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Research paper

Interconnected Markets: How Energy, Green Finance, and APEC Equities Drive Global Volatility

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Abstract

This study explores the evolving interconnectedness among energy markets (Crude Oil, Natural Gas, Heating Oil, GRNSOLAR, GRNWIND, and GRNBIO), gold, technology (NDXT), green bonds, and equity markets within APEC economies (S&P 500, TSX, NIKKEI 225, ASX 200, NZX 50, SSEC, SETI, MOEX, KOSPI, and TWII) from January 2014 to May 2024. Using a time-varying parameter vector autoregressive (TVP-VAR) model, the research unveils dynamic cross-market relationships, with a Total Averaged Connectedness Index (TACI) of 60.68%. This indicates that nearly 60% of forecast error variance originates from cross-market shock transmission, underscoring the high degree of global financial interdependence. Notably, the energy and emerging equity markets demonstrate a connectedness of 45% in the short term (1–5 trading days) as investors swiftly react to economic signals and external shocks. However, this interconnectedness diminishes to 15.48% in the long term, reflecting market resilience as initial impacts dissipate. These findings emphasize the significance of volatility transmission in shaping market dynamics and provide valuable guidance for investors and policymakers in navigating risks within an increasingly interconnected global financial landscape.

Keywords: *Energy Commodity; APEC Economies; TVP-VAR Connectedness; Interconnected Markets, Energy; Green Finance.*

1. Introduction

Over the past few decades, global energy consumption has rapidly risen, thus raising the issue of CO_2 emissions and consequently enhancing the rate of global warming, which poses a threat to ecosystems and the environment. This situation has increased awareness of the environment and the need to provide alternative energy forms to fight global warming, the effects of carbon dioxide emissions on the conventional energy sectors, and the increasing costs of fossil-based energy. Therefore, the clean energy sector has attracted a lot of interest from investors and policymakers. A report sourced from Bloomberg New Energy Finance (BNEF)[1] notes that global clean energy investment was \$332.1bn in 2018. Over the last five years, annual spending on clean energy has been above \$300 billion, and market analysts' predictions state that the sustainable energy sector could hit the \$2 trillion mark shortly.

As demand for and investment in the clean energy sector continues to grow rapidly, it has become increasingly important for investors and policymakers to understand the intricate connections and volatility transmission among clean energy, Gold, Technology, Green Bonds, and APEC Equity Markets. Nevertheless, the literature on the connection between these markets continues to provide mixed evidence (Kumar et al., 2012; Maghyereh et al., 2019). The correlation between crude oil prices and the stock prices of clean energy and technology companies has been studied in several studies, although the findings are inconclusive. Studies emphasize that this correlation depends on numerous factors, such as market conditions, timeframes, and external factors, such as technological advancements and policy changes (Ahmad, 2017; Bondia et al., 2016; Henriques & Sadorsky, 2008; Kumar et al., 2012; Maghyereh et al., 2019; Sadorsky, 2012). These contradictions indicate that additional research is necessary to explain the relationship between fossil fuel markets and clean energy investments.

1) New Energy Finance. Global trends in renewable energy investment 2018 (2018). Accessed at http://fs -unep -centre.org/publications/global-trends -renewable -energy investment - 2018.

The world is currently experiencing a lot of challenges, including the threat of new virus strains, high inflation, changes in monetary policies, and the transformation of central bank strategies in the aftermath of the COVID-19 pandemic. To this complicated picture, the unforeseen Russia-Ukraine war has been added, a so-called black swan crisis with worldwide political consequences and which has impacted the markets, raising inflation and interest rates. The literature on the impact of conflict and war on commodity markets, green bonds, and ESG indices is increasing as these assets are considered volatile during the crisis. Lundgren et al. (2018) noted that various uncertainty indicators, such as VIX and financial stress, have a significant impact on the returns and volatility of clean energy stocks. As Zhao (2020) noted, shocks may negatively affect the prices of clean energy stocks. Chakrabarti and Sen (2021) examined the market risks in relation to green energy equities and determined that these stocks possess defensive characteristics, which are of interest to investors who do not want to lose much. Moreover, there are still risks related to financial instability, and such major events as the COVID-19 pandemic highlight these weaknesses.

The world economy, including commodity markets, suffered significant losses, and energy prices have again skyrocketed after Russia invaded Ukraine on February 24, 2022. This shock came at a time when the world economy was starting to emerge from the long-term effects of the COVID-19 pandemic. Researchers have responded by increasingly applying the Financial Stress Index (FSI) to study the impact of financial instability on stock and commodity price volatility. The FSI has been used to measure the effects of economic uncertainty and stress on market volatility in studies by Gkillas et al. (2020), Saadaoui et al. (2022), and Trichilli and Boujelbene (2023), which provide insight into the overall consequences of geopolitical and financial shocks.

The recent literature has highlighted the influence of geopolitical risk (GPR) on energy and metal prices. Studies by Su et al. (2019), Li et al. (2021), Gong and Xu (2022), Umar et al. (2022), and Li et al. (2023) have emphasized the role of GPR in these markets. Bedowska-Slojka et al. (2022) specifically examine GPR as an investment strategy, using the wavelet coherence technique to determine whether GPR, particularly during the Russia-Ukraine conflict, can hedge against a variety of assets such as oil, gold, and silver. In a similar study, Umar et al. (2022) investigate the effects of Russian activities in Ukraine on global resources like oil, gas, and gold, through quantile regression to see how GPR behaves with asset prices in various market conditions (bearish, normal, and bullish). Together, the Russia-Ukraine war has increased financial instability, especially in commodity prices, and has led to heightened volatility in the global markets.

Green finance is a relatively new and rapidly developing sector, and it is also capable of demonstrating stronger and less decoupled growth than conventional financial markets (Born et al., 2021). As the attention on green finance is growing, the issue of portfolio diversification and risk management in terms of investment is becoming a matter of concern among investors and policymakers. This heightened interest is part of a wider trend towards sustainable investment strategies, which seek to reconcile financial performance with environmental goals. The studies by Lundgren et al. (2018), Vardar et al. (2018), Pham (2021), Trichilli et al. (2022), and Liu et al. (2023) highlight the importance of strategic solutions that can not only reduce downside risks but also contribute to long-term financial stability and environmental resilience. The pricing of green assets has emerged as a major area of concern, with investors, risk managers, and policymakers paying particular attention to it. With the world slowly shifting to clean energy sources, the new investment opportunities in equity are now taking the form of clean energy stocks. The past and recent clean energy finance literature was primarily concerned with the cross-sectional relationships between clean energy stock returns and oil prices, technology stocks, and major macroeconomic variables like financial market risk and uncertainty related to economic policies (Nasreen et al., 2020; Geng et al., 2021; Le et al., 2021; Saeed et al., 2021). These studies emphasize the complex relationships, which illuminate the way in which changes in economic conditions and the energy market may influence the value and performance of equity market investments. Studies have shown that the stock prices of clean energy are influenced by changes in oil prices and technology stock prices, and economic policy uncertainty may affect the stock prices of clean energy firms in various ways. Also, the commodity prices in the clean energy industry, including clean energy stocks, gas, oil, green bonds, and ESG indices, are a relatively unexplored field. This gap is a special opportunity to conduct further research, as the Connectedness between these investments and the ability to make informed decisions among investors, policymakers, and risk managers.

To fill this research gap, this paper will examine the dynamic interconnectedness and volatility transmission channels between energy, gold, technology, green bonds, and equity markets in the APEC region. Through the analysis of a detailed dataset between January 2014 and May 2024. This study will examine the interaction of these different markets, how they affect one another, and how they react to external economic and geopolitical changes as time goes by. The interconnectedness and volatility transmission that the study will focus on will shed light on the complicated relationships between markets. This will not only give a better insight into the factors that cause price changes in these markets but also assist in determining any spillover effects or feedback loops. As an example, the ripple effects of changes in energy, green bond, or technology markets on the performance of APEC equities can be quantified, and this study will do so. it will help to develop a more comprehensive framework to manage risks related to equity markets in APEC, a region with diverse economic structures and growth potential. This paper uses the spillover index methodology proposed by Diebold and Yilmaz (2009, 2012, and 2014) to examine the transmission channels of volatility shocks in energy, gold, technology, green bonds, and equity markets. The approach allows a precise evaluation of the extent and direction of interconnectedness among financial variables over time, which is useful in understanding the contagion effects among global markets. Although this method has been widely used, there are not many studies that have examined the dynamic interrelatedness between energy, gold, technology, green bonds, and equity markets in the APEC region, and in the context of recent financial crises. This paper fills this gap by examining the volatility spillover between these markets, considering the impact of recent economic shocks. The inclusion of these crisis periods will help the study to capture the changes in market behaviour and interconnectedness during times of financial stress, which will provide insight into how market shocks are transmitted in this heterogeneous economic region.

