%), and the lowest contributor is oil (47%). In addition, the transmission from technology to clean energy and the stock market is more than 25%, and for oil, it is around 16%. The weakest spillover effect is allocated among clean energy and oil, which shows a lower connectedness among them. According to net spillover, clean energy and oil are net receivers; however, technology and stock markets are net transmitters. The finding showed substantial connectivity among clean energy companies and technology companies, stock prices, and oil prices over the sample.

Table 2: Static connectedness spillover estimates

	CE	**TE**	**WTI**	**ST**	**Received**
CE	32.284	25.914	8.207	33.595	67.716
TE	22.558	32.700	11.162	33.580	67.300
WTI	10.555	16.352	52.570	20.524	47.430
ST	24.324	28.675	10.675	36.326	63.674
Transmitted	57.437	70.941	30.043	87.699	246.120
Including own	89.721	103.641	82.613	124.025	Spillover index
NET spillovers	-10.279	3.641	-17.387	24.025	**61.530%**

Note: FEVDs are computed from a VAR model with one lag selected by the Schwarz information criterion. The FEVDs are based on 10-step ahead forecasts. All calculations are based on monthly-realized volatility data from 2004 to 2020.

The dynamic spillover connectivity metric is then calculated using a rolling VAR model with a fixed window size of 48 months. The rolling total connectivity index is displayed in Figure 2. According to Figure 2, in the 2008 crisis (Lehman Brothers bankruptcy) and the global economic recession, the total volatility spillover index increased and reached around 74% (historic peak). After a brief transient decline at the end of 2010, overall connectivity grew substantially during the Eurozone's most crucial sovereign debt crisis. These results demonstrate the tremendous effect of the 2008 economic meltdown and the resulting European debt crisis on spillover volatility. This confirms the common opinion that commodity and financial market connections increase dramatically during heightened economic uncertainty. Any positive (negative) evidence is evaluated prudently in periods of confusion, thereby increasing interconnection. In autumn 2008, the economic crisis led to an increasing spillover index, and this strengthening came from risk aversion and uncertainty. Because of the recent international economic meltdown, market participants are becoming more aware of the market's vulnerability to shocks. As a result, a higher-level scenario has emerged.

Consequently, the evolution of global economic and financial factors is being given more attention, which eventually has been reflected in spillovers. This finding agrees with Ahmad (2017), which shows that the link among stock prices of new energy and technological Company and fossil fuel prices following the international crisis of 2008 has increased dramatically. Moreover, total spillover indicators, particularly spillover volatility, decreased in 2014. This decrease in total connectivity could be attributed to the July drop in WTI prices, supply considerations, such as rising US oil production, and changing OPEC (Organization of the Petroleum Exporting Countries) policy, droving the early dip in oil prices from mid-2014 to early 2015. Deteriorating demand prospects also played a role, especially between mid-2015 and early-2016. This result confirms Managi & Okimoto (2013), contrasting with Henriques & Sadorsky (2008).

The volatility in China's financial markets, which began in June 2015, ended in February 2016, and the spillover index increased from a low point in 2015 to a high one in 2016. Until 2019, more crises, such as those in Europe, Greece, Brazil, and Turkey, can be classified as causes of increasing spillover indexes.

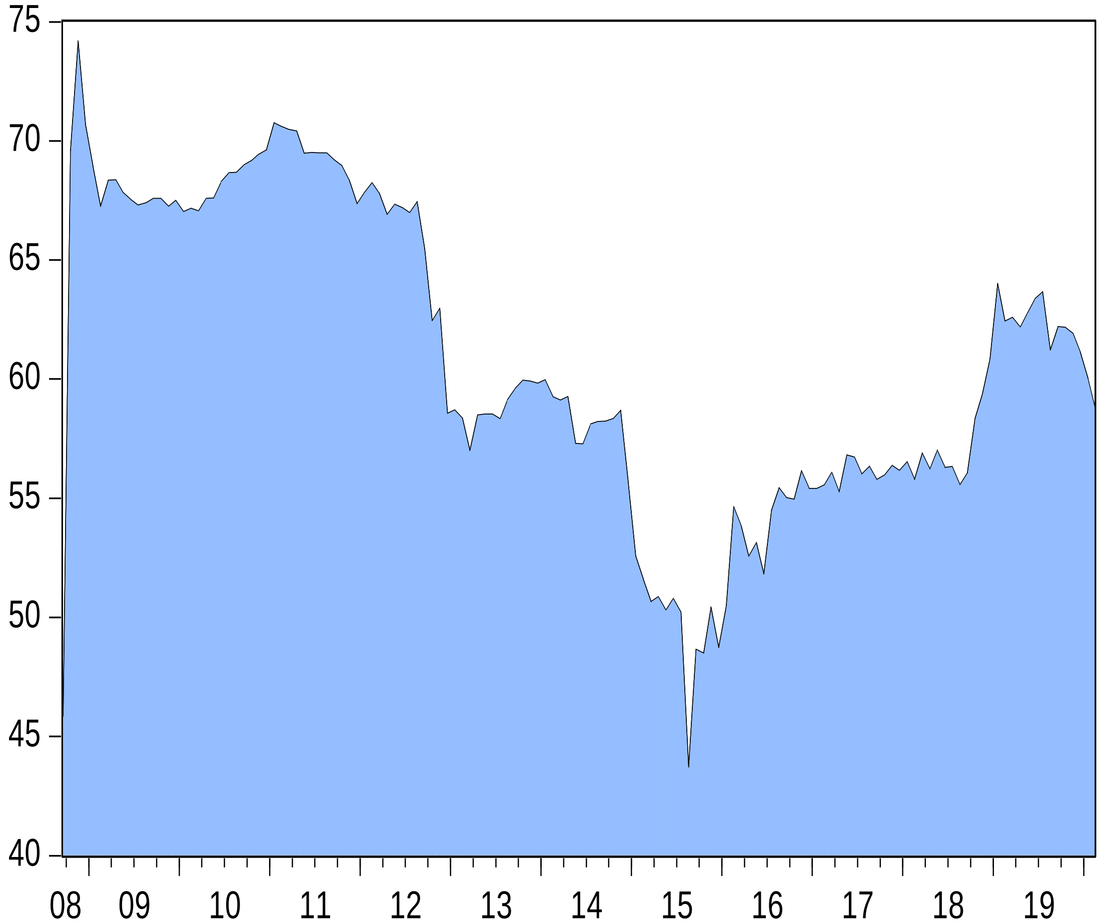


Figure 2: Rolling total volatility spillover index estimates among the clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series. Note: the X-axis shows the time (yearly), and the Y-axis demonstrates the percentage change in the total spillover index.

To discuss the dynamics of spillovers based on the specific asset, we used equations 6 and 7 to estimate the directional spillovers. The directional spillovers "TO" and "FROM" are shown in Figures 3 and 4, respectively. Besides, the directional volatility spillover index could be calculated by decomposing the overall spillover value.

As shown in Figures 3 and 4, the directional volatility spillover from other markets to clean energy has risen and reached around 15%. The Lehman bankruptcy and EU debt crisis can be considered the reasons for this increase until 2012. From 2013 to 2016, we had a dramatic decline, and it can be connected to the oil fall in 2014. The European stock market collapse, which can be seen in stock market Figure 3(b), confirms the sharp increase in volatility spillover since the end of 2015. The volatility spillover from another market to the stock oscillates between 15% and 25%.

According to panel (d) of Figure 3, transmitted shocks can be classified into three groups: 2008–2012; 2012–2015; and 2015–2019, indicating the volatile period. During this period, oil prices fluctuated because of political and economic events. However, oil transmitted shocks declined with passing time, reaching less than 5% from 24%. Figure 3(c) illustrates the shocks that were transmitted from the technology index to other markets, and it fluctuated around 17% over all the sample periods.

To investigate the effect of volatility spillover from other markets on clean energy, we can examine Figure 4(a). As we can see, the shocks were quite large and fluctuated around 20% from 2008 to 2012. From mid-2012, shocks received from other markets decreased, reaching less than 12%. However, from 2018 to 2020, these shocks increased by 16%. Spillover emanating from stock markets fluctuated between 14% and 18%. According to panel (c) of Figure 4, shocks started to decrease in 2008 and reached their lowest point in 2015, having a 6% range from the highest point to the lowest one. Finally, the volatility spillover in Figure 4(d) shows oscillation from 2008 to 2015 and 2015 to 2020, with the highest being 17% and the lowest being 2%.

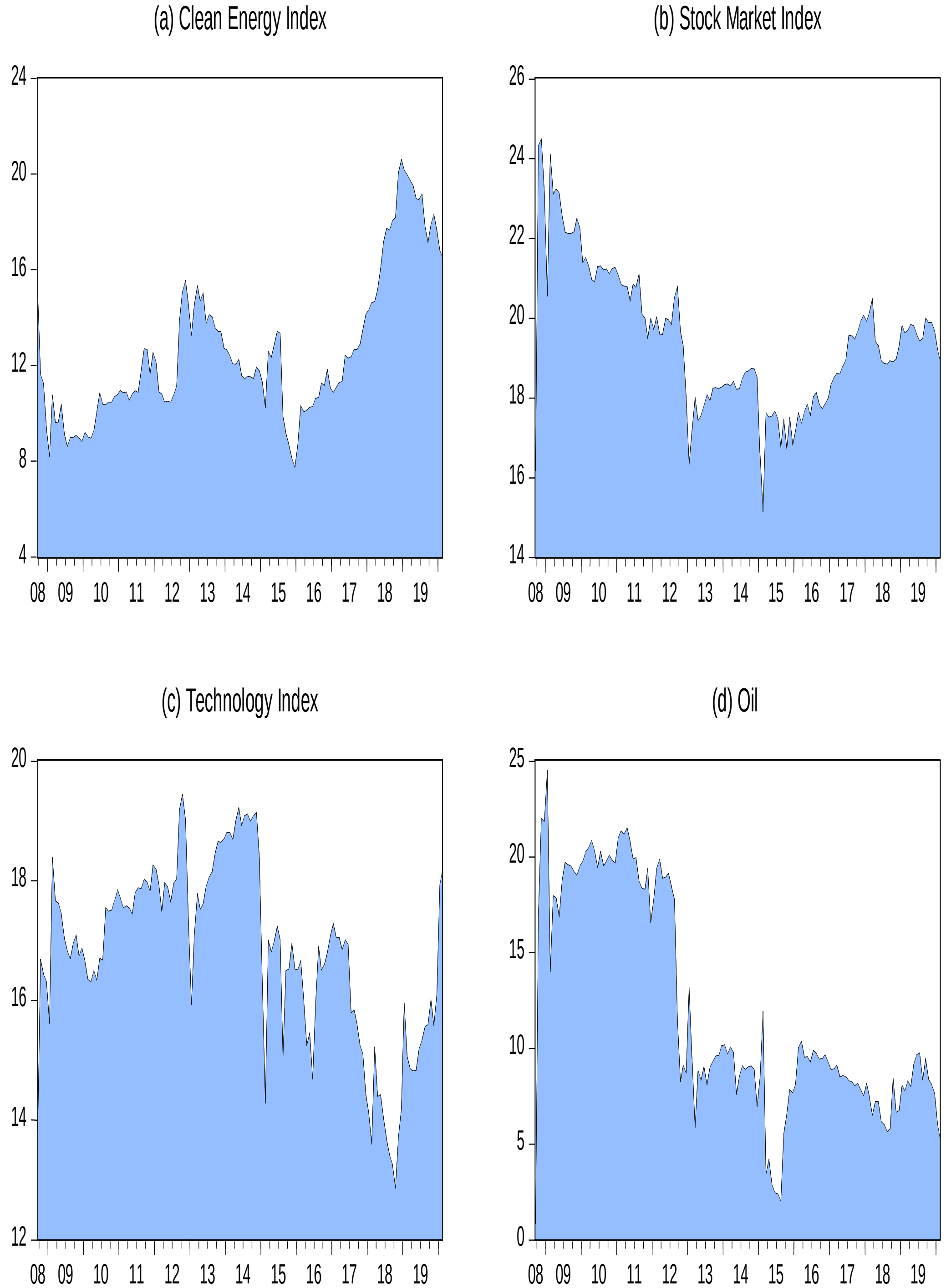


Figure 3: Directional spillovers TO among the clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series.

