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Are diversification benefits sustainable at uncertain times? Reflections from traditional indices and green and blue ETFs volatility Co-movement

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ABSTRACT

Thanks to the pressing environmental concerns, lately a substantive body of research have attempted to assess the magnitude of volatility spillover from traditional to the sustainable asset markets. Yet, we have insufficient understanding on varied diversification advantages of sustainable assets such as the blue and green ETFs against price movements in other asset markets. This is important because corporations are now legally bound to ensure a structural shift of production externalities as they steadfastly adopt sustainable practices across production lines. However, persistent market uncertainties can confuse investors of the potential diversification benefits as they do not stick to a strong sensemaking of the future return value of blue and green ETFs. In this circumstance, one would expect potential heterogeneity in the strength of dynamic interconnectedness among both classes of assets as economies move steadily from low to high uncertainty episodes. This paper analyzes the impact of the Covid-19 pandemic and Russia-Ukraine war on spillover dynamics and demonstrate by using a Quantile VAR framework. We study how the desired narrative of 'shock absorption' and 'shock dumping' characteristics of assets change during turbulent times. We surmise that uncertain times triggers highetend information asymmetric for a prolonged period and investors normally become 'short-term' gain-centric because they do not yet have a clear vision for long-term growth returns from traditional assets. A trade-off between traditional and sustainable assets acrue but there is a bias towards sustainable assets as stringent environmental laws pave the way for a secured diversification benefits from the latter class of assets.

1. Introduction

The irreversible concerns of climate change have forced a paradigmatic shift in thought processes of both policymakers and investors' interests towards financial innovations (Henriques & Sadorsky, 2018; Pham & Nguyen, 2021) and the greening of the financial system. Accordingly, green finance has promptly drawn attention of different stakeholders given that economies around the world endeavor to balance between growth and sustainability's purposes (Xu et al., 2024). In this context, green and blue financial instruments such as green bonds, blue bonds and green Exchange-Traded Funds (ETFs) have been used to mobilize financing for environmentally and socially eco-friendly projects. For instance, green bonds are utilized to finance eligible environment-friendly investments such as energy efficiency, pollution prevention and alternative energy (Naeem et al., 2024) whereas blue bonds serve to raise capital for preserving and sustainably oceans, seas and marine resources. On the other hand, ETFs emerge as interesting financial instruments which provide insightful benefits of little cost, transparent, diversified and flexible in trading, enabling more reliable diversification opportunities, asset allocation, possible hedging strategies and liquidity management (Naeem et al., 2023; Alomari et al., 2024). Yousefi and Najand (2022) underscore that ETFs offer liquidity for portfolio managers and investors, which help them respond meteorically to unexpected events and adjust consequently their portfolio allocations. As a matter of fact, Naeem et al. (2023) reveal that ETFs show their resilience during periods of heightened uncertainty due to the outbreak of Covid-19 pandemic. Buckle et al. (2018) report that the information transmission via such instruments is crucial for investors

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compared to other slowly traded or less-traded assets.

From an academic standpoint, many researchers have increasingly focused on apprehending the interdependence and co-movement between the green bond market and the financial, cryptocurrency and commodity markets. For instance, Reboredo and Ugolini (2020) show the existence of weak connections of green bonds with energy, stock and corporate bonds. Le et al. (2021) investigate the frequency and time domain volatility connectedness between green bonds, cryptocurrencies and Fintech. They display that Bitcoin can be considered as net transmitter of volatility shocks whereas green bonds are net volatility receivers. Other researchers have investigated the diversification opportunities of green bonds with other assets (e.g. Mensi et al., 2021; Naqvi et al., 2022) and showed their safe-haven and hedging abilities during turbulent times (e.g. Dong et al., 2023). In this regard, Pham and Nguyen (2021) underscore that the diversification benefits of green bonds change substantially across asset classes. This focus on investigating the linkage between such green financial instrument and other asset classes could be attributed to the fact that policymakers are worried about the resilience of the green bond market to shocks in other markets to foster sustainable financial system and fight against climate change for effective governmental climate policies (Ferrer et al., 2021).

As a matter of fact, Nguyen et al. (2020) reveal that green bonds become the attractive financing tool which is used for green projects given that the economy undergoes the migration towards decarbonization. Nevertheless, the interaction of other sustainable financial assets with financial markets and market uncertainties during calm and turbulent periods remains a somewhat under-explored area. Few studies have analyzed the co movement between green investments and hydrocarbon prices (e.g. Saeed et al., 2021; Naeem et al., 2021) and considered the effect of energy-related volatility indices (e.g. VIX and OVX) on clean energy stocks (e.g. Reboredo., 2018; López, 2018). So, little is known about their connections with other assets and potential diversification advantages in investment portfolios.

Against the above backdrop, this study fills the gap by investigating the dynamic spillover connectedness of green and blue Exchange-Traded Funds and uncertainty indices during calm and crisis periods. More precisely, we analyze the risk transmission between volatility indices and green and blue ETFs. We assess the connectivity and directional spillovers among the green and blue ETFs markets and uncertainty indices to unveil potential specific information about spillover effects during turbulent periods due to unforeseen events. From a methodological standpoint, we use the Quantile Vector Autoregression approach of Chatziantoniou et al. (2021) to study spillover connectedness between green and blue assets and uncertainty indices. Given the predominantly negative correlations anticipated between Blue/Green ETFs and volatility indices, our primary empirical focus is on spillovers at the median quantile (0.5), which reflects typical market conditions. Nevertheless, to provide comprehensive insights, we also present spillover analyses at lower and upper quantiles, representing bearish and bullish market conditions, respectively, in the Appendix. Furthermore, as robustness checks, we include additional spillover analyses employing Hamilton-filtered series at the median quantile.

This study contributes to the ongoing literature in different interesting aspects. First, most studies have largely focused on investigating the relationships between green bonds and other different assets (e.g. Naeem et al., 2021; Reboredo & Ugolini, 2020). For example, Naeem et al. (2021) report asymmetric relationships among green bonds, energy, metals and agricultural commodities whereas Roboredo and Ugolini (2020) reveal weak connections with energy, stock and corporate bonds. Our study attempts to explore the connections of other sustainable assets with financial markets and opens the door to analyze the main diversifying advantages of blue and green ETFs against the price movements in different markets. Second, we extend the literature by examining if and how different sustainable assets are related to volatility indices which measure market uncertainties and thereafter provide a thorough picture about the cross-market linkages of new and traditional assets. This research could therefore help investors to figure out the potential sheltering abilities of different sustainable assets. Third, and unlike previous studies which focus on the linkages between uncertainty indices and commodity, stock, Islamic markets (e.g. Lee et al., 2019; Dong et al., 2023) and green bonds (e.g. Wang et al., 2022), this research examines the relationship between different uncertainty indices and other sustainable financial assets. In this respect, the research outcome is expected to provide insightful illustration concerning the dynamics between different markets and the potential impacts of risk factors on asset prices across investment horizons. Finally, this research offers great opportunity to unearth the heterogeneity of dynamic interconnectedness among assets with the outbreak of Black Swan events. Our study analyzes the impact of the Covid-19 pandemic and Russia-Ukraine war on spillover effects through the Q-VAR methodology. In particular, it provides novel insights into how such relationship change during turbulent periods and different crises dynamically affect the spillover effect.

Overwhelmingly, foreshadowing the key empirical findings, we document that the effect of different implied volatility indices on the interconnectedness transmission mechanism across the sustainable ETF markets appears to be heterogeneous. From a static connectedness standpoint, the average connectedness among Blue/Green ETFs is higher compared to those across volatility indices. The VIX shows the highest average connectedness with other assets in comparison to other volatility indices. On the other hand, from a dynamic connectedness perspective, the shift in total connectedness is well-documented over time. Dissimilar reactions of sustainable ETFs to various market uncertainties are shown with the advent of unexpected events.

The rest of this paper is given as follows. A brief literature about sustainable financial assets and volatility indices is provided in Section 2. Section 3 presents the methodology, data and descriptive statistics. The empirical results are reported in Section 4. Section 5 discusses the empirical results and Section 6 concludes with the implications of our findings.

2. Literature review

Uncovering information about the interconnectedness and cross-market behavior seem to be of great importance for investors in achieving portfolio risk management and policymakers in establishing suitable financial regulation (Hanif et al., 2023). In particular, the emergence of blue and green assets, as a new financial asset class, has increasingly revived such for both investors and policymakers. That is why many researchers have focused on investigating the dynamic connectedness and volatility spillover between green bonds and other classical assets and their hedging benefits. For instance, Ferrer et al. (2021) analyze the time-frequency connectedness among the green bond market and many energy and financial markets. They report that the relationship between the financial and energy markets and the green bond market produces at shorter time horizons. This indicates that shocks are quickly transmitted among markets with an impact lasting less than a week. A high connectedness in volatility and return is evidenced between Treasury and investment-grade corporate bonds and green bonds. Naeem et al. (2021) investigate the asymmetric relationship between commodities and green bonds using the cross-quantilogram method. The study shows that asymmetric behaviors of green bonds in response to different groups of commodities are well-documented.

The diversification and hedging advantages of comprising green bonds to commodity portfolio is shown. The highest hedging benefit of green bonds against the fluctuations of some industrial metals, agricultural commodities and natural gas is also documented. Pham and Nguyen (2021) investigate the tail-dependence between green bonds and other asset classes comprising energy markets, stock markets and conventional bonds. The empirical findings report that the spillovers among green bonds and asset classes tend to vary highly among quantiles, implying that the hedging advantages of green bonds against conventional asset classes tend to vary through normal and extreme market conditions. Duan et al. (2023) study asymmetric spillovers from Bitcoin to traditional and green assets based on Quantile-on-Quantile approach. The study also explores the spillovers from gold to green and traditional assets to compare its effectiveness with Bitcoin. The results show that cross-market spillover characteristics display non-linearity and asymmetry from different standpoints implying different quantiles of the joint distribution of (in)dependent variables, data in volatility and return and before/after the health crisis. Compared to gold, Bitcoin tends to be more effective in hedging as it shows weaker or even more negative dependence with traditional and green assets. Xu et al. (2024) study the return connectedness of green bonds with many investment markets (e.g. oil, gold, currency and index exchange-traded funds). The research reports that the connectedness of green bonds with other assets tends to be somewhat low and can be used as a receiver in the network. Nevertheless, the connectedness has moved, and green bonds acted as a shock transmitter. Mensi et al. (2023) study frequency dynamic spillovers in volatility and return and the hedging ability of green bonds, gold, oil, silver and the US dollar index and volatility index against downside US stock prices with the advent of Covid-19 pandemic. They display the importance of short-term volatility spillovers compared to their short-term counterparts. AlGhazali et al. (2024) analyze the spillover dynamics and interconnectedness among green bond markets, sustainability indices and oil price shocks. They report the presence of time-varying connectedness between all variables. This is clearly shows a significant boost during times of crisis and extreme situations. Deng and Zhang (2025) show that the issuance of green bonds for the first time positively affects the performance of peer companies in the same industry. Maneejuk et al. (2025) analyze the upside and downside risk spillovers from green bonds, energy and agriculture sectors to European carbon markets. They reveal that risk spillovers are asymmetric. They also show that downside spillovers substantially upside ones across all markets.

Other researchers have rather preferred to analyze the relationship between market uncertainties and green bond markets. For instance, Pham and Do (2022) study if and how green bonds could play as hedging asset against implied volatility. They report substantial dynamic connectedness among green bonds and implied volatilities of the energy, commodity and stock markets. So, investors have to adopt an active portfolio management strategy in order to ensure the hedging effectiveness of green bonds against implied volatilities. Tian et al. (2022) examine the asymmetric impacts of the CBOE Crude Oil Volatility Index (OVX), the Climate Policy Uncertainty (CPU), Infectious Disease Equity Market Volatility (IDEMV) and Geopolitical Risks (GPR) on green bond prices. This study displays that green bond markets in the Europe, US and China show heterogeneities facing uncertainties. In particular, the asymmetric impact shown by the European green bond market is more extensive in the long term whereas the Chinese green bond market is asymmetrically influenced by uncertainties in the short term. Hanif et al. (2023) study the time-frequency dependence and risk connectivity among green stocks and oil shocks. The findings display that the dependence relationships are tighter whereas lag-lead patterns are mixed and time-varying. Total risk spillovers among the oil and green stock markets could be mostly conveyed over time is also documented. Gyamerah and Asare (2024) analyze the interconnectedness of green bonds and global economic uncertainty using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses framework. This works shows that the relationship between green bonds and financial markets is impacted by macroeconomic factors such as the Russia-Ukraine war and the Covid-19 pandemic. Green bonds could act as net transmitters of spillovers in the short run but change to net receivers in the long run during times of global economic uncertainties. Bouri et al. (2024) examine the effect of three global risk factors (geopolitical risk, economic policy uncertainty and crude oil volatility) on the returns and variance of commodity, Islamic stock and green bond markets among quantile distributions and different time horizons. Through the Granger causality, all three global risk factors have an impact on returns across all quantiles, except the middle and lowest quantiles. The positive volatility of geopolitical risk and economic policy uncertainty drives the negative and positive of the Islamic stock and green bond markets, respectively. Bouri et al. (2024) afterwards report the existence of comovement between asset returns and the global risk factors in the short run but decouple in the long run.