2. Review of literature

In the last few years, there has been a major emphasis on renewable energy across the globe due to the PCA that was signed in 2016 by 202 countries. Both parties are to cut carbon emissions with a unifying target of reaching net-zero carbon by 2050, to avoid global warming beyond 2 °C using fossil fuels and the promotion of renewable energy. For instance, hydrogen is considered one of the most important elements of the energy transition that the world requires for society to achieve the Sustainable Development Goals for 2030. Subsequently, the renewable energy sector is growing fast, and IRENA has forecasted a 77% global renewable energy mix by 2050 from the current 16% in 2020. The shift from fossil energy to renewable energy has attracted international interest (Caporale et al., 2023; Dutta et al., 2020; Lucey & Ren, 2023). These investments rose after the PCA, and specifically, during the COVID-19 crisis when governments transitioned from exploiting damaging energy sources to clean projects (Caporale et al., 2023). For instance, the countries in the European Union transferred money from the fossil fuel industry to renewable energy, thus addressing the climate risks (Peake and Ekins, 2017; Rietig, 2021).

Future impacts of the COVID-19 pandemic and the Russo-Ukrainian War, along with changes in laws and regulations and advances in clean energy technology, will raise the investment risk in these markets. Investors can therefore effectively manage the risk associated with their portfolio and at the same time enhance the returns of their portfolio through investment in the hydrogen economy and the renewable energy markets. Previous research (Alkathery and Chaudhuri, 2021) explored the relationship between renewable energy assets and energy products/energy sector equities. The returns of clean energy assets are characterized by the fluctuation in the crude oil price, as the evidence of the existence of a strong and significant COP effect on RES is well documented in the literature (Dutta, 2017; Reboredo, 2015; Reboredo et al., 2017; Reboredo and Ugolini, 2018). The COVID-19 pandemic is also identified to have high cross-over effects of oil price towards clean energy stocks (Peer et al., 2023; Ghabri et al., 2021).

The literature focuses on the characteristics of different sorts of assets, especially the energy market. Ji et al. (2018 use time series analysis to analyze both risk and return of the carbon and energy markets, with a focus on the green energy market. They establish that although there are significant return linkages, volatility connections are more pervasive and therefore provide an indication of the importance of volatility in capturing market synchronicity and systemic risks. This insight is useful for investors and policymakers in managing risks, managing their portfolios, and maintaining market stability during the transition to renewables. Nasreen et al. (2020 analyze the causal relationship between crude oil, technology, and renewable energy stocks and unveil the fact that there is a very low correlation between time domain and frequency domain causality. On this basis, Naeem et al. (2020 further explore the dynamic and frequency domain co-movement between oil price shocks and energy markets, electricity, renewable energy, and carbon. This is well captured in their research, which shows how the shale oil revolution has enhanced these interconnections, as energy markets gradually become more integrated and complex.

Market Volatility entails understanding the impacts of its changes across various industries and sectors. Elsayed et al. (2020 examine the correlations of oil price volatility with another seven markets and discover that the fluctuations in oil prices are closely related to these markets in a weak manner. But at the same time, they also emphasize the role of global stock along with energy indices as a buffer which can help to reduce any negative effect on the green market. Similarly, by employing the data on fossil fuel prices and green markets, Foglia and Angelini (2020 reveal that the COVID-19 pandemic enhances both static and dynamic volatility. Moreover, Chen et al. (2022 investigate the extreme volatility transmission between metals, renewable energy, and fossil fuel markets using the quantile regression technique. As they point out, these externalities are more pronounced in moments of volcanic market movements with either gains or losses. This signal indicates that generic mean-based models might underestimate the extent of market shocks during such episodes of volatility, and therefore, other forms of volatility modelling techniques ought to be employed.

In recent literature, more attention has been paid to the temporal aspect of market spillovers. Liu and Gong (2020), Lin and Su (2021), and Mokni et al. (2020 apply the spillover index model combined with TVP-VAR to investigate the connectivity of energy markets during the crisis period. According to their results, the investigated aspects show a positive association between internal market linkages under stress. To this end, Attarzadeh and Balcilar (2022) investigate the transmission of return and volatility between Bitcoin, crude oil, clean energy, and stock markets during the pandemic and find that Bitcoin plays a significant role in shock transmission. Likewise, Zhang et al. (2022 look at the effect of the pandemic on oil, gold, and Bitcoin and find that both gold and Bitcoin are more risky due to the disruption of the supply chain and volatility. Antonakakis et al. (2023) find that implied oil volatility essentially moves in tandem with the stock market as a net receiver of shocks. In the same vein, Umar et al. (2022 show that gold became a net receiver of volatility shocks in 2021 due to geopolitical tensions, especially the Russian conflict, which also affected long-run volatility linkages in financial markets. From the green finance perspective, Lu et al. (2023 argue that clean energy was the most dominant driver of return and volatility transmissions during the COVID-19 pandemic and its rising relevance in the global financial system.

Other subsequent research also remain concerned with the process of market integration during crises. Cunado et al. (2024 examine the impact of COVID-19 on energy and metal markets, where they point out that the pandemic has increased the level of market integration than it was in the Global Financial Crisis period. They note gold, silver and heating oil as the primary Commodity price volatility proxies while noting that the transmission of volatility through crude oil has weakened in recent years. Hence, Mishra et al. (2023 take a discourse on the Indian Commodity futures markets amidst the pandemic. They argue that the market linkages have especially risen, particularly for the precious metals and energy. Among all the tested variables, crude oil and zinc were identified as the main channels through which domestic volatility was transmitted, with gold and silver being more responsive to external volatility. To effect such a shift, the implication is that the type of diversification opportunities which are available in investors' portfolios during the crisis was lower.

Regarding the Russia-Ukraine war, a study by Ha (2023 examines the co-movement between crude oil, gold, and stock markets, and from this it is seen that both crude oil and gold maintained high volatility during the entire duration of the conflict. This paper explains how the war lengthened the fluctuation in the markets and even exacerbated conditions in the global financial markets. The study concludes that the geopolitical crisis has played a major role in escalating risks and level of uncertainty of financial systems across the globe as well as in destabilizing them. The global economic product which was useful in the international financial system, crude oil and gold acted like the channels through which volatility fluctuation occurred and intensified the general market risk during the war. Le, 2023 examines the relation between the cryptocurrency markets and renewable energy markets in the context of COVID-19 crisis and Russia- Ukraine war. From their analysis, the authors recognize a clear discontinuity in the volatility process of cryptocurrencies which transitioned from receiving stability during stable periods and then becoming volatility sources during volatile periods. This may have been occasioned by the fact that cryptocurrencies are more susceptible to shocks in the rest of the economy, particularly during periods of volatility. In addition, the study discusses the markets of renewable energy, and it was observed that these markets acted as carriers of shock when – Ukraine conflict happened. These changes in the markets were due to the disruption of the energy supply chain, Geopolitical risk affected energy pricing, and the markets. This study, therefore, concludes that both the cryptocurrency and renewable energy markets are no longer marginal markets that only add to the overall financial crisis during crises.

There are some studies on the characteristics of systemic risks that take place in the financial markets during a crisis. In Huang et al. (2023 analysing the WTI crude oil and natural gas, the authors discuss the transmittal of volatility between energy commodities and financial markets and suggest that WTI crude oil and natural gas were particularly significant as volatility transmitters during the COVID-19 pandemic. This resulted in a higher level of integration between the markets and thus a higher proportion of systemic risks. In the same manner, Nguyen et al. (2023 explain the impact of the pandemic on the volatility co-movement between cryptocurrency and energy markets. In their study, they discovered that crude oil and natural gas were identified as major volatility transmitters during the time of the crisis, whereas renewable energy and cryptocurrencies as the major volatility shock absorbers. Moreover, Aliu et al. (2024 discuss the effect of Bitcoin on different financial markets and conclude that it positively affects the gold price. However, the study could not determine the impact that Bitcoin has on other assets, for instance, the VIX and USDX. Due to its impact on the market, Bitcoin has attracted more attention for diversification, especially for a gold hedge. These findings underscore the changing nature of digital currencies, especially Bitcoin, as an essential component of investment management, especially in portfolios, during periods of increasing market risk and fluctuations.

