The importance of green energy ETFs in portfolio optimization and volatility transmission

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Abstract

This research significantly enhances our understanding of the role of green energy Exchange-Traded Funds (ETFs) in portfolio optimization. It provides practical insights into the advantages and disadvantages of diversifying into green assets. By employing a two-step high-dimensional network methodology, the study utilizes a TVP-VAR model and multivariate portfolio techniques to analyze risk contagion between traditional stocks and green energy ETFs and assess hedging efficacy. Spanning from January 17, 2020, to March 28, 2024, the research updates knowledge in three geographical areas – China, the European Union, and the United States and examines the connectedness between green and energy ETFs markets and conventional stocks, crucial for risk management amid geopolitical uncertainties. Our findings show that using multivariate portfolio techniques in the ETF market can help reduce investment risk. Additionally, the study sheds light on how changes in information transmission between energy and green energy ETFs and traditional equities affect the market. These insights can be valuable for investors looking to navigate the renewable energy sector.

Keywords: Green investments, ETFs, Stocks, Financial markets, Connectedness, Portfolio diversification, Hedging effectiveness, TVP-VAR.
JEL classification: G14, G15, G18.

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1. Introduction

In recent years, the global economy has been grappling with a heightened level of uncertainty triggered by a series of unprecedented shocks. From geopolitical tensions started by the COVID-19 pandemic, Russia's invasion of Ukraine to the Israeli-Palestinian conflict, these events have not only disrupted financial markets but also raised profound questions about the stability and resilience of the global economic system (Bouri et al., 2024; Karkowska & Urjasz, 2023; Naeem et al., 2023). In this context, our research on the role of green energy ETFs in portfolio optimization and risk management amid geopolitical uncertainties is particularly relevant and timely.

The presence of uncertainty poses significant challenges for investors in portfolio management. The ever-shifting landscape of economic conditions and the potential for contagion and crisis events make it increasingly difficult to anticipate and mitigate risks effectively. In the aftermath of the 2008 financial crisis, numerous investors sought ways to shield their assets from market fluctuations. Consequently, there was a surge in the introduction and popularity of ETFs designed to minimize volatility, fixed-income ETFs, and short and leveraged ETFs, catering to the preferences of investors (Fulkerson et al., 2015; Jain et al., 2021).

In recent years, the assets in passive funds have experienced rapid growth, emerging as a substantial segment within the global investment fund landscape. Investments, such as passively managed funds, provide diversified and low-fee portfolios, contrasting with actively managed funds that aim for higher returns through discretionary security selection and market turning points, generating higher fees and trading costs. According to Statista's report[3], the quantity of exchange-traded funds increased substantially between 2003 and 2022, globally. In 2022, there were 8,754 ETFs worldwide, up from 276 in 2003. Global ETFs managed assets worth nearly 10 trillion U.S. dollars as of 2022. ETFs offer several benefits, including cost-effectiveness, diversification, transparency, and trading flexibility. These attributes enable ETFs to facilitate effective investment selection, prospects for diversification, controlling liquidity, and potential hedging strategies (Naeem et al., 2023). The ability of investors to promptly react to unanticipated global developments is facilitated by the liquidity provided by ETFs; as a result, investors modify their portfolio allocations (Yousefi & Najand, 2022). This highlights the significance of information transmission via this medium in comparison to assets

[3] Number of ETFs globally 2003-2022, Published by Statista Research Department, Sep 14, 2023, https://www.statista.com/statistics/278249/global-number-of-etfs/

that are traded less frequently or at a slower pace (Buckle et al., 2018). However, this move toward passive investing could impact the securities markets in two significant ways. Firstly, this may lead to increased return correlation and diminished availability of security-specific price information. Additionally, the aggregate investment fund flows and market price dynamics may be impacted. Therefore, in the interest of a broad audience, the impetus toward passive investment heightens the necessity to gain a deeper understanding of the dynamic evolution of ETFs throughout different economic cycles.

On the other hand, increasing green energy demand and energy trade volumes between nations have contributed to increased volatility in the international energy market over the past two decades (Chen et al., 2021; He et al., 2018; Naeem et al., 2023). In 2022, global investments in renewable energy amounted to $0.5 trillion, of which 70% originated from private entities (IRENA & CPI, 2023). As a sustainable alternative to nonrenewable energy, green ETFs experienced explosive growth in 2020, with 552 ETFs and $174 billion in assets under management worldwide (UNCTAD, 2021). This has resulted in volatile prices for fossil fuels, as well as stimulated the development of green energy as a viable substitute (Bouri, 2023; Liu et al., 2020). Because of their high returns and risk management potential, green energy ETFs are gaining prominence to combat climate change, which is a global priority (Algarhi, 2023; Banerjee, 2024). Following, experts have developed an interest in the volatility structure that distinguishes energy ETFs from green energy ETFs to comprehend the implications this has on investment decisions, specifically in terms of the advantages it provides for diversification. Given climate change and the growing interest in the following area, our research aims to verify the volatility structure between energy and green energy ETFs compared to conventional indices. The research examines whether ETFs serve as efficient diversification instruments for investors amidst market turmoil and heightened volatility. In such periods, investors and fund managers tend to decrease their investments in less liquid assets and withdraw from risky ones—a behavior commonly referred to as 'flight to safety' or 'flight to quality.' This behavior could clarify the variations in asset allocation across ETFs during periods of elevated uncertainty.

The idea of replicating conventional stock market indices through various pension funds and private portfolios was popularised by Burton Malkiel. In the classic, ‘A Random Walk Down Wall Street’ he proposed 'buying the market' through a portfolio rather than relying on individual stocks (Sangvinatsos, 2017). This represented a modern form of investing to Markowitz's portfolio theory of selecting individual assets to optimize portfolio returns with minimal risk (Markowitz, 1959). Since then, there has been much research trying to identify which assets are useful as a hedge against uncertainty has been the subject of numerous studies (Beckmann et al., 2015; Elsayed et al., 2020; Mensi et al., 2021; Saha et al., 2022). Despite the evolving macroeconomic landscape, it remains essential to continuously validate emerging factors that alter the volatility dynamics within financial markets. Adapting to these changes ensures a comprehensive understanding of market behavior and facilitates informed decision-making amidst shifting economic conditions. However, the existing literature lacks complete explanations of the interactions between green energy and energy ETFs on a global scale. Although there have been studies conducted by Algarhi (2023), Banerjee (2024), D'Ecclesia et al. (2024), Yousefi and Najand (2022) that investigate the correlation in mentioned markets, there is a lack of research between regions in comparison to conventional stock indices. We aim to verify the relationship between green energy and energy ETFs in China, Europe, and the United States and the effectiveness of green ETFs' investment hedging possibility.

The research explores the role of green energy ETFs in portfolio optimization tools and the pros and cons of diversifying into green assets. It highlights the importance of assessing the interconnection between green and fossil energy ETF markets and the role of green energy ETFs as either net transmitters or net receivers of information about traditional stocks. To identify the interdependence and risk contagion among ETF markets, we develop a two-step high-dimensional network methodology. To begin, a TVP-VAR model was constructed as an extension of the approach proposed by Diebold and Yilmaz (2014). Following the findings of Broadstock et al. (2022), we employ multivariate portfolio techniques in the second phase to assess the efficacy of hedging. As a result, it provides a more comprehensive outlook on risk management strategies in the ETF market.

Second, this paper investigates financial interconnectedness by contrasting the volatility spillovers of conventional stock indices with those of green and fossil energy ETFs on the global scale during periods of significant geopolitical unrest. Our study spans a significant period, during which we have observed several noteworthy events, including the implementation of innovative environmental regulations, a series of volatility in the commodity and stock markets, the COVID-19 pandemic, the Russia-Ukraine war, and the Israeli-Palestinian conflict. The time frame spanned by the investigation is from January 17, 2020, to March 28, 2024. The research provides an extensive update to the current collection of knowledge in three separate fields. As far as our knowledge extends, no prior investigation of a similar kind has been conducted.

Furthermore, the correlation between green energy and energy ETFs and the structure of their volatility significantly influences hedging strategies and portfolio management.