On the other hand, some studies have studied the interplay between exchange-traded funds and other assets. For example, Alexopoulos (2018) explores the performance of portfolios of energy-related ETFs, under periods of market uptrend and market turmoil. The empirical findings show that one portfolio including all ETFs tends to outperform two disaggregated portfolios with conventional and clean ETFs separately. Dutta et al. (2020) explore the impact of uncertainty in energy sector firms on clean energy ETFs. This study reports the existence of a negative effect, revealing that a decline in clean energy asset returns is likely to occur when implied volatility levels tend to be high for energy sector firms. The relationship among the energy sector implied volatility index and clean energy ETFs is higher than during low volatility regimes. Çelik et al. (2022) examine dynamic connectedness and hedging opportunities among the realized volatilities of clean energy ETFs and energy implied volatilities and show the increase of the dynamic connectedness during turbulent times.

Clean energy ETFs (e.g. TAN, QCLN, PBW and SMOG) seem to be net volatility transmitters whereas OVX is a net volatility receiver. Goodell et al. (2022) investigate the interconnectedness between green investment funds and (non)traditional financial assets. Green indices seem to be highly correlated with global stock market performance, the returns of emerging markets, commodity markets and FinTech indices. Such assets can be considered as diversifiers to Bitcoin. Banerjee et al. (2024) analyze the changing dynamics of interconnectedness among clean and carbon-energy assets given that the exchange-traded funds (ETFs) differ in receiving and transmitting shocks among crisis and normal periods. This works reveals that the asymmetric connectedness among such assets tends to increase during crises. In particular, brown and clean assets seem to be net receivers during different periods. Sohag et al. (2023) investigate if oil equity can disclosure any crucial signal to green investments and vice-versa as substitute commodities. They also examine if dirty investments (oil equity) could transmit negative volatility spillovers to green investments (both equity and bond). The results show that dirty investment returns could positively react to both green equity and green bonds returns. Mand et al. (2023) study the time-varying relationships between four assets related to dirty and clean energy assets (United States Oil Fund, iShares Global Clean Energy ETF, EnergySelect Sector SPDR Fund and WTI futures). A long-term relationship among different assets is well-pronounced and clean energy ETF has a causal effect on most assets. Ozcelebi et al. (2023) show the variations in gold, the S&P500 index and oil prices affect changes in green bond ETFs. Nevertheless, only the S&P500 index influences the green bond ETFs during calm and turbulent periods. The VIX seems to be an important transmitter of the green bond ETFs. Wang et al. (2022) explore the dynamic connections between clean energy, carbon and green bonds. They show complicated relations between such assets, with alternating negative and positive trends.

Turbulence in financial markets could aggravate network connectivity, particularly during the Covid-19 pandemic. The Economic Policy Uncertainty and oil volatility index could be used as strong predictors among different distributions of cross-market connections, implying that co-movements among assets tend to be vulnerable to exogenous risks, under market conditions. Banerjee (2024) analyzes if the dynamics of interconnectedness between ecologically sustainable, green energy and brown ETFs have changed with the different market conditions, caused by the health and political crises. The empirical findings show that sustainable and green energy ETFs seem to be the main transmitters whereas brown energy ETFs could be receivers. The information transmission strengthens during the first two waves of the Covid-19 pandemic. Alomari et al. (2024) attempt to evaluate and analyze the spillover impacts and dynamic connectedness between ten US sector ETFs and different economic and financial uncertainty indices. This study shows the existence of stronger connectedness between ETFs and the different uncertainty indices, along with varying sensitivities.

3. Methodology and data

3.1. Q-VAR (Quantile vector autoregression)

This study analyses the volatility spillover relationships between Blue-Green ETFs and Volatility Indices using the Q-VAR methodology. The analysis employs the Q-VAR model developed by Chatziantoniu et al. (2021), based on Diebold and Yilmaz (2014) and Ando et al. (2018). The Q-VAR (r) is estimated as follows:

$$Q_t = \sigma(\alpha) + \sum_{j=1}^{r} \theta_j(\alpha) Q_{t-j} + \varepsilon_t(\alpha) \tag{1}$$

In Eq. (1),[1] $''Q_t''$ represents the vector of endogenous variables, $''\alpha''$ denotes a quantile within the range [0, 1], $''r''$ signifies the length of the lag, $''\sigma(\alpha)''$ is the Nx1 vector of the conditional mean vector, $''\theta_j(\alpha)''$ represents the NxN vector of the Q-VAR coefficients, and "$\varepsilon_t(\alpha)$" indicates the Nx1 error vector associated with the NxN variance-covariance matrix of $''\sum(\alpha)''$. Subsequently, the Generalized Forecast Error Variance Decomposition (GFEVD) is calculated, following the methodology of Koop et al. (1996) and Pesaran and Shin (1998)). GFEVD elucidates the impact of a shock in variable "j" on variable "i", providing insights into the inter-variable dynamic relationships.

$$\gamma_{ij}^{g}(H) = \frac{\sum \alpha_{ii}^{-1} \sum_{h=0}^{H-1} \left(e'_i Y_h(\alpha) \sum(\alpha) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e'_i Y_h(\alpha) \sum(\alpha) Y_h(\alpha)' e_i\right)} \tag{2}$$

$$\widetilde{\gamma}_{ij}^{g}(H) = \frac{\gamma_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

In Eq. (2), "e_i", is identified as the zero vector with the unit at the "i" th position, satisfying the conditions "$\left(\sum_{j=1}^{N} \widetilde{\gamma}_{ij}^{g}(H) = 1\right.$" ve "$\left.\sum_{i,j=1}^{N} \widetilde{\gamma}_{ij}^{g}(H) = N\right)$". These conditions reflect the distribution of the generalized impulse response over the forecast horizon. The Total Connectedness Index (TCI), which quantifies the overall volatility spillover among the series, is formulated in Eq. (4). This index provides a comprehensive measure of the connectedness and the extent of volatility transmission between the series under consideration.

$$\mathrm{TCI}(H) = \frac{\sum_{i,j=1,\ i \neq j}^{N} \widetilde{\gamma}_{ij}^{g}(H)}{N-1} \tag{4}$$

The total volatility transmitted from one series to others (from series i to series j) is calculated as follows:

$$\mathrm{B}_{i\to j}^{g}(H) = \sum_{j=1,\ i \neq j}^{N} \widetilde{\gamma}_{ji}^{g}(H) \tag{5}$$

The total volatility transmitted from all other series to a single series i (from series j to series i) is illustrated in Eq. (6):

$$\mathrm{B}_{i\leftarrow j}^{g}(H) = \sum_{j=1,\ i \neq j}^{N} \widetilde{\gamma}_{ij}^{g}(H) \tag{6}$$

The difference between the total volatility transmitted by a series to other series and the total volatility it receives from other series indicates whether the series is a net receiver or transmitter of volatility. This net position is a crucial metric in understanding the dynamic interplay of volatility within the network of series.

$$\mathrm{B}_{i}^{g}(H) = \mathrm{B}_{i\to j}^{g}(H) - \mathrm{B}_{i\leftarrow j}^{g}(H) \tag{7}$$

If the value resulting from Eq. (7) is positive, it indicates that the series is a net transmitter of volatility. Conversely, a negative value signifies that the series is a net receiver of volatility. The volatility spillover between two specific series is ascertained by decomposing the net volatility transmission (Kayahan et al., 2022). This decomposition allows for a detailed understanding of the directional flows of volatility within the network of series:

$$\text{Net Spillover Between Two Series}_{ij}(H) = \widetilde{\gamma}_{ji}(H) - \widetilde{\gamma}_{ij}(H) \tag{8}$$

The net spillover between a pair of series, namely series *"i"* and series *"j"*, quantifies the volatility transmission from series *"i"* to series *"j"* as well as from series *"j"* to series *"i"*. This measurement is instrumental in identifying the directional intensity and the dynamic interaction of volatility between the two specific series within the overall network.

3.2. Data and descriptive statistics

The study explores the volatility spillover relationship between Blue Economy, Green Finance, and volatility indices using daily data of Blue Economy and Green Finance ETFs and global volatility indices from October 8, 2020, to March 22, 2024. All data used in this analysis are obtained from investing.com. The primary reason for utilizing ETF data for Blue Economy and Green Finance is the limited accessibility of specific data related to the Blue Economy. The comprehensiveness of the themes they represent was considered in defining the Blue Economy and Green Finance ETFs along with volatility indices. Table 1 provides definitions related to the variables used in the analysis.

Table 1
Description of variables.

BLUE	BNP Paribas Easy ECPI Global ESG Blue Economy UCITS ETF
GNR	SPDR S&P Global Natural Resources ETF
CGW	Invesco S&P Global Water Index ETF
GRNB	VanEck Green Bond ETF
CNRG	SPDR S&P Kensho Clean Power ETF
TAN	Invesco Solar ETF
FAN	First Trust Global Wind Energy ETF
VIX	CBOE Volatility Index
OVX	CBOE Crude Oil Volatility
GVZ	CBOE Gold Volatility
MOVE	The Merrill Lynch Option Volatility Estimate
CVI	Crypto Volatility Index

BLUE, GNR, and CGW represent Blue Economy ETFs, while GRNB, CNRG, TAN, and FAN are Green Finance ETFs. VIX, OVX, GVZ, MOVE, and CVI denote various volatility indices. Specifically, BLUE refers to a global Blue Economy ETF, GNR to an S&P Natural Resources ETF, CGW to a global water index ETF, GRNB to a global Green Finance bond ETF, CNRG to a clean energy ETF, TAN to a solar energy ETF, and FAN to a wind energy ETF. The volatility indices include VIX, which measures S&P 500 index volatility indicative of global uncertainty; OVX, which assesses the volatility of crude oil prices; GVZ for gold price volatility; MOVE, which analyzes the volatility of U.S. Treasury bond yields; and CVI, which evaluates cryptocurrency volatility. The study aims to examine the integration of the blue economy and green finance into the financial system from a broader perspective and evaluate whether they can be considered alternative investment vehicles separate from the financial markets. It seeks to provide insights to policymakers, financial advisors, and investors on investor sentiment towards these sectors. For analysis, the study first converts these variables into return series. Table 2 displays the descriptive statistics of the return series [$100^*\ln(P_t/P_{t-1})$].

The findings indicate that the series with the highest average returns are the Blue Economy ETFs, while the Green Finance ETFs exhibit negative average returns. OVX and MOVE have positive average returns among the volatility indices, whereas the remaining indices display

[1] The Q-VAR method is employed using a 200 rolling window and at the 0.5 quantile level.

Table 2
Descriptive statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarq.-Bera	ADF
BLUE	0.046682	0.076	3.5752	−3.336	0.8961	−0.17	4.1701	54.6636*	−28.411*
GNR	0.039057	0.0582	4.4186	−6.0923	1.3953	−0.3	3.8535	40.0437*	−27.904*
CGW	0.02574	0.0409	6.3507	−4.2786	1.1261	0.185	4.6688	107.499*	−27.646*
GRNB	−0.01577	0	1.6904	−1.6593	0.3342	−0.04	4.7088	107.692*	−29.876*
CNRG	−0.0304	−0.0979	9.1736	−7.7598	2.2599	0.262	4.0018	47.0591*	−29.061*
TAN	−0.06302	−0.1918	12.059	−9.1656	2.7437	0.313	4.2971	76.3547*	−28.672*
FAN	−0.0309	−0.0562	6.3693	−5.205	1.4097	0.246	4.4866	90.1765*	−27.065*
VIX	−0.07715	−0.7304	48.021	−22.035	6.9196	1.022	8.0605	1095.94*	−23.387*
GVZ	−0.12781	−0.5383	30.206	−15.345	4.4239	1.234	8.6806	1411.31*	−31.693*
OVX	0.021907	−0.4399	63.607	−31.124	5.9629	1.568	20.197	11,242.2*	−23.567*
MOVE	0.010421	0.0329	21.463	−29.888	4.9412	0.096	5.8817	306.862*	−21.311*
CVI	−0.16812	−0.5363	33.186	−20.216	4.5164	1.726	13.691	4643.55*	−28.234*

negative average returns. The observation period for the study begins in October 2020, which encompasses the initial issuance of Blue Economy ETFs during the COVID-19 pandemic. Significant global events such as the Ukraine-Russia War, the SVB bankruptcy, and the Israel-Palestine conflict occurred throughout the observation period, impacting the global economy. Considering these periods of global uncertainty, the results suggest that Blue Economy ETFs diverged more from the global financial system than Green Finance ETFs. The negative average returns in Green Finance ETFs can be attributed to the rise in energy prices due to global uncertainties and the shift towards renewable energy sources as alternatives to fossil fuels.

Moreover, the global events during the observation period, especially the Ukraine-Russia and Israel-Palestine conflicts, created uncertainty around energy and oil supplies and subsequently increased the volatility measured by OVX. On the other hand, continuing global uncertainties post-COVID have affected the price volatility of traditional financial assets like U.S. Treasury bonds, which is reflected in the positive average return of the MOVE index. The negative average returns in other volatility indices could be explained by the lesser impact of post-COVID events on the financial assets they measure. Specifically for CVI, the cryptocurrency market experienced significant demand during and post-COVID, which eventually became more balanced as the market became better known. The higher standard deviations of the volatility indices compared to those of the ETFs suggest that volatility indices experience greater volatility than the Blue/Green ETFs. The distinct separation in standard deviations between ETFs and volatility indices may indicate their potential as alternative financial assets. Lower volatility in an asset suggests that its future prices are more predictable and, hence, less risky (Gökgöz et al., 2024). This points to Blue/Green ETFs being potentially less risky investment vehicles. The Jarque-Bera statistic, testing the normal distribution of the series, indicates that all series are not normally distributed. In contrast, the Augmented-Dickey-Fuller (ADF) test reveals that all series are stationary at level.

