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Portfolio Diversification and Dynamic Interactions between Clean and Dirty Energy Assets

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ABSTRACT

Clean energy, with its focus on environmental sustainability and efficiency, has gained significance as concerns over the impact of traditional energy growth. However, there is limited evidence on the value of clean energy investments. This paper explores the role of clean energy in a balanced investment portfolio by examining two traditional energy assets (crude oil and natural gas) and two clean energy assets (SPDR S&P Kensho Clean Power ETF and iShares Global Clean Energy ETF). Using a time-varying parameter vector autoregression (TVP-VAR) model on daily data from October 2021 to January 2024, we analyze the evolving connectedness between these assets. Our results highlight dynamic interactions, with green finance indices like CNRG acting as net shock transmitters, while traditional energy indices, such as WTI and gas, primarily receive shocks. The analysis suggests that green assets, particularly ICLN, enhance portfolio stability and hedging efficiency, especially in minimum correlation and risk parity portfolios. Fossil fuels, especially gas, exhibit higher volatility, requiring careful portfolio management. Ultimately, integrating ESG criteria and adapting investment strategies to market conditions may enhance responsible investing and long-term value creation.

Keywords: Clean Energy, Traditional Fuel, Dynamic Quantile Connectedness, Wavelet Analysis
JEL Classifications: C32, C5, F3, G15

1. INTRODUCTION

The relentless drive of global economic growth continuously fuels the demand for energy, prompting nations to secure energy supplies while maintaining reasonable prices through the development of integrated energy markets. However, the reliance on fossil fuels, which has underpinned industrial advancement for centuries, has significantly contributed to climate change and environmental degradation, raising concerns about sustainability. Consequently, renewable energy has emerged as a crucial alternative, offering a solution to the sustainability challenges many countries face. A new concept is emerging: "dirty energy stock indexes" which pertains to corporations that engage in the production or extraction of energy from non-renewable resources, such as coal, oil, and gas; in contrast to "clean energy stocks" which refers to companies that generate renewable energy through means such as wind, solar, and hydropower.

The shift to renewable energy has been boosted recently by Russia's unexpected invasion of Ukraine in February 2022, an event that has exacerbated uncertainties over access to fossil fuels. During this crisis, supply constraints pushed the global oil price to its highest level in eight years. This war has significant implications given the dependence of many European countries on Russian oil and gas exports. This geopolitical episode has heightened the urgency for diversifying investment portfolios to include alternative assets, such as clean energy stocks, to mitigate risks associated with volatile fossil fuel markets. Although, it is difficult to assess the ultimate impact of the war on global energy markets and the financial sector (Adekoya et al., 2022; Lo et al., 2022), the war's influence on energy policies in Europe could signify a pivotal moment, driving substantial investments into green energy sectors. Patt and Steffen (2022) provide early evidence that the war has shifted public policy support towards phasing out fossil fuels and promoting clean energy alternatives. Recent reports indicate a significant increase in renewable energy investments in Europe, spurred by policy shifts and a commitment to energy independence from Russian fossil fuels (IEA, 2023[1]).

It should also be noted that the switch to clean energy began long before the war between Russia and Ukraine. In fact, the 21st Conference of the Parties (COP21) set a global agenda to combat climate change, leading to significant investments in renewable energy technologies, including solar, wind, hydro, and geothermal power. A few years later, and despite the COVID-19 pandemic, global investments in renewable energy soared, highlighting a robust commitment to transitioning towards sustainable energy sources (Ahmad, 2017; Ding et al., 2022; Lundgren et al., 2018; Sharma et al., 2021). The WilderHill Clean Energy Index, has become a benchmark for tracking the performance of companies in the clean energy sector, reflecting the industry's growth and its appeal to investors seeking to align financial objectives with climate goals (Chen et al., 2022; Maghyereh et al., 2019).

Globally, over the last fifteen years, the clean energy sector has seen remarkable growth, with global investment in the energy transition hit $1.77 trillion in 2023, up 17% on the previous year and a new record (Bloomberg New Energy Finance, 2023). Despite the continued dominance of fossil fuels, the push for decarbonization, particularly post-COP26, has mobilized regulatory bodies, companies, financial institutions, and investors to prioritize clean energy investments (Farid et al., 2023; Papageorgiou et al., 2017; Ren and Lucey, 2022). Moreover, COP27 has emphasized the need for accelerated deployment of renewable energy technologies to meet the Paris Agreement targets, further boosting investment flows into the sector (UNFCCC, 2023).

This metamorphosis in the energy market has prompted a number of researchers to study various relationships between clean energy and other assets. The extant literature on the markets for dirty and clean energy reveals two predominant perspectives. The initial perspective emphasizes the replacement of conventional energy sources with cleaner alternatives (Henriques and Sadorsky, 2008; Bondia et al., 2016; Ferrer et al., 2018; Huang et al., 2011). This theory posits that an increase in oil prices incentivizes energy investors to transition towards renewable energy sources, resulting in a surge in clean energy adoption. This transition leads to higher profits for the renewable energy industry, culminating in robust performance of clean energy stocks in the capital markets. The second perspective, known as the dissociation hypothesis, posits that clean energy and conventional energy function within distinct markets and are not amenable to direct comparison (Ahmad, 2017; Attarzadeh and Balcilar, 2022; Yilanci et al., 2022).

On the other hand, other studies focus more on the impact of clean energy on portfolio diversification. Ahmad et al. (2018) demonstrated effective diversification using different assets, including clean energy stocks. Moreover, Saeed et al. (2020) investigated the use of clean energy assets as a hedge strategy against non-renewable energy investments. Other studies consider the relationship between clean energy stocks and the commodity market, while others researches examine the diversification benefits of combining oil and clean energy stocks in the same portfolio during periods of stress (Bouri et al., 2019; Junttila et al., 2018; Reboredo et al., 2017).

Given the intertwined nature of clean and dirty energy markets, understanding the volatility spillovers between these sectors and stock indices is essential for improving risk management strategies amidst significant geopolitical and environmental shifts. This study aims to investigate the dynamic interactions between clean and dirty energy assets, particularly in light of the ongoing Russia-Ukraine conflict and evolving environmental regulations, providing insights into portfolio diversification strategies in the context of a transitioning global energy landscape. The goal of this analysis is to investigate whether clean energy indexes may act as a hedge and safe haven for dirty energy stock indexes. This purpose is achieved by employing a time-varying parameter vector auto-regression (TVP-VAR) econometric framework-known for its ability to capture this type of relationship- and analyzing a comprehensive dataset spanning from October 2021 to January 2024.

Previous studies have highlighted the relationship between energy and the financial market under crises and extreme events. However, there are few studies comparing the impact of the Russia-Ukraine war and the COVID-19 pandemic on the nexus between dirty and green energy and the financial market. Therefore, the connectedness analysis would inform investors about the risk diversification strategy and the optimal asset allocation and open up new investment opportunities for market participants. Thus, identifying these linkages between dirty and green energy is crucial not only for investors developing effective investment strategies but also for governments and regulators aiming to manage potential disruptions in the energy and stock markets, to improve the progress of renewable energy and attain sustainable energy objectives, in light of climate change and pandemics.

We contribute to the literature in several ways. First, we investigate the dynamic linkages between global stock markets and both renewable and non-renewable energy indices to identify significant shifts in market dependencies. Second, we analyze the effectiveness of portfolio optimization strategies involving green energy, evaluating the benefits and drawbacks of including renewable energy stocks. Third, we estimate hedging ratios to provide actionable insights for investment portfolio managers. Finally, we offer a comprehensive analysis of the relative volatility of clean energy portfolios compared to traditional assets, providing valuable information for market participants and policymakers in the context of environmental sustainability.