Note: The X-axis specifies the time (yearly), and the Y-axis illustrates the percentage change in the directional spillover TO

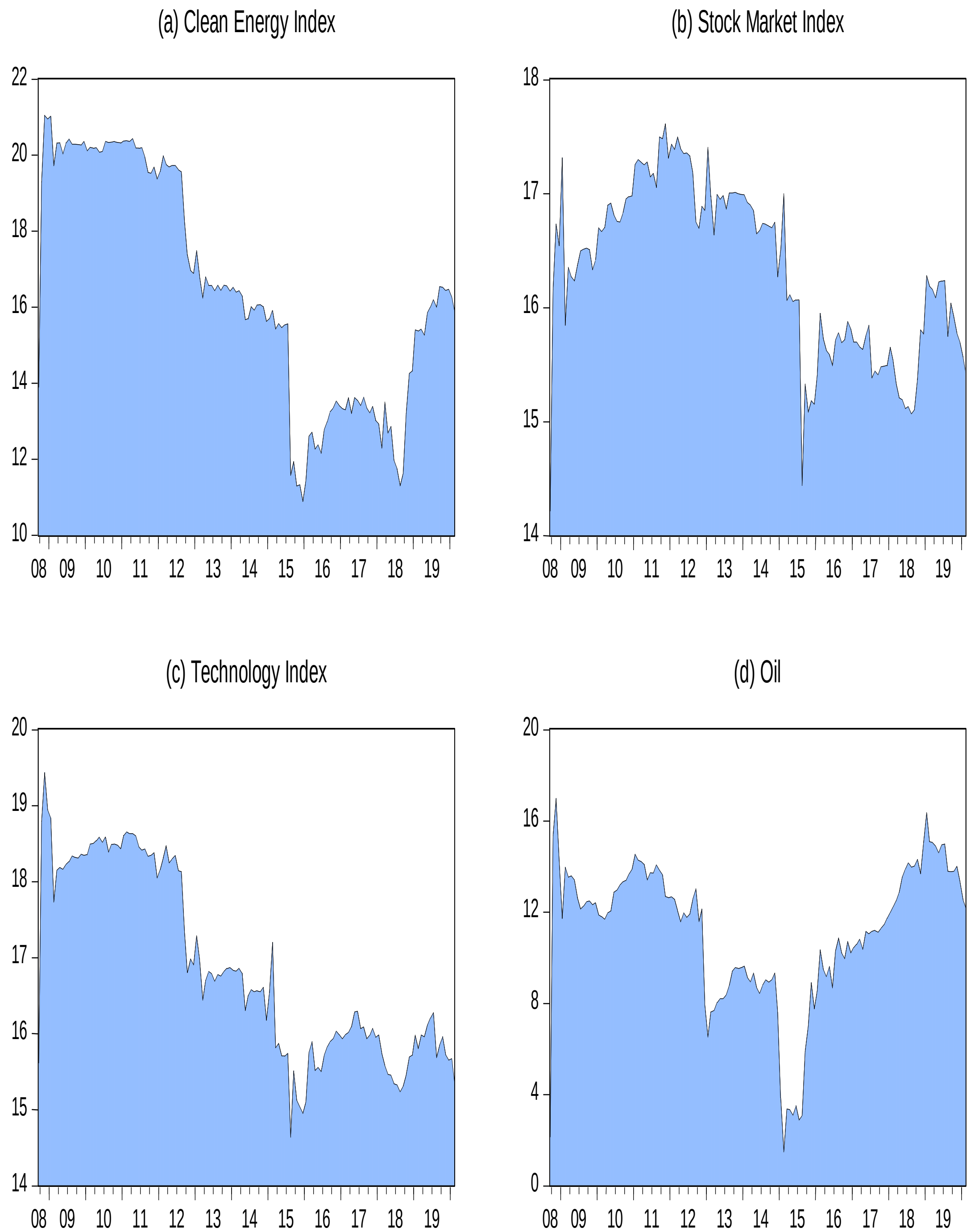


Figure 4: Directional spillovers FROM among the clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series.
Note: The X-axis specifies the time (yearly), and the Y-axis illustrates the percentage change in the directional spillover FROM

The pure time-domain method introduced by Diebold & Yilmaz (2012) allows us to find net spillovers among all variables. Dynamic net spillovers can be calculated by subtracting equation (7) from equation (6). In this way, we can understand which market is a net transmitter (recipient) of spillovers to (from) all other variables. In addition, according to Figure 5, the negative (positive) shaded (blue) values show the corresponding market as a net receiver (transmitter) of volatility effects from (to) other markets.

According to Figure 5, net spillovers show a substantial difference in time; the maximum values are typically achieved at the height of the global economic meltdown, such as the Lehman Brothers' bankruptcy, European debt, the Chinese market crash, and the oil crisis. Specifically, the clean energy stock market and oil emerge as net receivers of volatility spillovers from other markets. In contrast, technology and conventional stock markets are transmitters of volatility spillovers to all other markets. For example, as shown in Figure 5, from 2008 to 2017, clean energy was a net receiver of volatility spillovers from all other markets. In contrast, the oil market is a net transmitter of volatility spillovers to all other markets. However, after this period, the condition changed for both markets, and it shows that the dependence of other markets on the oil market started to decline.

In general, the oil and clean energy stock markets acted in the reverse direction during the whole sample. In this way, we have evidence that clean energy and oil work in reverse. On June 13, 2014, international military intervention started against the terrorist organization the Islamic State of Iraq and Syria (ISIS), and oil prices started to decline with the hope of peace in the Middle East. It can be considered a reason for the last large spike in the oil market, which acts as a net transmitter of volatility spillovers to all other markets.

One of the key points is that the conventional stock market is a major net transmitter to all other markets. The role of the technology index changed as net receivers or transmitters in the sample period, and it started as a net receiver until 2012, and from 2012 to 2017, it was a net transmitter. After that, it was a net receiver for two years, and in late 2019, it started to become a net transmitter to all other markets.

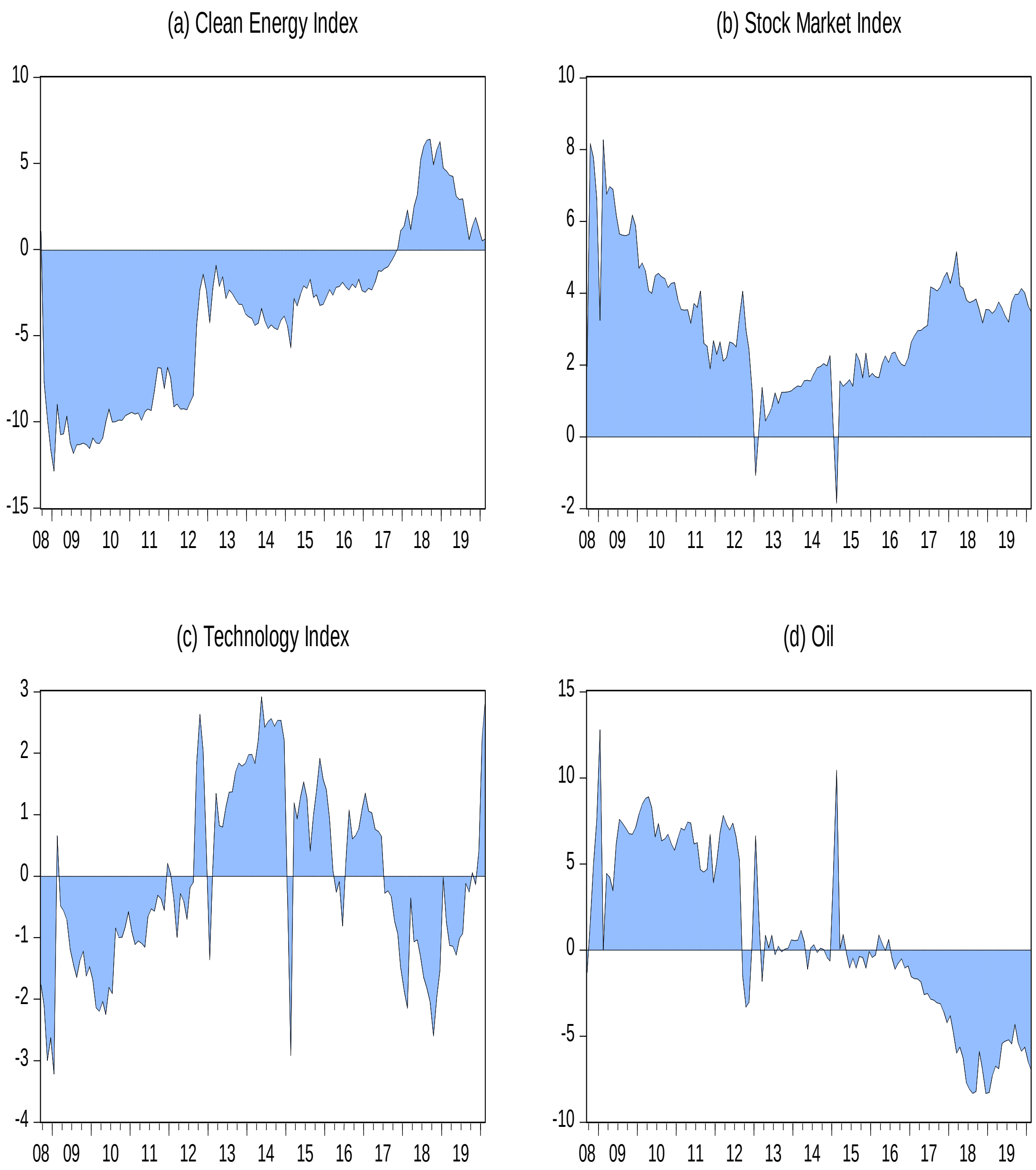


Figure 5: Net spillover among the clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series.
Note: Positive values indicate transmitting spillover while negative values indicate receivers of spillover. The X-axis specifies the time.

The following part focuses on the net pairwise spillover to highlight the major shocks being transmitted or received in Figure 6. Equation 9 is used to get pairwise directional spillover estimates. The results confirm that the green stock index is the net receiver of the shocks from technology, confirming the findings of Nasreen et al. (2020). In addition, oil transmitted the shocks to clean energy before 2014 and after the energy crisis; it was the receiver of the shocks from all other three assets, which contrasts with Sadorsky (2012). Moreover, this result confirms Ahmad (2017), especially after the energy crisis. Comparing Figures 5(a) and 6(a), we observe that clean energy and oil spillovers are not significantly different.

Furthermore, we can see the same condition in Figures 5(a) and 6(c), implying that the oil and technology markets played a causal role in the green energy stocks before 2014. After the oil crisis in 2014, their shocks became smaller.

Concerning Figure 6(b), we see a negative net pairwise from clean energy to conventional stock markets. We observe three large positive spikes, which can be considered significant changes in the oil market during the 2008 crisis, the Mideast and North African crises, and oil supply factors, respectively, from the last significant spike risk spillover effects, moving to conventional stock from the crude oil market, according to panel (d) of Figure 6. Furthermore, we observe that the technology index is mostly a net receiver of the conventional stock market and crude oil shocks compared to clean energy during the sample period.