Comprehending this dynamic is critical to effectively managing risks, optimizing asset allocation, and attaining diversification benefits. Continual research and flexible investment strategies will be crucial for navigating this dynamic and complex environment as the energy sector continues to evolve, especially in light of the growing significance of green energy. Therefore, our study uses three multivariate hedging portfolio techniques: Minimum Variance Portfolio, Minimum Correlation Portfolio, and Minimum Connectedness Portfolio to measure hedging effectiveness. This investigation aims to evaluate the effectiveness of various techniques in reducing a portfolio's susceptibility to market fluctuations. The results show the divergence in correlations which present portfolio managers with a potential risk-mitigation strategy. By incorporating Chinese assets, they might be able to hedge against potential losses incurred in the European and US markets. We strongly believe that the findings regarding the interdependence and spillovers of ETF markets within the green energy sector could have major implications for hedging and portfolio diversification. There is a noticeable absence of research that specifically investigates the return and volatility spillover between green energy and energy ETFs in comparison to traditional asset classes.

Furthermore, our findings demonstrate that the European Union is the primary propagator of volatility within the network, with fluctuations originating within the EU market significantly influencing other regions or investment sectors. The EU Clean Energy ETF shows a higher propensity to transmit volatility compared to conventional EU stocks, indicating the need for further investigation into sustainable investment instruments. The Chinese market is a net recipient of volatility, with external sources like the US or Europe playing a more substantial role. US conventional stocks are susceptible to volatility from both the EU Energy ETF and the EU Clean Energy ETF. The Chinese Clean Energy ETF imports volatility from all other markets in the network. Strong volatility transmission linkages occur within markets categorized by similar investment strategies.

The following sections of this study are organized as follows: Section 2 conducts a thorough review of the current literature, while Section 3 provides an extensive overview of the data employed in our empirical investigation. Section 4 sets out the methodology used to assess the interrelationships of volatility and analyses the data. Section 5 presents a detailed examination of the findings, and finally, Section 6 offers a comprehensive analysis of the implications derived from the results.

2. Literature Review

The literature review provides a comprehensive analysis of three essential topics shaping the ETF landscape. Firstly, it looks at the correlations that exist between ETFs and traditional asset classes, illuminating the complex relationships and their implications for portfolio diversification strategies. Secondly, it navigates the realms of price volatility and risk dynamics in the energy and green energy ETF markets, pointing out the nuances between these evolving markets. Finally, it undertakes an exploration of ETFs as a hedging strategy, uncovering their potential effectiveness in mitigating risk and hedging portfolios against market fluctuations. This review aims to provide critical insights for investors, researchers, and policymakers navigating the multifaceted terrain of ETF investments by synthesizing existing scholarship.

2.1 Correlations Between ETFs, and Traditional Asset Classes

Extensive evidence exists regarding the volatility connectedness of various financial markets; however, there is a lack of literature examining the volatility connectedness of exchange-traded funds, specifically in the context of geopolitical risk. Yousaf et al. (2024) investigate the profound interrelation among AI tokens, ETFs, and various asset categories utilizing the quantile VAR technique. Their analysis reveals moderate interconnectedness levels at average and median quantiles, wherein AI tokens notably exhibit a robust tendency to emit return spillovers. Under typical market circumstances, AI tokens could be diversification tools for conventional asset portfolios. Nonetheless, interconnectedness escalates at lower and upper quantiles, signaling their susceptibility to severe market disruptions. The research suggests that, during extreme market conditions, AI tokens and ETFs fail to mitigate the risk of other assets through diversification.

Investigating the risk-related performance of ESG investments using ETFs, Huang (2024) provides forecast combination methods with a scoring function to predict ETF VaR, incorporating economic value. The study shows that ESG ETFs provide better Value-at-Risk but identical modified Sharpe Ratio compared to Oil & Gas ETFs during the pandemic crisis. Additionally, pure ESG ETF investments do not generate excess returns in the long run. Gutierrez et al. (2009) examine the return and volatility of Asian iShares traded in the US, focusing on the unique trading schedules between the US and Asia. It reveals that Asian ETFs have higher overnight volatility than daytime volatility, influenced by local market information. However, returns for these funds are highly correlated with US markets, indicating investor sentiment and trade location. Chen & Xu (2023) verify whether ETF activities destabilize the stock market of the China Securities Index 300 from 2006 to 2020. They find that the coronavirus disease outbreak has increased the volatility effect of ETFs, highlighting the negative role of ETFs in destabilizing the stock market. Finally, Buckle et al. (2018) support the notion that ETFs have overtaken futures contracts as the primary tool for price discovery. Furthermore, it has been observed that spot markets have gained significant importance as grounds for establishing prices. This is likely the result of the fact that ETFs are predominantly constructed through physical replication of the spot index in the United States.

2.2 Comparing Price Volatility and Risk Dynamics: Green Energy and Energy ETFs Markets

Undoubtedly, COVID-19 and the Russian-Ukrainian war garnered increased attention from both academics and professionals on the interdependence of renewable energy and energy volatility (Banerjee et al., 2024; Dumitrescu et al., 2023; Karkowska & Urjasz, 2023; Korosteleva, 2022; Naeem et al., 2023). Naeem et al. (2023) investigate the impact of COVID-19 on intraday volatility spillovers between energy and other ETFs. Their findings indicate that oil and stock markets primarily send out information, whereas currency, bonds, and silver markets predominantly absorb it. Through wavelet analysis, it is evident that media coverage and fake news indexes play a substantial role in shaping investors' negative sentiments regarding their investments.

On the contrary, Rizvi et al. (2022) assess the strength of return and volatility spillovers from green and grey energy markets and show that green energy ETFs have a more pronounced return shock and are more attractive to investors after 2015. However, volatility spillovers from grey energy markets remain prominent and robust for some asset classes, such as bonds. The study conducted by Asai et al. (2022) has shed more light on the renewable energy exchange-traded funds. Their research findings indicate that the portfolio renewable energy ETFs, Wind, Solar, and Water seem to exhibit indirect mutual causality effects in the second moment and mean. However, when the oil market is considered, the causality effects become more pronounced, leading to indirect uni-cause effects between the Oil to Solar ETF and the Oil to Water ETF. Moreover, Karkowska and Urjasz (2023) examine the spillover effects of volatility from dirty and renewable energy markets onto global stock indices during periods of escalating geopolitical risk. Using volatility connectedness indices, they observed that clean energy indices, on average, exhibit reduced risk in comparison to global equity markets. Nevertheless, hedging in renewable energy assets incurs a greater expense than in non-renewable energy indices. Similarly, Algarhi (2023) finds weak dynamic correlations between green energy ETFs and grey and conventional funds, suggesting that these ETFs offer superior diversification. On the other hand, Pavlova and De Boyrie (2022) examined SRI ETFs for six months before the emergence of the COVID-19 crisis and concluded that ESG ETFs with higher sustainability ratings failed to safeguard them from losses during the period of decline.

2.3 Exploring energy ETFs as a Hedging Strategy

Spillovers of high returns and volatility not only demonstrate the interconnectedness of the markets but may also influence hedging and portfolio diversification strategies (Alomari et al., 2024; Chen et al., 2021; Kang et al., 2021; Maghyereh et al., 2016; Saeed et al., 2020; Sarwar et al., 2019). The literature review on the volatility structure between green energy and energy ETFs reveals several critical insights that affect investment decisions. Firstly, significant volatility spillovers have been identified between various types of renewable energy ETFs, such as solar, wind, and nuclear, with crude oil ETFs (Chang et al., 2018). These spillovers suggest that shocks in one type of ETF can influence the volatility of another, which is crucial for portfolio management and risk assessment. Secondly, the market efficiency of both renewable and non-renewable energy ETFs has been scrutinized, revealing a long-memory dependence across all ETFs, which indicates weak-form inefficiency (Saleem & Al-Hares, 2018). This inefficiency implies a predictable volatility structure, offering potential diversification benefits for international investors. Additionally, the relationship between financial ETFs and energy ETFs in both spot and futures markets has been found significant, suggesting these ETFs are suitable for constructing diversified financial portfolios (Chang et al., 2018).