The motivation for this study is to determine the optimal integration of green energy investments into international

1 International Energy Agency: www.iea.org

portfolios to maximize returns while adhering to sustainable investment principles. This involves examining the dynamic interactions and potential advantages of including green energy assets in a diversified investment strategy.

Our primary research question is: Do green investments enhance the value of a dirty energy investment portfolio?

This question holds significance for three key audiences. Firstly, the investment community seeks innovative opportunities and clarity on whether green assets can add value to existing investments. Secondly, regulators, policymakers, and compliance specialists are interested in understanding whether financial performance differs significantly among various asset classes, which could impact policy effectiveness. Lastly, the shift toward green energy investments underscores society's increasing awareness of the environmental costs of fossil fuel dependence. Investments in renewable energy signify efforts to reduce air pollution and mitigate climate change.

The remainder of this study is organized as follows. Section 2 reviews the literature, while Section 3 provides a description of the data used in our empirical analysis and the econometric methodology for estimating volatility connectedness. Section 4 discusses the empirical findings. Finally, Section 5 concludes with some discussion of the implications of the findings.

2. LITERATURE REVIEW

Over the last few decades, researchers are increasingly focusing on the development of studies and initiatives for environmental and climate risk management, in order to contribute both directly and indirectly to the promotion of environmentally friendly behaviour over the next decades. More specifically, there has been an increased interest in understanding the relationship between dirty and clean energy, particularly in light of events such as the COVID-19 pandemic in 2020 and energy market instability in 2022. According to Fuentes and Herrera (2020), Naeem et al. (2022) and Ren and Lucey (2022), exploring the linkages between these two energy sources is critical to advancing renewable energy development and achieving sustainable energy goals.

Ji and Fan (2016) provided a significant contribution to this field by employing a time-varying parameter vector autoregression (TVP-VAR) model to analyze the relationships between renewable energy stocks and traditional energy commodities. Their research highlighted that the connectedness between these assets is not static but evolves over time. This evolving nature is driven by various factors, including market conditions, technological advancements, regulatory changes, and geopolitical events. The TVP-VAR model is particularly useful in capturing these dynamic interactions as it allows for the parameters of the model to change over time, reflecting the real-world fluctuations in the energy markets. Ji and Fan's findings suggest that during periods of high volatility or economic stress, the relationships between clean and dirty energy assets can change significantly. For instance, during an oil price shock, the correlation between oil prices and renewable energy stocks may increase as investors reassess the relative value of clean versus dirty energy.

Other studies examine the impact of traditional energy prices (specifically oil prices) on the adoption and performance of renewable energy sources and the associated markets. Zhu et al. (2022) show that oil price increases negatively affect economic activity and stock prices. This motivates producers and investors to seek alternative energy sources. Kumar et al. (2012) find that rising oil prices encourage the substitution of renewable alternatives for conventional energy sources. The authors also find that the carbon price yield is not currently a relevant factor for the stocks of clean energy companies. Similarly, Hanif et al. (2021) examine the relationship between clean energy stocks and European emissions prices and find a strong long-term spillover between clean energy indices and the carbon price, with short-term volatility spillovers mainly between carbon prices and renewable energy indices.

Fahmy (2022) for his part, highlights that the growing awareness of climate risks among investors and their preference for green investments, affects the relationship between clean energy prices and oil and technology stocks.

Many researchers (Bondia et al., 2016; Ferrer et al., 2018; Wang and Cai, 2018; Attarzadeh and Balcilar, 2022) have studied the synchronisation trends between oil prices, technology, financial variables and clean energy indices. According to Bondia et al. (2016), the stock prices of alternative energy companies are influenced by the stock prices of technology companies, oil prices, and short-term interest rates. Ferrer et al. (2018) provide evidence that crude oil prices are not the main driver of the stock market performance of renewable energy companies, both in the short and long term. This suggests a disconnect between the alternative energy sector and the conventional energy market. Wang and Cai (2018) argue that the carbon market significantly explains the stock price movements of clean energy companies, while the stock prices of clean energy companies are also influenced by the carbon market. Attarzadeh and Balcilar (2022) analysed the volatility spillovers between renewable energy, oil and technology stock markets from 2004 to 2020 and found a bidirectional spillover effect, with the oil market acting as the main recipient of volatility.

In a more recent study, Ghabri et al. (2021) studied the impact of fossil energy market shocks on clean energy stock markets during the COVID-19 pandemic. The authors found that the crash in crude oil prices led to significant shocks in the clean energy market. In addition, the declaration of COVID-19 as a global pandemic led to an increase in natural gas and renewable energy prices following a substantial crash.

Further researches investigate the relationship between oil prices and clean energy stocks, particularly focusing on the nature and strength of this relationship over different time periods and market conditions. Specifically, Zhang et al. (2020) use wavelet quantile-on-quantile methods and find that the impact of oil price shocks on clean energy stocks varies across investment horizons and quantiles is asymmetric in the long run. Similarly, Yahya et al. (2021) investigated the relationship between oil prices and clean energy stocks and found a non-linear, long-run relationship between the two asset types. They confirmed that clean energy assets have been the dominant driver of oil prices in the recent post-financial crisis period. However, the global trend towards renewable energy remains uncertain after the Russian invasion. Vrînceanu et al. (2020) show that there is a weak link between oil and renewable energy markets, suggesting that the development and progress of the renewable energy industry is relatively unaffected by changes in oil prices.

More recently, Avazkhodjaev et al. (2022) study the shocks between renewable energy prices and clean energy stock prices from 2010 to 2021. They found that negative shocks outweigh positive shocks in renewable and clean energy production. They also found that renewable energy production prices have a significant impact on the stock prices of green economy companies, either positively or negatively. Farid et al. (2023) examined the co-movements between clean and dirty energy stock indices before and after the COVID-19 pandemic. Using a comprehensive sample of dirty energy stocks such as crude oil, fuel oil, diesel, gasoline and natural gas, the study found weak linkages between short-term clean and dirty energy stocks and a notable segmentation effect between dirty and clean energy markets.

Further studies have built on this foundation, exploring the implications of these dynamic interactions for portfolio diversification and risk management. For example, Reboredo (2015) examined the co-movement between oil prices and renewable energy indices using copula models, finding that the dependency structure is indeed time-varying and influenced by market regimes. During periods of market turmoil, the safe-haven properties of renewable energy assets become more pronounced, offering potential diversification benefits. The study conducted by Dias et al. (2023) covering the period 2018–2023 for five clean energy indexes and four dirty energy indexes examines whether clean energy indexes may act as a hedge and safe haven for dirty energy stock indexes during periods of market uncertainty. Their results indicate that during periods of global economic uncertainty, clean and dirty energy stock indices fail to demonstrate the qualities of hedge or safe-haven assets. These indexes fail to offer effective protection against market downturns or ensuring stability during economic turbulence.

Additional studies are currently investigating the link between conventional and clean energy prices and their impact on the composition of the investment basket. For example, Managi and Okimoto (2013) find a positive relationship between non-renewable energy prices and clean energy prices, highlighting the similarity of market reactions to clean energy and technology stock prices. He (2020) examines the risk management implications and diversification benefits of non-renewable energy portfolios, providing robust evidence of a time-varying dependence and asymmetric relationship between oil and East Asian stock markets. Ahmad (2017) finds that dynamic hedging performance suggests that the clean energy index, when combined with oil futures, may offer more profitable hedging opportunities than the technology index.