Fig. 1 displays the time variation graphs of the return series. It is apparent from these graphs that all series are volatile and fluctuate over time. Periods marked by global events with significant economic impacts show dramatic increases and decreases in the volatilities of the series. The global uncertainty caused by the Ukraine-Russia conflict (February 2023) is a common factor influencing the volatility across all series. Additionally, the volatilities of the series are notably affected by global factors such as the U.S. elections on November 3, 2020, the bankruptcy of Silicon Valley Bank (March 2023), and the Israel-Palestine War (October 2023). These events highlight the sensitivity of series to geopolitical and economic uncertainties.

4. Empirical results

The study uses the Q-VAR[2] methodology to analyze the connectedness between Blue/Green ETFs and volatility indices. In this part of the study, we first present the average interconnections among the series. These average connectedness reveal the impact of one series' volatility on the volatilities of the others. Next, we display TCI graph, which illustrates the changes in total connectedness over time among the series. This graph allows us to observe the impact of global events with significant economic effects on the overall volatility transmission among the series. Following this, we detail the volatility received and transmitted by each series to and from other series and demonstrate each series' status as a net volatility receiver or transmitter relative to the other series. This step involves highlighting the bilateral connectedness between the Blue/Green ETFs and the volatility indices and among the ETFs themselves. The final stage presents a connectedness network graph that summarizes the average interconnections, offering a visual representation of the relationships and dynamics between the Blue/Green ETFs and the volatility indices. Additionally, we statistically examine the impact of global events on dynamic connectedness using Wald statistical analysis. For this purpose, we base our observations on the onset dates of significant events covered in our observation period: the Ukraine-Russia conflict (February 2022), the SVCB bankruptcy (March 2023), and the beginning of the Israel-Palestine conflict (October 2023). We test whether there are significant differences in the average connectedness before and after these dates. This approach dynamically and statistically elucidates the impact of globally significant events on total and pairwise connectedness during our observation period. The empirical findings are reported in Appendix 1.

Table 3 showcases the average connectedness between the Blue/Green ETFs and the volatility indices, providing a quantitative summary of these relationships. The results show that the average connectedness among the series is 63.67 %. This indicates that 63.67 % of the volatility change in one series can be explained by changes in volatility in the other series. The average connectedness among Blue/Green ETFs is higher compared to the average connectedness among volatility indices. The VIX shows the highest average connectedness with all series compared to other volatility indices. On the other hand, the average connectedness between Blue/Green ETFs and volatility indices is generally low. This finding suggests that while Blue/Green ETFs are affected by global uncertainty, they diverge from mainstream market indicators.

[2] To analyze the general trend of connectedness among Blue ETFs, Green ETFs, and Volatility Indices, the Q-VAR method is employed using a 200-period rolling window at the 0.5 quantile level. However, please refer to Appendix A for insights into the trends at low (tau at 0.1) and high (tau at 0.9) quantile levels.

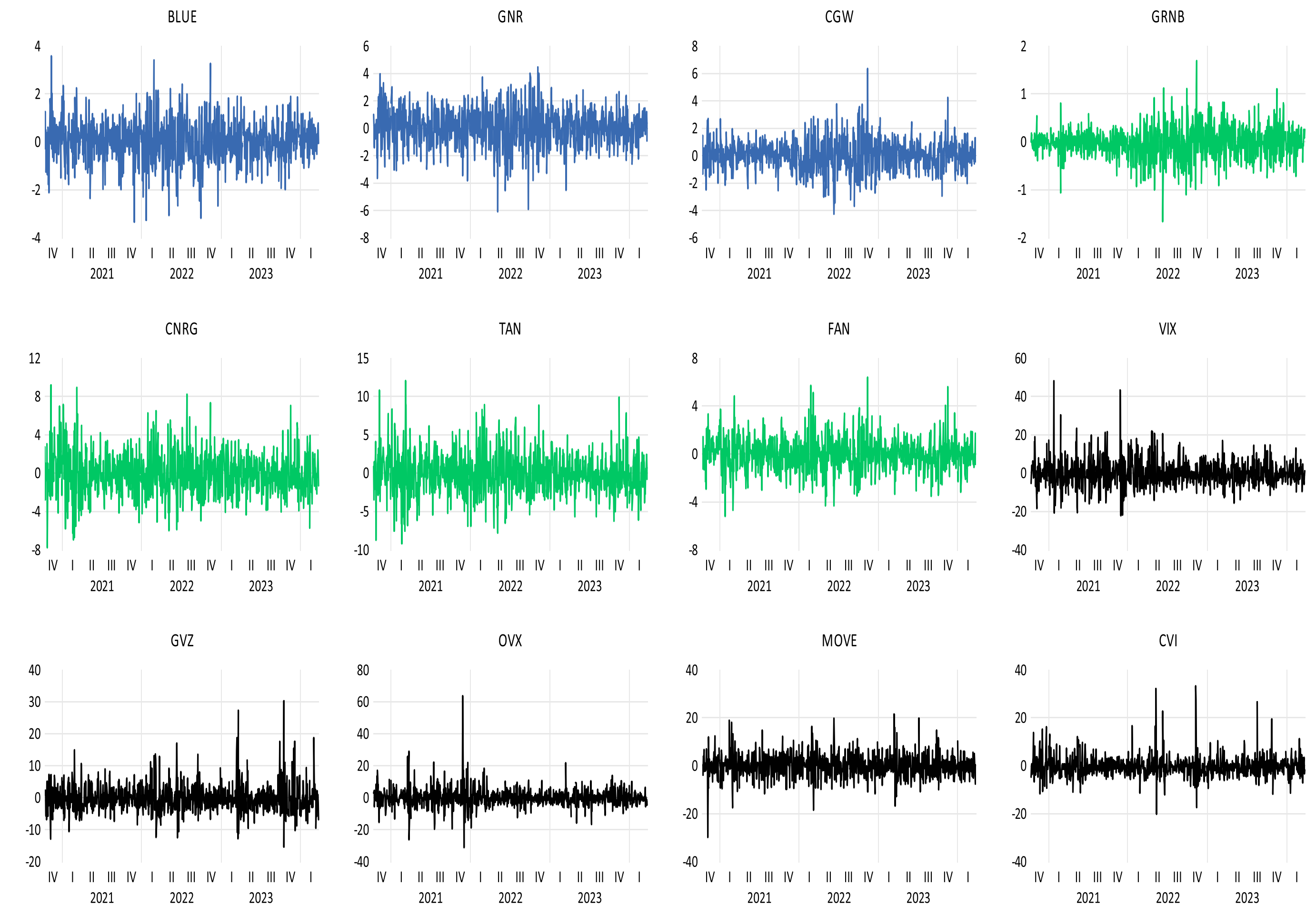


Fig. 1. Time series graphs of series.

Additionally, the impact of other series on the volatility of CVI is 26.25 %. This indicates that changes in CVI's volatility are explained mainly by its movements, marking it as more distinct than other series. The findings also illustrate that the average connectedness varies across the Blue ETFs, Green ETFs, and volatility indices. This suggests that while general evaluations of the examined series can be considered a group, a more detailed examination of each series separately may offer more comprehensive recommendations.

The weak connections between financial assets can explain their diversifying properties for each other (Baur & Lucey, 2010; Kayahan et al., 2022). The weak connectedness of Green/Blue ETFs with volatility indices suggests that adding commodities such as gold and oil, traditional financial assets like bonds, and cryptocurrencies to a portfolio containing Blue/Green ETFs enhances portfolio diversification. Conversely, adding Blue/Green ETFs to a portfolio containing commodities, traditional financial assets, or cryptocurrencies also improves diversification.

Furthermore, the weak connectedness of CVI with all series highlights its potential as a better diversifier than other series. This finding aligns with research that compares the diversifying properties of cryptocurrencies with gold and other commodities, suggesting that Bitcoin is a better diversifier than gold and other commodities as highlighted by Bouoiyour and Selmi (2015), Bouri et al. (2017), Klein et al. (2018), Al Janabi et al. (2019), Fang et al. (2020), Hsu et al. (2021), and Kandemir and Gökgöz (2022).

Average connectedness reflects the mean linkage among the series over the entire observation period. However, this period includes significant global events expected to influence the interconnectedness among the series. Additionally, dynamically examining the connectedness between series can shed light on how these linkages respond to global events, providing valuable insights. Therefore, it is crucial to dynamically analyze the connectedness among the series to understand their sensitivity to global incidents. Fig. 2 illustrates the changes in total connectedness over time among the series, capturing fluctuations in their relationships as influenced by varying economic conditions and global events. This dynamic analysis helps elucidate how external shocks and stresses in the global economy impact the interconnectedness of financial instruments, enhancing our understanding of market behaviour under different conditions.

TCI graph demonstrates how the interconnectedness among Blue Economy, Green Finance, and volatility indices changes over time. The total connectedness fluctuates between 54 % and 72 %, averaging 63.67 %. Before the onset of the Ukraine-Russia war in February 2022, total connectedness was at lower levels (54 %–58 %) compared to subsequent periods. With the escalation of the Ukraine-Russia conflict, total connectedness significantly increased, reaching its peak (72 %) during Silicon Valley Bank's bankruptcy in March 2023.

The heightened global uncertainties triggered by the Ukraine-Russia war brought global risk factors, particularly those related to energy supply, to the forefront. This increase in global uncertainty significantly impacted volatility indices such as VIX, which measures market uncertainty, and MOVE, which gauges bond price volatility. Uncertainties related to energy supply influenced OVX, while market uncertainties made gold, a traditional safe haven measured by GVZ, more volatile.

Table 3
Avarage of quantile connectedness.

	BLUE	GNR	CGW	GRNB	CNRG	TAN	FAN	VIX	GVZ	OVX	MOVE	CVI	FROM
BLUE	33.97	6.82	12.25	1.95	8.45	8.48	11.54	7.61	2.75	2	2.46	1.7	66.03
GNR	6.56	34.9	12.46	1.54	8.29	6.15	8.57	10.5	2.96	4.2	2.36	1.6	65.12
CGW	8.54	9.65	26.89	4.16	10.27	7.71	12.37	10.7	3.78	2.17	2.63	1.1	73.11
GRNB	2.51	2.36	8.09	57.31	4.68	4.78	8.21	3.29	1.94	0.77	5.37	0.7	42.69
CNRG	6	6.04	10.11	2.54	26.81	22.73	12.98	6.92	2.03	1.77	1.18	0.9	73.19
TAN	6.52	4.96	8.04	2.43	24.27	28.65	14.36	5.62	1.66	1.38	1.14	1	71.35
FAN	8.86	6.97	12.66	3.79	13.42	14.13	27.91	6.2	1.89	1.3	1.97	0.9	72.09
VIX	5.31	9.09	12.14	1.93	8.02	6.27	7.17	31.5	7.46	4.47	4.79	1.9	68.54
GVZ	3.71	3.68	6.11	1.57	3.4	2.5	2.94	11	48.1	4.84	9.34	2.8	51.93
OVX	3.33	7.02	4.77	0.67	3.52	2.67	3.06	8.18	6.49	56.99	2.73	0.6	43.01
MOVE	3.04	3.46	4.9	5.09	2.22	2.08	3.71	7.62	10.3	2.37	52.94	2.3	47.06
CVI	3.04	2.79	2.59	0.47	2.25	1.99	1.84	3.72	4.24	0.79	2.53	74	26.25
TO	57.42	62.9	94.14	26.13	88.79	79.49	86.74	81.4	45.5	26.05	36.5	15	700.39
Inc.Own	91.39	97.7	121	83.44	115.6	108.1	114.7	113	93.5	83.04	89.44	89	TCI
NET	-8.61	-2.27	21.02	-16.56	15.6	8.14	14.66	12.8	-6.48	-17	-10.56	-11	63.67

Note: Each row in the table indicates the percentage of change in a series attributable to the corresponding series in the columns. 'From' represents the average volatility received by a series throughout the period, while 'To' signifies the average volatility transmitted by that series to others over the same period. 'Net' expresses the difference between 'From' and 'To', whereas 'Inc. Own' denotes the total average volatility. The colour gradient from light yellow to dark green indicates increasing values of connectedness.

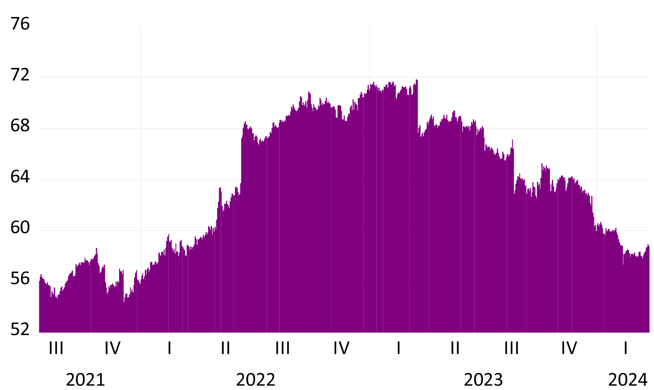


Fig. 2. TCI.

Additionally, the demand[3] for alternative financial assets, reflected in the CVI during this period, increased.

The global uncertainties caused by the same events also impacted the Blue Economy, particularly affecting sectors like maritime transport and boosting investments in sustainable products. The uncertainty of energy supply highlighted the importance of alternative and renewable Green Finance products and underscored the need for nations to adopt renewable energy sources. Consequently, both Blue Economy and Green Finance assets were affected during this period, leading to increased connectedness with volatility indices. This increased connectedness continued into subsequent periods and reached its maximum during the SVCB bankruptcy.

Table 4
Wald test results for TCI.

Event	Pre Mean TCI	Post Mean TCI	Mean Difference	Std. Er. of Dif.	Wald Statistic
Russia-Ukraine Conflict	57.31	67.16	9.85	0.215	2106.44***
SVB Collapse	63.58	67.68	4.11	0.354	134.46***
Israel-Palestine Conflict	64.95	65.04	0.089	0.272	0.11

Note: The "***" symbol indicates significance at the 1 % level.