However, as has been noticed, there is a huge number of publications that investigate this area, and thus our study would like to concentrate on a significant problem that has not been studied enough. Within the current literature, there is a clear trend towards the analysis of the interconnectedness of volatility in the financial and non-financial markets. However, attention has not been paid to the pattern of connectedness in returns and volatility in the APEC region. However, it is critically important to bear in mind both aspects to get a better understanding of the nature of the market interconnection and be able to deliver essential information to the investors. Furthermore, the best estimator should be employed in the estimation of connectivity since connectivity patterns may vary over time. Based on the above-identified research gap, the main goal of the study is to examine the co-movement of returns of Energy, Gold, Technology, Green Bonds, and APEC Equity Markets. More precisely, the research questions address portfolio consequences that may emerge in the COVID-19 and Russia-Ukraine war periods. Using a time-varying parameter vector autoregression (TVP-VAR) model, we investigate the connectedness of the selected asset indices and consider the impact of both COVID-19 and the Russia-Ukraine war. In the full sample and during the COVID-19 and Russia-Ukraine war period. We try to find out whether there are differences in return connectedness and spillover during the COVID-19 pandemic and the Russia-Ukraine war.

3. Data and methodology

3.1. Data

This study aims to examine the dependency patterns among the Energy (Crude oil, Natural Gas, Heating Oil, GRNSOLAR, GRNWIND, and GRNBIO), Gold, Technology (NDXT), Green Bonds, and APEC Equity Markets(S&P 500, TSX, NIKKIE225, ASX200, NZX50, SSEC, SETI, MOEX, KOSPI, TWII). The analysis covers an extensive period from January 2014 to May 2024, providing a robust dataset for assessing long-term dependency trends and short-term market fluctuations across these sectors. For each data series, daily returns are computed to capture the day-to-day movements in market value. The formula for calculating daily returns is: $r_{it} = 100 \times \ln\left(\frac{pi,t}{pi,t-1}\right)$. where pi,t represents the stock market index of country i at time t. The log-return formula normalises returns across markets and periods, which makes it suitable to compare returns. This type of analysis can be used to determine systemic risks, co-movement patterns, and the contribution of each sector to regional and global financial stability. Figure 1 shows these calculated returns, and there are notable differences over time throughout the entire sample period. In the data, there are visible spikes that represent significant economic, financial, or pandemic-related events, when markets are characterized by increased interconnectedness and volatility. These spikes indicate that major events, either global or regional, cause an increase in the intensity of relationships between energy markets and emerging stock markets, which influence volatility and patterns of returns. These time-varying patterns are important to understand how external shocks may affect market behaviour and interdependencies, and offer useful insights into the resilience and sensitivity of these markets to stress. This method therefore helps in providing a more holistic picture of the interaction between emerging economies' stock markets and global energy markets in different economic conditions.

The time trends in the cross-section of the different markets that have been used in this study indicate how various key events in the world have influenced various aspects of the relationship between energy markets and emerging stock markets in a fundamental manner. These are the Ebola virus outbreak (20142016), which increased market insecurity in the global markets; the Brexit vote (20152016) which caused political and economic instability in Europe and the world; the occurrence of shale oil and the crash of the Chinese stock markets (20152016), which shook the commodities, energy and stock markets respectively. Moreover, the US monetary policy in 2018 raised the interest rate, which triggered financial stringency, impacting capital flows and subsequently the global markets. Due to COVID-19 (2019-present) has led to unprecedented market disruptions, which led to fluctuating, steep volatility in energy and stock markets due to lockdowns, economic contraction, and disrupted supply chains. More recently, the Russia–Ukraine conflict has worsened the scarcity of energy around the globe, thus deepening insecurity and fluctuation on the market. These events have caused cycles of high cross-sensitivities between energy markets and stock returns, and each crisis has contributed to increasing the level of market integration. The fluctuations and spill-overs observed in the return series during these episodes show how integrated global energy and stock markets have become, especially to large shocks in the economic and financial systems, geopolitics, and pandemics.

3.2. Methodology

3.2.1. TVP-VAR-based connectedness approach

The DY method proposed by Diebold and Yilmaz (2014) has been extensively used in previous studies to examine directional volatility spillovers and the volatility transmission between markets. This method usually uses a rolling window method, which is effective but limited. In particular, the selection of the rolling window size may cause methodological issues, including the omission of some observations, as noted by Dai and Zhu (2022). To overcome these problems, Antonakakis et al. (2020) suggested a different model, the time-varying parameter vector autoregressive (TVP-VAR) model. In contrast to the traditional rolling-window approaches, TVP-VAR allows using flexible window sizes without dropping observations, which provides a more complete estimation procedure (Mishra and Ghate, 2022). This paper extends the study of Antonakakis et al. (2020) by using a TVP-VAR (1) model, which is chosen according to the Bayesian Information Criterion (BIC), to examine the interconnectedness of asset returns across different asset classes. This model can be mathematically represented as follows:

$$\lambda_t = B_{t\lambda_t} - 1 + \varepsilon_t, \varepsilon_t \sim N(0, S_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + u_t, u_t \sim N(0, R_t) \tag{2}$$

Whereλ_t, λ_{t-1} and the error term ε_t are specified as k × 1-dimensional vectors. $vec(B_t)$ Represents the vectorized form of B_t, and S_t and R_t represent the variance–covariance matrices. Note that B_t and S_t They are k × k-dimensional matrices. U_t is a k2 × 1 dimensional vector, and R_t is specifed by a k2 × k2 dimensional matrix.

The scaled Generalized Forecast Error Variance Decomposition (GFEVD) was used to perform the generalized spillover analysis, which is an aggregation of the H-step ahead forecast as described by Diebold and Yilmaz (2014). This method allows calculating both directional connectedness and net connectedness between asset returns, which can give an idea of the complex interdependencies between various markets. The methodology uses an n-variable structure, ($\lambda_t = \lambda_{t.1} \ldots \lambda_{t,n}$). This procedure records the dynamic relationships between the variables as time progresses, providing a strong depiction of how shocks in one market spread to others.

$$\lambda_t = \sum_{s=1}^{p} \vartheta_h \lambda_{t-s} + \varepsilon_t \tag{3}$$

In this model, ϑ_h is an n x n p-order lag polynomial of order P and represents a vector of white noise disturbances, with a non-diagonal error covariance matrix. This structure makes sure that the error terms take into consideration the possible correlations among variables, which is the interdependence of the system. The Vector Autoregressive (VAR(p)) process is also extended to its moving average (MA) representation. This transformation is important because it enables the analysis of the dynamic relationships between variables over time by writing them as a function of current and past disturbances. In particular, the VAR (p) model is rewritten as a Vector Moving Average (VMA) process, which is essential in computing forecast error variance decompositions and measures of connectedness. The TVP-VAR approach generalizes the conventional VAR by adding time-varying coefficients to the model. These coefficients change, reflecting the changing relationships between variables. The TVP-VAR is then converted into a time-varying Vector Moving Average (TV-VMA) specification, which can be specified in Eq. (4).

$$Z_t = B_t Z_t + \varepsilon_t = \sum_{z=0}^{\infty} A_{jt} \varepsilon_t t - j\# \quad (4)$$

Since A_{jt} denotes the square matrix of coefficients, the generalized forecast error variance decomposition (GFEVD) of the H-step forecast of the j-th asset return to shocks of the i-th asset return is given by the equation (usually Eq. (5)) as follows:

$$\phi_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_t \Sigma\, ej^2)}{\sum_{h=0}^{H-1} (e_i' A_t \Sigma\, ej)} \quad (5)$$

When ϕ_{ij}^{g}(H)is normalized, the spillover index can be represented as follows:

$$\Theta_{ij,t}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1,i=1}^{N} \Theta_{ij}^{g}(H)} \quad (6)$$