3. DATA AND METHODOLOGY

3.1. Data

The data for this study encompasses indices from both the green finance (clean energy) and traditional energy (dirty energy) sectors over the sample period from October 26, 2021, to January 5, 2024. For the green finance sector, the indices used are the SPDR S&P Kensho Clean Power ETF (CNRG) and the iShares Global Clean Energy ETF (ICLN). For the traditional energy sector, the indices considered are Crude Oil (WTI) and Natural Gas (GAS). The figure 1 illustrate daily returns for studied indices highlighting distinct volatility patterns. Traditional energy indices (WTI and GAS) exhibit more pronounced and frequent fluctuations, indicating higher volatility compared to the relatively stable clean energy indices (ICLN and CNRG). This contrast underscores the differing risk profiles of clean and traditional energy assets, with fossil fuels showing greater sensitivity to external shocks.

Descriptive statistics for these indices are detailed in table 1. The variance, indicative of the return volatility, is highest for GAS and lowest for the green finance indices (ICLN and CNRG), suggesting greater price fluctuations in the energy commodities. The skewness values show that the return distributions of ICLN and CNRG are positively skewed while the return distributions for WTI and GAS are negatively skewed. The kurtosis values, all significantly different from zero, indicate that the return distributions exhibit heavy tails and sharp peaks compared to a normal distribution. The Jarque-Bera test results confirm the non-normality of the return distributions for all indices. The Elliott-Rothenberg-Stock (ERS) unit-root test results indicate that all series are stationary. The Portmanteau tests for autocorrelation (Q[20] and Q2[20]) show significant autocorrelation in the returns and squared returns series for most indices, suggesting persistent return dynamics. Kendall's tau rank correlation coefficients reveal a strong positive correlation between the green finance ETFs (ICLN and CNRG), suggesting that they move together in response to market conditions. The correlations between the green finance indices and the energy commodities (WTI and GAS) are positive but much lower, reflecting the distinct dynamics and influences affecting these sectors.

3.2. Methodology

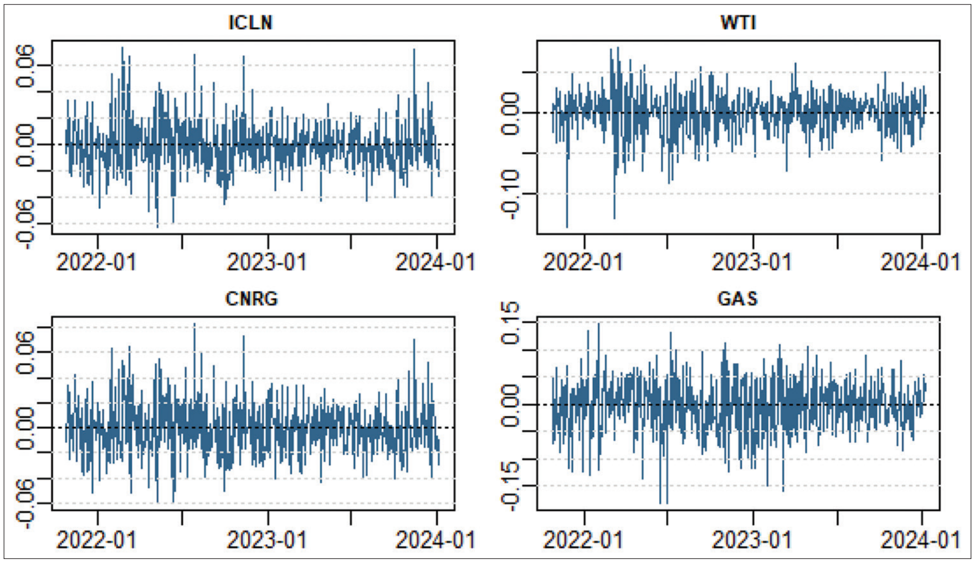
The analysis is conducted in three stages. The first stage involves econometric modelling and the immediate interpretation of connectedness measures. The second stage focuses on portfolio construction and evaluation. The final stage is dedicated to

Table 1: Descriptive statistics

Measures	ICLN	CNRG	WTI	GAS
Mean	−0.001	−0.001	0.000	−0.001
Variance	0.0001***	0.0001***	0.001***	0.002***
Skewness	0.524***	0.366***	−0.644***	−0.325***
Ex.Kurtosis	1.363***	0.537**	2.303***	0.426*
JB	67.476***	18.799***	158.996***	13.779***
ERS	−9.792***	−7.960***	−8.144***	−10.692***
Q (20)	17.048*	9.018	18.698**	14.040
Q2 (20)	28.890***	12.084	48.604***	27.194***
Kendall's tau correlations				
Variables	ICLN	CNRG	WTI	GAZ
ICLN	1.000***	0.781***	0.100***	0.059**
CNRG	0.781***	1.000***	0.108***	0.067**
WTI	0.100***	0.108***	1.000***	0.063**
GAS	0.059**	0.067**	0.063**	1.000*

Note: ***significance at 1%, **significance 5%, *significance at 10%.
ERS: Elliott-Rothenberg-Stock

Figure 1: Returns



robustness testing, where wavelet theory is employed to decompose the uncertainty data into various frequency components. The empirical methodology for modeling dynamic connectedness in a system of variables involves several key steps. Firstly, a multivariate Kalman filter TVP-VAR (Time-Varying Parameter Vector Autoregression) algorithm is implemented. Following this, the TVP-VAR is converted to a TVP-Variance Moving Average (TVP-VMA). This transformation allows the parameters and error variances to vary over time. These time-varying parameters and error variances form the foundation for the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD). These tools help in determining the extent to which a variable "*i*" is influenced by others and how much it influences all other variables. By summing the shares of the error variance for variable "*i*" due to all other variables "*j*", the total directional connectedness FROM all others is established, indicating the influence of all other variables on variable "*i*". Conversely, calculating the influence of variable "*i*" on all other variables "*j*" provides the total directional connectedness TO all others, which is derived by accumulating the effects (error variance) that variable "*i*" has on each other variable's forecast error variance. The net total directional connectedness is then obtained by subtracting the FROM measure from the TO measure (TO-FROM). Finally, the average amount of network co-movement, expressed as a percentage, is summarized in the total connectedness index (TCI). According to Monte Carlo simulations presented in Chatziantoniou and Gabauer (2021) and Gabauer (2021), it is shown that the own variance shares are by construction always larger than or equal to all cross-variance shares.

Then, to assess the financial significance of our findings, we will analyze historical investment performance by conducting back tests on portfolios, the estimated time-varying variance-covariance matrix of the TVP-VAR model is used for portfolio construction in the spirit of Antonakaksis et al. (2021). The assumptions underlying this analysis are that the investor can directly acquire the index (assuming there is an investable tracker or a similar investment vehicle for the index), that the investor is focused solely on investing in green ETFs, and that the investor is open to international investment opportunities. For robustness check, we use four approaches portfolio management based on time-varying connectedness. Finally, as Antonakaksis et al. (2021), recognizing that economic decisions and variables (both macroeconomic and financial) tend to respond differently to short-, medium-, and long-term fluctuations in uncertainties, we employ wavelet theory to break down the uncertainty data into various frequency components. We then conduct spillover analysis for each frequency across the examined assets. This study represents the first exploration of uncertainty spillovers between clean energy ETFs and commodities, integrating both time and frequency dimension.