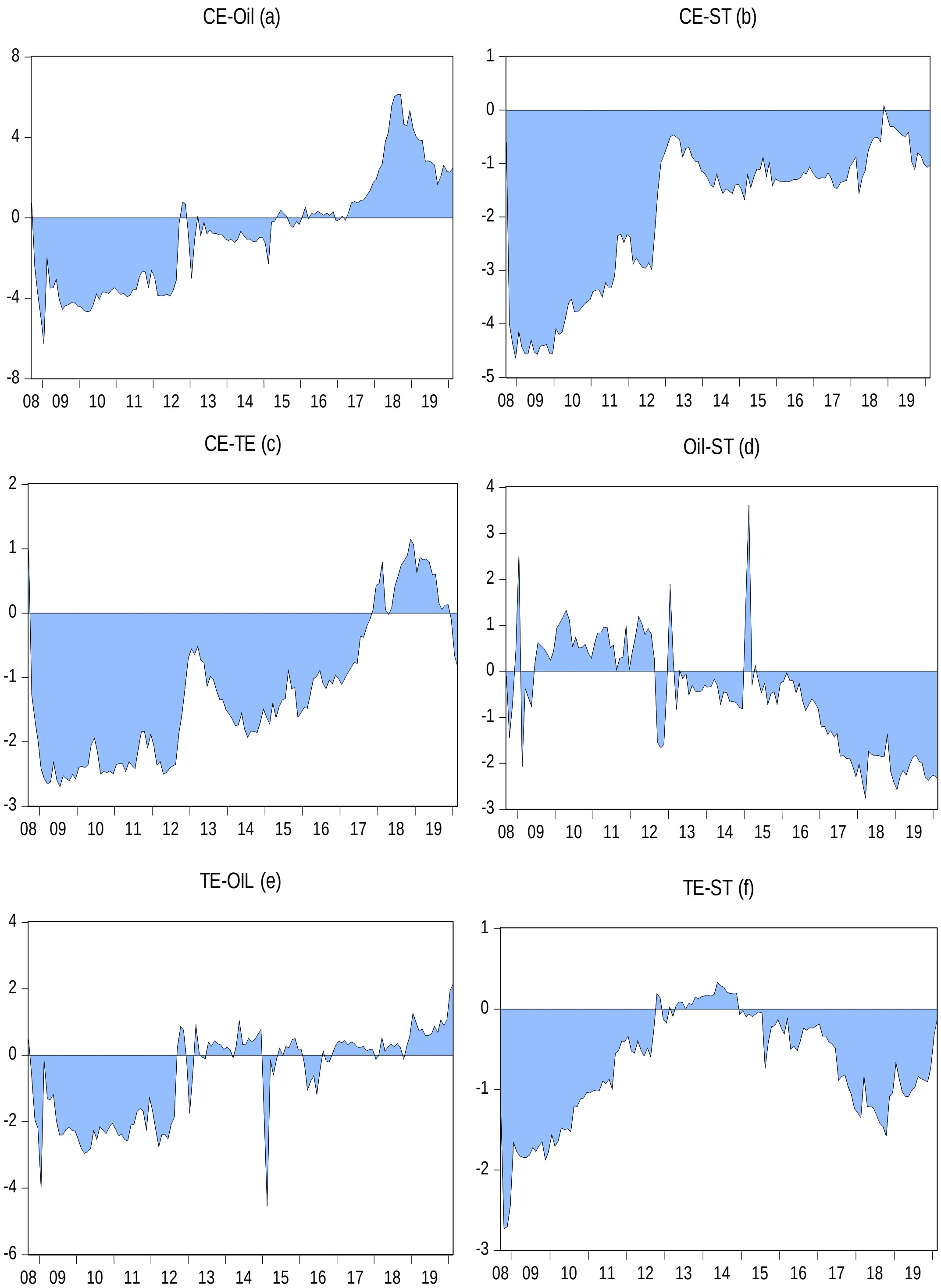


Figure 6: Net pairwise spillover among clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series.

Note: Positive values indicate transmitting spillover while negative values show receivers of spillover. The x-axis indicates the time (yearly).

2.6 Robustness Analysis

Dynamic financial time series interactions depend on market conditions. Asymmetric dynamics are similarly apparent compared to recessions and recovery times. Complex spillover interactions across time series data are much stronger during crisis periods. (see, more detail in Elie et al., (2019), Barndorff-Nielsen & Shephard (2002),(Balcilar & Ozdemir, 2013), Balcilar, Bekiros, et al., (2017)). Engle & Manganelli (2004) and Kouretas & Zarangas (2005) find that the characteristics of the financial time series can change significantly in terms of supporting distribution. As a result, the dynamic interaction between the behaviors of the asset prices under consideration can be unique in some quantiles compared to others. For example, there may be highly dynamic connections in one tail. In contrast, the connections in the other one may be very low, and the DY time domain index cannot provide reliable information on the spillovers. In other words, simple VAR cannot show interactions between variables in non-central quantiles. The data in this paper has a non-elliptical distribution and leptokurtic characteristics (kurtosis > 3, indicating tails fatter than normal distribution).

For robustness analysis, we use the quantile vector autoregression (QVAR) model to understand the effect of larger or smaller shocks compared to mean (linear VAR) shocks. Linear VAR can investigate average shocks. Large negative and positive shocks can change the dynamics of spillover. Therefore, the QVAR can allow us to check the dynamic spillover in tails. QVAR was introduced by Cecchetti & Li (2008) and followed by Xu et al. (2016). According to Chavleishvili & Manganelli (2017) and Balcilar et al. (2018), dynamic connections can be captured by quantile impulse response, and it is not possible to capture them by the linear VAR model. Therefore, we use the QVAR model to investigate the tail connectedness based on the approach of Cecchetti & Li (2008).

To determine whether spillovers through renewable energy, technology, oil, and stock markets change across different quantiles, we estimate the QVAR for different quantiles. Figure 7 displays rolling spillover indices in different quantiles (0.05, 0.25, 0.5, 0.75, and 0.95) that are extracted from the QVAR model, as well as a linear VAR is rolling spillover index considered as the "mean." As shown in Figure 7, spillover indices to determine whether spillovers through renewable energy, technology, oil, and stock markets change across different quantiles, we estimate the QVAR models for different quantiles. Deviations in the mentioned quantities appear in the range that the volatility spillovers reach the lowest level compared to linear VAR spillovers, and the existing deviations did not reach 5%. However, we notice that the most significant deviation is in the lower (q = 0.05) and higher (q = 0.95) quantiles than the mean results.

The shortest distance between the mean and the 0.05-th and 0.95-th quantiles occurs in two different periods, the first from the end of 2008 to 2011 and the second from 2018 to 2020. The spillover for the 0.95-th quantile is substantially more prominent for the entire period. For the 0.05-th quantile, the volatility spillover is partially greater than the VAR result in some parts of the sample. Therefore, the volatility spillover is more relevant to the large positive volatility than the average shocks. Significant negative volatility does not generate bold spillovers among the clean energy, oil, technology, and stock markets.

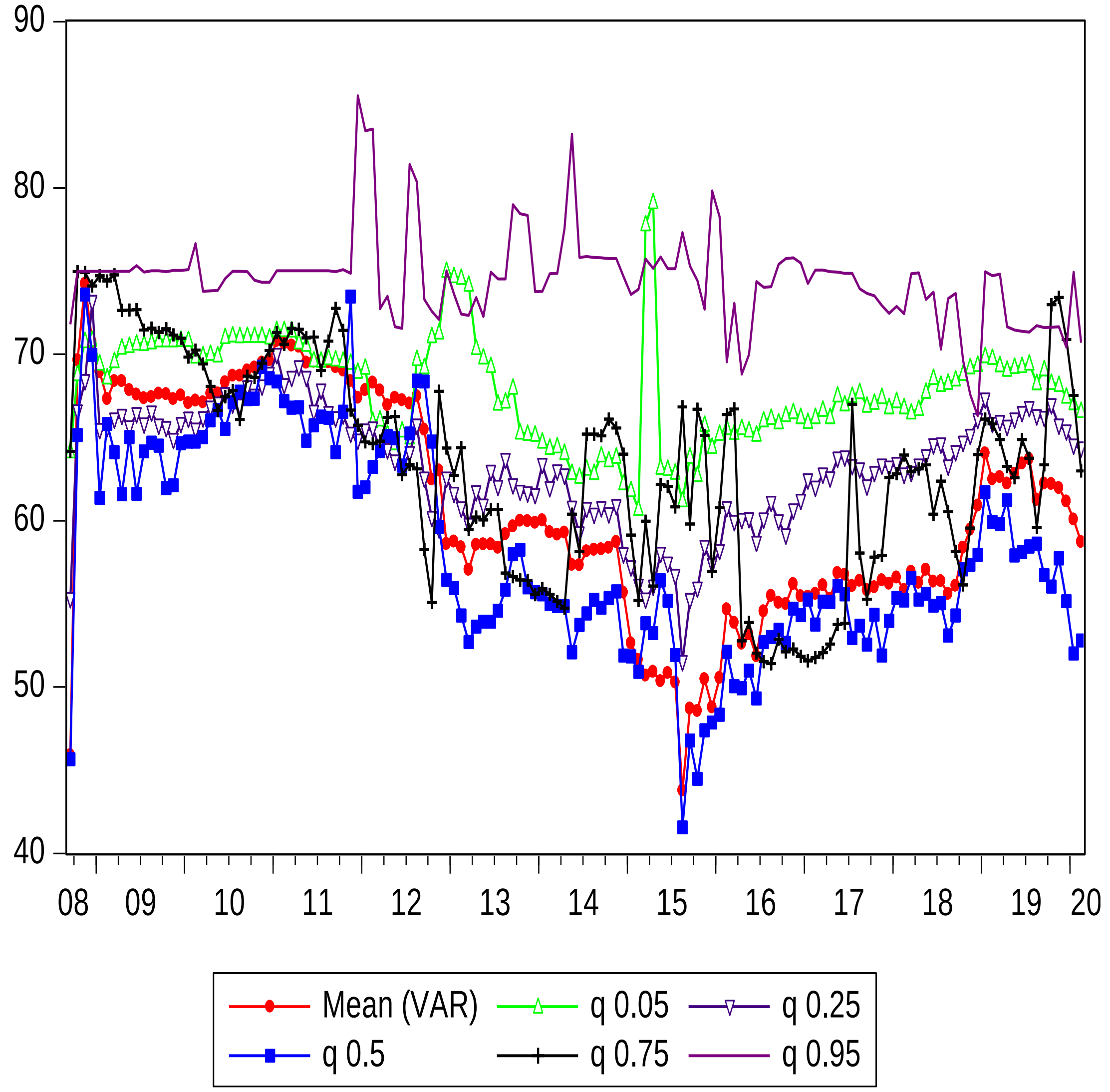


Figure 7: Comparing the total volatility spillovers between the linear VAR (mean) and different quantiles by the QVAR model among the clean energy (CE), S&P 500 (ST), technology (TE), and crude oil (WTI) series. Note: The X-axis specifies the time and the Y-axis shows the percentage change in the total spillover index in the mean and different quantiles.

2.7 Conclusion

Over the last few decades, the massive development of the green sector has resulted in a strong desire to realize the potential of alternative energy corporations and their relationship with the oil market and economic variables. This article evaluates the dynamics of the volatility spillovers between the clean energy companies, oil prices, and two notable sectors, namely the S&P 500 as a conventional stock performance index and the technology index from September 2004 until February 2020. To that end, we used the spillover index methodology based on generalized forecast error variance decomposition introduced by Diebold & Yilmaz (2012). In essence, the Diebold and Yilmaz method provide an insightful estimation of connectedness, which can be made dynamic with a rolling estimation over time. The linear VAR model results show that the clean energy index and oil price are the net risk or volatility receivers.

In contrast, the conventional stock and technology indices are the net transmitters of the shocks. The S&P 500 is the largest transmitter of volatility spillovers, while oil is the smallest of the four markets. In addition, during crises such as 2008, the total connectedness rises sharply. Based on the results, there is a strong bidirectional spillover between these markets. Balcilar et al., (2018) estimate dynamic spillovers between gold, oil, and the S&P 500. They conclude that in financial and non-financial economic instability periods, the importance of oil and gold as a safe haven has shifted throughout time. According to our results, the role of oil prices in the energy market will change with the stock markets, and energy will be compensated with clean energy in the following decades. Additionally, we can conclude that the S&P 500 and the technology markets play a critical role in the clean energy market according to net pairwise spillover results.