The SVCB bankruptcy introduced further uncertainties in the global economy, particularly affecting the banking sector, which influenced volatility indices such as VIX and the MOVE index measuring the volatility of U.S. 10-year Treasury bonds. These uncertainties also led to changes in investment strategies. Table 4 presents the statistical demonstration of the impact of globally significant events on the total connectedness among the series.

The Wald statistic findings indicate that the impact of the Russia-Ukraine conflict and the SVCB bankruptcy on the total connectedness changes is significant. In contrast, the impact of the Israel-Palestine conflict on total connectedness is statistically insignificant. The Wald statistic value related to the Russia-Ukraine conflict is much higher than other values, demonstrating that the influence of the Russia-Ukraine conflict on total connectedness is substantially more significant than that of the SVCB collapse. The results derived from the Wald statistic

[3] During the Ukraine-Russia War, a series of sanctions were implemented by primarily the United States and European countries. Among these sanctions was the restriction of the SWIFT system, which facilitates international money transfers. In response to these limitations, cryptocurrencies, notably Ripple, were utilized as an alternative means for international money transactions. This shift undoubtedly contributed to cryptocurrencies becoming a prominent topic, highlighting their potential as an alternative financial infrastructure in times of geopolitical tension and restricted access to traditional financial systems.

findings are consistent with those observed in the graph depicting changes in the Total Connectedness Index (TCI) over time.

The responses of Blue Economy, Green Finance, and volatility indices to global shocks can vary across groups and series. Thus, examining the net volatility received and transmitted by each series separately will provide valuable insights into their sensitivity to global shocks. Fig. 3 displays the graphs of changing net connectedness over time among the series.

The net directional connectedness graphs reveal variations in the direction of net volatility transmission among the series. Throughout the observation period, CGW consistently acts as a net transmitter of volatility, while other Blue Economy ETFs alternate between receivers and transmitters of volatility. Similarly, among Green Finance ETFs, GRNB consistently appears as a net receiver of volatility. In contrast, CNRG is a net transmitter, and the positions of other Green Finance ETFs vary over time. Among the volatility indices, VIX consistently acts as a net transmitter of volatility, while other volatility series generally serve as receivers. The reasons for these differences in positioning as net transmitters or receivers within their respective groups may stem from the interplay of volatility transmission among them. The findings highlight that the intensities of net volatility transmissions change over time. Periods of significant increases decreases, or reversals in net volatility transmissions coincide with the onset of the Ukraine-Russia War, the SVCB bankruptcy, and the onset of the Israel-Palestine War.

During the onset of the Ukraine-Russia War, the BLUE ETFs shifted from being a net receiver to a transmitter of volatility and then back to a receiver. The intensity of net volatility received by the GNR series reached its highest level, and similarly, the intensity of net volatility transmitted by CGW peaked. Likewise, in February 2022, sharp increases or decreases in net volatility transmissions were observed among the Green Finance ETFs and volatility index series. The global uncertainty and geopolitical tensions caused by the Ukraine-Russia War, along with energy supply issues, impacted the indices' volatility. The global uncertainty notably affected VIX, while its impact on mainstream market assets influenced MOVE, the shift toward safe-haven assets such as gold affected GVZ and the orientation towards alternative financial assets impacted CVI. Uncertainties in energy supply are also associated with effects on OVX. Additionally, maritime transport plays a crucial role in the transportation of oil and many commodities, and restrictions in maritime transport are expected to impact the Blue Economy and investments in it. Constraints on energy supply underscore the importance of renewable and sustainable energy investments, which are expected to influence Green Finance ETFs and investments. Investor behaviour is sensitive to global events, and this sensitivity has been reflected in the findings during the periods of the SVCB bankruptcy and the Israel-Palestine conflict, showing how these events impacted the net directional volatility transmissions.

The findings demonstrate the sensitivity of the series to global events and how responses to global events vary among the series. While the net directional connectedness results reveal the overall position of a series as a net receiver or transmitter of volatility against all other series, they do not show the bilateral volatility transmission relationships among the series. We illustrate the pairwise connectedness between series in Fig. 4. Fig. 4a (blue graphs) displays the pairwise connectedness between Blue Economy ETFs and volatility series, Fig. 4b (green graphs) shows the connectedness between Green Finance ETFs and volatility indices, and Fig. 4c (purple graphs) presents the connectedness between Blue Economy ETFs and Green Finance ETFs.

The pairwise directional connectedness graphs show that the relationships between the pairs change over time, with periods of increased and decreased net transmissions, as well as changes in direction. Blue Economy ETFs generally act as net transmitters of volatility against volatility indices other than VIX. Precisely, CGW generally positions itself as a net transmitter of VIX during the Ukraine-Russia war, while other Blue Economy ETF series are typically net receivers of volatility from VIX. CGW, focusing on the narrow scope of the water sector market, would not typically be expected to influence VIX directly. However, when sector-specific effects create global uncertainties, an indirect impact on VIX can be anticipated. Geopolitical risks associated with the Ukraine-Russia war have restricted the trade of commodities and many other products, where maritime transport plays a crucial role, and these restrictions also significantly impact maritime transportation.

Changes in general market perceptions due to these restrictions can alter VIX, suggesting that the linkage between CGW and VIX may stem

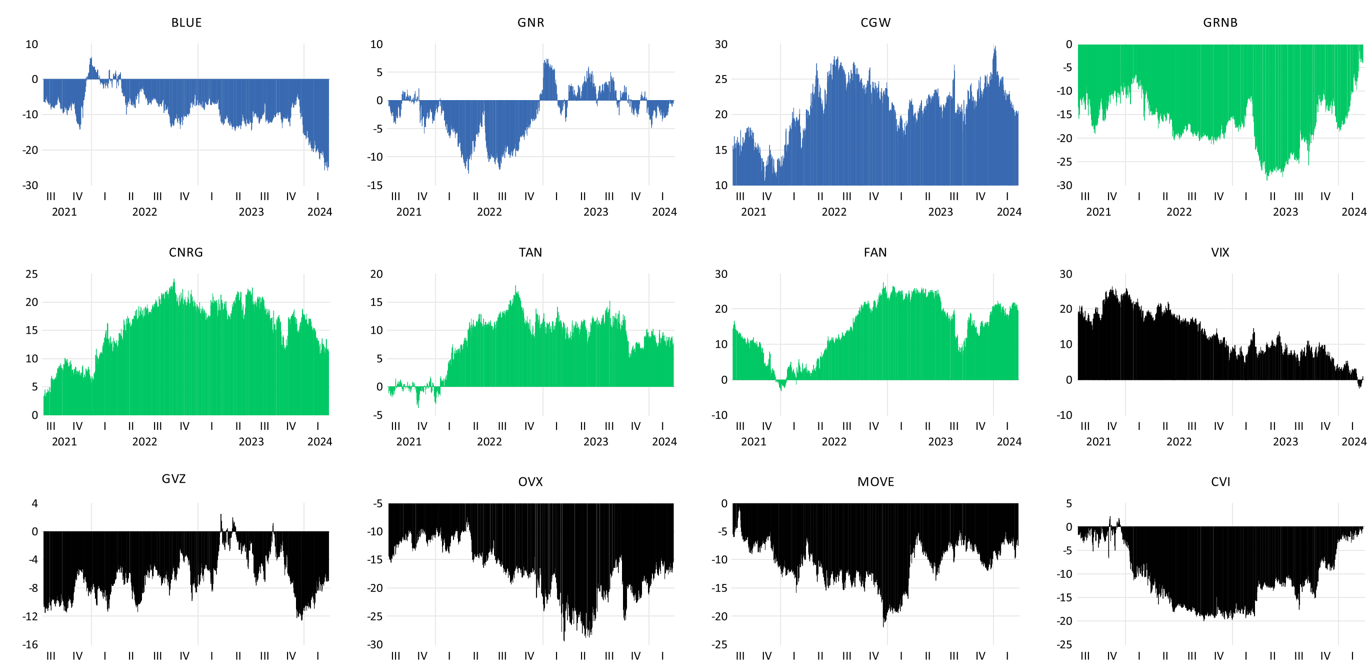


Fig. 3. Net directional connectedness.
Note: In the net connectedness graphs, positive values indicate that a series acts as a net transmitter of volatility against other series during that period, while negative values signify that the series is a net receiver of volatility from other series in the same period.

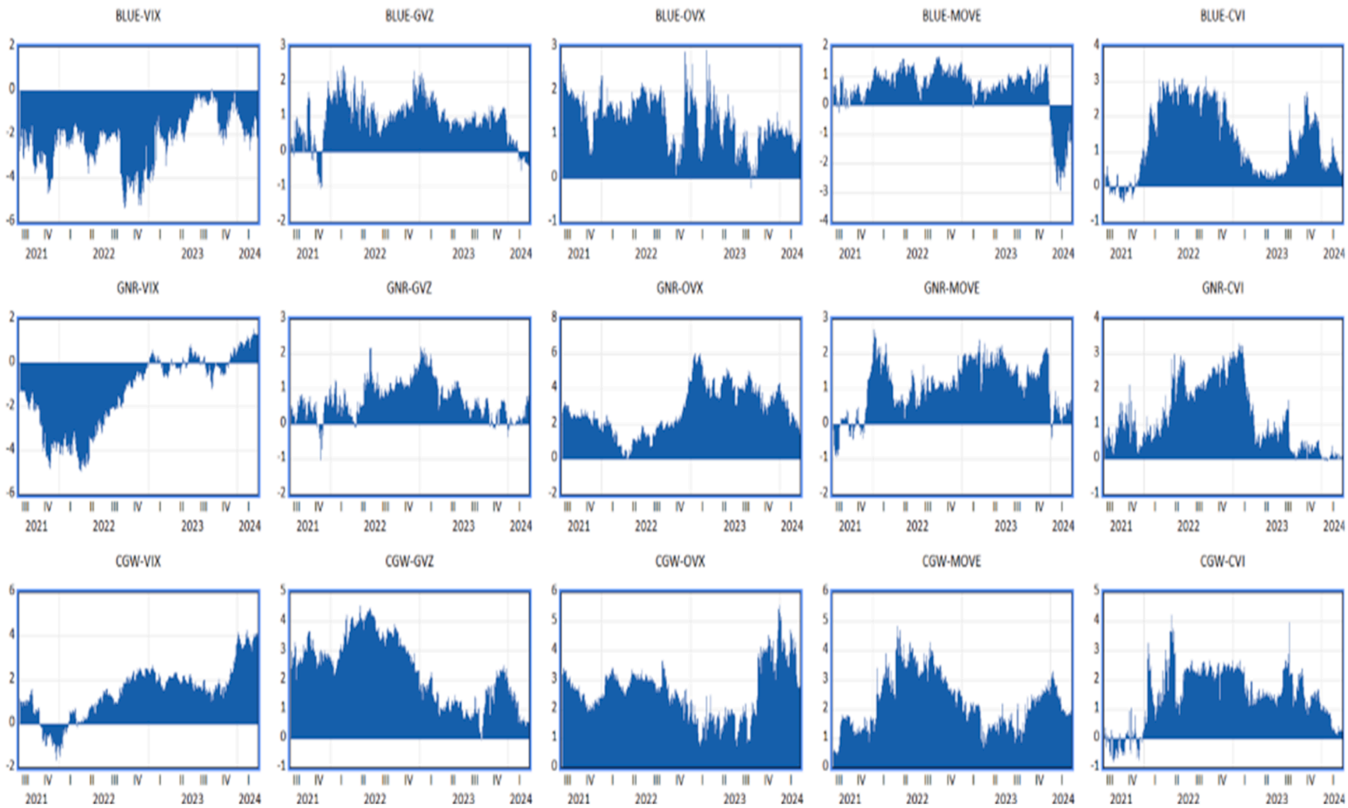


Fig. 4a. Net pairwise directional connectedness “BLUE ETF-volatility index.

from broader market reactions rather than a direct relationship. Furthermore, environmental factors such as global warming and climate change, when perceived as global risks, can lead to broad market reactions, potentially influencing VIX. These reactions can also affect investor behaviour in CGW, thus explaining the observed volatility transmission relationship. When considered with previous findings (Table 3), the position of Blue Economy ETFs as net transmitters of volatility against volatility indices other than VIX could be attributed to weak connectedness. On the other hand, developing sustainable products and renewable energy resources can be expected to influence OVX, which measures oil price volatility. Moreover, as sustainability issues become increasingly prominent, the resulting growth in investments in this area can affect the demand for other financial investment instruments. This situation can also be explained by global uncertainties caused by adverse environmental factors, highlighting the connectedness and complex dynamics within financial markets and the broader global economic environment.