3.2.1. Modelling time-varying connectedness using a TVP-VAR

Here, we describe the key econometric structure of the TVP-VAR model. For simplicity, we present it as a first-order VAR, which our later empirical work, guided by the Bayesian information criterion, confirms as the appropriate lag order. The TVP-VAR model can be expressed as follows:

$$y_t = \emptyset_t y_{t-1} + \varepsilon_t \, (\varepsilon_t \,|\, F_{t-1} \sim N(0, H_t)) \tag{1}$$

$$vec(\emptyset_t) = vec\emptyset_{t-1} + \epsilon_t \, (\epsilon_t \,|\, F_{t-1} \sim N(0, \omega_t)) \tag{2}$$

F_{t-1} represents all information up to $t-1$. y_t is the return series, and ε_t is the error variance $m \times 1$ dimensional vectors, $\emptyset_t$ and H_t are $m \times m$ dimensional matrices with, handle the time-varying error variance and parameter variance, respectively, indirectly accounting for changes in volatility. ϵ_t and $vec(\emptyset_t)$ are $m^2 \times 1$ and ω_t is a $m^2 \times m^2$ dimensional matrix with ϵ_t is the error term captures the random fluctuations in the evolution of the VAR model parameters over time. To calculate the GIRF and GFEVD, the TVP-VAR must first be converted into its TVP-VMA representation using the Wold representation theorem, which states that

$$z_t = \sum_{i=1}^{p} \emptyset_{it} z_{t-i} + \varepsilon_t \quad = \sum_{j=1}^{\infty} A_{it} \varepsilon_{t-j} + \varepsilon_t \tag{3}$$

z_t is the vector of endogenous variables at time t, p represents order of the VAR process, indicating the number of lags considered in the model. $\emptyset_{it}$ is the coefficient matrix associated with z_t. ϵ_t is the vector of errors for the VAR model. A_{it} is the coefficient matrix associated with the error ϵ_t. GIRFs, where K is the forecast horizon, are not contingent on or influenced by the structure or order of the errors. The GIRF approach effectively captures the dynamics among and between all variables j. This can be expressed by:

$$GIRF(\varphi_{ij,t}(K))$$

$$GIRF(K,\sqrt{H_{jj}},F_{t-1}) = H_{jj,t}^{-1/2} A_{K,t} H_t \epsilon_t \tag{4}$$

The GFEVD then demonstrates each variable's distinct contribution to the forecast error variance of variable *i*, indicating the extent to which one variable, in percentage terms, influences the forecast error variance of another variable in the system. This can be expressed as follow:

$$GFED_{ij,t}(K) = \frac{\sum_{t-1}^{K-1} GIRF_{ij,t}^2}{\sum_{j}^{m} GIRF_{ij,t}^2}, \sum_{j=1}^{m} GIRF_{ij,t}(K) = 1,$$

$$\sum_{i,j=1}^{m} GIRF_{ij,t}(K) = m, \tag{5}$$

Having these measures for GIRF and GFEVD at our disposal, we can effectively quantify the influence of variable iii by others, as well as the reciprocal influence of variable *i* on all others. Moreover, we can assess whether variable iii has a greater impact on others than it is impacted by them. To achieve this, we utilize the following three metrics:

The total directional connectedness *FROM* all others, is computed as follows:

$$FROM_{i\leftarrow j,t} \frac{\sum_{j=1,i\neq j}^{m} GFED}{\sum_{i=1}^{m} GFED} * 100 \tag{6}$$

The influence of all the others on variable i has to be strictly below 100% since the influence of i to itself has been excluded.

The total directional connectedness TO all others:

$$TO_{i\rightarrow j,t} \frac{\sum_{j=1,i\neq j}^{m} GFED}{\sum_{j=1}^{m} GFED} \times 100 \tag{7}$$

It is common practice to analyze metrics of total system connectedness. While these measures do not offer the same level of detail as those described earlier, they provide a single metric that indicates whether overall patterns of connectedness within the system are weak or strong. This metric is known as the Total Connectedness Index (TCI). Based on Monte Carlo simulations outlined in Chatziantoniou and Gabauer (2021) and Gabauer (2021), it has been demonstrated that the shares of variance attributable to an individual variable are always greater than or equal to the shares of variance attributable to all other variables. This implies that the TCI falls within the range of $\left[0, \frac{m-1}{m}\right]$.

Since we are interested in expressing the average level of network co-movement as a percentage, which should fall between 0 and 1, a slight adjustment to the TCI is necessary:

$$Net_{i,t}(K) = TO_{i\rightarrow j,t} - FROM_{i\leftarrow j,t} \tag{8}$$

Finally, the definition of TCI can be modified to obtain pairwise connectedness index (PCI) scores between variables i and j as follows:

$$TCI_t^e(K) = \frac{\sum_{i,j=1,i\neq j}^{m} Adj - GFED}{k} \text{ with } 0 < TCI_t^e(K) < 1 \tag{9}$$

$TCI_t^e(K)$ is the adjusted Total Connectivity Index for forecast horizon K. This index measures the average amount of network co-movement among variables for this time horizon. *Adj-GFED* represents the *Adjusted-Generalized Forecast Error Variance Decomposition* (*Adj-GFEVD*) between variables *i* and *j* for forecast horizon K. It quantifies the contribution of variable *j* to the forecast error variance of variable *i*, adjusted for the impact of other variables in the system. The measures outlined above illustrate the extent and severity of econometric connectivity between the various bond markets we examine. These metrics help bridge the gap between statistical and economic significance and concretely demonstrate the financial materiality of our findings. Ultimately, they address the crucial question of whether recognizing the green credentials or orientation of bonds leads to a financial premium.

3.2.2. Portfolio implications: Dynamic allocation and risk assessment

3.2.2.1. Minimum variance approach

One of the most widely used methods in portfolio construction is the Minimum Variance Portfolio (MVP) approach. This procedure aims to create a portfolio with the lowest possible volatility by incorporating multiple assets, as introduced by Markowitz (1959). The portfolio weights can be determined using the following formula:

$$OW^* = \frac{[Var - Cov]_t^{-1} I}{I[Var - Cov]_t^{-1} I} \tag{10}$$

Here, OW^* is portfolio weight vector, I is a m-dimensional vector of ones, and $[Var - Cov]_t^{-1}$ represents the $m \times m$ conditional variance-covariance matrix for period t.

3.2.2.2. Minimum connectedness approach

Building on the concepts of the previously mentioned portfolio techniques, we introduce the minimum connectedness portfolio (MCoP). This approach utilizes pairwise connectedness indices instead of the variance or correlation matrix. By minimizing the interconnectedness across variables and reducing their spillovers, the portfolio becomes less susceptible to network shocks. As a result, investment instruments that neither influence nor are influenced by others will be assigned higher weights. This can be represented as:

$$OW^* = \frac{[PWConnect]_t^{-1} I}{I[PWConnectCorr]_t^{-1} I} \tag{12}$$

Where $\left[PWConnect\right]_t^{-1}$ is the pairwise connectedness index matrix, and I is the identity matrix.

3.2.2.3. Risk-parity approach

Following the methodology of Maillard et al. (2010), we employ the risk-parity portfolio approach. This technique allocates portfolio weights so that each asset contributes equally to the overall portfolio risk. The rationale is that a portfolio with equal risk contributions is expected to perform better and be more resilient during market downturns and economic crises. This can be formalized as the following minimization problem:

$$min\sum_{i,j=1}^{N}(OW_{it}^{*}(Var-Cov)OW_{t}^{*}))i-OW_{jt}^{*}(Var-Cov)t'OW_{j}^{*2} \tag{13}$$

3.2.2.4. Portfolio back testing: Hedging effectiveness

To evaluate portfolio performance, we utilize the hedge effectiveness score. In the spirit of Ederington (1979) hedge effectiveness is given by:

$$HE=1-\frac{Var(Hedg)}{Var(Unhedg)} \tag{14}$$

Var (Hedg) represents the variance of the portfolio returns, and Var (Unhedg) the variance of the unhedged asset. HE represents the percent reduction in the variance of the unhedged position. The higher the HE the larger is the risk reduction.