Where e_j is a vector that has 1 on the place of the jth asset return, and $\sum_{j=1}^{N} \Theta_{ij}^{g}(H) = 1$ and $\sum_{ij=1}^{N} \Theta_{ij}^{g}(H) = N.\sigma_{jj}^{-1}$ The standard deviation of the error term serves as a key measure of variability in the model's residuals, capturing the extent of unexplained deviations in the system. From this framework, several connectivity metrics were derived to analyze the interrelations among variables: the Total Connectedness Index (TCI), "FROM" connectedness, "TO" connectedness, net directional connectedness, and net pairwise directional connectedness. These indices, calculated based on the connectivity measures outlined in Equations (7) and (11), respectively, provide a comprehensive view of how shocks propagate within the system:

Total connectedness index (TCI):

$$TCI_t^{g}(H) = \frac{\sum_{i,j=1,i\neq 1}^{N} \Theta_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N} \Theta_{ij,t}^{g}(H)} = \frac{\sum_{i,j=1,i\neq 1}^{N} \Theta_{ij,t}^{g}(H)}{N} * 100 \quad (7)$$

FROM AND TO connectedness Index

$$TD_{i-j}(H) = \frac{\sum_{i=1,i\neq 1}^{N} \Theta_{ji,t}^{g}(H)}{\sum_{j=1,i\neq j}^{N} \Theta_{ji,t}^{g}(H)} * 100 \quad (8)$$

$$TD_{j-i}(H) = \frac{\sum_{i=1,i\neq 1}^{N} \Theta_{ij,t}^{g}(H)}{\sum_{i=1,i\neq j}^{N} \Theta_{ij,t}^{g}(H)} * 100 \quad (9)$$

Net directional connectedness index (NDC):

$$CI_{i,t}^{g}(H) = TD_{i-j}(H) - TD_{i-j}(H) \quad (10)$$

Net pairwise directional connectedness index

$$NPDC_{i,j}(H) = \left(\Theta_{ji,t}^{g}(H) - \Theta_{ij,t}^{g}(H) \right) * 100 \quad (11)$$

3.3. Preliminary analysis

In this study, we investigate the interconnectedness between Energy (Crude oil, Natural Gas, Heating Oil, GRNSOLAR, GRNWIND, and GRNBIO), Gold, Technology (NDXT), Green Bonds, and APEC Equity Markets (S&P 500, TSX, NIKKIE225, ASX200, NZX50, SSEC, SETI, MOEX, KOSPI, TWII). Table 1 and Figs. 1 presents the descriptive statistics and evolution of returns. Table 1 provides a detailed summary of the descriptive statistics for various financial markets, energy commodities, green assets, and other indices, offering insights into their risk-return profiles and distributional characteristics. The mean returns indicate that MOEX exhibits the highest average performance (0.059), while Green Bonds display a slightly negative mean (-0.003), reflecting challenges in this asset class. Crude Oil, with a negative mean (-0.107), suggests significant price declines, likely due to crises such as the COVID-19 pandemic. Variance highlights the volatility differences, with Crude Oil showing the highest variance (50.801) and Green Bonds the lowest (0.14), reinforcing their roles as high-risk and stable assets, respectively.

Table 1: Descriptive Statistics

	Mean	Variance	Skewness	Kurtosis	JB	Q(10)	Q2(10)
S.P.500	0.047	1.222	-0.525***	14.995***	24582.357***	136.512***	2389.326***
TSX	0.024	0.894	-1.000***	37.670***	154813.612***	93.970***	2032.525***
Nikkei.225	0.042	1.625	0.097**	4.074***	1809.763***	14.769***	322.945***
ASX.200	0.019	0.926	-0.789***	11.246***	14029.205***	61.411***	2447.012***
NZX.50	0.037	0.519	-0.443***	12.241***	16386.423***	18.517***	1006.530***
SSEC	0.024	1.756	-0.415***	7.890***	6847.663***	12.617**	691.315***
SETI	0.009	0.838	-1.359***	19.547***	42372.467***	25.452***	725.524***
MOEX	0.059	6.743	25.403***	1090.093***	129558231.906***	21.741***	0.339
KOSPI	0.022	1.22	0.179***	5.340***	3116.166***	11.619**	1132.789***
TWII	0.04	0.943	-0.086*	6.257***	4261.906***	13.593**	332.973***

Crude. Oil	-0.107	50.801	-32.316***	1335.624***	194526969.893***	251.829***	75.337***
Natural. Gas	0.059	15.942	1.018***	15.717***	27324.091***	33.143***	137.078***
Heating oil	0.019	4.964	-0.360***	7.812***	6695.949***	5.275	441.815***
GRNSOLAR	0.08	5.326	2.135***	31.912***	112775.425***	29.694***	18.526***
GRNWIND	0.047	2.945	-0.215***	4.712***	2435.690***	14.653***	159.176***
GRNBIO	0.019	4.286	-0.080*	9.251***	9312.396***	33.042***	977.105***
Green. Bond	-0.003	0.14	-0.084*	4.280***	1996.421***	41.045***	409.013***
Gold	0.028	0.841	0.064	3.849***	1613.851***	6.867	141.593***
Electricity	0.033	1.454	0.022	16.272***	28807.517***	90.489***	2691.802***
NDXT	0.06	2.601	-0.219***	5.671***	3519.866***	73.575***	1535.850***

J-B denotes the Jarque Bera statistics, ***, **, and * correspond to the 1%, 5%, and 10% levels of statistical significance. The ERS test pertains to the unit root test by Stock et al. (1996). Q (20) and Q2 (20) signify the Ljung–Box statistics used to examine serial correlation in the original series and squared residuals.

The skewness values reveal asymmetry in return distributions, with assets like Natural Gas (1.018) and GRNSOLAR (2.135) showing positive skewness, indicative of large occasional positive returns. Conversely, Crude Oil (-32.316) and several equity markets display significant negative skewness, reflecting sharp downward movements. High kurtosis across all variables, particularly in MOEX (1090.093) and Crude Oil (1335.624), indicates heavy tails and extreme price movements, signifying their susceptibility to global shocks. The Jarque-Bera test rejects normality for all assets at a 1% level, except for Gold, highlighting non-normal distributions with heavy tails and skewness. Serial correlation, as measured by the Ljung-Box Q(10) and $Q^2(10)$ tests, indicates significant dependencies in returns and volatility clustering for most assets, particularly in equity indices like S&P 500 and TSX, and energy commodities like Crude Oil and Natural Gas. Among asset classes, equity indices show moderate volatility and negative skewness, with regional markets like SSEC and SETI displaying higher kurtosis, reflecting vulnerabilities to extreme events. Energy commodities, especially Crude Oil and Natural Gas, exhibit high variance, extreme skewness, and kurtosis, underscoring their exposure to geopolitical and economic shocks. Green assets like GRNSOLAR and GRNBIO show higher mean returns but significant kurtosis, indicating potential for high rewards accompanied by elevated risks. Conversely, Green Bonds show minimal variance, aligning with their reputation for stability. Gold, as a safe-haven asset, demonstrates lower skewness and kurtosis, underscoring its role as a stabilizing force during uncertainty. The NASDAQ Clean Energy Index (NDXT) exhibits moderate returns but significant kurtosis, driven by fluctuations in technological advancements and investor sentiment.

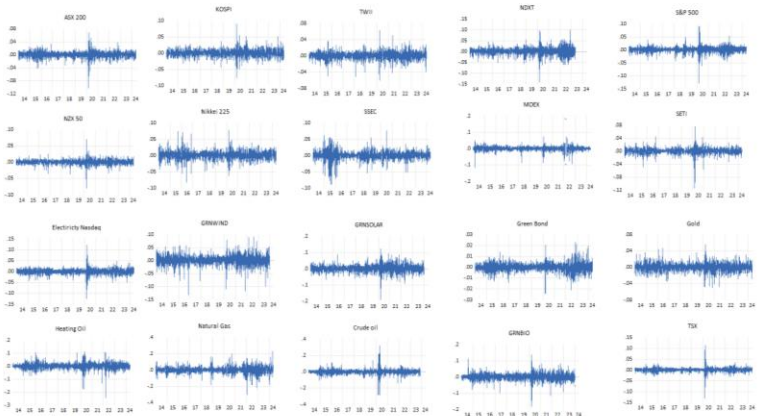

Fig. 1: Trends in the Return Series.