Furthermore, the literature indicates that the volatility of ETFs, including both renewable and non-renewable energy ETFs, exhibits long memory dependence, suggesting potential diversification opportunities for investors (Saleem & Al-Hares, 2018). The causality effects in returns and volatility vary depending on the specific assets and periods, highlighting the need for a nuanced understanding of these dynamics in investment strategy formulation. The study conducted by Lin and Chang (2020) The study conducted by Lin and Chang (2020) identified a substantial effect of stock market volatility on the oil ETF and the energy fund, thereby establishing a predictive relationship between the stock market and the movements of oil and energy funds. Saeed et al. (2020) determined that clean energy securities are more effective than green bonds in hedging against crude oil prices and energy ETFs by calculating the hedging ratios of clean and green assets against these variables. According to a study by Shahzad et al. (2020), the structure of the clean energy stock markets in Europe and the United States is comparable; however, the European clean energy market is more dynamic and volatile, which may appeal to investors seeking high returns.

3. Data Statistics

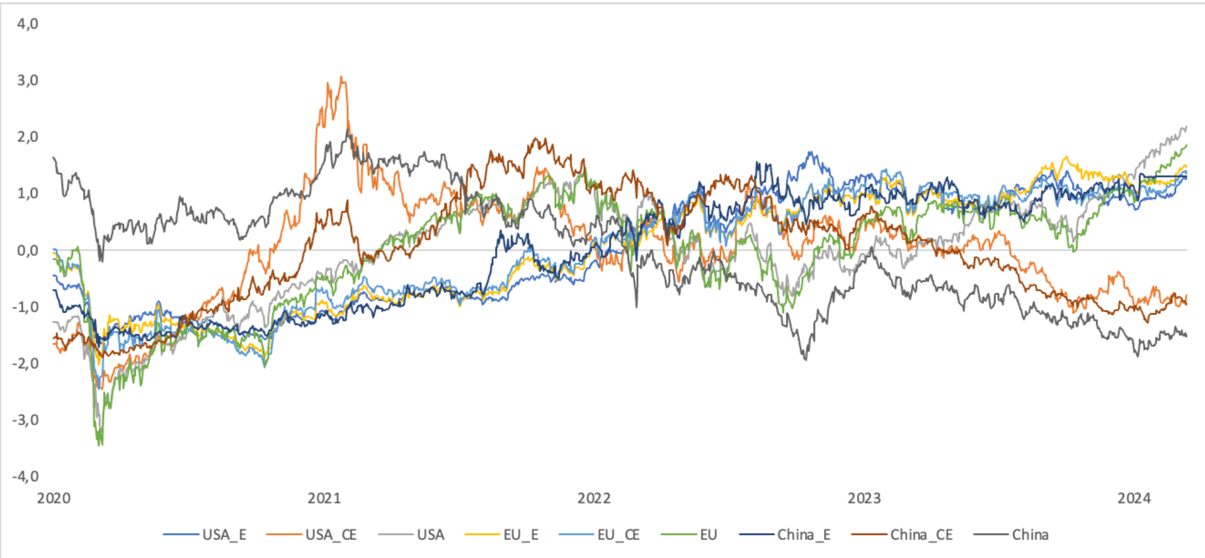
This investigation utilizes daily time series data on Exchange Traded Funds (ETFs) in the energy and clean energy sectors, along with conventional stock market indices, from three major economic regions: the United States, Europe, and China. The data encompasses a period ranging from January 17, 2020, to March 28, 2024. The extent of the observation window is restricted due to constraints in data availability. The analysis incorporates the following variables:

1. Energy ETFs:
- USA_E (Xtrackers MSCI USA Energy UCITS ETF): The ETF specifically tracks the performance of energy sector companies within the United States.
- EU_E (iShares MSCI Europe Energy Sector UCITS ETF): This ETF focuses on the energy sector in Europe. It holds stocks of European companies involved in oil and gas exploration, production, refining, or related services.
- China_E (Global X MSCI China Energy ETF) is an ETF that tracks the performance of companies in the MSCI China Investable Market Index.
2. Clean Energy ETFs:
- USA_CE (SPDR S&P Kensho Clean Power ETF): The ETF includes the USA companies that are involved in solar, wind, hydro, and geothermal energy sources. It also invests in companies focused on technologies related to these renewable sources.
- EU_CE (Amundi STOXX Europe 600 Energy ESG Screened UCITS ETF Acc): This ETF is designed to expose investors to European companies in the energy sector while also considering ESG factors.
- China_CE (Global X China Clean Energy UCITS ETF USD Acc) is an ETF that invests in companies positioned to benefit from the growth of clean energy in China.
3. Conventional stocks:
- USA (S&P 500): Index that tracks the performance of 500 of the largest publicly traded companies in the United States.

- EU (STOXX Europe 600 Index): The index includes 600 of the leading companies from various sectors within developed European markets.
- China (Hang Seng Index): Index that tracks the performance of the largest and most actively traded companies on the Hong Kong Stock Exchange.

Standardized variables in Figure 1 illustrate a correspondence in trend patterns between the European Energy ETF, European Clean Energy ETF, and conventional European stock market indices. This suggests a potential co-movement between these asset classes. Furthermore, US indices exhibit greater heterogeneity, while Chinese indices display the most significant heterogeneity.

Fig. 1. Energy ETFs, Clean Energy ETFs and Conventional Indices.



Continuously compounded returns were calculated using the formula: $r_{i,t} = \ln(P_{i,t} - P_{i,t-1}) * 100$. To minimize potential biases arising from asynchronous trading, a two-day rolling average return was determined. This approach adheres to the methodology established by Forbes and Rigobon (2002). Figure 2 depicts logarithmic returns, highlighting the anomalous behavior of the Chinese stock market relative to the others. Notably, the data coincides with previously documented periods of heightened market volatility associated with global events such as the COVID-19 pandemic, the Russo-Ukrainian War, and the Israeli-Palestinian conflict.

Fig. 2. Percentage changes of Energy ETFs, Clean Energy ETFs, and Conventional Indices.