4. RESULTS

4.1. Total Connectedness Index (TCI)

The interconnectedness indices among the energy and commodity markets illustrate significant variations, highlighting the diverse influence dynamics between different assets as detailed in Table 2. The "to" connectedness values fluctuate between 4.40% (GAS) and 53.23% (CNRG). Conversely, the "from" connectedness values vary from 8.19% for GAS to 48.61% (CNRG), demonstrating a significant variation. Notably, GAS displays the lowest connectedness in both the "to" and "from" categories, indicating its weak influence and response dynamics within the network, while the clean energy index (CNRG) shows the highest connectedness level. The NET values provide a net measure of connectedness for each asset, reflecting both their influence on others and the impact they receive. For instance, while ICLN and CNRG are significant contributors to overall connectedness, indices like primarily GAS and WTI act as net receivers of shocks from other assets. These results are consistent with the findings of Attarzadeh and Balcilar (2022). Incremental Own Connectedness (Inc.Own) values further elucidate the degree to which individual assets influence the overall connectedness of the market. A closer examination reveals that ICLN and CNRG exert substantial influence, as indicated by their notably high values in the "Inc.Own" row. Lastly, the conditional total connectedness index (cTCI) compared to total connectedness index (TCI) offers valuable insights into the importance of direct connections among variables. The ratios observed imply a substantial degree of direct linkages that extend beyond the general interconnectedness of the market. These findings underscore the presence of distinct, influential connections among energy and commodity assets, emphasizing their roles within the broader economic landscape.

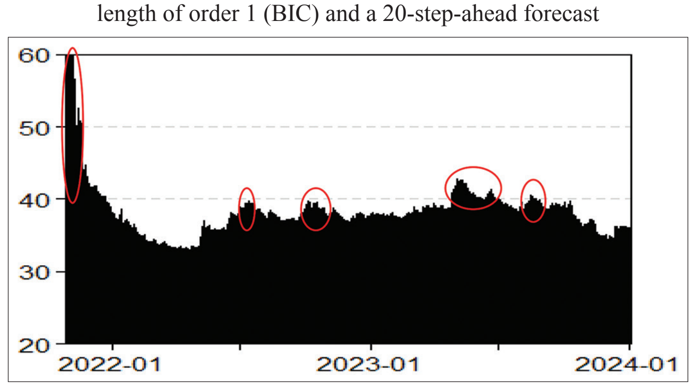
The Figure 2 illustrates the dynamic total connectedness index (TCI) over the sample period from October 26, 2021, to January 5, 2024. The average TCI value corresponding to the period is approximately 38.30% (Table 1), implying that co-movements within these energy indices are moderate. On average, 38% of the forecast error variance in one index can be attributed to shocks from other indices included in the network. However, the results potentially mask the dynamics and influences of specific events shaping the linkages between the different indices, which could trigger substantial deviations from the average TCI value of 38%.

Thus, we extend our analysis by exploring the richer time-varying output from our dynamic econometric framework. Within the framework of our analysis, large TCI values indicate strong co-movements across the network. In the Figure 2, total connectedness within our network varies considerably, ranging from a low of below 30% to a high over 80% during November 2021. This initial peak may be associated with the market adjustments following the ongoing global energy crisis, while the latter peak could correspond to economic uncertainties and policy changes related to climate initiatives and energy transitions. In such period, the energy market experienced a significant crisis due to a combination of factors: A rapid post-pandemic surge in global energy demand, supply chain disruptions, and geopolitical tensions. This implies that the connectedness across the various indices not only reacts to events associated with the green finance and energy markets under examination but can do so swiftly and by considerable amounts. A closer inspection reveals that the TCI exhibits several distinguishable peaks and troughs across the sample period.

Table 2: Average dynamic connectedness

Measures	ICLN	CNRG	WTI	GAS	FROM
ICLN	51.79	45.47	1.78	0.96	48.21
CNRG	44.99	51.39	2.10	1.52	48.61
WTI	3.44	4.53	90.11	1.92	9.89
GAS	1.80	3.22	3.17	91.81	8.19
TO	50.23	53.23	7.04	4.40	114.90
Inc.Own	102.02	104.61	97.15	96.22	cTCI/TCI
NET	2.02	4.61	−2.85	−3.78	38.30/28.72
NPT	2.00	3.00	1.00	0.00	

Figure 2: Dynamic total connectedness .
Notes: Results are based on a TVP-VAR (0.99, 0.99) model with lag length of order 1 (BIC) and a 20-step-ahead forecast



The Total Connectedness Index (TCI) shows a pronounced peak around mid-2022 corresponding to the war between Russia and Ukraine, followed by variations and another peak during the second and third quarters of 2022. The Consumer Price Index for energy rose by 33.3%, with gasoline prices increasing by 58.1% and fuel oil by 59.3%. Efforts by Europe to replace Russian gas led to increased LNG prices and electricity costs. This crisis highlighted the volatility and vulnerabilities within the global energy supply chain. Such results underscore the dynamic nature of connectedness within the green finance and energy sectors, underlining the importance of considering time-varying aspects to fully understand the interdependencies and risk transmission mechanisms[2]. Also, there are smaller peaks observed in the second quarter and mid-third quarter of 2023. These peaks reflect periods of heightened co-movements, suggesting turbulent times where the indices in our network are deemed relatively equally risky.

4.2. Net Total Directional Connectedness

The figure 3 illustrates the net connectedness dynamics for Green Energy (ICLN and CNRG) and traditional energy indices, namely Crude Oil (WTI) and Natural Gas (GAZ), from early 2022 to early 2024. Throughout most of this period, the green energy indices, ICLN and CNRG, primarily act as net transmitters of shocks, except at the end of 2021, when they briefly serve as net receivers due to heightened market volatility. This pattern indicates their susceptibility to external disturbances. Conversely, traditional energy indices, WTI and GAZ, function as net receivers of shocks during this time. However, at the end of 2021, marked by geopolitical tensions, all indices frequently shift between being net receivers and transmitters of shocks. As time progresses, the roles of these indices stabilize, resulting in reduced intensity of both transmission and reception of shocks. This dynamic underscores the varying responses and stability levels between green and traditional energy sectors in times of uncertainty. These observations are consistent with the findings of Avazkhodjaev et al. (2022).

4.3. Dynamic Portfolios Analysis

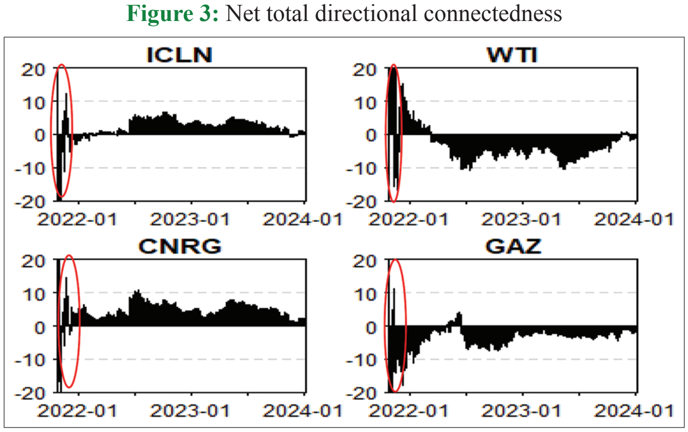
In this section, we solely focus on the energy markets, namely the green and dirty ones. To evaluate which portfolio technique is most appropriate we construct the four methods, namely: (i) minimum variance portfolios (MVP); (ii) minimum correlation portfolios (MCP); (iii) risk-parity portfolios (RPP) and minimum connectedness portfolio (MCoP). Hedge effectiveness score is used to evaluate the relative performance of each portfolio.