4. Empirical analysis

4.1. Total averaged volatility connectedness

Intensifying the given APEC regional markets' integration issues, we study time-varying spillover effects of the interconnected system, which comprises Crude Oil, Natural Gas, Heating Oil, GRNSOLAR, and GRNWIND, Gold, Technology sector (NDXT), Green bonds, and the regional equity markets, namely, S&P 500, TSX, NIKKEI 225, ASX 200, NZ To this end, we assess all these impacts concerning different horizons and both the static and dynamic system in TVP-VAR in terms of returns and volatilities connectedness of the assets. The degree to the variables interact with each other is shown in Table 2. The Volatility Spillover (TO) quantifies the effects of the variables in the vertical axis on the ones in the horizontal axis. On the other hand, Volatility Spillover (FROM) shows how the variables on the O-horizon are affected by those on the V-horizon. The narrative of these interactions, based on the analysis, is described in detail below.

Table 2 provides the overall average connectedness of energy commodities with the GFM, and Tables 3 and 4 represent the short-horizon (1 to 5 trading days) and long-horizon (5 to infinite trading days) connectedness, respectively. The TACI is calculated at 60.68 % which means that, on average, this proportion (60.68 %) of the forecast error variance within this network is due to shock transmission across these markets that are interconnected. The rest of the 39.32% are the peculiarities that are unique to each market. This high level of volatility transmission is consistent with Ding et al. (2021) and Wang et al. (2022), who found that during the COVID-19 crisis, overall, total volatility transmission in energy and financial markets was above 60%. This transmission still stayed above 40% even after the peak of the pandemic, proving that global crises shape cross-market risk contagion deeply.

From the frequency decomposition perspective, it is evident that most intermarket connectedness is explained by short-term (1 to 5 trading days) volatility transmission of 45.20% while long-term (5 to infinite trading days) transmission is only 15.48%. This difference shows the prevalence of short-term forces behind the fluctuations of interconnected markets, especially in conditions of increased international tension, including the COVID-19 pandemic. These outcomes stress the contribution of external impulses in increasing cross-market integration and in the dominance of short-term effects for market dynamics.

The FROM Total values in Table 2 indicate that the S&P 500, TSX, and ASX as the three most affected variables that receive the highest spillover effects from other components within the system. These equity markets have been revealed as being highly correlated and sensitive to shocks emanating from other markets. On the other hand, they found out that Natural Gas (23.06) is isolated, having the least aggregate impact within the system. Likewise, SSEC (43.45) and Gold (42.78) have less external influence, while gold still acts as a safe-haven asset as tested in traditional beliefs. This goes a long way in showing that while major equity indices are highly sensitive to carryover effects, Natural Gas, Gold are much more robust.

Table 3: Averaged Volatility Connectedness in the Short Run (1–5 Traded Days)

	S.P.500	TSX	Nikkei.225	ASX.200	NZX.50	SSEC	SETI	MOEX	KOSPI	TWII	Crude.Oil	Nat-ural.Gas	Heating.Oil	GRNSOLAR	GRNWIND	GRNBIO	Green.Bond	Gold	Electricity	NDXT	FROM.1.5
S.P.500	20.61	11.5	1.68	1.54	0.95	0.5	0.99	1.6	1.01	1.17	1.45	0.38	1.47	7.74	2.11	4.44	0.77	0.62	4.87	14.3	59.09
TSX	11.89	21.44	1.45	1.95	0.93	0.57	1.25	1.83	1.08	1.14	2.92	0.38	2.67	5.72	2.29	5.35	0.76	0.54	3.4	8.47	54.58
Nik-kei.225	7.69	5.54	24.25	2.84	2.09	1.33	1.39	2.05	3.46	2.85	1.46	0.63	1.4	3.87	1.51	2.15	1.94	1.65	1.35	5.97	51.16
ASX.200	8.12	7.42	2.7	21.64	3.55	0.8	1.28	1.32	2.45	2.39	1.32	0.37	1.32	3.77	2.04	2.74	1.01	0.67	2.48	5.7	51.44
NZX.50	5.67	4.64	2.21	4.28	29.89	0.59	1.31	1.71	1.56	1.92	0.94	0.53	0.81	2.9	1.97	1.79	0.83	0.62	2.27	4.61	41.17
SSEC	2.17	2.12	2.27	1.4	0.88	44.88	1.88	1.14	3.02	4.08	1.04	0.81	1.3	2.65	1.24	1.5	0.83	0.91	0.69	2.21	32.16
SETI	3.48	3.43	2.15	1.84	1.78	1.63	36.55	1.72	3.06	3.12	0.76	0.55	1.01	1.86	2.31	2.64	0.83	0.89	1.74	2.72	37.52
MOEX	3.3	3.39	1.78	1.29	1.66	0.66	1.47	43.04	1.73	2.12	1.62	0.69	1.53	1.75	1.63	2.16	1.39	1.16	1.16	2.58	33.06
KOSPI	4.59	3.85	4.24	3.04	1.7	1.84	2.31	2.01	27.08	5.76	0.91	0.71	0.88	3.04	2.07	2.43	1.21	0.82	1.42	4	46.84
TWII	5.39	4.18	3.02	2.69	1.84	2.24	2.21	1.7	5.25	25.38	0.81	0.7	0.8	3.64	1.55	2.95	1.23	0.65	1.38	4.96	47.2
Crude.Oil	2.26	4.21	1.31	0.55	0.54	0.76	0.58	1.33	0.66	0.66	37.84	0.75	19.15	1.82	0.62	3.09	0.66	0.76	0.72	1.58	42.03
Nat-ural.Gas	1.23	1.27	0.89	0.55	0.9	1.03	0.74	1.4	1.21	0.96	1.25	63.46	1.33	0.95	0.6	1.1	0.83	0.86	0.78	1.01	18.89
Heating.Oil	2.31	3.78	1.62	0.61	0.61	1.03	0.92	1.49	0.79	0.72	18.67	0.83	36.09	1.87	0.62	3.26	0.7	1.05	0.74	1.77	43.41
GRNSOLAR	9.46	6.66	1.59	1.22	0.7	1.71	0.74	1	1.27	1.32	1.29	0.38	1.33	26.14	3.09	4.64	0.62	0.72	1.33	11.96	51.03
GRNWIND	4.16	4.24	1	1.28	1.15	0.98	2.05	1.83	1.47	1.51	0.84	0.33	0.94	4.31	36.28	3.22	2.75	1.11	2	3.85	39.02
GRNBIO	6.49	7.37	0.61	1.13	0.65	0.71	1.52	1.63	1.17	1.24	3.02	0.52	2.94	5.23	2.77	30.34	0.99	0.86	1.72	5.58	46.16
Green.Bond	1.91	1.78	2.16	0.67	0.98	0.62	0.79	1.63	0.79	1.28	1.05	0.57	0.86	0.94	3.01	1.43	41.72	11.26	1.57	1.66	34.97
Gold	1.42	1.07	2.12	0.8	0.77	0.71	0.64	1.75	0.88	0.85	1.15	0.55	1.51	1.22	1.33	1.27	12.95	46.94	1.26	1.34	33.57
Electricity	8.84	5.79	1.1	1.32	1.51	0.57	0.82	1.37	0.87	1.04	0.89	0.54	0.77	2	2	2.27	1.46	1	41.57	4.15	38.31
NDXT	15.82	9.01	1.67	1.39	0.8	0.66	1	1.33	1.08	1.23	0.98	0.36	1.12	10.53	2.2	4.16	0.76	0.57	2.46	23.47	57.12
TO	106.22	91.24	35.55	30.39	24	18.96	23.91	29.84	32.82	35.35	42.38	10.58	43.13	65.81	34.98	52.6	32.51	26.7	33.35	88.41	TACI

	S.P.500	TSX	Nikkei.225	ASX.200	NZX.50	SSEC	SETI	MOEX	KOSPI	TWII	Crude. Oil	Natural. Gas	Heating oil	GRNSOLAR	GRNWIND	GRNBIO	Green. Bond	Gold	Electricity	NDXT	FROM. Total
NET	47.14	36.65	-15.61	-21.05	-17.17	-13.2	-13.61	-3.22	-14.02	-11.85	0.35	-8.31	-0.28	14.77	-4.04	6.45	-2.46	-6.87	-4.96	31.29	45.20

Notes: Findings have been derived using a TVP-VAR model based generalized forecast error variance decomposition accompanied by the frequency spectral description using the BK-18 procedure.