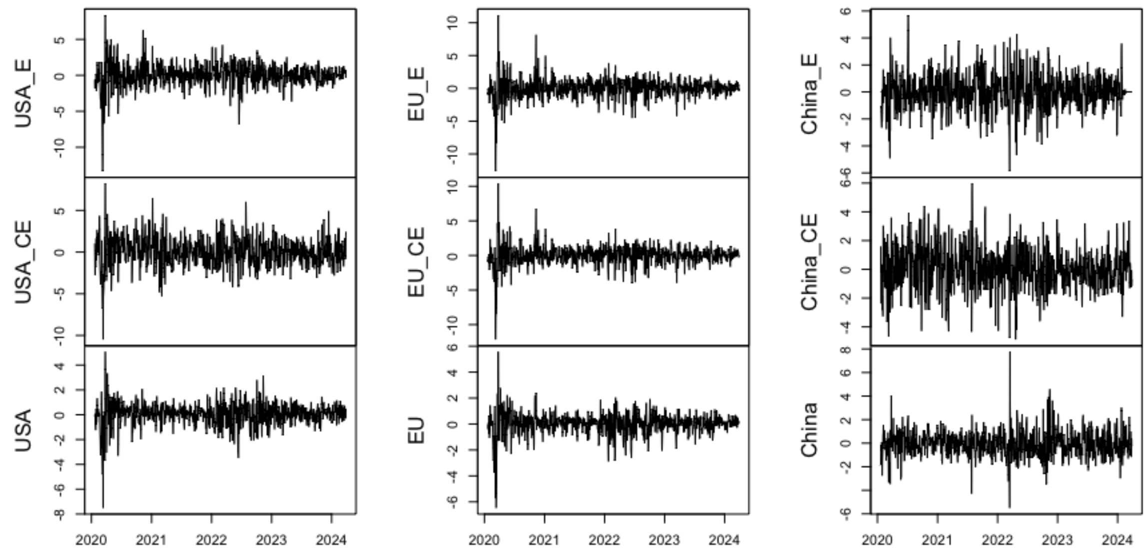


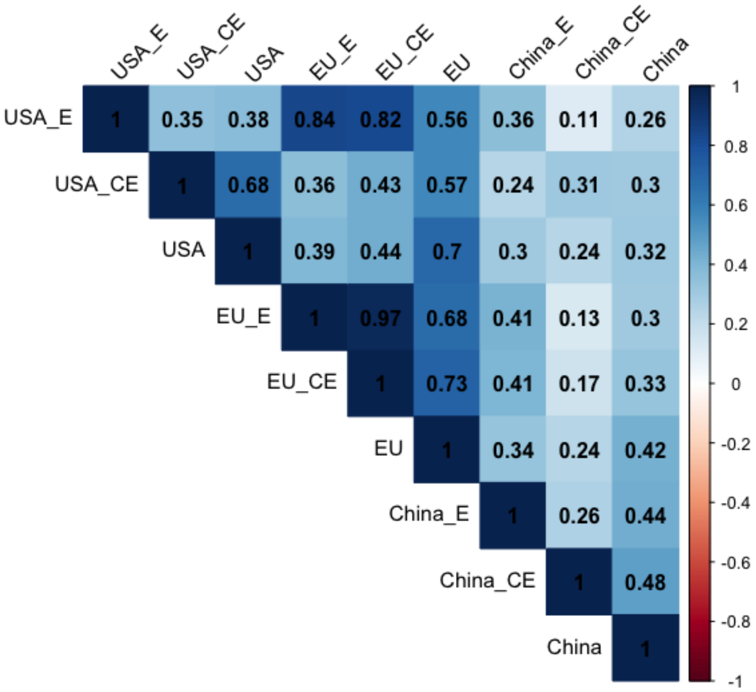
Table 1 provides a synopsis of the key descriptive characteristics of the variables under investigation. It is noteworthy that the mean value associated with the Chinese conventional stock index is negative. Further scrutiny unveils a left-skewed distribution and excess kurtosis for all time series except the aforementioned stock index. As a result, all examined series exhibit statistically significant deviations ($p < 0.01$) from a normal distribution. The normality tests employed corroborate the non-normal distribution of all the data series. In addition, stationarity tests validate the stationarity of all time series. Collectively, these statistical analyses provide compelling support for the selection of a Time-Varying Parameter Vector Autoregression (TVP-VAR) model for subsequent analyses.

Table 1. Summary Statistics.

	USA_E	USA_CE	USA	EU_E	EU_CE	EU	China_E	China_CE	China
Mean	0.053	0.029	0.042	0.033	0.024	0.017	0.045	0.025	-0.052
	(0.267)	(0.578)	(0.122)	(0.473)	(0.573)	(0.483)	(0.242)	(0.561)	(0.116)
Variance	2.464	2.92	0.797	2.301	1.906	0.662	1.607	2.049	1.178
Skewness	-0.990***	-0.025	-0.893***	-0.411***	-0.656***	-1.182***	-0.047	0.051	0.383***
	(0.000)	(0.738)	(0.000)	(0.000)	(0.000)	(0.000)	(0.523)	(0.486)	(0.000)
Ex.Kurtosis	8.818***	2.082***	7.514***	11.616***	13.355***	10.889***	1.614***	0.829***	3.744***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	3706.401***	196.714***	2706.517***	6153.159***	8170.795***	5633.331***	118.552***	31.693***	662.833***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-9.709	-9.321	-12.713	-9.067	-9.689	-11.619	-6.830	-12.685	-4.188
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	289.963***	339.759***	256.068***	324.250***	324.067***	335.148***	245.639***	250.771***	273.332***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q2(20)	492.302***	355.435***	608.491***	707.783***	748.072***	820.003***	166.918***	197.364***	191.750***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Pearson correlation coefficients, depicted in Figure 3, quantify the linear association between Energy ETFs, Clean Energy ETFs, and Conventional Indices. The analysis exposes a robust positive correlation (0.84) between the US and EU Energy ETFs. Conversely, a feeble positive correlation (0.13) is observed between the Chinese Clean Energy ETF and the EU Energy ETF. This divergence in correlations presents portfolio managers with a potential risk-mitigation strategy. By incorporating Chinese assets, they might be able to hedge against potential losses incurred in the European and US markets.

Fig. 3. Pearson rank correlation coefficients.



4. Methods

This investigation posits a two-tiered methodological paradigm for the examination of Energy ETFs, Clean Energy ETFs, and Conventional Indices. The first phase concentrates on the development and estimation of econometric models, in conjunction with the assessment of metrics that quantify the systemic interconnectedness inherent within the financial network. Subsequently, the focus transitions towards the design and appraisal of investment portfolios within the second phase.

4.1. Analysis of Linkages in a TVP-VAR Framework

Antonakakis et al. (2020) advanced the study of dynamic connectedness within systems by introducing a time-varying parameter vector autoregression (TVP-VAR) modeling approach. Their work extends the foundational framework of Diebold and Yilmaz (2014) through the integration of a recursive variance-covariance matrix updating scheme. This novel scheme draws upon Kalman filtering techniques and the use of forgetting factors (Koop & Korobilis, 2013), enabling the model to effectively adapt to potential structural changes within the system under analysis.

The TVP-VAR model can be structured as follows:

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

$$vec(\Phi_t) = vec(\Phi_{t-1}) + \zeta_t , \zeta_t \, | F_{t-1} \sim N(0, \Xi_t) \tag{2}$$

where F_{t-1} represents the cumulative dataset at time step $t-1$, y_t and ε_t, each with dimensions $(n \; x \; 1)$ vector. Φ_t and H_t, both with dimensions $(n \; x \; n)$. ζ_t and $vec(\Phi_t)$ are with dimensions $(n^2 \; x \; 1)$. Ξ_t with dimension $(n^2 \; x \; n^2)$.

Within the framework of analyzing dynamic processes, the Time-Varying Parameter Vector Autoregression (TVP-VAR) can be reconfigured into a Vector Moving Average (VMA) representation. This VMA reformulation offers a significant computational advantage, enabling the efficient estimation of both the Generalized Impulse Response Function (GIRF) and the Generalized Forecast Error Variance Decomposition (GFEVD).

The Generalized Impulse Response Function (GIRF) measures the dynamic, time-varying effects of an exogenous shock on a specific variable and all other variables within a system. It does so over a defined forecast horizon, enabling predictive analysis.

The Generalized Forecast Error Variance Decomposition (GFEVD) reveals the relative contribution of exogenous shocks from different system variables to the forecast error variance of a target variable. This analysis is expressed mathematically as:

$$\theta_{ij}(h) = \frac{\sigma_{jj}^{-1} \sum_{S=0}^{h-1} (e_i^T \Psi_S \Sigma e_j)^2}{\sum_{S=0}^{h-1} (e_i^T \Psi_S \Sigma \Psi_S^T e_i)}, \tag{3}$$

where Σ represents the variance-covariance matrix associated with the error vector ε_t, σ_{ij} is the jth element of the diagonal of the matrix Σ, and e_j is an $n \times 1$ possessing a value of 1 at the i-th position and 0 elsewhere.

Non-orthogonality among exogenous shocks impacting model variables can introduce bias when aggregating individual forecast error variance contributions. To mitigate this, row-wise normalization is employed within the variance decomposition matrix:

$$\tilde{\theta}_{ij}(h) = \frac{\theta_{ij}(h)}{\sum_{j=1}^{K} \theta_{ij}(h)}. \tag{4}$$

As a result, for each period t: $\sum_{j=1}^{K} \theta_{ij}(h) = 1$ and $\sum_{j=1}^{K} \theta_{ij}(h) = n$.

The following connectedness metrics are outlined below:

Total connectedness indices (TCI):

$$S(h) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\theta}_{ij}(h)}{K} \times 100. \tag{5}$$

Total directional connectedness (TDC) from others:

$$S_i(h)^{*} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\theta}_{ij}(h)}{K} \times 100. \tag{6}$$

Total directional connectedness (TDC) to others:

$$S_i(h)^{**} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{\theta}_{ji}(h)}{K} \times 100. \tag{7}$$

Net total directional connectedness (Net TDC):

$$S_i(h) = S_i(h)^{**} - S_i(h)^{*}. \tag{8}$$

4.2. Assessing Risk and Return in Portfolio Optimization

The present investigation will leverage historical portfolio backtesting to assess the financial implications of the proposed strategies. This analysis will juxtapose traditional portfolio construction methodologies with cutting-edge techniques that incorporate network connectedness analysis. Aligned with the research presented by Broadstock et al. (2022), we will employ multivariate portfolio optimization frameworks to quantify the effectiveness of implemented risk mitigation measures.