Green Finance ETFs, except GRNB, are generally net transmitters of volatility against volatility indices. This finding could be related to Green Finance’s focus on renewable energy, alternative energy, and sustainable environmental practices. Environmental risks and uncertainties related to energy supply can contribute to global uncertainties. The increasing adoption of renewable energy sources and incentives for such alternatives could impact the demand for fossil energy resources, potentially influencing indices like OVX that measure oil price volatility. Sensitivity towards sustainability, exemplified by initiatives such as the Paris Climate Agreement, undoubtedly affects Green Finance investments. These incentives are expected to impact mainstream investment vehicles like gold and bonds and alternative investments like cryptocurrencies. The distinct role of GRNB, compared to other Green Finance ETFs primarily focused on renewable energy, can be attributed to GRNB representing a global Green Finance bond ETF. This makes GRNB’s behaviour in the market different, as it is less directly tied to the volatile shifts in energy supply and prices that more specifically affect clean energy (CNRG), solar energy (TAN), and wind energy (FAN) ETFs. The observation period covered in the analysis includes significant events like COVID-19, the Ukraine-Russia war, and the Israel-Palestine conflict, which specifically caused volatility in energy supply and prices—this period highlighted the importance of investments in sectors such as clean, solar, and wind energy, which are represented by ETFs like CNRG, TAN, and FAN. These developments underscore the significance of Green Finance investments during global uncertainty, particularly in energy supply, which directly impacts these sectors. GRNB’s distinct role as a more encompassing ETF, in contrast to the more specific ETFs like CNRG, TAN, and FAN, may explain its differentiated behaviour as a less volatile and perhaps more stable investment during global uncertainty. This differentiating factor contributes to GRNB’s unique positioning as a net receiver rather than a transmitter of volatility, distinguishing it from other Green Finance ETFs more directly impacted by the volatile energy market.

The pairwise connectedness between Blue Economy ETFs and Green Finance ETFs show distinct patterns, especially with CGW differing from other Blue Economy series and GRNB differing from other Green Finance series. BLUE and GNR, except against GRNB, act as net transmitters of volatility towards other Green Finance ETFs, while the connectedness of CGW with Green Finance ETFs varies over time. When considered alongside previous findings (Table 3), this suggests that CGW has a stronger connectedness with Green Finance ETFs compared to other Blue Economy ETFs, leading to changes in the mutual transmission of volatility over time. On the other hand, the fact that Green Finance ETFs are net transmitters of volatility against Blue Economy ETFs can be linked to the analysis period covering especially energy crises. During this time, the demand for renewable and alternative energy sources increased, which could explain the stronger transmission from Green Finance ETFs. Blue Economy ETFs, being newer and less known than Green Finance ETFs, might also contribute to these dynamics.

The findings on pairwise connectedness also demonstrate that the intensity or direction of net connectedness changes during periods with

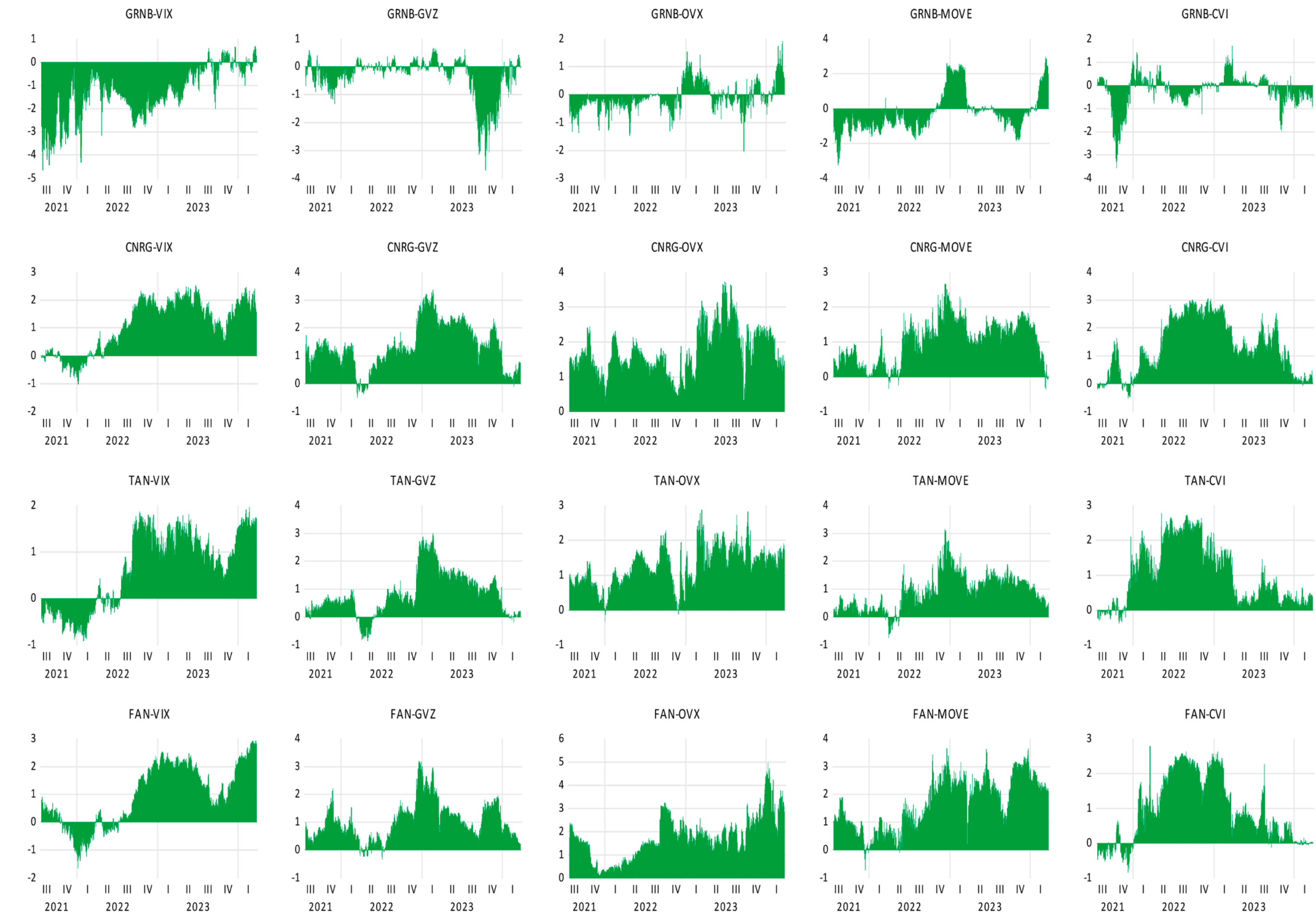


Fig. 4b. Net pairwise directional connectedness “GREEN ETF-volatility index.

significant global events. We present the Wald statistic results that demonstrate the statistical significance of globally significant events on pairwise connectedness in Table 5.

From Table 5, the results reveal that the global events studied significantly impact bilateral connectedness. Although a few results indicate that the impact of these events is statistically insignificant, showing the significant influence of these global events. The effect of the events on connectedness varies across the time series. While the Ukraine-Russia conflict generally stands out across all bilateral connections, the SVCB bankruptcy emerges as a more influential event in the connections between Blue and Green ETFs and VIX. In some cases, the Israel-Palestine conflict is a more significant event in the connections between ETFs and volatility indices. Similar varied results can be observed in the pairwise connectedness between Blue and Green ETFs. These findings are consistent with earlier parts of the analysis and highlight the impact of global events on connectedness.

Fig. 5 summarises the average bilateral connections among the series, highlighting how these relationships evolve over time and under different global circumstances.

The network of net pairwise connectedness indicates that series within their groups tend to have higher average connectedness than their interactions with other groups. Volatility indices other than VIX generally act as net receivers of volatility compared to other series. VIX, however, is a net transmitter of volatility against most other series, except for CNRG and CGW. Green Finance ETFs, on average, act as net transmitters of volatility against Blue Economy ETFs. This dynamic suggests that Green Finance ETFs, which often involve investments tied to renewable and sustainable energy, might be more influenced by or more influential on market movements than Blue Economy ETFs, which focus on industries related to marine and aquatic resources. Additionally, the weak connectivity between Blue Economy and Green Finance ETFs with volatility indices underlines their divergence from mainstream markets. This aspect makes them good diversification options within investment portfolios that contain traditional assets. The distinct behaviours of these ETFs from conventional market movements suggest that they can provide a cushion or counterbalance against market volatilities typically observed in more traditional financial assets.

5. Discussion of results

An ongoing interest in international portfolio diversification has attracted investors and researchers to search for markets and assets that could offer a cushion against exogenous shocks due to the outbreak of unexpected events. In this regard, it is predominantly important not only to explore cross-asset (or cross-markets) relationships, but also to examine the existence of spillover, its direction and the size of spillover shocks during periods of financial turmoil. From an investment perspective, the degree of connectedness and the magnitude of net return spillover contributions by different asset classes are essential for enhancing the effectiveness of hedging strategies. From an academic standpoint, the majority of studies have increasingly investigated between Bitcoin, gold and other asset classes such as equities and energy commodities (e.g. Snene Manzli et al., 2024; Alnafisah et al., 2024; Alnafisah et al., 2025), but few studies have examined the spillover phenomenon and the directional connectedness among volatility indices and other asset classes (in particular sustainable assets).

Against this backdrop, we attempt to investigate the pattern of spillover and connectedness among implied volatility indices and green/

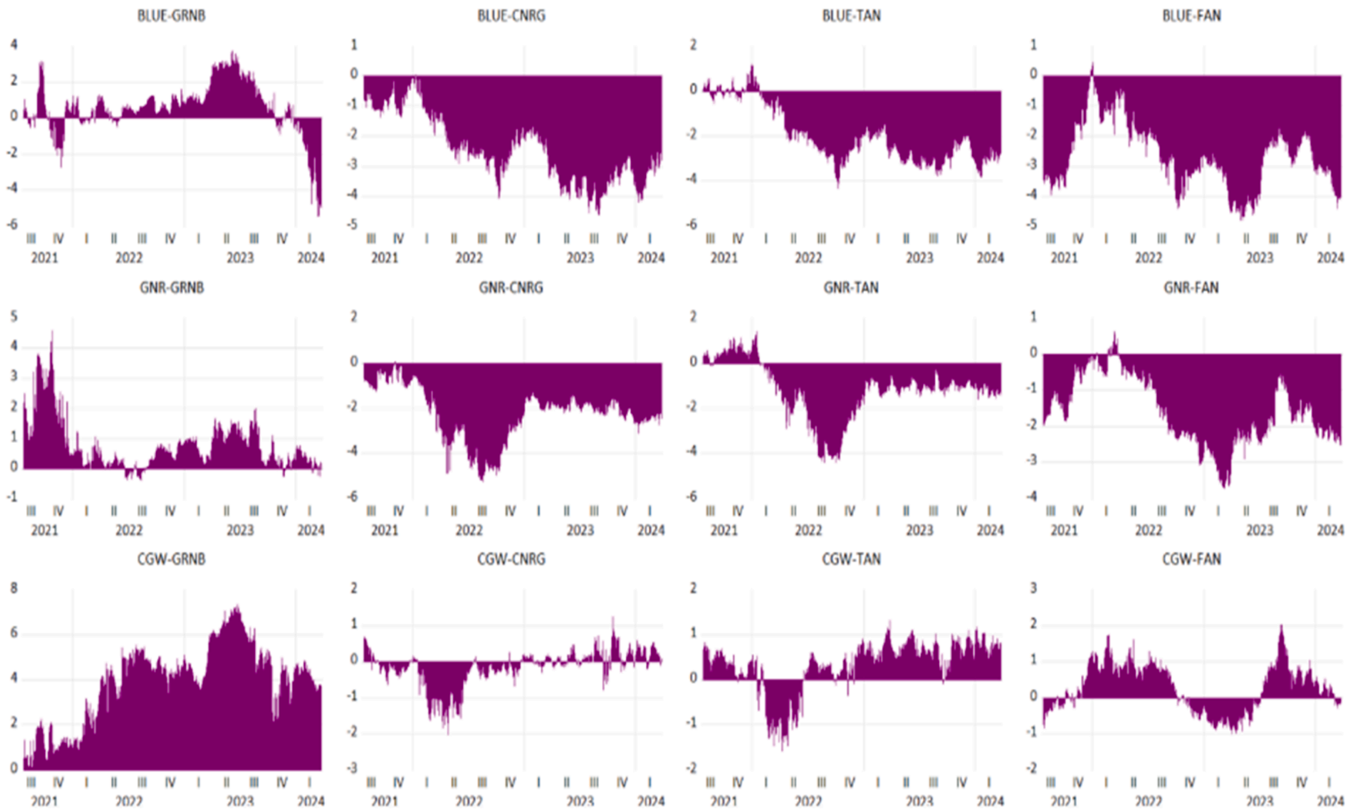


Fig. 4c. Net pairwise directional connectedness "BLUE ETF-GREEN ETF.

blue ETFs over the period 08/10/2020–22/03/2024. In particular, we estimate the total and net directional spillovers between different asset classes to assess the strength of spillover and connectedness among different asset classes. In particular, uncertainty indices are generally known as measure of investor risk aversion among different financial markets (Amoako et al., 2022) and VIX is particularly viewed as the overall investor fear gauge. Using such indices in this study is in line with prior studies (e.g. Urom & Ndubuisi, 2023; Ahmad et al., 2022) to reflect global factors. In this study, we use the Q-VAR approach to offer an effective visualization of the static and dynamic connectedness between implied volatility indices and Green-Blue ETFs and help gauge the power and the magnitude of the potential directional spillovers. It also enables to evaluate how exogenous shocks are disseminated from market to another.