Table 2: Averaged Volatility Connectedness

	S.P.500	TSX	Nikkei.225	ASX.200	NZX.50	SSEC	SETI	MOEX	KOSPI	TWII	Crude. Oil	Nat-ural. Gas	Heating oil	GRNSOLAR	GRNWIND	GRNBIO	Green. Bond	Gold	Electricity	NDXT	FROM. To-tal
S.P.500	25.52	14.39	2.06	1.96	1.21	0.62	1.29	2.22	1.38	1.48	1.81	0.45	1.77	9.74	2.83	5.7	0.99	0.78	6.02	17.77	74.48
TSX	15.67	27.51	1.91	2.62	1.3	0.73	1.6	2.68	1.5	1.49	3.71	0.49	3.26	7.8	3.14	7.1	1.03	0.68	4.47	11.3	72.49
Nik-kei.225	10.87	7.99	29.8	3.97	2.63	1.68	1.93	2.79	4.6	3.68	1.82	0.73	1.8	5.62	2.2	3.09	2.33	2.06	1.87	8.55	70.2
ASX.200	11.35	10.75	3.59	27.47	4.68	1.05	1.88	2.21	3.41	3.18	1.8	0.46	1.74	5.43	3.04	4.14	1.38	0.91	3.47	8.06	72.53
NZX.50	8.5	7.13	2.99	6.4	38.41	0.81	2.05	2.69	2.41	2.83	1.33	0.65	1.04	4.54	3.07	2.78	1.27	0.78	3.52	6.81	61.59
SSEC	3.09	3.01	2.81	1.75	1.16	56.55	2.45	1.61	3.86	5.5	1.38	1.04	1.71	3.78	1.74	2.17	1.12	1.13	0.89	3.25	43.45
SETI	5.4	5.43	2.62	2.64	2.39	2.13	45.94	2.55	4.12	4.17	1.05	0.71	1.41	2.9	3.4	4.16	1.14	1.08	2.55	4.2	54.06
MOEX	4.82	5.08	2.18	1.81	2.2	0.92	2	54	2.32	2.77	2.19	0.88	2.06	2.59	2.26	3.31	1.74	1.45	1.68	3.75	46
KOSPI	6.71	5.68	5.38	4.17	2.36	2.33	3.22	3.1	33.89	7.44	1.34	0.81	1.23	4.61	3.08	3.77	1.76	1.14	2.06	5.92	66.11
TWII	7.82	6.31	4	3.88	2.53	2.94	3.13	2.76	7.13	31.81	1.18	0.79	1.14	5.54	2.52	4.54	1.75	0.9	2.01	7.3	68.19
Crude. Oil	3.01	5.55	1.64	0.76	0.74	0.98	0.68	1.85	0.89	0.83	46.82	0.98	23.36	2.37	0.78	4.03	0.85	0.91	0.91	2.06	53.18
Nat-ural. Gas	1.53	1.54	1.06	0.64	1.1	1.32	0.88	1.67	1.45	1.11	1.64	76.94	1.76	1.17	0.68	1.34	1.03	0.97	0.94	1.24	23.06
Heating. Oil	3.09	5.04	1.95	0.81	0.85	1.38	1.16	2	1.05	0.92	23.24	1.09	44.47	2.46	0.82	4.31	0.86	1.28	0.93	2.3	55.53
GRNSOLAR	12.09	8.77	1.99	1.61	1.01	2.02	0.94	1.59	1.77	1.74	1.78	0.48	1.74	33.22	4.23	6.12	0.84	0.99	1.75	15.33	66.78
GRNWIND	6.13	6.18	1.29	1.78	1.56	1.14	2.52	2.47	1.97	2.01	1.11	0.4	1.18	6.3	45.63	4.68	3.59	1.53	2.87	5.67	54.37
GRNBIO	8.65	9.9	0.82	1.57	0.93	0.89	2.04	2.37	1.59	1.67	3.87	0.71	3.72	6.86	3.81	38.49	1.24	1.03	2.41	7.41	61.51
Green. Bond	2.75	2.47	2.49	0.92	1.37	0.79	1.02	2.32	1.09	1.68	1.34	0.75	1.03	1.32	3.99	2.16	52.8	14.93	2.39	2.39	47.2
Gold	1.85	1.45	2.64	1.04	1.06	0.9	0.78	2.33	1.14	1.06	1.34	0.7	1.88	1.59	1.85	1.78	15.84	57.22	1.79	1.77	42.78
Electricity	11.01	7.36	1.27	1.75	1.93	0.77	1.16	1.68	1.18	1.26	1.04	0.64	0.93	2.49	2.62	2.94	1.95	1.33	51.62	5.07	48.38
NDXT	19.24	11.05	2.03	1.69	0.99	0.81	1.26	1.87	1.44	1.56	1.29	0.41	1.36	13.02	2.95	5.27	0.97	0.75	3.06	28.96	71.04
TO	143.56	125.08	44.73	41.78	31.98	24.18	31.98	42.76	44.33	46.39	54.27	13.17	54.12	90.11	49.02	73.41	41.69	34.65	45.59	120.15	TACI

NET	69.08	52.59	-25.47	-30.75	-29.62	-19.27	-22.07	-3.24	-21.78	-21.8	1.09	-9.88	-1.41	23.33	-5.35	11.9	-5.52	-8.14	-2.79	49.11	60.68

Notes: Findings are derived from a TVP-VAR model with the number of lags equal to one and selected using Bayesian information criterion (BIC) and a 200-step-ahead generalized forecast error variance decomposition.

Table 4: Averaged Volatility Connectedness in the Long Run (5-Infinite Traded Days)

	S.P.500	TSX	Nikkei.225	ASX.200	NZX.50	SSEC	SETI	MOEX	KOSPI	TWII	Crude.Oil	Natural.Gas	Heating.Oil	GRNSOLAR	GRNWIND	GRNBIO	Green.Bond	Gold	Electricity	NDXT	FROM.5.Inf
S.P.500	4.91	2.9	0.39	0.42	0.26	0.12	0.3	0.62	0.36	0.31	0.36	0.07	0.3	2	0.72	1.26	0.22	0.17	1.15	3.47	15.39
TSX	3.78	6.07	0.47	0.68	0.37	0.15	0.35	0.85	0.43	0.35	0.79	0.12	0.59	2.08	0.85	1.75	0.27	0.15	1.07	2.83	17.91
Nikkei.225	3.18	2.46	5.55	1.13	0.53	0.35	0.54	0.74	1.14	0.83	0.36	0.1	0.39	1.75	0.69	0.94	0.39	0.41	0.52	2.58	19.04
ASX.200	3.23	3.33	0.89	5.84	1.13	0.25	0.61	0.89	0.96	0.78	0.48	0.09	0.42	1.66	1.01	1.4	0.37	0.23	0.99	2.36	21.08
NZX.50	2.83	2.49	0.78	2.11	8.52	0.22	0.74	0.98	0.85	0.92	0.39	0.12	0.23	1.64	1.09	0.99	0.44	0.16	1.24	2.2	20.43
SSEC	0.91	0.89	0.54	0.34	0.27	11.68	0.57	0.47	0.84	1.43	0.34	0.22	0.41	1.13	0.5	0.67	0.29	0.22	0.2	1.03	11.29
SETI	1.92	1.99	0.47	0.8	0.61	0.5	9.39	0.83	1.06	1.05	0.29	0.16	0.4	1.05	1.09	1.52	0.31	0.2	0.81	1.49	16.53
MOEX	1.52	1.69	0.4	0.52	0.54	0.25	0.53	10.96	0.59	0.65	0.57	0.19	0.53	0.84	0.62	1.15	0.36	0.29	0.52	1.17	12.95
KOSPI	2.12	1.83	1.15	1.13	0.66	0.49	0.9	1.08	6.81	1.69	0.42	0.1	0.35	1.56	1.01	1.34	0.55	0.32	0.64	1.91	19.27
TWII	2.43	2.13	0.99	1.19	0.69	0.7	0.93	1.06	1.88	6.43	0.37	0.09	0.35	1.9	0.97	1.59	0.52	0.25	0.63	2.34	21
Crude.Oil	0.75	1.34	0.33	0.21	0.2	0.22	0.1	0.52	0.23	0.17	8.98	0.23	4.21	0.55	0.16	0.94	0.2	0.15	0.19	0.48	11.16
Natural.Gas	0.3	0.27	0.17	0.1	0.2	0.29	0.14	0.27	0.24	0.15	0.39	13.49	0.43	0.22	0.08	0.24	0.2	0.11	0.16	0.22	4.17
Heating.Oil	0.77	1.25	0.33	0.2	0.24	0.35	0.23	0.51	0.26	0.2	4.57	0.26	8.38	0.59	0.2	1.05	0.16	0.23	0.19	0.54	12.12
GRNSOLAR	2.63	2.11	0.4	0.39	0.31	0.31	0.19	0.59	0.5	0.42	0.49	0.1	0.41	7.07	1.14	1.49	0.22	0.27	0.42	3.37	15.75
GRNWIND	1.97	1.94	0.29	0.5	0.41	0.16	0.47	0.64	0.49	0.5	0.27	0.08	0.23	1.99	9.34	1.47	0.83	0.42	0.88	1.81	15.35
GRNBIO	2.16	2.54	0.21	0.44	0.28	0.17	0.52	0.74	0.42	0.43	0.85	0.19	0.78	1.63	1.04	8.15	0.26	0.18	0.69	1.83	15.35
Green.Bond	0.83	0.69	0.32	0.25	0.39	0.16	0.23	0.69	0.31	0.4	0.3	0.17	0.17	0.39	0.98	0.73	11.07	3.67	0.82	0.74	12.23
Gold	0.44	0.38	0.52	0.24	0.3	0.2	0.13	0.58	0.26	0.21	0.19	0.15	0.37	0.36	0.52	0.51	2.89	10.28	0.53	0.43	9.22
Electricity	2.17	1.57	0.17	0.44	0.42	0.2	0.33	0.3	0.31	0.23	0.15	0.1	0.16	0.49	0.62	0.68	0.49	0.33	10.05	0.93	10.07
NDXT	3.42	2.04	0.36	0.3	0.19	0.15	0.27	0.55	0.36	0.33	0.31	0.05	0.24	2.49	0.75	1.11	0.22	0.18	0.59	5.49	13.91
TO	37.34	33.84	9.18	11.38	7.97	5.22	8.07	12.92	11.51	11.04	11.9	2.6	10.99	24.31	14.04	20.8	9.17	7.95	12.24	31.74	TACI