4.2.1. Minimum Variance Portfolio

The Minimum Variance Portfolio (MVP) strategy is a quantitative optimization framework designed to construct a portfolio exhibiting the lowest achievable variance (risk) for a specified level of expected return. Grounded in the tenets of Modern Portfolio Theory (Markowitz, 1959), this strategy calculates optimal asset weights within the portfolio. The central optimization problem can be expressed as:

$$w_{Zt} = \frac{Z_t^{-1} I}{I Z_t^{-1} I} \tag{9}$$

where w_{Zt} represents the vector of optimal portfolio weights, I denotes a vector of ones, Z_t represents the conditional variance-covariance matrix of asset returns for period t.

4.2.2. Minimum Correlation Portfolio

Christoffersen et al. (2014) propose a portfolio construction methodology that utilizes conditional correlations rather than conventional covariance metrics. These conditional correlations are established through the following matrix definition:

$$C_t = diag(Z_t)^{-0.5} Z_t diag(Z_t)^{-0.5} \tag{10}$$

Following this, the asset weights within the minimum correlation portfolio (MCP) are calculated as:

$$w_{Ct} = \frac{C_t^{-1} I}{I C_t^{-1} I} \tag{11}$$

4.2.3. Minimum Connectedness Portfolio

The Minimum Connectedness Portfolio (MCoP) aims to mitigate systemic risk within an asset portfolio through the minimization of inter-asset dependencies. Departing from conventional variance or correlation-based methods, the MCoP employs pairwise connectedness indices (Broadstock et al., 2022). This approach prioritizes assets demonstrating low reciprocal influence within the portfolio's structure, promoting resilience against system-wide disturbances. The optimization procedure determines asset weights as follows:

$$w_{Pt} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I} \tag{12}$$

where PCI_t represents the pairwise connectedness index matrix at time t.

4.2.4. Hedge Effectiveness

Hedge effectiveness (HE) quantifies the degree to which a hedging strategy mitigates the volatility of an underlying asset's value. It can be calculated as (Ederington, 1979):

$$HE = 1 - \frac{var(y_p)}{var(y_{unhedged})} \tag{13}$$

where $var(y_p)$ represents the variance of the hedged portfolio's returns and $var(y_{unhedged})$ is the variance of the unhedged asset's returns.

A higher HE value signifies more substantial risk reduction, implying greater hedging efficiency.

5. Results

This section presents the primary findings of the research. The initial analysis involved the employment of a time-varying vector autoregression model (TVP-VAR) to scrutinize dynamic relationships among variables. Subsequently, a simulation framework was implemented to model the performance characteristics of the investment portfolio under diverse conditions.

5.1. The Interdependence of Energy ETFs, Clean Energy ETFs and Conventional Stocks

Analysis of intermarket connectedness in Table 2 reveals elevated levels of co-dependence between European and United States stock indices compared to Chinese markets. This observation, as reflected by the averaged connectedness measures in the table's diagonal and off-diagonal elements, suggests potential avenues for portfolio diversification strategies. The differential interconnectedness across markets highlights a promising approach to enhance portfolio robustness.

An examination of the Chinese Clean Energy ETF reveals that 60.77% of its index variations stem from internal idiosyncratic shocks, with the remaining 39.23% attributable to exogenous influences. A comparable analysis of the Chinese Energy ETF demonstrates a modestly weakened effect, with internal factors accounting for 46.12% of the fluctuations and external factors contributing 53.88%. In contrast, the partitioning of volatility for conventional Chinese equities suggests that 39.94% originates from internal shocks, while 60.06% emanates from external sources. It is noteworthy that 11.13% of the exogenous volatility experienced by conventional Chinese stocks can be attributed to conventional European Union stocks. In contrast, the EU Energy ETF exerts a more pronounced influence on the Chinese Energy ETF, accounting for 10.14% of its external volatility.

An investigation of the Total Connectedness Index (TCI) revealed a mean value of 59.34% across the observation window. This signifies a moderate degree of synchronous movement amongst global stock markets. It is crucial to acknowledge that this reflects an average value, and fluctuations characterized by heightened dynamism within subintervals may be counterbalanced by phases of relative stability. Periods of amplified dynamism frequently coincide with geopolitical or economic events, such as the COVID-19 pandemic, the conflict between Russia and Ukraine, and the Israeli-Palestinian conflict that transpired during the examined timeframe, potentially influencing the average value.

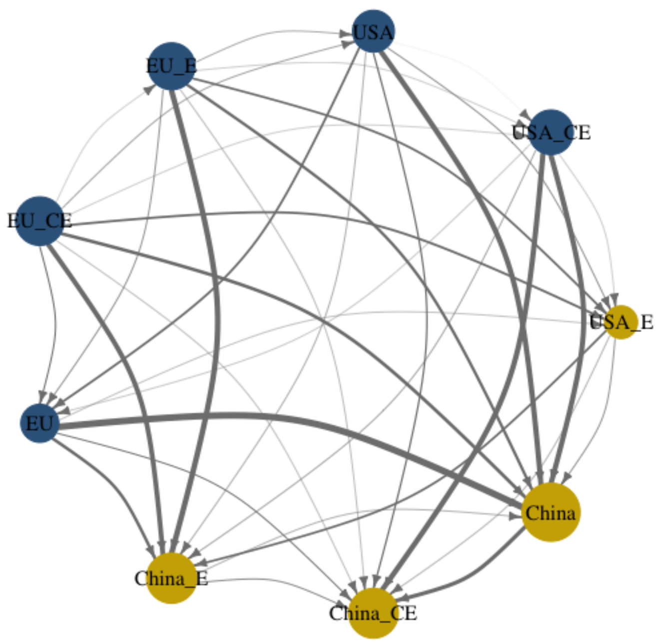
Table 2. Average connectedness table.

	USA_E	USA_CE	USA	EU_E	EU_CE	EU	China_E	China_CE	China	FROM
USA_E	34.17	3.95	4.29	22.96	21.00	7.13	3.86	1.01	1.62	65.83
USA_CE	3.44	49.97	19.61	3.81	5.31	10.04	2.95	2.35	2.52	50.03
USA	3.16	19.52	45.45	3.98	4.98	14.78	3.86	1.77	2.49	54.55
EU_E	20.45	3.30	3.12	29.46	26.69	10.73	3.77	0.71	1.79	70.54
EU_CE	18.31	4.80	4.02	26.22	27.94	12.06	3.74	0.90	2.01	72.06
EU	6.49	10.61	17.36	11.86	13.64	32.10	3.38	1.17	3.39	67.90
China_E	6.36	3.88	4.71	10.14	9.32	6.94	46.12	4.60	7.94	53.88
China_CE	1.78	8.45	3.60	1.41	1.57	2.62	5.83	60.77	13.97	39.23
China	2.74	8.50	8.55	5.10	5.90	11.13	8.75	9.40	39.94	60.06
TO	62.73	63.00	65.27	85.49	88.41	75.43	36.14	21.90	35.72	TCI
NET	-3.10	12.97	10.72	14.95	16.34	7.53	-17.74	-17.33	-24.34	59.34

Notes: Results are obtained from TVP–VAR(0.99,0.99) with one lag and a 20-step-ahead forecast.

Examination of Figure 4 demonstrates that the European Union acts as the primary propagator of volatility within the network. This suggests that fluctuations originating within the EU market have a statistically significant influence on volatility levels observed in other geographical regions or investment sectors. Interestingly, within the European Union, the EU Clean Energy ETF exhibits a demonstrably higher propensity to transmit volatility compared to conventional EU stocks. The results are in line with Çelik et al. (2022) who emphasize that green ETFs as a cheap alternative for hedging long position risks. This observation necessitates further investigation into the potential influence of sustainable or environmentally-focused investment instruments on market dynamics within the EU. Conversely, the Chinese market appears to function as a net recipient of volatility, implying that external sources, such as the United States or Europe, play a more substantial role in driving volatility levels within China. However, it is noteworthy that US conventional stocks exhibit susceptibility to volatility originating from both the EU Energy ETF and the EU Clean Energy ETF. Notably, the Chinese Clean Energy ETF is the sole index identified to import volatility from all other markets represented in the network. Additionally, the analysis reveals the strongest volatility transmission linkages occurring within markets categorized by similar investment strategies, such as Energy ETFs, Clean Energy ETFs, and conventional stocks.