The empirical findings show the non-uniform connectedness profiles among different asset classes. In particular, the impact of five implied volatility indices in the interconnectedness transmission mechanism among the sustainable ETF markets seems to be heterogeneous. From static connectedness perspective, the average connectedness across Green/Blue ETFs is stronger in comparison to those among volatility indices. The VIX displays the strongest average connectedness (12.6 %) with other assets compared to other volatility indices. This result confirms this of Xu et al. (2025) who show that VIX is the main risk factor driving the pricing of risk transmission for the global financial system. On the other hand, the average connectedness among Green/Blue ETFs and uncertainty indices is not high and seems to be weak. The inclusion of classical assets such as gold and oil to a portfolio composed by Green/Blue ETFs improves portfolio diversification and offer real opportunities to hedge risks. From a dynamic connectedness perspective, the change in total connectedness is well-documented over time. Dissimilar response of Green/Blue ETFs to different market uncertainties is recorded according to adverse events (the Ukraine-Russia conflict (February 2022), the SVCB bankruptcy (March 2023), and the beginning of the Israel-Palestine conflict (October 2023) are well-documented. We clearly display the sensitivity of connectedness transmission mechanism to global averse events and spillover effects vary over time. Indeed, before the advent of Ukraine-Russia war, the total connectedness seems to be at lower levels in comparison to subsequent periods. However, it tends to heighten with the outbreak of political crisis and reaches its peak during the bankruptcy of Silicon Valley Bank. As a matter of fact, Yousaf et al. (2023) display the uncertainty due the Russia-Ukraine war substantially raises the connectedness between the volatilities of global financial, particularly in the short run. The war influences volatility connectedness at the middle quantile. The SVCB fallout delivers more uncertainty in the global economy, which thereafter affects volatility indices such as VIX and the MOVE. Blue/Green Finance assets are substantially influenced during this period, involving high connectedness with volatility indices.

Afterwards, the direction and size of net connectedness illuminates to pair net transmitters and recipients (Amoako et al., 2022). In terms of recipient/transmitter role, CGW tends to be a net transmitter of volatility whereas other Blue ETFs change between receivers and transmitters of volatility. GRNB seems to be a net receiver of volatility. However, CNRG is a net transmitter whereas the profiles of other Green ETFs change with time. VIX seems particularly to act as a net transmitter of volatility whereas other volatility indices act as receivers. Such findings corroborate those of Xu et al. (2025) who report that the VIX seems to be a major transmitter whereas the COVOL is a recipient of aggregated global ESG. The VIX is also the main transmitter to four regional ESGs. The outcome from the network connectedness underlines and illustrates how volatility shocks are disseminated across markets and helps investors learn more information about the connectedness and contagion effect for effective asset allocation strategies. In this context, implied volatility indices generally act as net recipients of volatility. Nevertheless, VIX acts as a net transmitter of volatility against most other series, except for CGW and CNRG. Overall, Green ETFs, act as net transmitters of volatility against Blue ETFs. Compared to conventional ETFs, distinctive behavior of sustainable ETFs underscores that they can

Table 5
Wald test results for net pairwise directional connectedness.

Panel A: Wald Test Results for Connectedness Between Blue ETFs and Volatility Indices

Pairwise	Event	Pre Mean	Post Mean	Mean Difference	Std. Er. of Dif.	Wald Statistic
BLUE-VIX	Russia-Ukraine Conflict	−3.593	−2.882	0.711	0.077	85.741***
BLUE-VIX	SVCB bankruptcy	−3.820	−1.512	2.307	0.065	1251.849***
BLUE-VIX	Israel-Palestine Conflict	−3.261	−1.336	1.925	0.107	326.344***
BLUE-OVX	Russia-Ukraine Conflict	1.324	1.207	−0.117	0.053	4.807***
BLUE-OVX	SVCB bankruptcy	1.271	1.159	−0.112	0.050	4.988***
BLUE-OVX	Israel-Palestine Conflict	1.281	0.866	−0.415	0.050	67.918***
BLUE-GVZ	Russia-Ukraine Conflict	0.509	0.638	0.129	0.077	2.823***
BLUE-GVZ	SVCB bankruptcy	0.622	0.584	−0.038	0.043	0.813
BLUE-GVZ	Israel-Palestine Conflict	0.594	0.730	0.136	0.080	2.887*
BLUE-MOVE	Russia-Ukraine Conflict	0.163	0.581	0.419	0.052	65.837***
BLUE-MOVE	SVCB bankruptcy	0.448	0.568	0.120	0.038	9.984***
BLUE-MOVE	Israel-Palestine Conflict	0.436	0.891	0.455	0.064	49.810***
BLUE-CVI	Russia-Ukraine Conflict	0.191	1.487	1.296	0.042	973.064***
BLUE-CVI	SVCB bankruptcy	1.392	0.819	−0.573	0.058	97.108***
BLUE-CVI	Israel-Palestine Conflict	1.219	1.035	−0.185	0.064	8.405***
GNR-VIX	Russia-Ukraine Conflict	−3.183	−1.176	2.007	0.121	273.021***
GNR-VIX	SVCB bankruptcy	−2.368	−0.163	2.205	0.086	653.603***
GNR-VIX	Israel-Palestine Conflict	−1.803	−0.237	1.567	0.098	253.676***
GNR-OVX	Russia-Ukraine Conflict	2.601	2.941	0.340	0.075	20.715***
GNR-OVX	SVCB bankruptcy	2.399	3.780	1.381	0.076	330.168***
GNR-OVX	Israel-Palestine Conflict	2.828	3.156	0.329	0.075	19.420***
GNR-GVZ	Russia-Ukraine Conflict	0.288	0.889	0.601	0.050	145.885***
GNR-GVZ	SVCB bankruptcy	0.871	0.527	−0.344	0.037	85.272***
GNR-GVZ	Israel-Palestine Conflict	0.824	0.221	−0.604	0.034	310.407***
GNR-MOVE	Russia-Ukraine Conflict	0.166	1.166	1.000	0.081	153.256***
GNR-MOVE	SVCB bankruptcy	0.779	1.266	0.487	0.044	119.894***
GNR-MOVE	Israel-Palestine Conflict	0.889	1.358	0.469	0.039	147.157***
GNR-CVI	Russia-Ukraine Conflict	1.587	1.809	0.222	0.093	5.629***
GNR-CVI	SVCB bankruptcy	2.251	0.794	−1.457	0.057	657.562***
GNR-CVI	Israel-Palestine Conflict	1.928	0.457	−1.471	0.049	884.927***
CGW-VIX	Russia-Ukraine Conflict	−0.404	1.384	1.788	0.087	418.930***
CGW-VIX	SVCB bankruptcy	0.603	1.735	1.132	0.067	281.932***
CGW-VIX	Israel-Palestine Conflict	0.892	1.708	0.817	0.080	105.496***
CGW-OVX	Russia-Ukraine Conflict	2.598	2.445	−0.153	0.042	13.236***
CGW-OVX	SVCB bankruptcy	2.566	2.310	−0.256	0.052	23.870***
CGW-OVX	Israel-Palestine Conflict	2.391	3.165	0.775	0.046	284.389***
CGW-GVZ	Russia-Ukraine Conflict	3.429	2.431	−0.998	0.079	159.685***
CGW-GVZ	SVCB bankruptcy	3.279	1.427	−1.852	0.044	1780.931***
CGW-GVZ	Israel-Palestine Conflict	2.767	1.781	−0.986	0.059	279.025***
CGW-MOVE	Russia-Ukraine Conflict	1.402	2.444	1.042	0.048	461.812***
CGW-MOVE	SVCB bankruptcy	2.341	1.958	−0.383	0.053	52.704***
CGW-MOVE	Israel-Palestine Conflict	2.172	2.518	0.347	0.043	63.978***
CGW-CVI	Russia-Ukraine Conflict	0.685	2.073	1.387	0.050	755.337***
CGW-CVI	SVCB bankruptcy	1.627	2.031	0.405	0.056	51.840***
CGW-CVI	Israel-Palestine Conflict	1.747	1.892	0.145	0.050	8.347***

Panel B: Wald Test Results for Connectedness Between GREEN ETFs and Volatility Indices

Pairwise	Event	Pre Mean	Post Mean	Mean Difference	Std. Er. of Dif.	Wald Statistic
GRNB-VIX	Russia-Ukraine Conflict	−3.046	−1.148	1.898	0.110	298.201***
GRNB-VIX	SVCB bankruptcy	−2.069	−0.595	1.474	0.081	329.069***
GRNB-VIX	Israel-Palestine Conflict	−1.813	0.296	2.109	0.070	901.501***
GRNB-OVX	Russia-Ukraine Conflict	−0.364	0.214	0.578	0.038	234.691***
GRNB-OVX	SVCB bankruptcy	−0.071	0.391	0.462	0.050	86.678***
GRNB-OVX	Israel-Palestine Conflict	−0.043	1.074	1.117	0.062	320.830***
GRNB-GVZ	Russia-Ukraine Conflict	−0.065	−0.164	−0.099	0.059	2.761*
GRNB-GVZ	SVCB bankruptcy	−0.079	−0.265	−0.187	0.034	29.401***
GRNB-GVZ	Israel-Palestine Conflict	−0.077	−0.641	−0.564	0.052	119.483***
GRNB-MOVE	Russia-Ukraine Conflict	−1.762	−0.261	1.501	0.090	276.647***
GRNB-MOVE	SVCB bankruptcy	−0.798	−0.198	0.600	0.078	58.856***
GRNB-MOVE	Israel-Palestine Conflict	−0.583	−0.692	−0.109	0.064	2.883*
GRNB-CVI	Russia-Ukraine Conflict	−0.140	−0.025	0.115	0.053	4.732**
GRNB-CVI	SVCB bankruptcy	−0.134	0.111	0.245	0.033	54.588***
GRNB-CVI	Israel-Palestine Conflict	−0.097	0.308	0.406	0.050	66.399***
CNRG-VIX	Russia-Ukraine Conflict	−0.397	1.237	1.634	0.047	1221.809***
CNRG-VIX	SVCB bankruptcy	0.464	1.674	1.210	0.058	433.930***
CNRG-VIX	Israel-Palestine Conflict	0.810	1.356	0.546	0.073	56.094***
CNRG-OVX	Russia-Ukraine Conflict	1.035	2.196	1.161	0.053	485.982***
CNRG-OVX	SVCB bankruptcy	1.311	3.164	1.853	0.034	3047.134***
CNRG-OVX	Israel-Palestine Conflict	1.766	3.259	1.493	0.058	667.204***
CNRG-GVZ	Russia-Ukraine Conflict	1.231	1.497	0.266	0.044	35.961***
CNRG-GVZ	SVCB bankruptcy	1.187	1.930	0.743	0.041	322.192***
CNRG-GVZ	Israel-Palestine Conflict	1.413	1.633	0.220	0.057	14.822***

(continued on next page)

Table 5 (*continued*)

Panel B: Wald Test Results for Connectedness Between GREEN ETFs and Volatility Indices

Pairwise	Event	Pre Mean	Post Mean	Mean Difference	Std. Er. of Dif.	Wald Statistic
CNRG-MOVE	Russia-Ukraine Conflict	0.643	1.545	0.903	0.040	521.122***
CNRG-MOVE	SVCB bankruptcy	1.198	1.631	0.433	0.047	84.587***
CNRG-MOVE	Israel-Palestine Conflict	1.269	1.926	0.657	0.038	300.832***
CNRG-CVI	Russia-Ukraine Conflict	0.111	1.219	1.108	0.052	449.962***
CNRG-CVI	SVCB bankruptcy	1.057	0.805	−0.252	0.055	20.663***
CNRG-CVI	Israel-Palestine Conflict	1.028	0.539	−0.490	0.045	118.760***
TAN-VIX	Russia-Ukraine Conflict	−0.679	0.691	1.370	0.039	1214.455***
TAN-VIX	SVCB bankruptcy	0.095	0.956	0.862	0.052	272.798***
TAN-VIX	Israel-Palestine Conflict	0.321	0.884	0.564	0.062	82.748***
TAN-OVX	Russia-Ukraine Conflict	0.431	1.708	1.277	0.039	1056.216***
TAN-OVX	SVCB bankruptcy	0.972	2.308	1.336	0.043	958.978***
TAN-OVX	Israel-Palestine Conflict	1.330	2.145	0.815	0.047	296.19***
TAN-GVZ	Russia-Ukraine Conflict	0.389	1.001	0.612	0.036	282.705***
TAN-GVZ	SVCB bankruptcy	0.651	1.283	0.632	0.038	274.787***
TAN-GVZ	Israel-Palestine Conflict	0.844	1.022	0.178	0.048	13.783***
TAN-MOVE	Russia-Ukraine Conflict	0.789	1.393	0.604	0.040	232.598***
TAN-MOVE	SVCB bankruptcy	1.117	1.535	0.418	0.042	98.789***
TAN-MOVE	Israel-Palestine Conflict	1.215	1.596	0.382	0.039	97.209***
TAN-CVI	Russia-Ukraine Conflict	0.146	0.711	0.566	0.055	106.734***
TAN-CVI	SVCB bankruptcy	0.805	0.154	−0.650	0.044	219.461***
TAN-CVI	Israel-Palestine Conflict	0.607	0.415	−0.191	0.054	12.779***
FAN-VIX	Russia-Ukraine Conflict	−0.380	0.796	1.176	0.071	278.053***
FAN-VIX	SVCB bankruptcy	0.154	1.279	1.125	0.064	311.329***
FAN-VIX	Israel-Palestine Conflict	0.487	0.898	0.411	0.070	34.7467***
FAN-OVX	Russia-Ukraine Conflict	1.263	2.013	0.750	0.082	83.344***
FAN-OVX	SVCB bankruptcy	1.511	2.503	0.992	0.061	268.18***
FAN-OVX	Israel-Palestine Conflict	1.684	3.091	1.406	0.058	582.935***
FAN-GVZ	Russia-Ukraine Conflict	0.926	1.205	0.279	0.053	27.47***
FAN-GVZ	SVCB bankruptcy	1.112	1.204	0.092	0.045	4.297**
FAN-GVZ	Israel-Palestine Conflict	1.134	1.214	0.080	0.044	3.314*
FAN-MOVE	Russia-Ukraine Conflict	1.071	2.280	1.209	0.058	435.046***
FAN-MOVE	SVCB bankruptcy	1.713	2.595	0.882	0.050	310.484***
FAN-MOVE	Israel-Palestine Conflict	1.905	2.825	0.920	0.047	375.273***
FAN-CVI	Russia-Ukraine Conflict	0.314	1.151	0.837	0.046	326.672***
FAN-CVI	SVCB bankruptcy	1.147	0.607	−0.540	0.049	122.527***
FAN-CVI	Israel-Palestine Conflict	1.049	0.313	−0.736	0.043	289.985***