NET	21.95	15.93	-9.86	-9.7	-12.45	-6.06	-8.46	-0.03	-7.76	-9.96	0.74	-1.57	-1.12	8.56	-1.31	5.45	-3.06	-1.27	2.17	17.82	15.48

Notes: Findings have been derived using a TVP-VAR model based on generalized forecast error variance decomposition, accompanied by the frequency spectral description using the BK-18 procedure.

The results of net spillover values also show that several variables are important volatility givers since they have positive net values. Of these, the S&P 500 has the highest contribution to spillover in volatility with 69.08, which supports its mediating function on global markets. Likewise, the TSX (+52.59) shows a high ability to spread volatility across the system. In the context of green finance and technology, the stocks of GRNSOLAR (+23.33) and the NDXT (Technology Index) (+49.11) are the most sensitive to volatility transfers. The evaluation of the net spillover values further shows that several variables play primary roles in the dimension of volatility receivers, by displaying negative net spillover values. Some of these, like the Nikkei 225 (-25,47), ASX 200 (-30.75), NZX 50 (-29,62), SSEC (-19.27), SETI (-22.07), KOSPI (-21.78), and TWII (-21.80) show pronounced reactions to external volatility. Also in the energy and green financial industry, there are other variables such as Natural Gas (-9.88), Heating Oil (-1.41), GRNWIND (-5.35%), GRNBIO (-5.52 %), Green Bonds (-5.52 %), Gold (-8.14 %), and Electricity (-2.79 %) that come out as other significant receivers of volatilities. This shows that these markets are, in fact interconnected in the sense that their movements are driven mostly by externalities from other factors in the system.

4.2. Total dynamic volatility connectedness

To assess the dynamic aspects of the volatility connectedness, we concentrate on the measures shown in Fig. 2. The figure shows the Total Average Connectedness Index (TACI) trend over time that is represented by the black-coloured area, where TACI was decomposed into short-run are colored red, and the long-run are coloured green. The patterns of volatility transmission have some important characteristics. The volatility of TACI rose in late February 2020, as COVID-19 began to spread globally. It also corresponds with large movements in financial markets – consecutive drops in US stock indices and a steep drop in the price of oil. These events became the triggers of the rapid spread of turmoil through global financial markets as supported by Adekoya and Oliyide (2021), Bouri et al (2021), Lin and Su (2021), and Wang et al (2022). Secondly, COVID-19 was still presenting new variants which threatened public health and economic recovery, and the TACI gradually decreased after reaching its maximum in March 2020. This trend may be due to governments' fast responses to preserve the financial markets, although some of the countries adopted less stringent measures of fighting the COVID-19 pandemic, such as the policy of herd immunity (Lin and Su, 2021; Wang et al., 2022). Notably, China was still an exception; they had been more active in containing the virus.

Third, a frequency domain analysis of the volatility transmission also shows that short-term spillovers were more prominent during the early stages of the pandemic. This implies that an exchange of shocks within a short time frame facilitated change in the investors' expectations and behaviour. Lastly, the dynamic volatility transmission shows a new upward movement from 2022, as can also be seen in Figure 3. This increase may be due to the Russia-Ukraine conflict, which has raised geopolitical risks, thereby increasing market risk across the world. This shows that interconnected markets are very sensitive to other major external shocks, and it is crucial to observe these dynamics for risk management and policy measures.

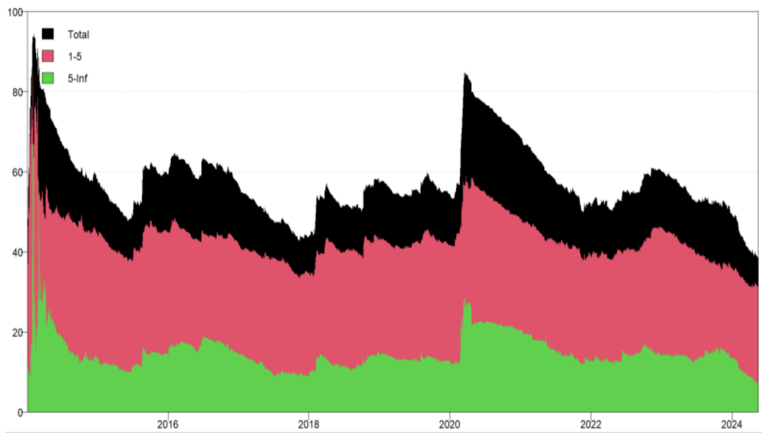

Fig. 3: Dynamic Total Volatility Connectedness.

4.3. Net total directional volatility connectedness

Figure 3 offers a complete picture of the volatile fluctuations of directional volatility spillovers in the international interconnected network of financial markets. It consists of three subplots: Figure 3(a) shows the net total directional spillovers emitted TO other markets, Figure 3(b) shows the spillovers received FROM other markets, and Figure 3(c) shows the net total directional connectedness as the difference between the two. In Figure 3(a), the dynamic evolution of spillovers transmitted TO other markets shows how each of the variables acts as a volatility transmittal within the system. These variables help propagate shocks, indicating their role in defining the volatility of interconnected markets. The levels and directions of these transmissions vary over time, and there is a peak during major global events such as a pandemic with COVID-19 or military events like the Russia-Ukraine war.

Figure 3(b), however, shows the spillovers received FROM other markets, where each variable receives the volatility shocks. This perspective enables one to decipher how such external shocks are metabolized within given markets while highlighting their susceptibility to infection from related markets. Finally, Figure 3(c) captures both measures and gives the net total directional connectedness. This measure, which is defined by the difference between the spillovers TO and FROM other classified variables, is net volatility for givers or takers. Positive values suggest that a market or variable is a net volatility transmitter, and contributes more to the dissemination of volatility than it receives. On the other hand, negative values indicate that a market is a receiver of volatility; that is, it is an area that endures more shocks than it brings to other markets. This is because the net connectedness in this context underlines the interactive patterns of variables, in terms of how these change roles in response to market events and external shocks.