Our findings refute Sadorsky (2012) assertion that oil is a valuable hedge for renewable energy companies. According to the data, oil price variations are not the most significant factor influencing the profitability of renewable energy and technology businesses. These companies have the power to change direction in reaction to a less dependent business climate on the oil market. Investors may believe that scientific advancements and inventions are crucial to the profitability and stock value of renewable energy and technology companies. The oil market may lose its relevance because of the dominance of renewable energy companies and the rise of energy-efficient industrial processes.

The sign of a close link among CE and Tech enterprises implies that policymakers should recognize that the clean energy market's future depends on new technology innovation and uptake. As a result, renewable energy companies must have an energy strategy to compete with technological product novelty. This study's empirical findings are useful for investors, financial managers, and portfolio managers dealing with market uncertainty during oil price shocks. The insights can also help technology businesses identify hedging and arbitrage opportunities. When dealing with oil and stock portfolios, investors must also consider the duration and nature of oil price shocks.

The result of this thesis may have substantial implications for investment decisions and risk assessment from different financial perspectives. Moreover, policymakers should also be aware that, if oil prices remain low, alternative energy production industries do not need specific policies to reduce their susceptibility to oil shocks and simplify the energy sector's shift into a sustainable one. Instead, policies that promote green energy expansion should be ideally geared towards improving investment and clean energy innovations.

Finally, in the empirical economics literature, there are various methods for modeling nonlinear relationships among financial variables. The vector threshold autoregressive, vector smooth transition autoregressive, and vector- Markov switching autoregressive models are the most used parametric nonlinear VAR models. The results of this study can be further extended with these nonlinear models with the different interconnected markets in local or international marketplaces.

Chapter 3

ON THE DYNAMIC RETURN AND VOLATILITY CONNECTEDNESS OF CRYPTOCURRENCY, CRUDE OIL, CLEAN ENERGY, AND STOCK MARKETS: A TIME-VARYING ANALYSIS

3.1 Introduction

Intermarket linkage is a substantial component of international finance, as measured by returns and volatility spillovers, and has significant implications for portfolio and hedging decision-making. The empirical literature has received considerable attention as a result of evidence of improved market integration facilitated by globalization and technological advancement. For example, during times of crisis, financial market volatility increases dramatically, resulting in spillovers across markets. Naturally, one would prefer to quantify and control such outbreaks, providing an alarm system for emerging disasters and monitoring them.

In recent years, cryptocurrency markets have exploded in popularity, and crypto has reached the level of a trustable asset to invest in. As the most popular one, Bitcoin, this new digital asset garnered considerable attention. By resolving puzzles, Bitcoin enables decentralized systems to safely and equitably issue new coins and confirm transactions. The Bitcoin network becomes more competitive as the number of transactions grows. The crypto mechanism that confirms blocks and compensates miners becomes much more sophisticated, making power and energy fluctuation more difficult to foresee. According to the British Broadcasting Channel (BBC), Cambridge academics estimate that Bitcoin consumes approximately 121.36 terawatt-hours (TWh) of electricity each year, which is more than Argentina's consumption with a population of 46 million. According to the Digiconomists, BTC transaction consumes the equivalent of 53 days of electricity for an average American family. These studies show how important financial and energy industries are to the future of cryptocurrencies.

The need to check the role of Bitcoin started in 2016, which gained a lot of attention in the investment and financial press. In 2017, BTC price raised sharply by more than 1300 percent, valuing the entire market at more than 215 billion dollars, with this figure expected to exceed one trillion dollars by 2022. As a result, investigating and assessing the relationships between the returns and volatility of BTC and other markets is significant for both investors and those who are working as policymakers. Any indication of significant returns and volatility spillovers among BTC and other types of assets could have an impact on asset choice, allocation, risk assessment decisions, and regulatory measures aimed at ensuring global financial system stability. It is also important for politicians who use cryptocurrencies as part of their reserves or experiment with their own domestic crypto.

Despite the Bitcoin mining process's heavy reliance on energy, practical information on how Bitcoin is related to energy investments, particularly clean energy stock investments, is limited. Furthermore, despite their substantial interconnection (especially Bitcoin's reliance on energy), the dynamics and economic links between clean energy, Bitcoin, and the financial market have not been sufficiently investigated.

Against this backdrop, the goal of this research is to see how closely BTC is linked to renewable energy, fossil fuels, and the stock market in general. Additionally, as the Bitcoin mining industry grows, this study sheds light on the strategy investors should employ when constructing a portfolio of these assets. Additionally, the study examines whether diversifying a Bitcoin portfolio with environmentally friendly assets such as green energy stocks is beneficial.

This study fills the gap by estimating dynamic connectedness among these assets using a TVP-VAR model. The study estimates both return and volatility spillovers among Bitcoin, clean energy, stock prices, and fossil fuels. In addition, we compare the TVP-VAR results with results from a rolling window VAR (RW-VAR) in terms of total connectedness indexes for robustness analysis. Naeem & Karim (2021) and Hung (2021) have studied the link among cryptocurrencies and green stocks. They make use of the bivariate copula model, the QQ (quantile-on-quantile) regression, as well as Granger causality-in-quantiles. Our study contributes in a variety of ways to a better understanding of Bitcoin, oil, clean energy, and the stock market connectedness. We define multivariate market reliance, which reflects the network of direct and indirect shock transmission between markets. Thus, our research identifies the shock transmitters and receivers explicitly within a network of Bitcoin, oil, clean energy, and stock market investments.

This thesis extends the literature that analyzes the connectedness among BTC and other financial markets. The focus of the study is close to Dyhrberg (2016), Katsiampa (2017), Balcilar et al. (2017), Symitsi and Chalvatzis (2018), Akyildirim et al. (2020), and Naeem and Karim (2021).

Our findings indicate that return and realized volatility spillovers among BTC, stocks, and energy are time varying. Additionally, the study's findings indicate the presence of a negligible spillover between BTC and green stocks investment during non-crisis periods. The conclusion suggests that investing in Bitcoin and clean energy may provide investors with diversification benefits. However, during times of crisis, such as a Bitcoin crash or an energy crisis, this investment strategy may be ineffective, as the spillovers between cryptocurrency and clean energy investments increase significantly. The extreme fluctuations in connectedness that occur during a crisis show that constant dependencies are implausible. Additionally, Bitcoin's low correlation with stock indices during non-crisis periods demonstrates its investment potential. Additionally, we discovered that cryptocurrency investors' environmental consciousness has a significant effect on the spillovers between cryptocurrency and green investments, particularly during times of high Bitcoin prices, such as 2018 and 2021.

The following is a breakdown of this section structure. A literature review is presented in Section 2, and the data and methodology are presented in Section 3. The empirical findings are discussed in Section 4, Section 5 contains discussion, and the main conclusion and policy recommendation are presented in Section 6.

3.2 Literature Review

The enormous volume of Bitcoin trading is well known to consume a significant amount of energy. As a result, while cryptocurrency has economic benefits, it also can hasten environmental destruction **(**Krause and Tolaymat 2018**).** The multidimensional evolution of financial technology paints a beautiful picture of current trading while simultaneously warning about the negative repercussions on our future environment

(Truby 2018; Corbet et al. 2021).

The current literature investigates the impact of Bitcoin trading on the financial market and environmental sustainability. According to a recent analysis by Jiang et al. (2021), maintaining the Bitcoin blockchain in 2024 will require 296.59 Twh, which will lead to the production of 130.50 million metric tons of carbon. Polemis and Tsionas (2021) investigated 50 countries to find the causal relationship between Bitcoin usage and CO2 emissions. Surprisingly, lower Bitcoin miner returns have a rapid effect on environmental circumstances. This study emphasizes the impact of renewable energy and long-term mining hardware disposal in reducing Bitcoin's carbon emissions at the regional level.

The financial linkages between Bitcoin and energy investments have been established in the literature due to cryptocurrency's strong reliance on energy.

On average, Ji et al. (2019) show a weak link among the crypto and energy markets such as heating oil, natural gas, and oil price although this link varies over time. The bidirectional and unidirectional spillover between cryptocurrency and crude oil spot prices were investigated by Okorie & Lin (2020). Bitcoin represents a bidirectional spillover of volatility. Jareño et al. (2021) report that oil shocks are linked significantly with cryptocurrency returns. They also point out that oil and cryptocurrency became more intertwined in 2020, especially in the first wave. Continuing efforts to find relationships between digital currencies and the financial market to account for the bivariate reliance between Bitcoin and other markets, Naeem and Karim (2021) use the bivariate copula model. Baur et al. (2015) find that BTC could be a diversifier. Bonds and equity's low connection was the evidence of this conclusion, and Ji et al. (2018) reached the same conclusion using the directed acyclic graph approach.

On the other hand, they did not consider the relationship between return and volatility in different markets. However, there is limited empirical research on Bitcoin's return and volatility spillovers to other markets. Balcilar et al. (2017) use trade volume data to predict BTC returns and volatility. They claim that while transaction volume can assist in anticipating returns in some cases, it does not provide information on volatility. Katsiampa (2017) applies multivariate generalized autoregressive conditional heteroskedasticity (GARCH) to estimate Bitcoin volatility and discovers the importance of integrating conditional variance's LR and SR components. According to Bouri et al. (2017), Bitcoin can be used to hedge against commodity indices and uncertainty indicators. Bouri et al. (2018) employ a smooth transition VAR-GARCH in the mean model. Their findings imply that spillovers among BTC and other markets analyzed are affected by the time and market situations under which they were utilized. Bitcoin is linked to other assets primarily through return rather than volatility.

Concerning the literature that investigates the dynamic connectedness of assets. Ji, Zhang, et al. (2018) uses a systematic time-series technique to investigate the risk and return connection of carbon and energy markets, particularly the green sector. The volatility connectedness among the underlying markets, according to their research, is stronger than the return connection. Ferrer et al. (2018) investigate the short-term volatility spillovers among energy and various financial variables. Nasreen et al. (2020) investigate the time-frequency relationship between crude oil and the stock prices of renewable energy and technology businesses. The results show that the underlying markets have weak connectedness in the frequency and time domain. Using the Diebold-Yilmaz (DY) index (Diebold and Yilmaz 2009; 2012), Naeem et al. (2020) looks on the time and frequency relationships between oil price shocks and other energy markets, including electricity, clean power, and carbon. During the shale oil revolution, the study found a surge in connection across the underlying markets. Dutta et al. (2020) examine the impact of implied volatility in the energy sector on green investment returns. According to their research, a rise in energy companies' implied volatility causes a drop in green stock returns. Evidence also suggests that the parameter estimates have an asymmetric impact.

Elsayed et al. (2020) examine the volatility connection between crude prices and seven assets over time. The study's key findings indicate that oil price volatility has an insignificant influence on those markets. More crucially, the findings show that global stock and energy indices are transmitters of shocks to the green market. According to Foglia and Angelini (2020), During the pandemic crisis, the static and dynamic volatility of oil prices, as well as the renewable energy market, increased.

The literature focuses primarily on studying volatility connectivity. However, this may be misleading because the dynamics of return and volatility connectivity may differ, and both may provide meaningful information to investors. Additionally, the connectedness might be time-varying, and one needs to estimate this using an optimal estimator. Therefore, this research purpose to examine the time-varying linkage of BTC, S&P 500, CE, and WTI prices in return and volatility using a TVP-VAR model, which is an optimal estimator of time-variation in parameters.

3.3 Data and Empirical Methodology

3.3.1 Data

The four asset classes examined in the study are the S&P 500 (S&P500), Bitcoin (BTC), the Wilder Hill Index (CE), and the West Texas Intermediate (WTI) crude oil price (OIL). The data used is at the daily frequency for both the return and volatility series, covering the period from November 11, 2013, to September 30, 2021. Oil is the most commonly traded commodity, and any volatility in oil prices impacts other markets. The oil price we use is the spot WTI crude oil price. The Bitcoin spot price was chosen based on market capitalization and trading frequency, and the S&P 500 composite index was chosen as a common stock representing overall market performance and sentiment. In addition, the Wilder Hill CE Index was chosen to follow the performance of green investments. The data was extracted from Fusion Media (www.investing.com) and Datastream.