Panel C: Wald Test Results for Connectedness Between BLUE and GREEN ETFs

Pairwise	Event	Pre Mean	Post Mean	Mean Difference	Std. Er. of Dif.	Wald Statistic
BLUE-GRNB	Russia-Ukraine Conflict	0.043	0.636	0.593	0.071	68.981***
BLUE-GRNB	SVCB bankruptcy	0.317	0.870	0.553	0.070	62.405***
BLUE-GRNB	Israel-Palestine Conflict	0.596	−0.205	−0.801	0.063	161.969***
BLUE-CNRG	Russia-Ukraine Conflict	−1.136	−3.169	−2.033	0.041	2417.624***
BLUE-CNRG	SVCB bankruptcy	−2.299	−3.534	−1.235	0.059	441.707***
BLUE-CNRG	Israel-Palestine Conflict	−2.565	−3.880	−1.315	0.056	554.362***
BLUE-TAN	Russia-Ukraine Conflict	0.043	−2.809	−2.852	0.040	5118.089***
BLUE-TAN	SVCB bankruptcy	−1.592	−3.315	−1.723	0.070	604.211***
BLUE-TAN	Israel-Palestine Conflict	−2.015	−3.397	−1.382	0.078	317.522***
BLUE-FAN	Russia-Ukraine Conflict	−1.607	−3.064	−1.457	0.084	300.1***
BLUE-FAN	SVCB bankruptcy	−2.464	−3.279	−0.814	0.073	125.467***
BLUE-FAN	Israel-Palestine Conflict	−2.756	−2.612	0.144	0.067	4.584**
GNR-GRNB	Russia-Ukraine Conflict	1.385	0.695	−0.690	0.075	84.647***
GNR-GRNB	SVCB bankruptcy	0.776	0.991	0.214	0.056	14.7278***
GNR-GRNB	Israel-Palestine Conflict	0.893	0.505	−0.388	0.078	24.526***
GNR-CNRG	Russia-Ukraine Conflict	−0.723	−2.394	−1.671	0.037	2094.761***
GNR-CNRG	SVCB bankruptcy	−1.987	−2.089	−0.102	0.059	3.039*
GNR-CNRG	Israel-Palestine Conflict	−1.989	−2.269	−0.279	0.053	27.905***
GNR-TAN	Russia-Ukraine Conflict	0.606	−1.483	−2.089	0.046	2068.093***
GNR-TAN	SVCB bankruptcy	−0.970	−1.111	−0.141	0.068	4.318**
GNR-TAN	Israel-Palestine Conflict	−1.001	−1.148	−0.148	0.055	7.142***
GNR-FAN	Russia-Ukraine Conflict	−0.876	−1.542	−0.667	0.075	78.511***
GNR-FAN	SVCB bankruptcy	−1.101	−1.968	−0.866	0.066	172.862***
GNR-FAN	Israel-Palestine Conflict	−1.391	−1.412	−0.020	0.050	0.16***
CGW-GRNB	Russia-Ukraine Conflict	1.384	4.355	2.972	0.065	2069.755***
CGW-GRNB	SVCB bankruptcy	3.165	4.729	1.564	0.112	194.725***
CGW-GRNB	Israel-Palestine Conflict	3.715	3.523	−0.191	0.086	4.905**
CGW-CNRG	Russia-Ukraine Conflict	−0.003	−0.220	−0.218	0.026	69.785***
CGW-CNRG	SVCB bankruptcy	−0.220	−0.078	0.142	0.027	27.18***
CGW-CNRG	Israel-Palestine Conflict	−0.199	0.039	0.238	0.035	46.486***
CGW-TAN	Russia-Ukraine Conflict	0.543	0.283	−0.260	0.032	65.622***
CGW-TAN	SVCB bankruptcy	0.231	0.555	0.324	0.032	104.924***
CGW-TAN	Israel-Palestine Conflict	0.310	0.576	0.266	0.039	46.981***
CGW-FAN	Russia-Ukraine Conflict	0.409	0.475	0.066	0.062	1.126
CGW-FAN	SVCB bankruptcy	0.547	0.291	−0.256	0.060	18.004***
CGW-FAN	Israel-Palestine Conflict	0.397	0.947	0.549	0.041	181.702***

Note: The symbols "***", "**", and "*" indicate significance levels of 1 %, 5 %, and 10 %, respectively.

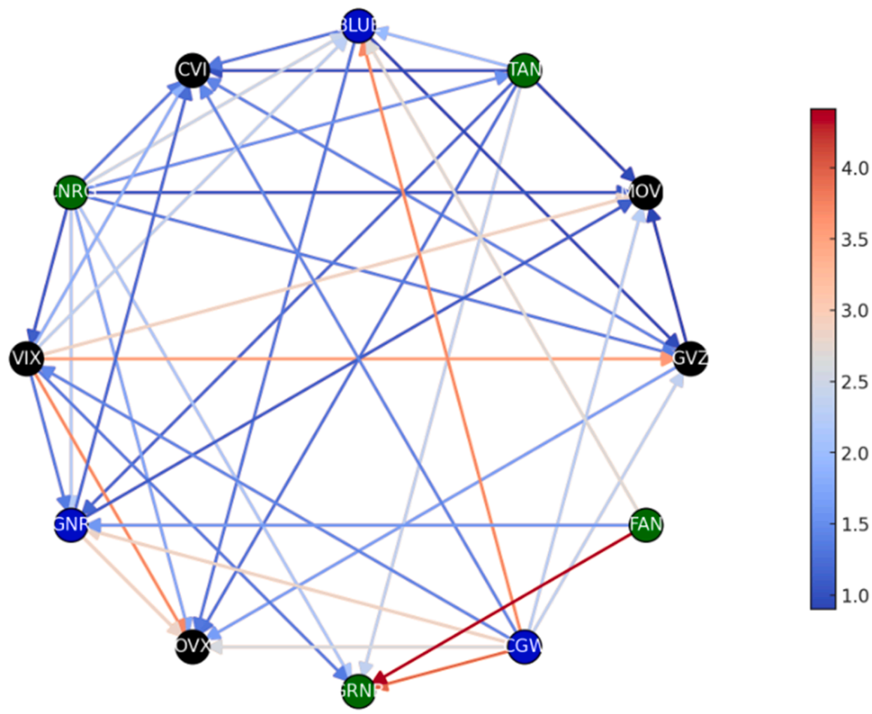


Fig. 5. Network plot of avarage pairwise connectedness.
Note: The average network connectedness graphs display the net volatility spillovers among the series. Blue nodes represent Blue Economy ETFs, green nodes denote Green Finance ETFs, and black nodes indicate the volatility index series. The arrow's direction indicates the volatility flow from the net transmitter to the net receiver. The intensity of the net spillover increases from dark blue to dark red. Only net spillovers equal to or greater than 1 % are depicted to enhance visual clarity.

deliver a cushion or counterbalance against market uncertainties observed in other traditional financial markets. As a matter of fact, Kang et al. (2021) examine directional connectedness among oil, gold, stock market, uncertainty factors and US sector equity ETFs over the long and short runs. They show that market expectations of VIX, followed by its expectations of OVX, highly affect the US sector ETFs prices and returns. Spillovers among US sector ETFs and oil, stock, gold and uncertainty indices tend to be asymmetric in the long and short runs.

To date, many studies have focused on broad asset classes and analyzed the effect of volatility indices on financial markets. For instance, Lin and Su (2020b) detect negative relationships among OVX and Islamic stocks. Pham and Do (2022) identify the time-varying spillover effects among uncertainty indices (VIX, GVZ and OVX). Shahid et al. (2023) show the risk transmission mechanism among the Socially Responsible Investments (SRI) and volatility indices (OVX, GVZ and VXSLV (silver volatility index)). Sheikh et al. (2023) explore how index returns of shariah and conventional indices of the Europe, Asia and USA are impacted by variations in gold prices, oil prices, gold-VIX and oil-VIX. They show that GVZ, VIX and OVX affect simultaneously returns of all indices. Implied volatility indices influence significantly volatility of index returns during the health crisis. Stock prices respond more favorably to oil prices than to oil spot prices. Nevertheless, there is less known about the connectedness framework among global volatility indices and Blue/Green ETFs. In particular, the choice of including volatility indices in our study is a worthwhile as they capture faster the dynamics of information and contagion across traditional and new markets (e.g. Boateng et al., 2022). The outcome from this research provides a thorough understanding of sustainable ETF markets and establishing effective investment strategies.

6. Conclusion

The alarming increase in issues connected with environment and climate change predominantly contributes to the emergence of sustainable assets such as green bonds. In this regard, a bunch of studies has focused on the volatility and return connectedness among sustainable assets and volatility indices. Nevertheless, there is a little knowledge about the diversification benefits of sustainable assets such as the green and blue ETFs against the price fluctuations in different markets. As well, the outbreak of unexpected and adverse events such as the health crisis has increasingly impacted market uncertainties, which ultimately make investors confused about the potential diversification advantages of sustainable assets. Against this backdrop, we estimate and investigate the pattern of spillover and connectedness across implied volatility indices and Green/Blue ETFs. In this regard, we estimate the total and net directional spillovers among various financial assets. We also examine the effect of the Russia-Ukraine war and Covid-19 pandemic on spillover dynamics. We use the Quantile-VAR approach developed by Chatziantoniu et al. (2021) to compute different connectedness measures from static and dynamic perspectives. This allows us to learn to what extent the desired narrative of 'shock dumping' and 'shock absorption' features of assets vary over turbulent times.

The empirical results of our study add to the existing literature concerning the connectedness transmission mechanisms of uncertainty indices and sustainable ETF markets. They could deliver insightful information for different stakeholders in evaluating the connectedness framework across markets. Our findings clearly show dissimilar levels of static and dynamic connectedness and shock transmission among various asset classes. On average, the connectedness among Green/Blue ETFs and volatility indices is low. The contagious spillovers across different asset classes are well-documented during turbulent times. The outcome of the study successfully detects the role of transmitter and receiver for each asset. For instance, the VIX seems to be a net transmitter of volatility. Including implied volatility indices seems to be particularly interesting for better understanding the change in connectedness across sustainable ETF markets and traditional financial markets. As well, uncertain times prompt broadened information asymmetric for a lengthened period and investors become 'short-run' profit-centric as they could not possess an insightful vision for long-run growth returns. A trade-off between sustainable and implied volatility indices increased but there is a bias towards green and blue assets given that rigorous environmental laws cobble the way for secured diversification advantages from sustainable assets.

Understanding and distinguishing the difference in dynamic volatility connectedness transmission mechanism across sustainable and traditional assets has multiple practical and policy implications. Our comprehensive consideration of different sustainable asset classes and various uncertainty factors could help different stakeholders to offer a thorough analysis of the transmission mechanism between markets. In particular, our findings could help investors and policymakers to gain a comprehensive understanding of investment in sustainable asset markets during episodes of high uncertainty. Based on our findings, policymakers and market regulators could effectively react to market risk contagion impacts and develop more proactive strategies. They also help them to articulate ingenious guidelines to handle the negative effects of health crisis/war-triggered uncertainty between sustainable and classical asset markets. Our empirical results could enhance the ability to detect financial market vulnerabilities and risks within the system composed by traditional and sustainable asset markets. Our empirical results also invite to improve the climate-related financial regulations. Apprehending the sensitivity of sustainability of ETFs to market volatility helps to evaluate systemic risk. In this respect, policymakers should consider to what extent volatility influences capital allocation towards sustainable investments. This study could also help investors to acquire thorough understanding of investment in Blue/Green ETF markets during normal and financial and how such markets respond to volatility from traditional markets. Investors who want to invest in sustainable asset markets need to be conscious about the risk transmission among implied volatility indices and sustainable ETFs, especially the VIX.

Future research could investigate the dynamic connectedness and spillover effects across implied volatility indices and Green/Blue assets based on the frequency-dependent connectedness method to better explore the behavior of connectedness at high and low frequencies. In particular, it could help to apprehend how the volatility transmission mechanism behaves at low and high frequencies. Additionally, the QQ approach could serve as a valuable complementary methodology for future research due to its ability to explicitly assess asymmetric spillovers and cross-quantile interactions, thereby enriching our understanding of complex dependency structures under varying market conditions.

CRediT authorship contribution statement

Halilibrahim Gökgöz: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Azza Bejaoui:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Conceptualization. **Tapas Mishra:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Conceptualization. **Ahmed Jeribi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Low and high quantiles Q-VAR connectedness

This appnedix section illustrates the Q-VAR connectedness among our series composed of Blue and Green ETFs and Volatility Indices at low and high quantile levels. We employ a quantile level of 0.1 for low quantiles and 0.9 for high quantiles. The findings are reported comparatively for low and high quantile levels. The results indicate that the connectedness at both low and high quantile levels is higher than that at the median quantile level (tau at 0.5). Particularly during market downturns or upswings, the sensitivity of Blue and Green ETFs to each other and volatility indices is heightened. However, the connectedness of Blue and Green ETFs with VIX during these periods is relatively lower than the median quantile connectedness.