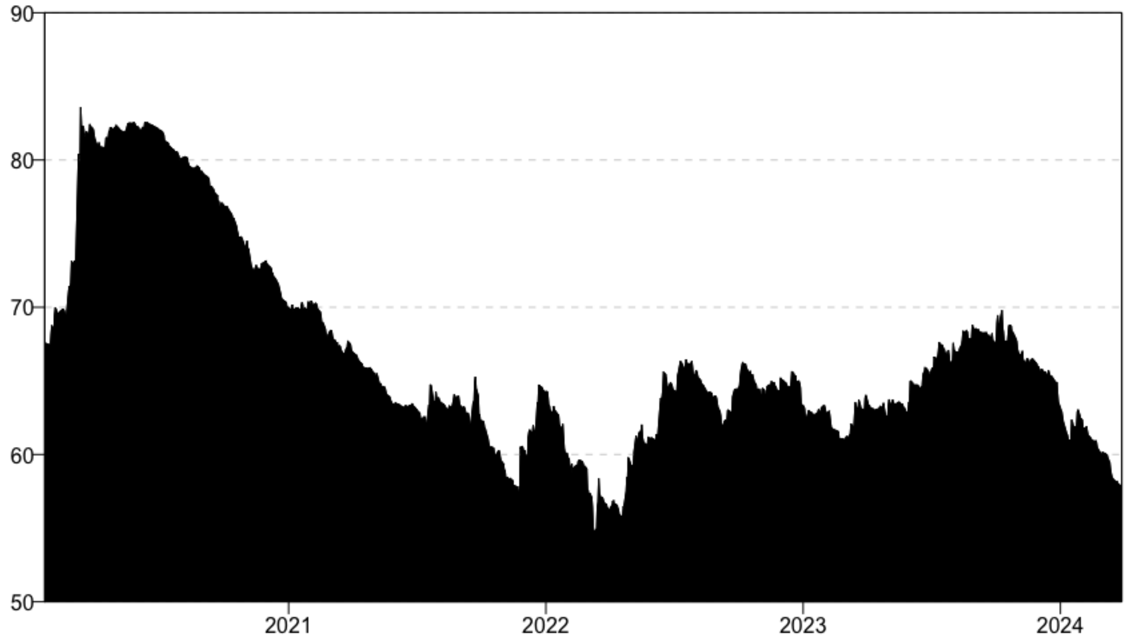
Fig. 4. A network of volatility spillovers.



Notes: This figure depicts a directed network representing interactions among Energy ETFs, Clean Energy ETFs, and Conventional Indices. Nodes are scaled proportionally to their net pairwise directional connectedness, a metric quantifying the extent to which an index influences or is influenced by others within the network. Arrows indicate the directionality of these relationships.

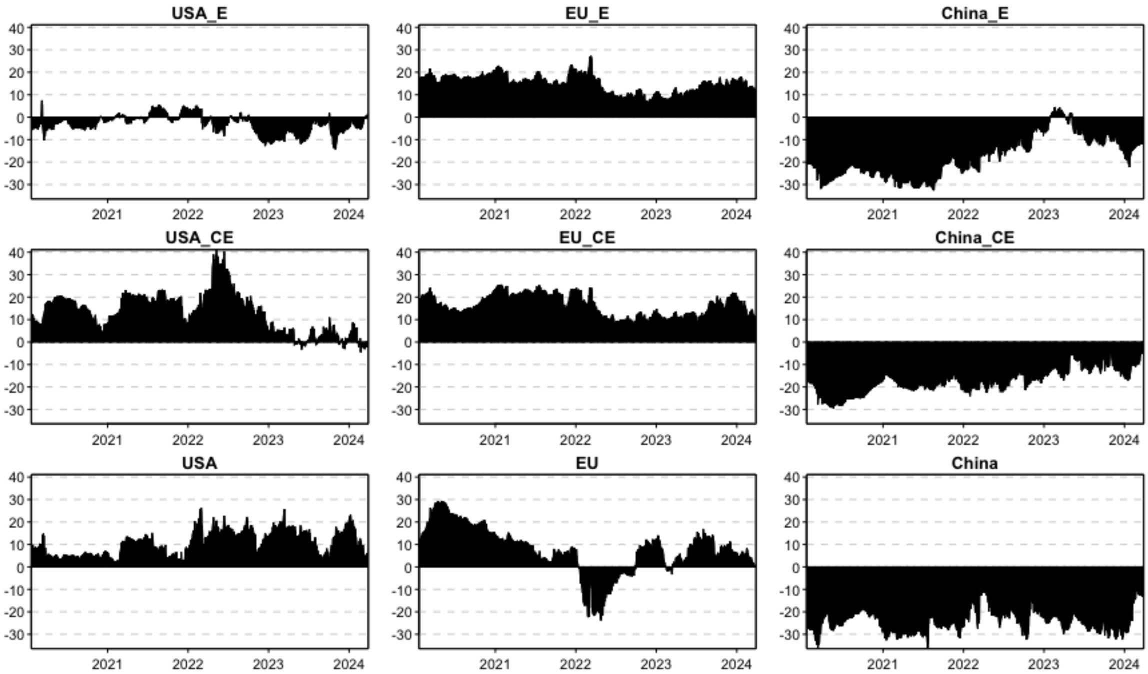
In recognition of the limitations associated with the static approach, a more temporally sensitive investigation into connectedness was subsequently undertaken. As exemplified in Figure 5, the TCI value demonstrates substantial fluctuations across the observation period, encompassing a range of 55% to 83%. This observation provides empirical support to the hypothesis that political and economic stimuli exert a significant influence on stock markets. Notably, the index exhibited a minimum value at the beginning of 2022. The index reached its peak at the initiation of the COVID-19 pandemic, followed by a sustained decline persisting until the beginning of 2022. The outbreak of the Russo-Ukrainian War then incited another surge in the TCI value. A subsequent rise in TCI was observed in October 2023, coinciding with another geopolitical conflict (Israel's war with Hamas) arising from rocket attacks launched from the Gaza Strip targeting Israeli territory. Then the index gradually decreased its value, approaching the level of 58% at the end of March 2024.

Fig. 5. Dynamic Total Connectedness (TVP–VAR(0.99,0.99) with one lag and a 20-step-ahead forecast).



This subsequent stage of the inquiry focused on quantifying the total directional dependence within the chosen Energy ETFs, Clean Energy ETFs, and conventional stocks. A distinction was established to differentiate between net volatility transmitters (positive index values) and net volatility receivers (negative index values) across the time series. This categorization is visually represented in Figure 6. Notably, the Chinese Clean Energy ETF and conventional Chinese stocks consistently exhibited the unique characteristic of being exclusive net receivers of volatility shocks throughout the entire observation period. In contrast, the EU Energy ETF and EU Clean Energy ETF markets assumed the opposing role, acting as prominent net volatility transmitters. The European stock markets displayed a dynamic behavior, demonstrating temporal fluctuations between the roles of net transmitter and net receiver. Specifically, European stocks transitioned towards the role of significant net transmitter during the 2020-2021 timeframe. The analysis confirms that the United States stock market stands as the most robust net transmitter of volatility within the investigated system. The US Energy ETF exhibited the greatest number of role changes within the examined system, although it is noteworthy that its volatility transmission values are among the lowest compared to other markets.

Fig. 6. Dynamic net total directional connectedness.