The time variations of daily data across the sample period are depicted in Figure 8. While the dynamics of the clean energy index, Bitcoin price, and S&P 500 show an upward trend, the path taken by oil has fluctuated in the last seven years. The oil price recovered from its lowest price in 2020 to $75 at the end of this period. Bitcoin and clean energy prices rose significantly during the COVID-19 epidemic and reached a new all-time high. The S&P500 index is shown in Figure 8, fluctuating around a steadily increasing curve. Furthermore, S&P500 reached a new high (around 4500).

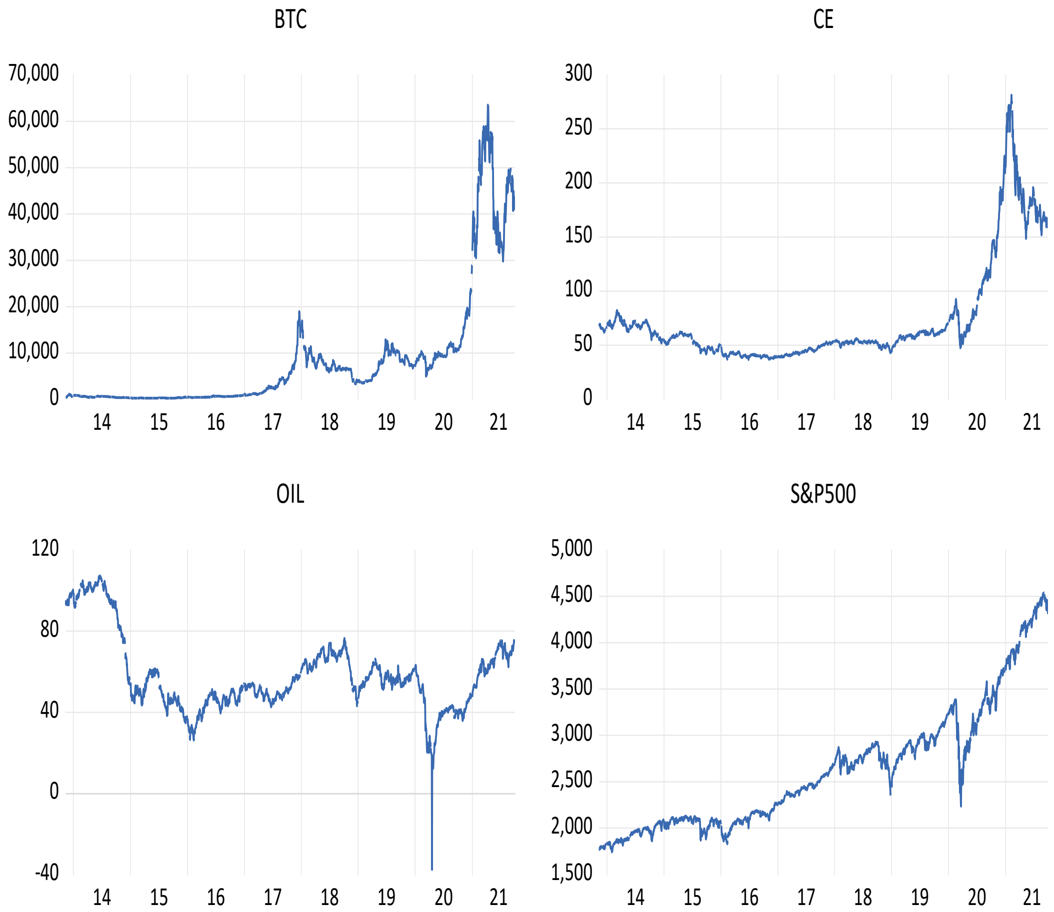


Figure 8: Time series plots of Bitcoin price, WTI price, clean energy index, and S&P 500 index

We calculate the daily realized volatility by employing the method proposed by Rogers and Satchell (1991) and Rogers et al. (1994), which uses H (High), L (Low), O (Open), and C (Close) prices of the asset in the following the formula:

$$V_t = 100 \times \sqrt{N \times \left[\ln\left(\frac{H_t}{O_t}\right) \times \ln\left(\frac{H_t}{C_t}\right) + \ln\left(\frac{L_t}{O_t}\right) \times \ln\left(\frac{L_t}{C_t}\right)\right]}$$

where $V_{j,t}$ Presents realized volatility of at day t and N is the number of trading days. The daily returns, R_t, are calculated as the percentage of log returns is the closing price $P_{j,t}$, that is $R_{j,t} = \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) \times 100$.

Figure 9(a) shows the return series of all four markets, which shows an increased fluctuation after 2019 due market's negative sentiment caused by the Corona pandemic. Figure 9(b) displays the realized volatility of the four markets: S&P 500 (VS&P500), Bitcoin (VBTC), the green Energy Index (VCE), and oil price (VOIL). Realized volatility in the oil price increased between 2014 and 2016 when the oil price fell. Also, the COVID-19 pandemic crisis in early 2020 increased realized volatility significantly. Moreover, realized volatility rose markedly for clean energy and conventional stocks during the pandemic.

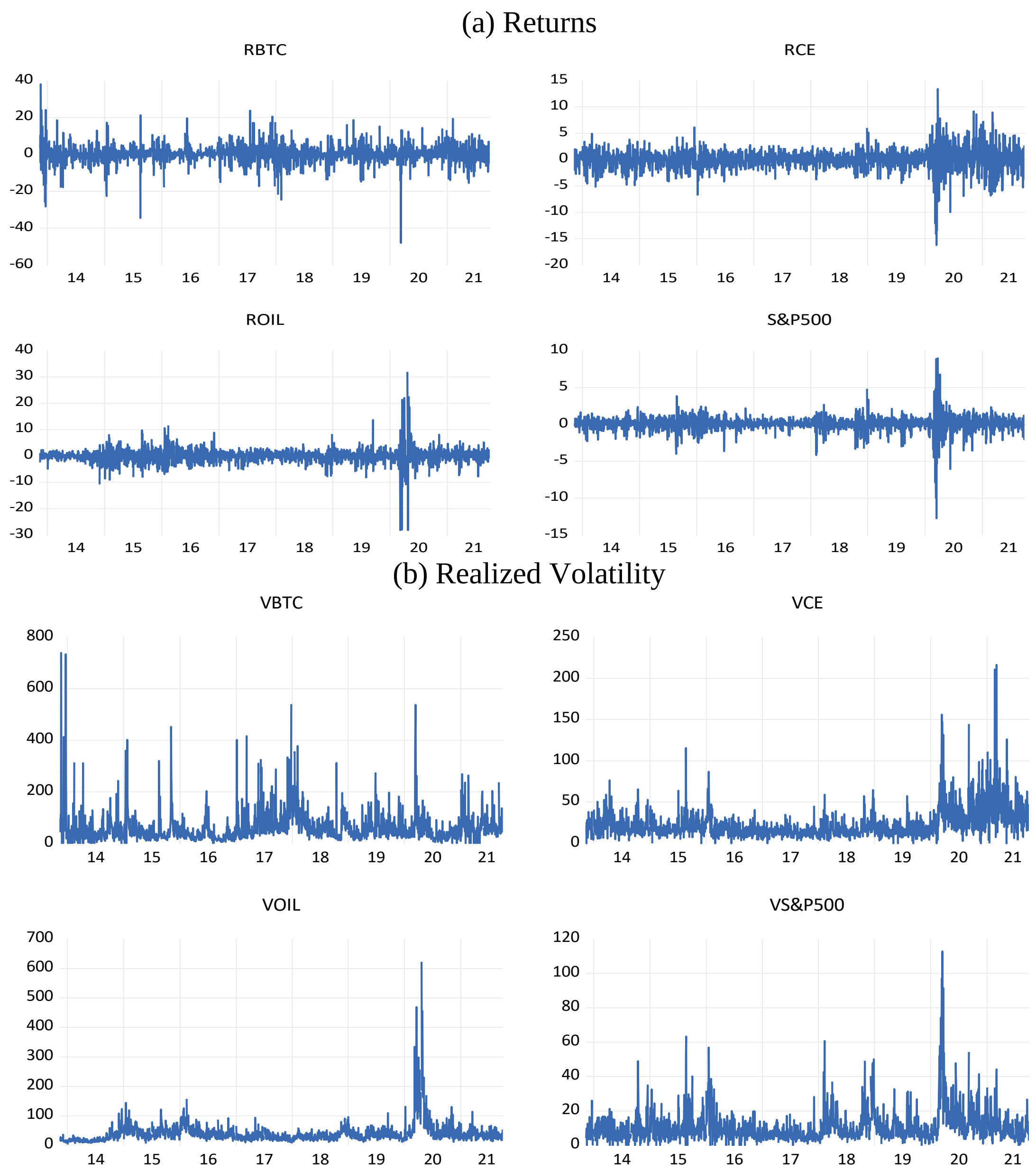


Figure 9: Returns (a) and realized volatility (b) of Bitcoin, clean energy index, WTI price, and S&P 500 index

According to statistics given in Table 3, Bitcoin has the highest average daily return in terms of both return and volatility, with 0.249 and 60.566, respectively, and oil has the lowest average daily return. Bitcoin also has the highest average realized volatility. Furthermore, all realized volatility series have excess kurtosis and are positively skewed. As demonstrated by the Jarque-Bera test, all series are not normally distributed. For all series, the generalized least squares Dickey-Fuller unit root test is significant, implying that all returns and realized volatility series are stationary Elliot et al. (1996).

Table 3: Statistical properties of the series

	S&P500	CE	WTI	BTC
		Returns		
Mean	0.047	0.046	0.019	0.249
Variance	1.187	4.046	8.764	25.374
Skewness	-1.050*	-0.596*	0.225*	-0.483*
Excess Kurtosis	22.303*	7.495*	26.106*	10.195*
JB	41486.151*	4761.451*	56357.036*	8668.772*
ADF-GLS	-6.565*	-8.970*	-5.893*	-12.292*
		Realized volatility		
Mean	10.953	22.998	40.202	60.566
Variance	88.646	316.103	1245.594	3542.784
Skewness	3.601*	3.437*	6.730*	3.969*
Excess Kurtosis	22.282*	21.416*	74.065*	27.101*
JB	45330.422*	41821.257*	468453.830*	65924.493*
ADF-GLS	-19.888*	-8.023*	-17.653*	-8.166*

Note: JB is the Jarque-Berra test of normal distribution, and GLS-ADF is the generalized least squares Dickey-Fuller unit root test. * denotes significance at the 1%level.

3.3.2 Empirical Methodology

As previously stated, we investigate the transmission mechanism in a time-varying manner using the methodology outlined in a TVP-VAR model and DY spillover index of Diebold and Yilmaz (2009; 2012). To capture the dynamics of connection, the suggested TVP-VAR model eliminates the necessity for the researcher to roll a fixed-length sample window. The method uses Bayesian shrinkage to predict high-dimensional systems without having to use computationally intensive simulation methods. The resulting dynamic connection index and directional connectivity metrics would be immune in rolling window estimating persistence. This methodology overcomes the shortcomings of the generalized VAR approach. Let the $n \times 1$ dimensional vector of variables be defined as $Y_t = (OIL_t, CE_t, S\&P500_t, BTC_t)'$ with $n = 4$. Then, the TVP-VAR model of order p can be written as follows:

$$Y_t = \Phi_t Z_{t-1} + \epsilon_t, \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{10}$$

$$\text{vec}\,(\Phi_t)\& = \text{vec}(\Phi\omega_{t-1}) + \eta_t \qquad \eta_t \sim T(0, \Omega_t) \tag{11}$$

where $Z_{t-1} = (Y_{t-1}, Y_{t-2}, \dots, Y_{t-p})'$ is an $np \times 1$ vector, $\Phi_t = (\Phi_{1t}, \Phi_{2t}, \dots, \Phi_{pt})'$ is an $n \times np$ coefficient matrix with $n \times n$ coefficient sub-matrices Φ_{it}, $i = 1,2, \dots, p$. ϵ_t and η_t are $n \times 1$ and $np \times 1$, respectively, normally distribute error vectors with time-varying variance-covariance matrices Σ_t and Ω_t, which are $n \times n$ and $np \times np$, respectively. Using the Wold representation theorem, the vector moving average (VMA) form of the TVP-VAR model in Eqs. (10)-(11) can be written as

$$y_t = \sum_{i=1}^{p} \Phi_{it} y_{t-i} + \epsilon_t = \sum_{j=1}^{\infty} \Psi_{jt} \epsilon_{t-j} \tag{12}$$

where Ψ_{it} are linear functions of $\{\Phi_{1t}, \Phi_{2t}, \dots, \Phi_{pt}\}$. The fundament of time-varying coefficients of vector moving average (VMA) model can be used to obtain generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GEFD) as defined by Koop et al. (1996) and Pesaran and Shin (1998). The GEFD defined by Diebold & Yilmaz (2012), which can be understood as the variance of variable i explained by variable j, $\varphi_{ij,t}(H)$, at forecasting step H, and its normalized version, $\tilde{\varphi}_{ij,t}(H)$, can be calculated as:

$$\varphi_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{t=1}^{H-1} \left(e_i' \Psi_t \Sigma_t e_j\right)^2}{\sum_{t=1}^{H-1} \left(e_i' \Psi_t \Sigma_t \Psi_t' e_i\right)}, \qquad \tilde{\varphi}_{ij,t}(H) = \frac{\varphi_{ij,t}(H)}{\sum_{j=1}^{n} \varphi_{ij,t}(H)} \tag{13}$$

where e_i is a zero vector with unity on the i position, $\sum_{j=1}^{n} \tilde{\varphi}_{ij,t}(H) = 1$, and $\sum_{j,i=1}^{n} \tilde{\varphi}_{ij,t}(H) = 1$.