Figure 4 plots the cumulative return of the four alternative portfolios: MVP, MCP, MCPp, and RPP. The plot illustrates that these four portfolio methods perform with a visible level of equivalence, sharing the same underlying dynamics. The portfolios experience a modest dip in cumulative returns around mid-2022, followed by a pattern of decline until early 2023. There is a notable decrease in cumulative returns, which continues with some fluctuations throughout 2023. Worth noting that the MVP cumulative return outperforms during the first half of 2023. By the end of 2023, the portfolios show a slight recovery in cumulative returns, but they remain below the levels observed at the beginning of the plotted period. This pattern reflects the broader market dynamics and potential economic factors influencing the performance of these portfolios during the given timeframe.

To give a more concrete understanding of the composition of the individual portfolios, we illustrate the dynamic portfolio weights in Figure 5. Under casual inspection, it is fairly immediate that the MVP composition differs markedly from MCP, RPP and MCoP, while MCP and MCoP share closely matching compositions with each other and RPP. Addressing first the similarity between the compositions for MCP and MCoP, from a mechanical perspective this is perhaps not a tremendous surprise, since each are derived from the same time-varying variance covariance matrix. Having said that, the transformations involved to arrive at the final information to be fed into the portfolio calculations diverge in a

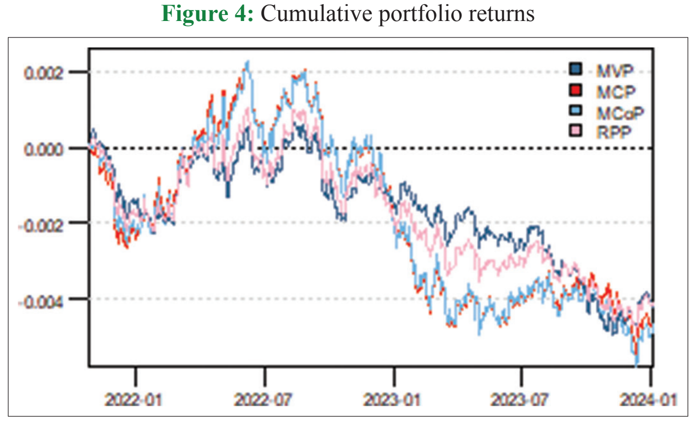
2 World Economic Forum: "Factors contributing to the global energy crisis and trends in energy demand" (World Economic Forum). Available at: World Economic Forum. U.S. Bureau of Labor Statistics: "Consumer price changes and significant increase in energy prices from November 2020 to November 2021" (Bureau of Labor Statistics). Available at: Bureau of Labor Statistics. International Energy Agency (IEA): "Global energy crisis, impact of geopolitical factors, and government responses" (International Energy Agency). Available at: International Energy Agency.

Figure 3: Net total directional connectedness



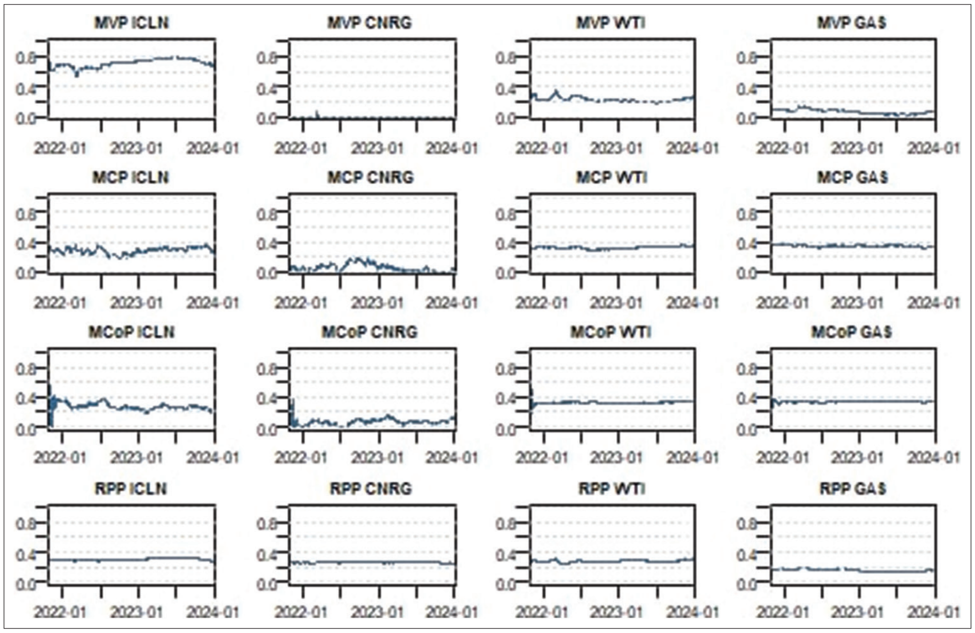
Results are based on a TVP-VAR (0.99, 0.99) model with lag length of order 1 (BIC) and a 20-step-ahead forecast)

Figure 4: Cumulative portfolio returns



Results are based on the time-varying variance covariance matrices retrieved from the TVP-VAR (0.99, 0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio and MCoP to the minimum connectedness portfolio. The dotted gray lines depict returns on individual bond indices

Figure 5: Dynamic multivariate portfolio weights



Results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR (0.99, 0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio, and MCoP to minimum connectedness portfolio) Cumulative returns

substantial fashion. Whereas for MCP, the variance-covariance is "simply" converted into a correlation matrix, for MCoP a much more involved sequence of calculations is required. Hence although the initial building blocks are similar for all four methods, the divergence in transformations does not make it immediately obvious that they should result in closely correlated portfolio weights.

The minimum variance (MVP) portfolio focusing on the assets that contribute least to portfolio variance likely gives significant importance to clean energy assets due to their lower volatility compared to traditional energy assets. Slight changes in MVP weights suggest that while clean energy stocks are still strongly present, adjustments are made in response to volatility changes, in particular when market risk for energy commodities increases. The minimum correlation portfolio (MCP), designed to minimize the correlation between assets and the minimum connectivity portfolio (MCoP) focusing on minimizing connections between assets, show more dynamic weight changes reflecting the evolving interrelationships between clean and polluting energy sectors. In both MCP and MCoP portfolios, the weights of ICLN, gas and WTI are similar whereas the weight of CNRG is very low but the allocation more balanced compared to the PVM, with adjustments made in response to changes in correlations and connectivity. Finally, the Risk Parity Portfolio (RPP) aims to equalize the risk contribution of each asset, resulting in a more even allocation of assets, with a constant allocation maintained to balance the risks among all assets, Independent of market conditions. Clean energy assets, particularly in the MVP and RPP, could dominate because of their lower risk and reduced volatility, while fossil fuel assets, although more isky, offer valuable diversification, their weighting is more dynamic and responsive to changing market conditions. In sum, these portfolios highlight the importance of strategic balance between clean and polluted energy to achieve different investment objectives, whether it is minimizing risk, correlation or connectivity.

Having recognized some empirical similarity between MCP and MCoP, we dig deeper into the implications for portfolio and risk management. For this purpose, we compare and contrast the MCoP approach together with standard portfolio analysis techniques, MVP, MCP and RPP, by examining the hedging effectiveness score for each method. These results are presented in Table 3, allowing for a more objective comparison of the returns generated by each portfolio. Confirming the results of multivariate portfolio weights in Figure 5, the analysis of Table 3 indicate that green stocks contribute a non-trivial role to an energy investment portfolio. By way of example, the portfolio weights for green indices range from approximately 71% under the MVP to 30% and 26% under the RPP for respectively ICLN and CNRG. Interestingly, the green indices weights are around 28% and 5% for MCP and 20% and 17% for MCoP.