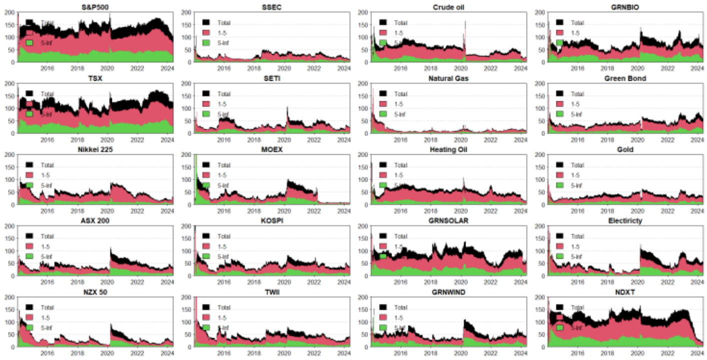

Fig. 3: A) Dynamic Total Directional Volatility Connectedness to Others.

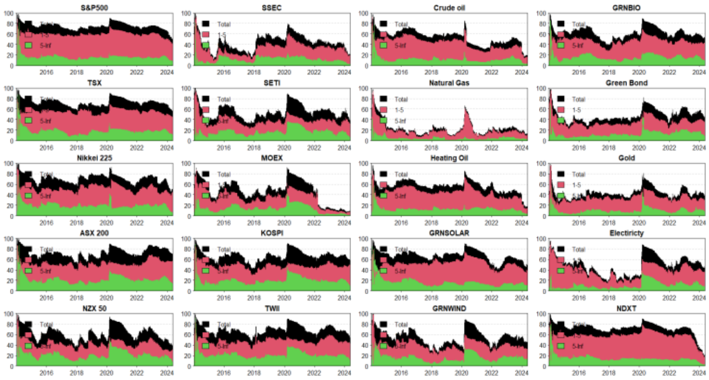

Fig. 3: B) Dynamic Total Directional Volatility Connectedness from Others.

Figure 3(a) shows the volatility transmitted TO others, where equity markets such as S&P 500, Nikkei 225, and TSX appear as the dominant volatility transmitters and have high spillover effects during the analysed period. These markets, especially during the global crises, including the COVID-19 pandemic and Russia-Ukraine conflict, show how they act as conduits of volatility around the world. As for energy commodities, the connectedness of crude oils shows significant volatility during crises and the connectedness of natural gas and heating oil also more volatile during crises, though not as sharply as crude oil. GRNBIO, GRNSOLAR, and GRNWIND are green assets, and their volatility transmission coefficient is moderately rising, which proves the increasing importance of green assets in sustainable investments. Gold, being an example of a haven asset, has relatively low spillovers and occasional sharp increases during financial turmoil. In addition, the current short-term (1–5 days) spillovers are more prevalent in crises than long-term ones, showing the speed of shock transmission.

On the other hand, Fig. 3(b) shows that volatility received FROM others explains the openness of various markets to shocks. The S&P 500, TSX, and Nikkei 225 equity indices are much appreciated by others for their levels of volatility in response to global financial shocks. ASX 200, NZX 50, and TWII show moderate reception of the spillover effect with a sharp rise during major events in the international market, which shows that Australia, New Zealand, and Taiwan are an integral part of the global financial system. The energy commodities like crude oil, natural gas, and heating oil are found to be more vulnerable to external shocks in crises like the 2020 oil market crash and Russia Russia-Ukraine war. Newly developed green assets such as GRNSOLAR, GRNWIND, and GRNBIO show a rising trend in volatility reception, proving their participation in the world markets. On the other hand, Gold and Green bonds show a stable spillover reception pattern, which supports lower volatility. Electricity gets a moderate though steady flow of spillover, while the NDXT (NASDAQ Clean Energy Index) receives quite some spillover attention, especially during active interest in the clean energy technologies.

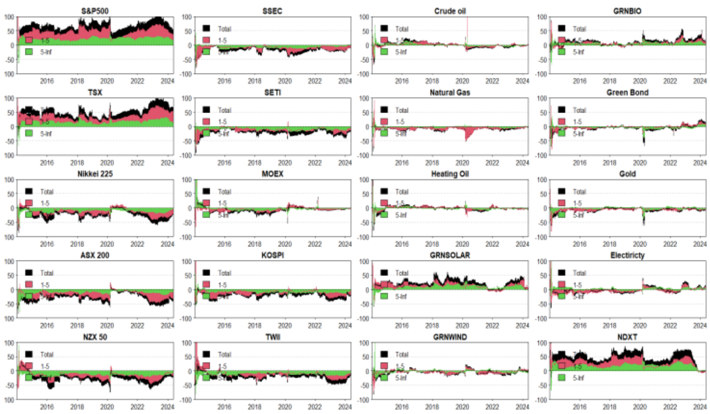

Fig. 3:C) Dynamic Net Total Volatility Directional Connectedness.

Finally, Fig. 3(c) presents the dynamic net total volatility directional connectedness, where the change in roles of various markets in terms of either being net sources or uses of volatility is depicted. The equity markets, including S&P 500 and Nikkei 225, always operate as net volatility givers, especially in crises, thus supporting the overall superpower of the markets on global financial systems. On the other hand, regional indices such as the SSEC and MOEX mainly buffer and exhibit the ability to respond to external shocks. Crude oil and natural gas are both net gives and takes in different periods, while heating oil is sometimes a volatility giver. Of the green assets, GRNBIO and GRNSOLAR are identified as significant volatility givers, which, in turn, implies their increasing systemic relevance, whereas GRNWIND and green bonds are in a more balanced area. Gold provides credibility of being a volatile asset during financial crises, while electricity also exhibits volatility but with occasional flare-ups during energy crises. The volatility is again transmitted by the NDXT due to rising market interest in clean energy technologies.

4.4. Discussion

The TVP-VAR frequency connectedness model used in this study gives a detailed understanding of volatility transmission for energy commodities (Crude Oil, Natural Gas, Heating Oil, GRNSOLAR, GRNWIND, GRNBIO), Gold, Technology (NDXT), Green Bonds, and APEC Equity Markets (S&P 500, TSX, Nikkei 225, ASX 200, NZX 50, SSEC). The analysis provides several important insights into the nature of market interconnectedness. First, a large share of the mean total spillover across these markets is due to the propagation of network-wide volatility during the sample period. This is a clear pointer to the fact that the interconnectivity of the global financial system is rising, due to the financialization of energy commodities as noted by Ma et al. (2021). It also stresses the increased possibility of systemic risk spillovers due to the current global pandemic. Second, it is evident that the total volatility transmission pattern is significantly more time-varying, rising to a very high level during the COVID-19 outbreak and falling rapidly after that point. This decline could be associated with different government priorities: some aimed at financial stability, while others at combating the pandemic (Lin and Su, 2021; Wang et al., 2022). Finally, the net and total frequency domain decomposition of volatility spillovers shows that the main driving force of the spillover is located in the short-term components during the entire period. This implies that the COVID-19 crisis resulted in market expectations regarding increased uncertainty and a reduced time horizon. Combined, these results serve to underscore the active nature of the volatility transmission across international markets and the centrality of short-term fluctuations at the time of crisis.

5. Concluding remarks

This paper aims to investigate the dynamic volatility spillover of energy commodities comprising Crude Oil, Natural Gas, Heating Oil, GRNSOLAR, GRNWIND, and GRNBIO, Gold, Technology (NDXT), Green Bonds, and APEC Equity Markets including S&P 500, TSX, Nikkei 225, ASX 200, NZX 50, and SSEC during pre- and mid-COVID-19 via According to the findings, the cross-market volatility transmission was significantly increased by the global pandemic, with a clear time-varying relationship. Furthermore, the analysis of the volatility spillovers in the frequency domain reveals a dominant short-run structure over the period under consideration, suggesting a significant change in market expectations and increasing the level of short-term volatility and systemic risk. Our study also reveals that energy commodities act as a conduit for volatility in a manner that depends on the period. During the global pandemic, energy commodities are not only bearers of volatility but also are subject to it, which further underlines their financialization as well as their growing power and weakness. Therefore, volatility transmission analysis is crucial in the context of portfolio diversification and risk hedging with energy commodities serving in both roles. Therefore, it is recommended that policymakers and investors take the time-varying volatility spillover among energy commodities and other financial assets into consideration, especially with the rising importance of energy markets in the global financial system.

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