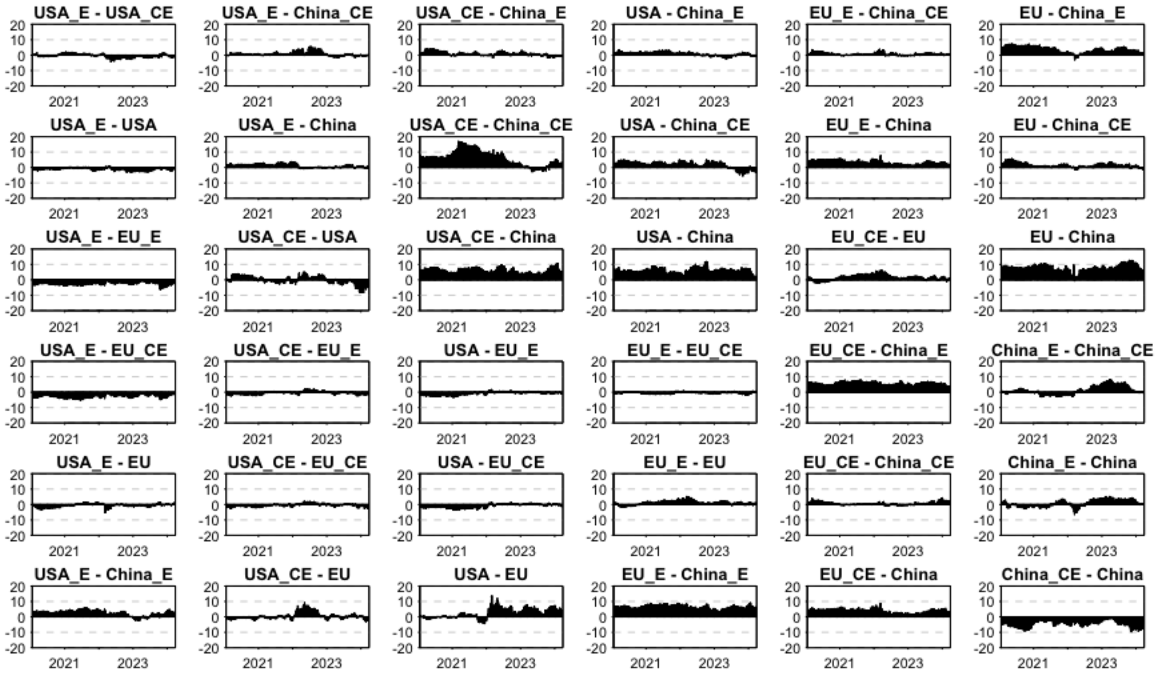


While the analysis of net total connectedness efficiently pinpoints net transmitters and receivers of volatility shocks within the examined Energy ETFs, Clean Energy ETFs, and conventional stocks network, it cannot illuminate the complex interdependence between network variables. This interdependence holds significant value for constructing optimal portfolios. To address this, Figure 7 presents a visualization of net pairwise connectedness.

Initial observations of the European market reveal a high degree of interconnectedness among the European Energy ETF, Clean Energy ETF, and conventional stocks. A similar trend is evident in the United States market, where the US Energy ETF, US Clean Energy ETF, and traditional US stocks appear to act as net exporters of volatility shocks to their European counterparts during specific periods, irrespective of their green or conventional classification. Similar trends have been reported by Shahzad et al. (2020) in their work on the weak form market efficiency and multifractal scaling behavior of renewable energy stock indices. These findings suggest that investors in green stocks should be cognizant of the potential for volatility transmission from conventional assets. In recent years, growing apprehensions regarding climate change have had an impact on the environment, as well as diverted the focus of investors towards renewable energy investments (Wan et al., 2021).

Interestingly, green assets exhibit a comparable level of efficacy to conventional assets when it comes to transmitting and absorbing volatility shocks across various markets, particularly within the US and European contexts. This is likely attributable to the market capitalization and strategic location of the United States market, which are both crucial factors in portfolio risk management and fund allocation. Conversely, the Chinese market displays characteristics of a net importer of volatility shocks relative to both European and American markets. This observation underscores the potential benefits of implementing risk hedging and portfolio diversification strategies in the Chinese market.

Fig. 7. Net Pairwise Directional Connectedness.



5.2. Portfolio Diversification Strategies

Figure 8 depicts three distinct portfolio allocation methodologies. A preliminary inspection of the graph reveals divergent trajectories between the Minimum Variance Portfolio and other approaches (Minimum Correlation Portfolio and Minimum Connectedness Portfolio). Further investigation uncovers temporally invariant trends characterized by a significant decrease in index values during the first semester of 2020. This decline can likely be attributed to the COVID-19 pandemic. Subsequently, the results demonstrate period-on-period enhancement, culminating in peak performance at the outset of 2023.

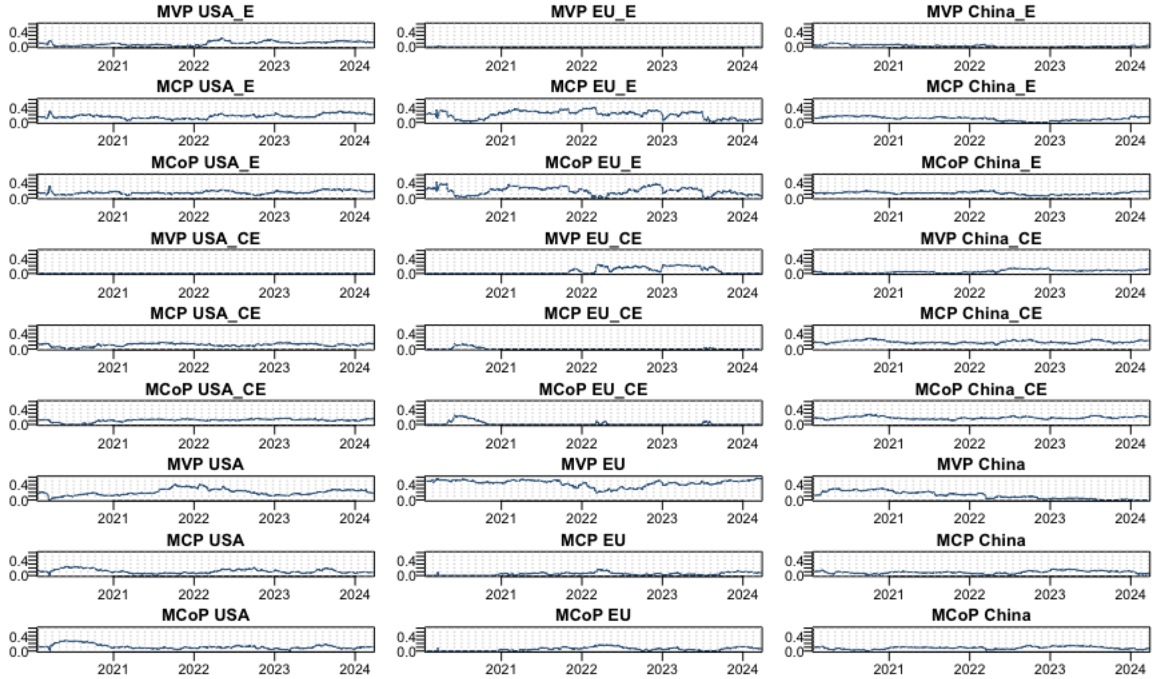
Fig. 8. Portfolio Performances under MVP, MCP, and MCoP.

Notes: MVP - Minimum Variance Portfolio, MCP - Minimum Correlation Portfolio, MCoP - Minimum Connectedness Portfolio.

To analyze the composition of individual portfolios, we present dynamic portfolio weights in Figure 9. Preliminary inspection reveals a substantial dissimilarity between the MVP and the MCP/MCoP. The latter two exhibit increased compositional consistency in comparison.

A thorough investigation emphasizes qualitative divergences between the MCP and MCoP dynamic portfolio weightings, despite initial similarities. Both portfolios demonstrate a reduced allocation towards the European Energy ETF in the first half of 2022; however, their subsequent behavior deviates. The MCP maintains a predominantly stable weighting in this asset class until the end of the observation period. Conversely, the MCoP weighting exhibits an initial 2022 decline followed by a subsequent increase, reaching a 2023 value statistically equivalent to its 2021 allocation. This pattern underscores the qualitative differences between the two portfolio weightings. Analogous nuanced variations likely exist within the weightings of other portfolio constituents.

Fig. 9. Dynamic Multivariate Portfolio Weights: Results are based on the TVP–VAR(0.99,0.99) with one lag and a 20-step-ahead forecast.



To illuminate the possible ramifications of optimizing investment portfolios and managing risk, we employ a comparative empirical analysis to assess three methodologies: MVP, MCP, and MoCP. The core objective of this investigation is to quantitatively determine the relative effectiveness of these aforementioned techniques in mitigating a portfolio's vulnerability to systematic market fluctuations. The consolidated findings of this comparative analysis are presented in Table 3.

Our analysis, emphasizing empirically determined hedge effectiveness ratios (Table 3), demonstrates that the Minimum Variance Portfolio (MVP) approach leads to statistically significant decreases in asset volatility within a portfolio. This hypothetical portfolio, with allocations of 9% (US Energy ETF), 0% (US Clean Energy ETF), 20% (US conventional stocks), 0% (EU Energy ETF), 6% (EU CleanEnergy ETF), 44% (EU conventional stocks), 3% (Chinese Energy ETF), 5% (Chinese Clean Energy ETF), and 12% (Chinese conventional stocks), exhibits substantial volatility reductions across asset classes: 78%, 82%, 33%, 77%, 72%, 19%, 67%, 74%, and 55% respectively. These reductions hold both economic and statistical significance.