The dirty energy sources as oil and gas seem to be similarly important for MCP and MCoP portfolio techniques as the average weights are all around 30%. The MVP and RPP successively consist of (22% and 6%) and (28% and 16%) respectively for MVP and RPP portfolios techniques. Regarding the hedge effectiveness ratios in the same table, the results for MVP approach suggests that if on average we invested 71% in ICLN, 22% in WTI and 6% in gas with no investing in CNRG, then the volatility of each asset in this portfolio would be statistically significantly lowered by 30%, 44%, 63% and 89%, respectively. These volatility reductions are financially meaningful, moreover, they are statistically significant at a 0.1% significance level. The almost same insights could be drawn from the RPP portfolio technique. In fact, the volatility could respectively reduce by 22%, 37%, 59% and 88%.

Table 3: Dynamic multivariate portfolio weights

Variables	Mean	Std.Dev.	0.05	0.95	HE	P-value
Minimum variance portfolio (MVP)						
ICLN	0.71	0.05	0.62	0.78	0.30	0.00
CNRG	0.00	0.01	0.00	0.00	0.44	0.00
WTI	0.22	0.03	0.19	0.28	0.63	0.00
GAS	0.06	0.03	0.03	0.12	0.89	0.00
Minimum correlation portfolio (MCP)						
ICLN	0.28	0.04	0.20	0.34	-0.26	0.01
CNRG	0.05	0.05	0.00	0.16	-0.01	0.93
WTI	0.32	0.01	0.29	0.34	0.34	0.00
GAS	0.34	0.01	0.32	0.36	0.81	0.00
Minimum connectedness portfolio (MCoP)						
ICLN	0.20	0.02	0.17	0.23	-0.15	0.09
CNRG	0.17	0.02	0.14	0.21	0.08	0.36
WTI	0.32	0.01	0.31	0.33	0.39	0.00
GAS	0.31	0.02	0.30	0.32	0.82	0.00
Risk-parity portfolio (RPP)						
ICLN	0.30	0.01	0.28	0.33	0.22	0.00
CNRG	0.26	0.01	0.25	0.27	0.37	0.00
WTI	0.28	0.01	0.25	0.30	0.59	0.00
GAS	0.16	0.02	0.13	0.18	0.88	0.00

Turning towards the other portfolios, for the MCP approach if on average we invested 28% in ICLN, 5% in CNRG, 32% in WTI and 34% in gas, we observe that the volatility of the assets in this portfolio is not reduced by the introduction of green indices while reduced by 34% and 81% by the introduction of both WTI and gas. The results are for the most part statistically significantly lower compared to its initial value. Almost the same result is observed for the MCoP portfolio, where when we invest 20% in ICLN, 17% in CNRG and 32% in WTI and 31% in gas, the volatility would not decrease by the introduction of ICLN but would decrease by the introduction of CNRG, WTI and gas by 8%, 33% and 30%. All of the volatility reductions are statistically significant at least on the 10% significance level, except for CNRG for MCP and MCoP.

ICLN is more prominent in portfolio construction compared to CNRG, as reflected by its higher weights across different portfolio strategies (e.g., 0.28 in the Minimum Correlation Portfolio and 0.30 in the Risk-Parity Portfolio). These higher weights suggest that ICLN plays a more significant role in minimizing risk and achieving portfolio objectives. In contrast, CNRG has lower weights and less contribution to portfolio risk management, indicating that ICLN is likely more valuable for risk mitigation and hedging purposes.

Our results differ from those of previous studies by offering greater precision in assessing the hedging role of clean energy indices. While their hedging capability is modest compared to dirty energy ones, our findings provide a clearer understanding of their specific role and dynamics in the market.Overall, findings relating to portfolio analysis seem to confirm the presence of a dynamic network which allows for diversification opportunities. We do not have enough evidence from this singular application of the technique to draw any firm conclusions or claim if this is likely to be the case in other applications. This is something that future research may wish to remain cognizant of, i.e. the possibility that risk-parity portfolios give rise to lower volatility with equal returns performance, relative to minimum correlation portfolios.

Table 4: Decomposed components — connectedness

Panel A: Contribution TO others				
Components	ICLN	CNRG	WTI	GAS
1	47.46175	51.27931	5.354976	9.656870
2	47.93135	49.48450	6.475626	8.455309
3	50.21829	53.99229	19.879396	21.550000
4	65.06909	66.31266	18.929424	21.959272
5	57.56043	53.73771	17.434384	23.320597
6	53.42699	51.48898	17.410786	25.271095
7	53.62733	55.28670	52.519439	26.425715
8	48.09760	37.34022	54.187437	48.583797
Panel B: Contribution FROM others				
Components	ICLN	CNRG	WTI	GAS
1	48.56918	48.93037	10.56279	5.690564
2	46.93219	48.53667	10.22539	6.652536
3	50.48766	53.29613	24.41155	17.444637
4	48.54620	55.15632	46.01919	22.548745
5	51.93450	53.32983	23.15091	23.637879
6	53.57161	54.53959	24.06308	15.423577
7	58.48365	58.34509	39.87245	31.157991
8	51.42053	51.98465	40.09059	44.713297
Panel C: Total connectedness index				
Component				Value
1				28.43823
2				28.08670
3				36.40999
4				43.06761
5				38.01328
6				36.89946
7				46.96480
8				47.05226

Next, we examine Table 4 which addresses and reports the reward-to-volatility (Sharpe) ratios, showing how much profit can be expected from a given portfolio with risk equal to one standard deviation. We find that the daily mean return is highest for MCP and MCoP, followed by RPP and MVP. Even though, MVP has the lowest mean return it is also exposed to the lowest risk followed by MCoP, MCP, and RPP. The MCoP portfolio displays the largest reward-to-volatility value at 0.0720 followed by MCP (0.0711), RPP (0.0655), and MVP (0.0602).

4.4. Robustness Analysis: Wavelet Approach

The wavelet approach decomposes a signal in the frequency domain rather than the time domain, forming the components according to variations and trends across different time aggregation levels. While we cannot precisely recognize the specific aggregation level, the initial components correspond more closely to short-term variations, but the final components represent long-term phenomena. Figure 6 shows the total connectedness index derived from the TVP-VAR model.

The Figure 6 presents a detailed wavelet decomposition of daily returns indices for the four energy-related assets studied: ICLN, CNRG, WTI, and GAS. Using the Maximal Overlap Discrete Wavelet Transform (MODWT), the series are fragmented down into eight levels, each on behalf of different frequency components. Levels 1 to 4 capture the short-term, high-frequency variations, where ICLN and CNRG display more pronounced volatility, representing greater sensitivity to immediate market conditions. Conversely, levels 5 to 8 highlight the long-term, low-frequency trends, screening smoother, more stable patterns, particularly in ICLN and CNRG. This analysis reveals the distinct short-term and