Total connectedness index (TCI) construct by generalized forecast error variance decompositions and is calculated by the following formula;

$$c_t(H) = \frac{\sum_{i,j=1,i\neq j}^{n} \tilde{\varphi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\varphi}_{ij,t}(H)} \times 100 \quad (14)$$

Intuitively, it can be defined as the average spillover from all other markets to a given asset, ignoring the market's effect on itself due to lags. Therefore, firstly, we are concerned with the spillovers of variable i to all others j, which indicate the total directional connectedness to others:

$$c_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\varphi}_{ij,t}(H)}{n} \times 100 \quad (15)$$

Secondly, we calculate total directional connectedness from others:

$$c_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\varphi}_{ji,t}(H)}{n} \times 100 \quad (16)$$

In addition, net directional connection can be calculated by subtracting Eq. (15) from Eq. (16).

$$c_{i,t}(H) = c_{i\rightarrow j,t}(H) - c_{i\leftarrow j,t}(H) \quad (17)$$

Finally, by calculating net pairwise directional connection (NPDC) as below, we may infer bidirectional linkages and demonstrate that variable i affects variable j or vice versa.

$$\text{NPDC}_{ij}(H) = \left[\tilde{J}_{jit}(H) - \tilde{J}_{ijt}(H)\right] \times 100 \quad (18)$$

The Bayesian information criterion (BIC) is used to select the order of the TVP-VAR, which gives $p = 8$ for both the returns and volatility.

3.4 Empirical Results

3.4.1 Averaged Dynamic Connectedness

Table 4 presents the average full sample return and volatility spillover indices, as well as their decomposition as receivers and transmitters among WTI, CE, stocks, and Bitcoin. The numbers in Table 4 represent the average of the spillover values obtained from the estimated TVP-VAR model for the sample period from November 11, 2013– to September 30, 2021. Total connectedness index (TCI) values are close to each other with 25.13% and 23.96% for return and volatility, respectively, which means around 25% of returns is the spillover effect from other markets on average; also around 24% for realized volatility is spillover volatility from other assets on average.

The results show that oil and Bitcoin are net receivers with -4.31% and -0.08% for returns, respectively, and stocks (clean energy and conventional) are net transmitters. In contrast to the return results, oil and Bitcoin are net transmitters with 2.07% and 2.15% in realized volatility estimations. The role of stocks changed to net receivers with -2.13% for S&P500 and -2.09% for the clean energy index. By considering Table 4 Panel (a), the most significant contributor is clean energy stocks with 41.60%, followed by conventional stocks (40.26%), oil (12.96%), and Bitcoin (5.72%).

The net spillover for S&P500 is 30.44% to CE, and 7.08% and 2.75% for oil and Bitcoin, respectively. Additionally, clean energy contributes 2.2% for Bitcoin, 8.69%, and 30.70% for oil and S&P500, respectively. Overall spillover between oil and Bitcoin is the lowest magnitude for both return and realized volatility, which are 0.85% and 1.87%, respectively, implying that there exists lower pass-through among them. Also, spillovers between Bitcoin, S&P 500 is 2.2%, and it followed by clean energy and oil. The analysis confirms that transmission of shocks from other to BTC is very low.

Concerning the outcomes of realized volatility in Table 4, TCI is 23.96%, and it is quite the same as the TCI for returns. In addition, the volatility spillovers from S&P 500 index are 23.96%, 8.79%, and 1.77% for clean energy, oil, and Bitcoin, respectively. Moreover, the lowest volatility spillover is from CE to BTC by 1.75%, and the highest is from S&P500 to CE with 24.25%. The findings for RV spillover from BTC to other have a similar intensity (about 3%), although it is more significant than the case for return spillover. The bidirectional RV spillover from WTI to other is higher than the return one.

In terms of risk spillover, we can conclude that Bitcoin can be a safe haven on average for investors from 2013 to 2021 because the RV spillover to Bitcoin is quite small, and it is a net transmitteror rather than a recipient. In addition, shocks from WTI and other assets do not have a significant effect on Bitcoin during this period.

Table 4: Average dynamic connectedness

(a) Return spillover

	S&P500	CE	OIL	BTC	Received
S&P500	61.57	30.70	5.52	2.20	38.43
CE	30.44	60.96	6.59	2.01	39.04
OIL	7.08	8.69	82.73	1.50	17.27
BTC	2.75	2.20	0.85	94.20	5.80
Transmitted	40.26	41.60	12.96	5.72	100.54
Including own	101.83	102.56	95.69	99.92	
NET spillovers	1.83	2.56	-4.31	-0.08	TCI=25.13%

(b) Volatility spillover

	VS&P500	VCE	VOIL	VBTC	Received
VS&P500	63.36	24.25	10.09	2.30	36.64
VCE	23.96	64.74	8.67	2.63	35.26
VOIL	8.79	7.17	81.44	2.61	18.56
VBTC	1.77	1.75	1.87	94.60	5.40
Transmitted	34.51	33.17	20.63	7.54	95.86
Including own	97.87	97.91	102.07	102.15	
NET spillovers	-2.13	-2.09	2.07	2.15	TCI=23.96%

Note: The underlying variance decompositions are produced using the TVP-VAR model with a 10-day-ahead forecast window in return and volatility spillovers. The numbers reported in the are the average of the spillover values obtained from the estimated TVP-VAR model over the sample period from November 11, 2013, to September 30, 2021.

3.4.2 Dynamic Total Connectedness

In comparison to the average TCI, we observe that the total connectedness index, given in Figure 10, across the sample period based on the TVP-VAR model varies between 16% and 55% for return and between 11% and 49% for realized volatility. The overall images indicate that the coronavirus pandemic will cause similar prominent peaks in early 2020. WHO declared a worldwide health crisis in January 2020, and in March, COVID-19 announced as a pandemic, which corresponds to the peak level in Figure 10 for both return and volatility spillovers.

The realized volatility results exhibit more pronounced peaks and troughs. Six significant occurrences stand out in particular. The first peak corresponds to the oil crash, during which oil fell to 44 dollars per barrel from a high of 107 dollars per barrel in June 2014, while the second peak corresponds to the August 2015 stock market selloff. The third peak is connected to Syria's civil war. The fourth peak occurs in the United States following the election of a new president. The next two prominent peaks, in January 2018 and January 2020, respectively, correspond to the great crypto crash and the start of the COVID-19 pandemic.

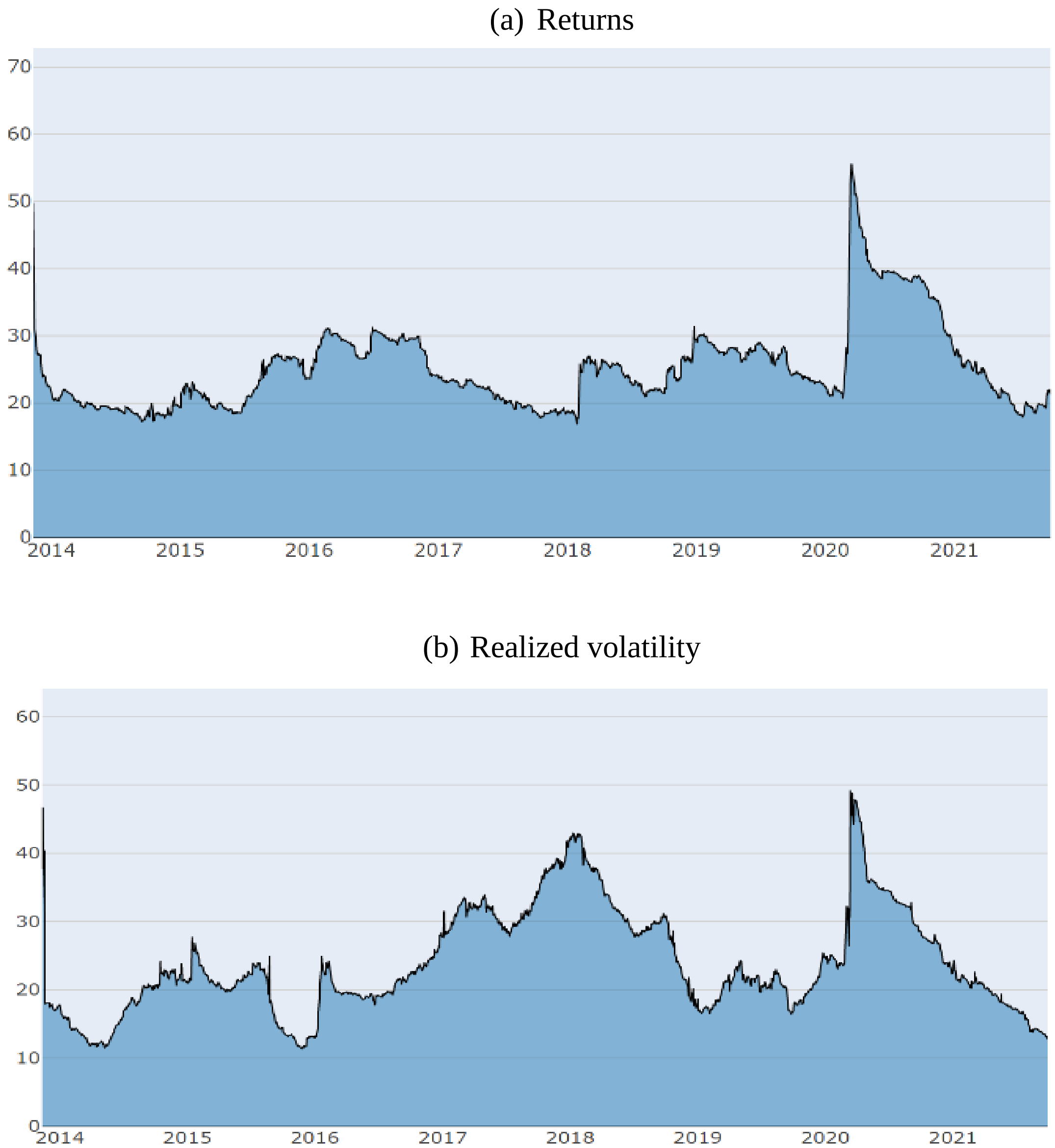


Figure 10: Total return and volatility spillover indices from the TVP-VAR

3.4.3 Rolling VAR Results

The rolling window VAR estimates of total connectedness are shown in Figure 11. The two indices behave similarly across the entire sample. Despite this, the TVP-VAR estimates have distinct features from the RW-VAR. To begin with, jumps in the total connectedness index calculated using the TVP-VAR method are more frequent and significant than those calculated using the RW-VAR method. This is right for all considerable global economic issues since 2014, such as the 2014 energy crisis, the 2018 crypto meltdown, and the 2020 coronavirus pandemic. As another illustration, the difference in behavior between the two indices during the global financial crisis is also significant, with the RW-VAR-based total connectedness index exhibiting greater smoothness. The TVP-VAR index accurately captures all important events leading up to the international economic crisis, whereas the rolling window index can capture only the effect of the 2020 coronavirus pandemic.