This investigation explores the efficacy of the MCP approach in mitigating volatility within an investment portfolio. The MCP strategy employs a standardized allocation, averaging 16% (US Energy ETF), 20% (EU Energy ETF), and 10% (Chinese Energy ETF). This allocation is contrasted with a benchmark portfolio exhibiting a lower weighting of Clean Energy ETFs (USA 11%, EU 1%, China 18%). The analysis demonstrates statistically significant reductions in volatility across a majority of the investigated asset classes, encompassing Energy ETFs, Clean Energy ETFs, and conventional stocks (except US and EU indices). Notably, the US Clean Energy ETF exhibits a pronounced 70% decrease in volatility when incorporated within the MCP framework. However, it is crucial to acknowledge that the volatility of conventional stock holdings may potentially increase under this approach.

In conclusion, the MCoP strategy, employing average capital allocations of 15% (US Energy ETF), 18% (EU Energy ETF), and 13% (Chinese Energy ETF), demonstrably reduces volatility across the European Union, United States, and Chinese Clean Energy ETFs (statistical significance level of 1%). The most substantial volatility reductions are observed in the US (70%), EU (54%), and Chinese (57%) Clean Energy ETFs.

Our empirical analysis indicates that both MCP and the MCoP strategies possess the capability to mitigate risk via the allocation of environmentally sustainable assets. The MVP displays notable effectiveness specifically within the Clean Energy ETF, whereas MCP and MCoP strategies demonstrate a broader potential for volatility reduction. These results are in line with those obtained by Alomari et al. (2024).

Table 3. Average MVP, MCP, and MCoP Allocations, and HE.

Minimum Variance Portfolio						
	Mean	Std.Dev.	5%	95%	HE	p-value
USA_E	0.09	0.05	0.02	0.17	0.78	0.00
USA_CE	0.00	0.00	0.00	0.00	0.82	0.00
USA	0.20	0.08	0.10	0.36	0.33	0.00
EU_E	0.00	0.00	0.00	0.00	0.77	0.00
EU_CE	0.06	0.08	0.00	0.21	0.72	0.00
EU	0.44	0.09	0.26	0.53	0.19	0.00
China_E	0.03	0.03	0.00	0.09	0.67	0.00
China_CE	0.05	0.04	0.00	0.12	0.74	0.00
China	0.12	0.10	0.00	0.28	0.55	0.00
Minimum Correlation Portfolio						
	Mean	Std.Dev.	5%	95%	HE	p-value
USA_E	0.16	0.05	0.08	0.26	0.65	0.00
USA_CE	0.11	0.04	0.03	0.16	0.70	0.00
USA	0.11	0.05	0.05	0.21	-0.08	0.20
EU_E	0.20	0.10	0.04	0.34	0.63	0.00
EU_CE	0.01	0.02	0.00	0.09	0.55	0.00
EU	0.04	0.04	0.00	0.10	-0.30	0.00

China_E	0.10	0.05	0.00	0.17	0.46	0.00
China_CE	0.18	0.03	0.14	0.25	0.58	0.00
China	0.09	0.03	0.03	0.15	0.27	0.00
Minimum Connectedness Portfolio						
	Mean	Std.Dev.	5%	95%	HE	p-value
USA_E	0.15	0.04	0.08	0.22	0.65	0.00
USA_CE	0.11	0.04	0.01	0.15	0.70	0.00
USA	0.11	0.06	0.05	0.25	-0.09	0.14
EU_E	0.18	0.10	0.02	0.34	0.62	0.00
EU_CE	0.02	0.05	0.00	0.16	0.54	0.00
EU	0.05	0.04	0.00	0.14	-0.31	0.00
China_E	0.13	0.03	0.06	0.18	0.46	0.00
China_CE	0.18	0.03	0.13	0.23	0.57	0.00
China	0.08	0.03	0.03	0.13	0.26	0.00

6. Concluding and discussions

As sustainable practices continue to advance and global efforts to reduce reliance on fossil fuels increase, investing in renewable energy assets has become a profitable option. However, the oil market remains highly vulnerable to global economic and market trends, which could significantly impact the allocation of energy assets in investment portfolios. This raises an important question: do renewable energy ETFs help to reduce portfolio risk?.

We started by using the approach suggested by Diebold and Yilmaz (2014) and created the TVP-VAR model to analyze connectedness. Then, we reviewed the methodology proposed by by Broadstock et al. (2022), Christoffersen et al. (2014), and Markowitz (1959) to assess the effectiveness of hedging using multivariate portfolio techniques. Our study on the interdependence between regions in the energy EFTs market provides useful insights into global portfolio strategies.

Our analysis highlights the significant role of the EU as a major source of volatility propagation. Fluctuations in the EU market have a substantial impact on other regions and investment sectors, indicating the interconnected nature of the global financial landscape. This underscores the importance of closely monitoring EU market developments for investors and policymakers alike. Additionally, our study shows that sustainable investment instruments, such as the EU Clean Energy ETF, have a differential impact on volatility transmission compared to traditional EU stocks. The EU Clean Energy ETF is more likely to transmit volatility, which calls for further investigation into the dynamics of sustainable investment instruments and their implications on market volatility. Morover, our research has uncovered some interesting patterns in the way volatility is transmitted across global financial markets, with China being a net recipient of volatility. However, we found that external sources like the US and Europe significantly impact volatility within the Chinese market, highlighting the interconnectedness of global financial markets and the need for a comprehensive understanding of volatility transmission mechanisms. Our analysis also revealed that US conventional stocks are vulnerable to volatility originating from both the EU Energy ETF and the EU Clean Energy ETF. This emphasizes the importance of diversification strategies for investors looking to mitigate the impact of volatility originating from international markets. Lastly, volatility transmission linkages exist among markets with similar investment strategies. This highlights the importance of considering investment correlations in risk management. This study is in line with the findings of Nekhili and Bouri (2023), Bouri (2023), and Cui et al. (2022), emphasizing the importance of taking into account the spillover effects of skewness and kurtosis. Failure to do so may result in underestimating the risk propagation among ETFs and conventional indices, posing a threat to financial stability. Moreover, the observed periods of heightened dynamism in ETF markets present a compelling narrative that underscores the profound impact of geopolitical and economic events on market dynamics. Throughout the examined timeframe, significant events such as the COVID-19 pandemic, the conflict between Russia and Ukraine, and the Israeli-Palestinian conflict have coincided with spikes in market activity, potentially exerting influence on average market values.

Furthermore, by analyzing the performance of investment portfolios using the MVP, MCP, and MCoP strategies, we demonstrate that portfolio construction can substantially reduce the investment risk associated with conventional assets. In a multivariate portfolio context, we observe that the investment risk of nearly all ETFs has been substantially reduced. Upon examining the different weights assigned to the executed portfolio techniques, it becomes evident that the portfolio weights for MVP are comparatively less significant for all ETFs under consideration, when compared to MCP and MCoP. This highlights the presence of a degree of dynamic network that could potentially provide opportunities for diversification. Our findings correspond with the results reported by Dutta et al. (2020) that there is a positive correlation between the price of oil and renewable energy ETFs during periods of turbulence. Xia et al. (2019) discovered a close relationship between fossil energy and renewable energy, whereas Dutta (2018) investigated a comparable correlation between crude volatility and the energy sector.

In conclusion, the volatility structure between green energy and energy ETFs plays a significant role in shaping investment decisions. The findings from various studies suggest significant relationships and volatility spillovers between different types of ETFs, which can influence risk and return profiles. The dynamic nature of these relationships, along with the evolving methodologies for predicting and managing volatility, provides a rich tapestry of insights for investors, portfolio managers, and policymakers aiming to optimize returns while managing risks in an environmentally conscious manner. The results of increasing renewable energy ETFs are crucial for policymakers to formulate supportive policies for the clean energy sector and to provide investors with new financial instruments. Moreover, investors who are attuned to the escalating discourse surrounding climate change may prioritize renewable energy ETFs by favoring regions, or policies that reduce carbon emissions. Considering the relevance of geopolitical risk-induced market changes, future research may include an analysis of structural breaks in the volatility structure.

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