Figure 6: Daily return indices and decompositions

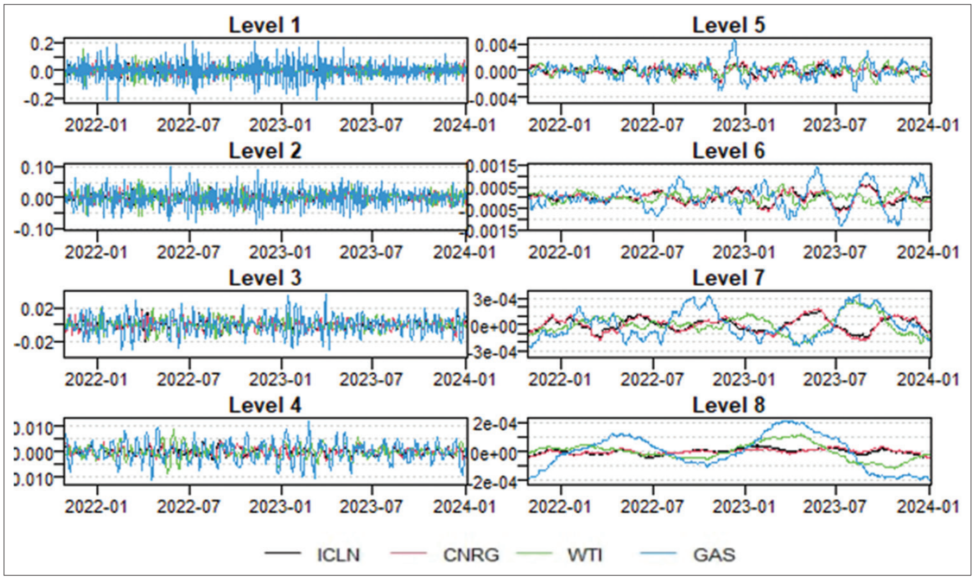
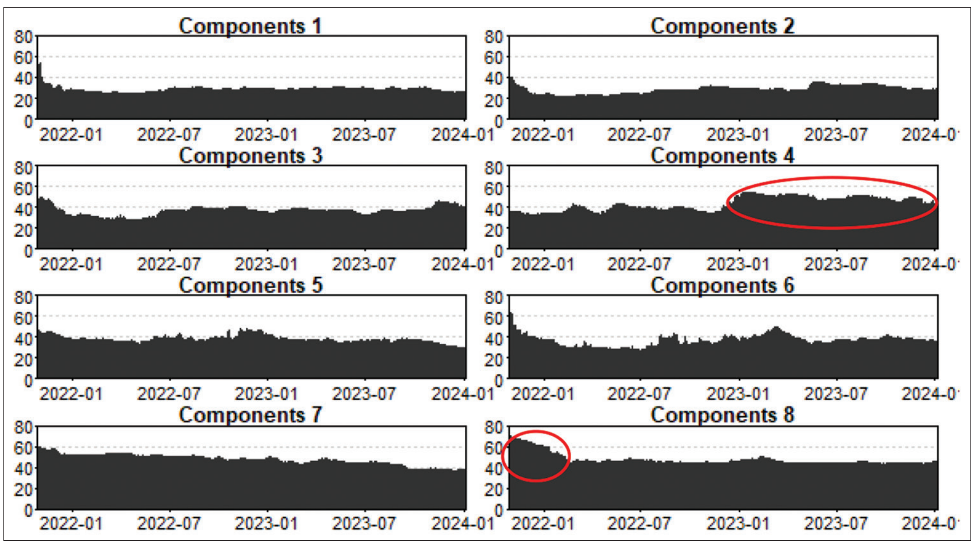


Figure 7: Dynamic total connectedness index of the clean and dirty energy indices



long-term volatility characteristics of these assets, offering valuable insights for investors and analysts in understanding the behavior of these energy-related markets across various time horizons.

As we observe from Panels A and B of Table 4, both the spillover effect originating from and to any given economy rise as we move from shorter to longer horizons, thus providing an indication that the choc spillovers between markets appear with a significant lag. Our findings corroborate the ones of Antonakaksis et al. (2021), who also report such lagged effects. In Panel C, we report the total connectedness index for each component. Again, the total connectedness of the system rises at longer horizons. It rises from 28.43% to reach 47.05%. This finding reflects that in the long-run most of the uncertainty variations should be attributed to exogenous influences, given that in the long-run the economy has time to adjust to any potential cause of domestic uncertainty.

The Figure 7 displays the total connectedness index (TCI) across eight wavelet components, highlighting the interconnectedness among ICLN, CNRG, WTI, and GAS over various time scales. These results are aligned with previous empirical findings of Farid et al. (2023), whose research highlighted the weak correlations between short-term clean and dirty energy stocks and a notable segmentation effect between dirty and clean energy markets. In the high-frequency components (1 to 4), the TCI fluctuates between 40% and 60%, indicating strong short-term interactions among the assets especially in the fourth wave. This suggests that in the short run, shocks or news events in one market quickly spill over to others, affecting both clean and dirty energy assets. The TCI in the mid-term components (5 and 6) shows instability but with values generally ranging between 30% and 40% with two peaks at the end of the first quarter of 2022 (50% in the fifth component) and at the end of 2021 (60% in the sixth component). This level of connectedness suggests that while there is still interaction among the assets, it is less pronounced than in the mid-term. The mid-term connectedness might reflect market responses to medium-term economic trends or policy changes affecting the energy sector.

In the low-frequency components (7 and 8), the TCI averages around 50%, indicating a higher level of interconnectedness over the long term. Notably, there were high values between late 2021 and early 2022, where the TCI peaked between 50% and 70%, likely reflecting the impact of significant market events during that period. However, as time progressed, the TCI stabilized at around 40%, representing a more consistent long-term relationship among the assets. This stability suggests that though the markets are interconnected, the long-term trends are driven by broader, slower-moving factors, with less frequent but more significant interactions.

To sum it up, the TCI across the wavelet components reveals distinct patterns of connectedness at different time scales. Short-term fluctuations display strong and volatile interactions, particularly during periods of market stress. In contrast, mid- to long-term connectedness is more stable, with significant events like those in late 2021 and early 2022 momentarily increasing interconnectedness afore settling down.

These wavelet-based results align with and confirm our previous findings, providing further evidence of the dynamic nature of connectedness across different time scales between clean and dirty assets.

5. CONCLUSION

In this study, we examined risk transmission between clean energy assets (ICLN and CNRG) and traditional fossil fuels (WTI and Gas), emphasizing the role of socially responsible investment (SRI) in portfolio diversification. Through a time-varying parameter vector autoregression (TVP-VAR) model, we assessed how significant global events—such as the COVID-19 pandemic, the Russia-Ukraine conflict, and the Gaza war—have influenced the dynamic connectedness among these assets. Using daily data from October 26, 2021, to January 5, 2024, we explored various portfolio construction techniques, including the minimum variance, minimum correlation, risk-parity, and minimum connectedness portfolios, while employing wavelet analysis to capture spillover effects across different frequency components.

Our findings reveal that connectedness between clean and traditional energy sources spikes during global crises, with major peaks linked to the COVID-19 pandemic, the Russia-Ukraine war, and the Gaza conflict. However, these impacts were typically short-lived, suggesting limited long-term effects on connectedness. In portfolio analysis, the Minimum Variance Portfolio (MVP) achieved the highest hedging efficiency, particularly for Gas, which exhibited the highest individual hedging efficiency across all portfolios. Conversely, clean energy assets, particularly ICLN, provided relatively low hedging efficiency, indicating they may be less effective in risk management.

This study offers meaningful insights for different stakeholders. For investors, it highlights the potential of SRI in portfolio performance without compromising returns, supporting the case for integrating ESG criteria in investment strategies. For policymakers and regulators, the findings offer a perspective on the evolving interactions between green and traditional energy assets, underscoring the potential need for standardized green bond definitions. Finally, for bond issuers, the evidence suggests that attracting green capital need not require a trade-off in financial returns, as long as balanced investment strategies are employed. Overall, our research underscores the importance of adaptive, ESG-aligned investment strategies that can contribute to sustainable investing and long-term value creation.

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