Additionally, the magnitude of the local peaks varies significantly between the two estimates. The result persuades us to pay closer attention to the details of TVP-VAR-based connectedness analysis. Perhaps more importantly, the TVP-VAR index more accurately reflects market conditions than the rolling window. The TVP-VAR index drops more quickly when financial markets return to their normal state after big market changes.

(a) Returns

(b) Realized volatility

Figure 11: The RW-VAR based total return and volatility spillover indices

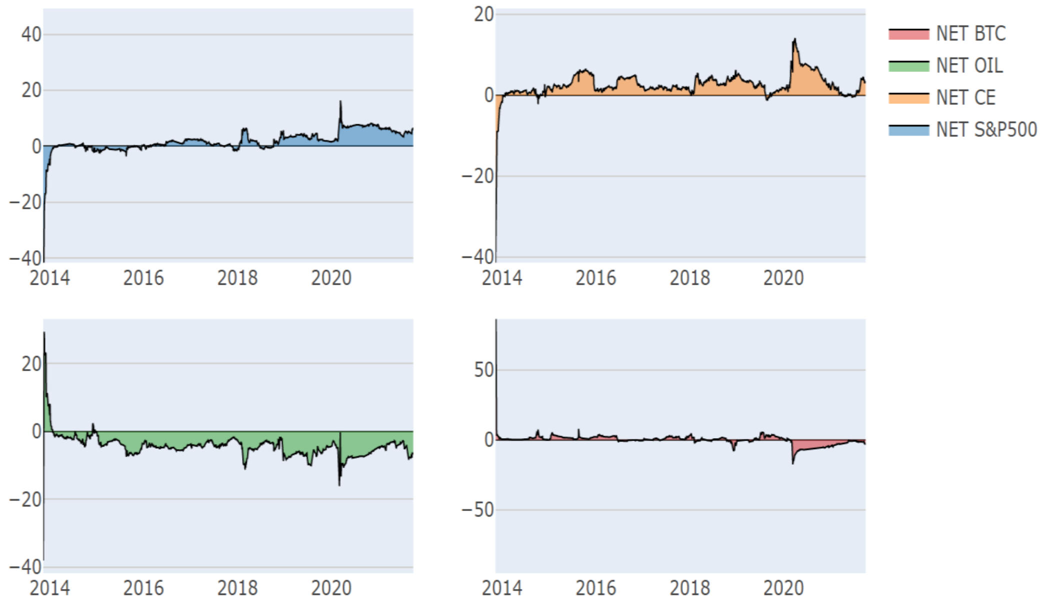
3.4.4 Net Total Directional Connectedness

The net total directional connectedness is calculated using the formula in Eq (7). As illustrated in Figure 5(a), conventional and clean energy stocks are net transmitters for the majority of the sample period, whereas oil is a net receiver for the majority of the period. Until the early 2020s, Bitcoin was a net transmitter, but the spillover effect was negligible. After 2020, it becomes a net receiver with a similar small spillover index magnitude, confirming our findings in Table 4. As demonstrated in panel (b) of Figure

12, the conventional stock is a net risk receiver until 2019, at which point it becomes a net risk transmitter. Following 2018, clean energy was largely a net volatility receiver.

The findings confirm that Bitcoin and oil are net transmitters during the majority of the sample periods. In general, this finding corroborates the findings in Table 4. It implies that stock markets, including CE and conventional one, transfer price shocks to BTC and WTI and receive volatility shocks from BTC and WTI.

(a) Returns



(b) Realized volatility

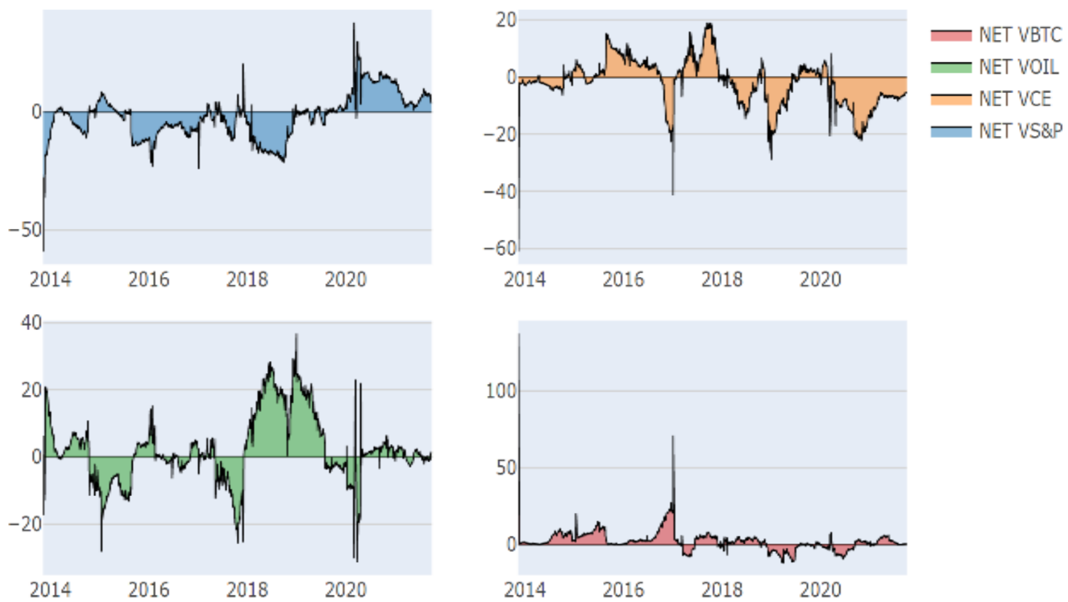


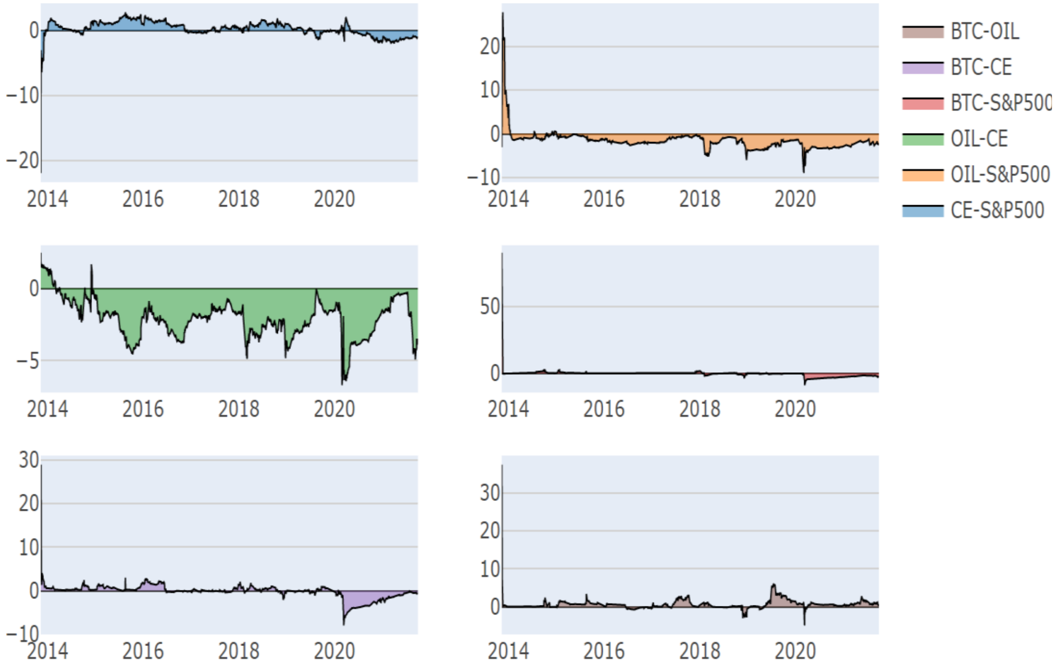
Figure 12: Net total directional return and volatility spillover estimates

3.4.5 Net Pairwise Directional Connectedness

We analyzed the net pairwise directional connectedness in order to more clearly distinguish the propagation processes of return and realized volatilities across the four assets we study. We can define the net transmitters (receivers) between pairs of markets using the NPDC. Figure 13 shows the NPDC estimates, with Panel (a) depicting return spillovers and Panel (b) depicting volatility spillovers.

We are particularly interested in the net pairwise spillover with Bitcoin because it appears to be the most disconnected from other markets. The six distinct combinations of pairwise net return spillovers for the four variables are depicted in Panel (a) of Figure 13. Bitcoin acts as a shock absorber for oil, receiving shocks from the conventional stock market. From early 2014, Bitcoin contributed to clean energy shocks, but following the coronavirus pandemic, it became a receiver of clean energy shocks in return. According to Panel (b) of Figure 13, Bitcoin continues to be the primary source of volatility for clean energy, following the same trend as the traditional stock market. In comparison to clean energy and conventional stock markets, oil became a net receiver of volatility during all major crises, including the oil crash of 2015, the great crypto crash of 2018, and the COVID-19 pandemic. However, oil is a net transmitter of volatility during periods devoid of major crises. Additionally, prior to the Corona virus pandemic, CE was a contributor to the S&P500's volatility.

(a) Returns



(b) Realized volatility

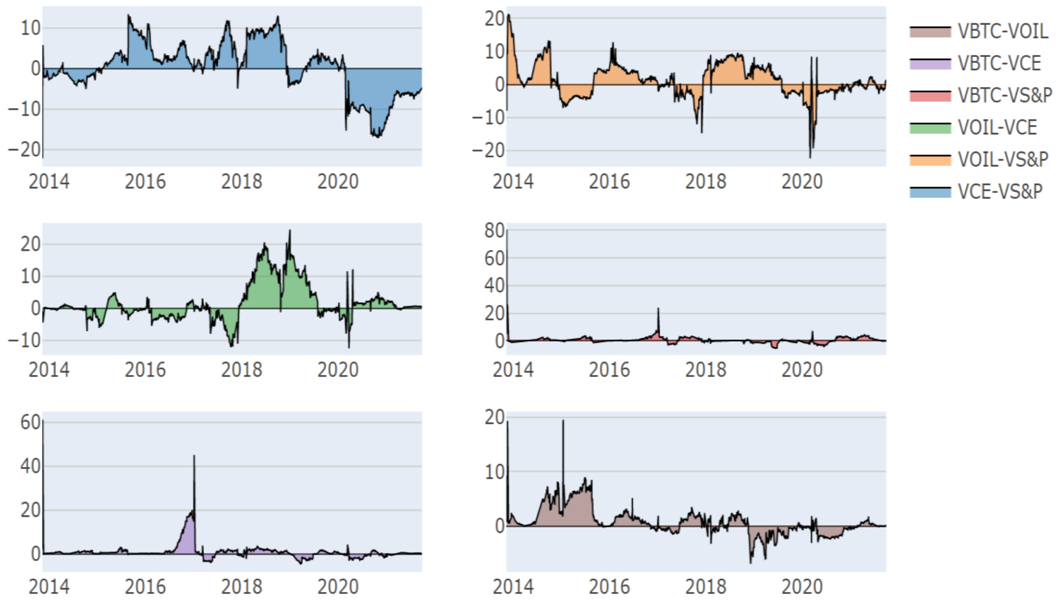


Figure 13: Net pairwise directional return and volatility connectedness estimates

3.4.6 Network Structure

The network plot in Figure 14 depicts the relationship between the S&P500, CE, OIL, and BTC, using the net average pairwise spillover values from Table 4. The direction of the arrows indicates the direction of spillover flow. Edges (arrows) are weighted using average net pairwise directional spillover estimates. The nodes in red (green) indicate the network receiver (transmitter). The average net total spillover determines the size of the nodes. Additionally, we use a 25% threshold to highlight significant spillovers and conceal insignificant ones. The 25% thresholding effectively eliminates all net directional pairwise spillovers less than the 0.75-th quantile.

Figure 14 corroborates our findings in Table 4, as it demonstrates oil as a significant net return shock receiver, while Bitcoin's net return spillover is quite small in Panel (a) of Figure 14. Additionally, clean energy is the sole net transmitter between these four markets, transmitting return shocks to all other markets. Oil and Bitcoin are net transmitters of return shocks in Panel (b) of Figure 14, whereas clean energy and the S&P 500 are net receivers. Additionally, the traditional stocks are the sole net receiver of risk from these four markets.

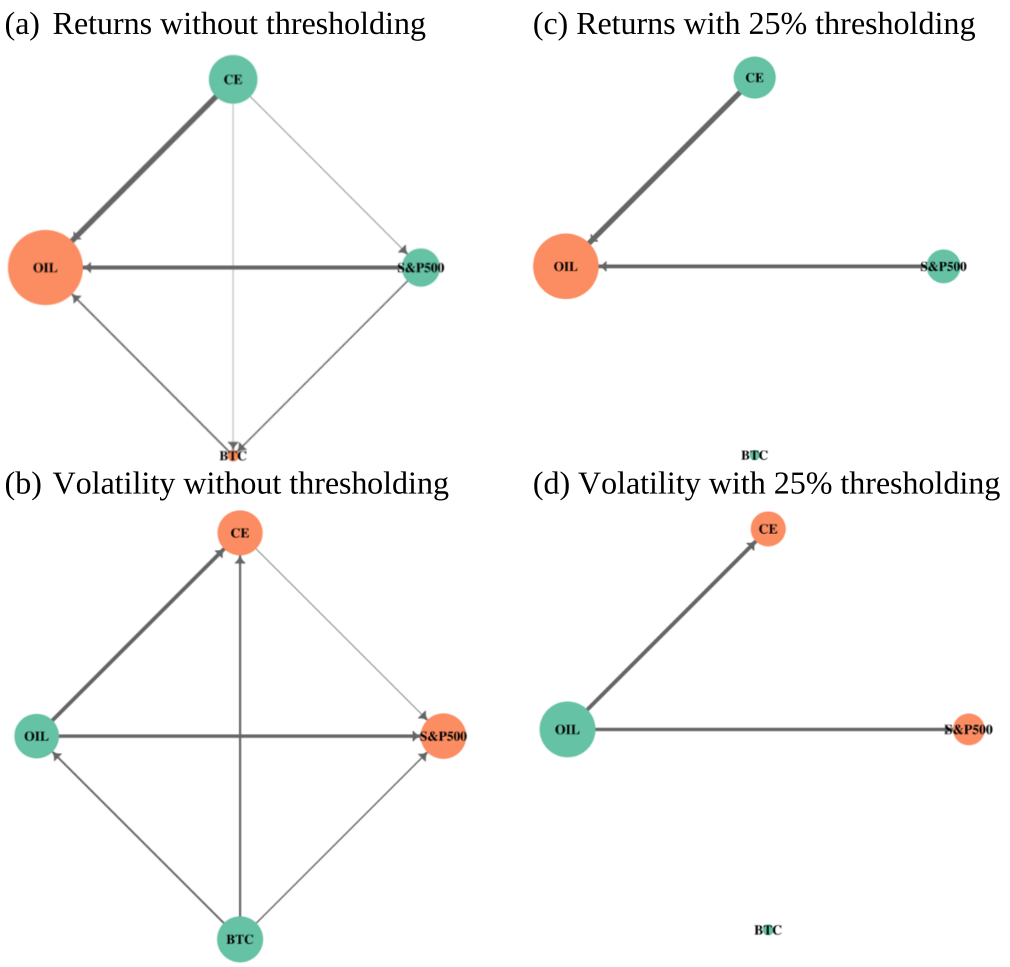


Figure 14: Network plot of net return and net volatility spillovers

Considering the thresholding network diagrams in Panels (c) and (d) of Figure 14 for return and volatility spillovers, respectively, BTC is disconnected from all other markets in terms of both return and volatility spillovers. The oil market is the sole return receiver, while it is the sole transmitter of risk to CE and the S&P 500.

3.5 Discussion

Our results support Ji et al. (2019), as we obtain evidence that shows low connectedness between Bitcoin and oil. In addition, bidirectional spillover was found between oil and Bitcoin, which supports Okorie and Lin (2020). By contrast, to Jareño et al. (2021) and Bouri et al. (2018), we find that oil shocks have a significant linkage with Bitcoin volatility. Moreover, we support Baur et al. (2015), Bouri et al. (2017), and Ji, Bouri, et al. (2018) suggestions to use BTC as a diversifier and hedge against any uncertainty. We use the low connectedness of BTC to other assets to support our recommendation. By contrast to Naeem et al. (2020), during booming US oil production, which caused oil prices to crash in 2014–2016, we do not find significant connectedness between WTI and CE stocks.

Furthermore, we find that oil price and stock market connectedness are time-varying, and they are not pure transmitters of shocks to the CE market, which contrasts with Elsayed et al. (2020). The rise in the CE index and the oil price meltdown during the Corona pandemic crisis confirm Foglia and Angelini (2020), demonstrating that the dynamic volatility of WTI prices and the CE market intensified. This result can confirm our results in terms of dynamic volatility during the pandemic crisis.

3.6 Conclusion and Policy Recommendation

The TVP-VAR-based spillover index-based connectedness method is utilized to determine the dynamic linkage in return and realized volatility between the BTC prices, the conventional stock index, the Wilder Hill CE index, and the WTI crude oil price.

We use the TVP-VAR approach to overcome the shortcomings of the static VAR models. We use daily data from November 11, 2013, to September 30, 2021. In terms of return connectedness, CE and conventional financial markets are net transmitters, so it can be argued that stock prices can be well thought out as an exogenous source of shocks. However, the total net return spillover is around 25%. In contrast to the return spillover results, oil and Bitcoin markets are net transmitters of volatility.

Our findings suggest that stock markets, such as CE and traditional stocks, transmit return shocks to BTC and WTI prices during our study period. On the other hand, they receive volatility shocks from BTC and WTI prices. Furthermore, the realized volatility results show that large shocks caused by events such as the COVID-19 pandemic and cryptocurrency crashes have a massive impact on connectedness during this period.

Our study provides evidence to support the existence of time-varying connectedness among BTC, WTI, CE, and the stock market. Our results indicate that the total connectedness of these markets can be divided into three major periods: (i) the period from 2014 to 2017, (ii) the period from 2018 to 2020, and (iii) the period after 2020. The rapid growth of cryptocurrencies marks the first stage. During this period, positive expectations regarding cryptocurrencies lead to increased connectivity regarding return and volatility. From 2018 to 2020, the second period is marked by the Bitcoin meltdown and a significant amount of negative publicity for cryptocurrencies, such as cryptocurrency hacking. The third period, which begins in early 2020, corresponds to the Corona pandemic, which caused the financial-economic crisis and encouraged investors to invest in safe and liquid assets.

This thesis extends the empirical findings on information transmission among cryptocurrencies and energy markets. In summary, the study demonstrates that the realized volatility connectedness of Bitcoin and financial markets is greater than their connectedness in terms of returns. While our findings have practical consequences for investors in terms of hedging and diversification strategies, they also have ramifications for environmentally concerned policymakers. Specifically, the results suggest that fossil fuel and clean energy stocks are weakly related to Bitcoin during non-crisis periods. Hence, investors might opt to hedge their Bitcoin portfolio with either fossil fuel or clean energy investments.

Furthermore, a policy encouraging green financial markets may encourage Bitcoin investors to use green assets as their primary diversification strategy. However, it should be noted that such a program might not be desirable to environmentally aware investors. As a result, the development of technology that lowers the carbon footprint of the Bitcoin mining process may make cryptocurrencies more appealing to environmentally sensitive investors.

BTC has the potential to be a hedging tool against any type of uncertainty, be it political, economic, or natural. The exploration of the primary reasons for this phenomenon is left to future research. Nevertheless, we believe our results are noteworthy and may be valuable to researchers and Bitcoin market actors in evaluating the impact of BTC on the energy and other markets. As a limitation of this paper, it would be useful to expand it by focusing on various methodologies. For example, the QVAR model can explore the consequences of shocks that are larger than the average shock. We will leave that to future studies. Our study is also limited in terms of country-specific experiences. Further research may look at how each country is different because of different economic factors.

Chapter 4

CONCLUSION

In view of the importance of clean energy as regards alternatives for energy consumption, this thesis attempts to find the dynamic connectedness among CE, traditional stock, green technology, cryptocurrency, and WTI. During a crisis, spillover effects rise in the markets, and any price shocks from one asset can transfer to other assets and change other asset prices. Therefore, investigating the role of assets in terms of shock receivers/transmitters is important. In order to untangle the Dynamic Connectedness of the Stock, WTI, CE, Green technology, and cryptocurrency, the thesis uses two separate case studies in two different chapters.

In chapter 2, the thesis empirically determines the Dynamic Connectedness of the Stock, Oil, Clean Energy, and Technology Markets. In this section, the sample period chosen is from September 2004 until February 2020. For that purpose, we used a spillover index methodology based on Diebold & Yilmaz (2012) generalized forecast error variance decomposition (GFEVD). The Diebold and Yilmaz technique, in essence, provides an informative evaluation of connectedness that may be made dynamic by rolling estimation over time. The CE index and the WTI price are the volatility receivers, according to the outcomes of the linear model. The stock market and technology indices, on the other hand, are net shock transmitters. The S&P 500 is the most significant source of volatility spillovers, whereas oil is the lowest of the four markets.

Sadorsky (2012) concludes that nonrenewable energy is a useful hedge for green stocks is contradicted by our findings. According to the data, oil price variations are not the most important factor influencing the profitability of renewable energy and technology businesses. These companies have the clout to change course in reaction to a less dependent business climate on the nonrenewable energy market. Investors may believe that scientific breakthroughs and technologies are critical to renewable energy and technology firms' profitability and stock value. Because of energy-efficient production processes, the oil market may lose its role. According to quantile VAR, the volatility spillover is more relevant for large positive volatility than average. In addition, negative volatility does not result in bold spillovers across these four markets.

Chapter 3 investigates the dynamic return and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets. In a daily dataset spanning November 11, 2013, to September 30, 2021, the time-varying parameter vector autoregression (TVP-VAR) is used to evaluate connectedness dynamics and solve the drawbacks of static VAR models.

Our results imply that stock values, such as green and traditional stocks, transmitted return shocks to BTC and WTI prices during the study period. Bitcoin and oil prices, on the other hand, cause them to experience volatility shocks. Furthermore, the realized volatility results reveal that major shocks like the COVID-19 pandemic and cryptocurrency collapses significantly impacted connectedness throughout this period.

In conclusion, the research shows that the realized volatility connectedness of bitcoin and other assets is larger than their returns connectedness. Our conclusions have implications for investors in terms of hedging and diversification strategies and policymakers who are concerned about the environment. Specifically, the findings imply that during non-crisis periods, WTI and CE stocks are only marginally associated with Bitcoin. As a result, investors may choose to diversify their Bitcoin holdings by investing in either fossil fuels or renewable energy.

Due to limitations on the number of variables included in the connectedness analysis, we include only four asset classes that are more effective in the energy sector. Gold is the most popular precious metal and has the lowest volatility. Gold is utilized as an effective hedge when stock market risks are taken into account. Gold is one of the significant assets in portfolio diversification, it acts as safe haven during a crisis and in a successful portfolio, investors should consider the role of this irreplaceable asset. we leave the connectedness of gold and green stocks for future study. In addition, the role of gold and bitcoin as safe haven may change during different types of crises among financial and non-financial markets. therefore, the portfolio managers should consider the role of gold as hedging their investment risk.

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