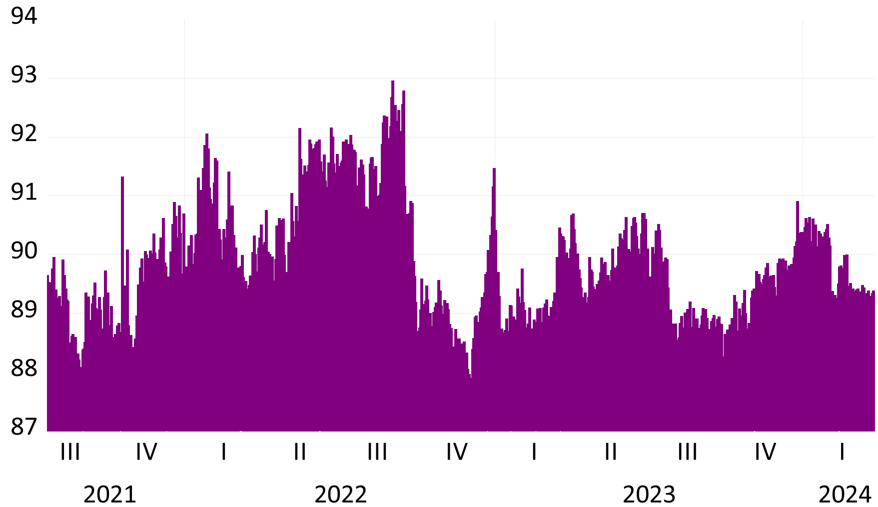
For a more detailed examination of these average connectedness findings, please refer to Table A1 and Fig. A5. The dynamic findings, including the Total Connectedness Index (TCI) and net bilateral directional connectedness, are presented in Figs. A1-A4. These dynamic findings differ both from each other and from the connectivity findings at the median quantile level (tau at 0.5) examined in the main text. For instance, whereas Blue and Green ETFs are generally net receivers of volatility at the median quantile level throughout the period against NTPDC, they are generally net transmitters of volatility at low and high quantile levels. This reflects the tendency for ETFs to fall with rising VIX and rise with falling VIX during market downturns and upturns, respectively. Similar asymmetric interactions are present in other connectedness findings.

Furthermore, in line with our median quantile connectedness findings and Wald statistic results, the intensity or direction of dynamic connectivities change during periods marked by globally significant events. For a more detailed examination of these dynamic connectedness findings, refer to Figs. A1-A4.

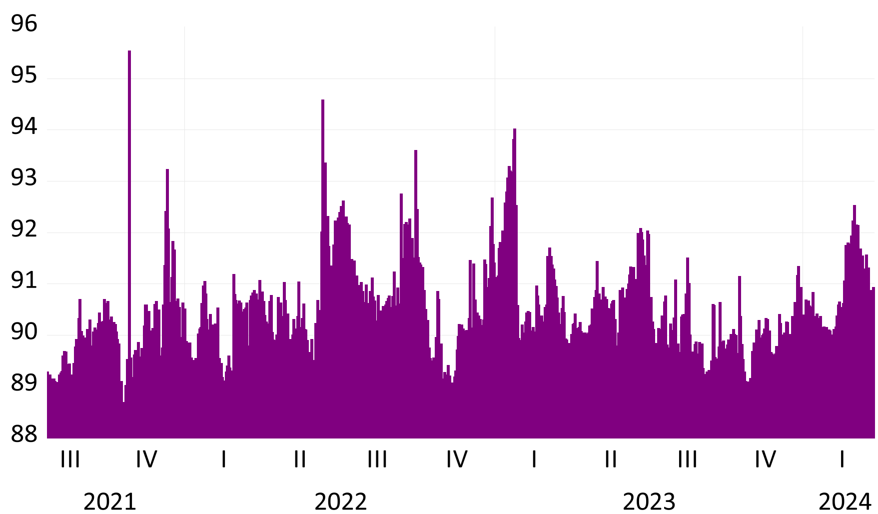
Table A1
Average quantile connectedness at lower and upper quantile levels.

Panel A: Q-VAR Connectedness at tau 0.1													
	BLUE	**GNR**	**CGW**	**GRNB**	**CNRG**	**TAN**	**FAN**	**VIX**	**GVZ**	**OVX**	**MOVE**	**CVI**	**FROM**
BLUE	16.12	10.04	11.19	7.95	10.59	10.35	10.81	3.96	4.46	4.4	5.39	4.74	83.88
GNR	9.99	16.1	11.54	7.48	10.7	9.99	10.42	3.61	4.95	4.03	5.59	5.61	83.9
CGW	10.69	11.42	16.18	8.9	11.5	10.34	11.85	2.61	3.61	3.74	4.56	4.58	83.82
GRNB	8.13	8.23	9.93	17.4	9.45	9.18	9.65	5.14	5.78	6.15	5.1	5.87	82.6
CNRG	9.58	9.87	11.08	8.18	14.44	13.45	11.14	3.45	4.36	4.16	5.26	5.02	85.56
TAN	9.69	9.45	10.27	8.25	13.71	14.73	11.29	3.55	4.62	4.09	5.29	5.04	85.27
FAN	10.31	10.07	11.44	8.64	11.73	11.72	15.12	3.24	4.2	3.94	4.81	4.79	84.88
VIX	5.04	4.57	4	6.58	4.58	4.54	4.35	21.86	12.77	10.65	11.94	9.12	78.14
GVZ	5.58	5.86	5.09	7.05	5.55	5.39	5.26	11.66	19.78	8.82	11.55	8.41	80.22
OVX	5.96	5.69	5.9	7.88	6.37	6.14	6.24	10.45	9.35	20.16	9.1	6.76	79.84
MOVE	6.11	6.58	5.68	5.8	6.51	6.34	5.61	10.82	11.39	7.97	19	8.18	81
CVI	6.07	6.66	6.28	7.32	6.61	6.25	6.26	8.95	8.89	6.68	8.97	21.07	78.93
TO	87.15	88.44	92.39	84.03	97.29	93.68	92.89	67.45	74.38	64.63	77.55	68.14	988.03
Inc.Own	103.27	104.54	108.57	101.43	111.74	108.41	108.01	89.31	94.17	84.79	96.56	89.21	TCI
NET	3.27	4.54	8.57	1.43	11.74	8.41	8.01	-10.69	-5.83	-15.21	-3.44	-10.79	82.34
Panel B: Q-VAR Connectedness at tau 0.9													
BLUE	16.88	9.92	11.08	7.4	10.25	10.35	11.02	4.22	4.6	4.86	4.66	4.77	83.12
GNR	10.06	16.59	11.61	7.37	10.44	10.05	10.51	3.95	4.88	4.43	4.86	5.25	83.41
CGW	10.4	11.19	15.66	8.6	11.13	10.31	11.66	3.6	4.12	4.48	4.27	4.58	84.34
GRNB	7.89	7.74	9.84	17.61	9.18	9.26	9.73	5.58	6.03	6.74	4.47	5.93	82.39
CNRG	9.33	9.54	10.95	7.61	15.25	14.05	11.66	3.55	4.37	4.51	4.6	4.59	84.75
TAN	9.44	9.05	10.11	7.67	13.85	15	11.58	4	4.75	4.76	4.87	4.93	85
FAN	9.76	9.36	11.13	8.24	11.49	11.47	14.45	4.21	4.84	5.09	4.72	5.23	85.55
VIX	5.63	5.19	4.94	6.66	5.56	5.91	5.23	19.36	11.62	10.71	10.47	8.72	80.64
GVZ	5.83	5.89	5.45	6.92	6.16	6.65	5.96	11.07	17.74	9.53	10.6	8.19	82.26
OVX	6.55	6.29	6.23	7.37	6.4	6.71	6.33	10.57	9.7	17.98	8.71	7.16	82.02
MOVE	6	5.85	5.36	5.45	6.26	6.66	5.66	10.95	11.22	9.14	19.33	8.13	80.67
CVI	6.43	6.87	6.69	6.77	7.03	7.21	6.66	9.05	8.51	7.29	8.16	19.33	80.67
TO	87.32	86.88	93.38	80.08	97.76	98.62	95.99	70.74	74.63	71.53	70.39	67.49	994.83
Inc.Own	104.2	103.48	109.04	97.69	113	113.62	110.44	90.1	92.37	89.51	89.72	86.81	TCI
NET	4.2	3.48	9.04	-2.31	13	13.62	10.44	-9.9	-7.63	-10.49	-10.28	-13.19	82.9

Note: This table displays the average connectedness among our sample consisting of Blue and Green ETFs and Volatility Indices at low and high quantiles. Panel A shows the average connectedness among the series at the 0.1 quantile level, while Panel B illustrates the average connectedness at the 0.9 quantile level. The colour gradient from light yellow to dark green indicates increasing values of connectedness.

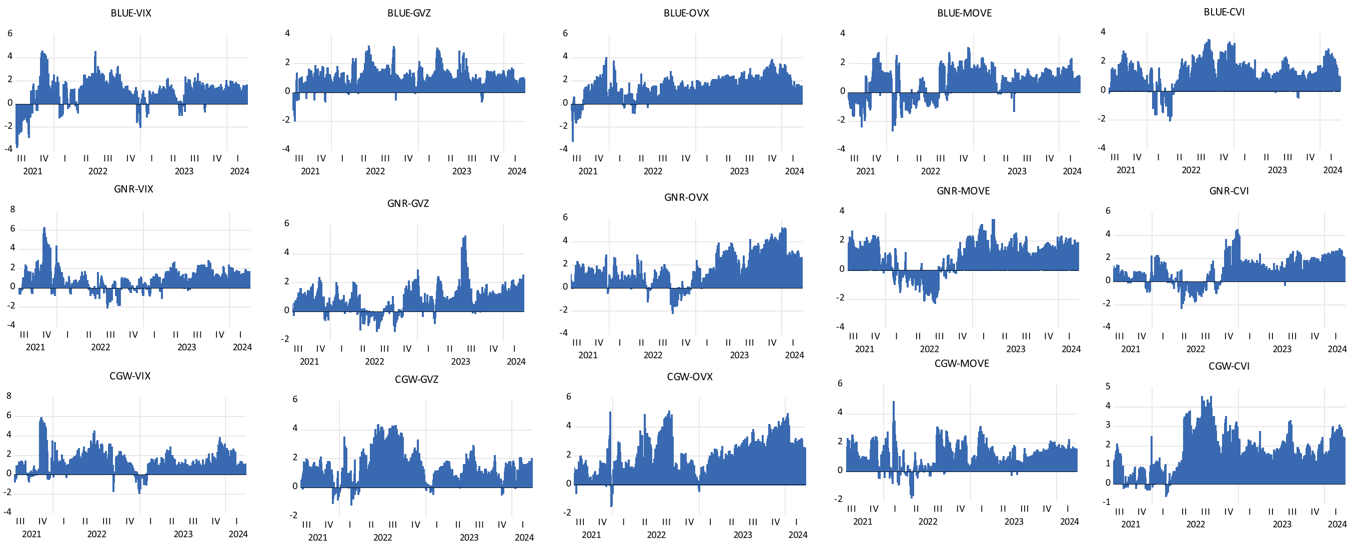


Panel A: TCI at the 0.1 Quantile Level

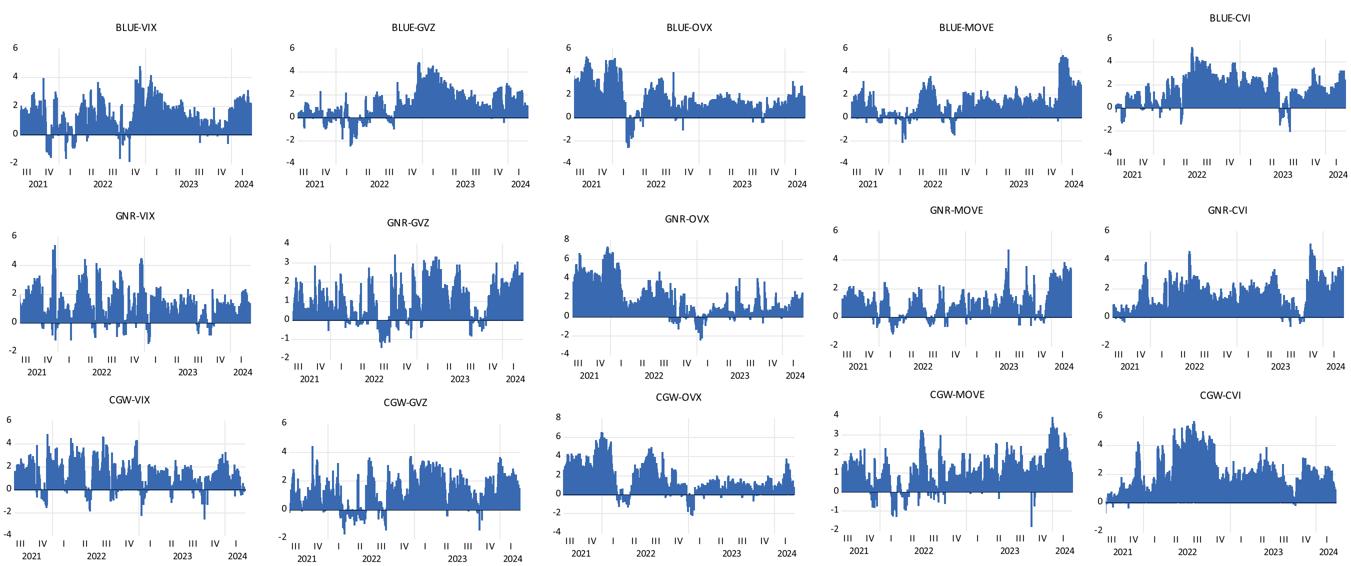


Panel B: TCI at the 0.9 Quantile Level

Fig. A1. TCI at low and high quantile levels.

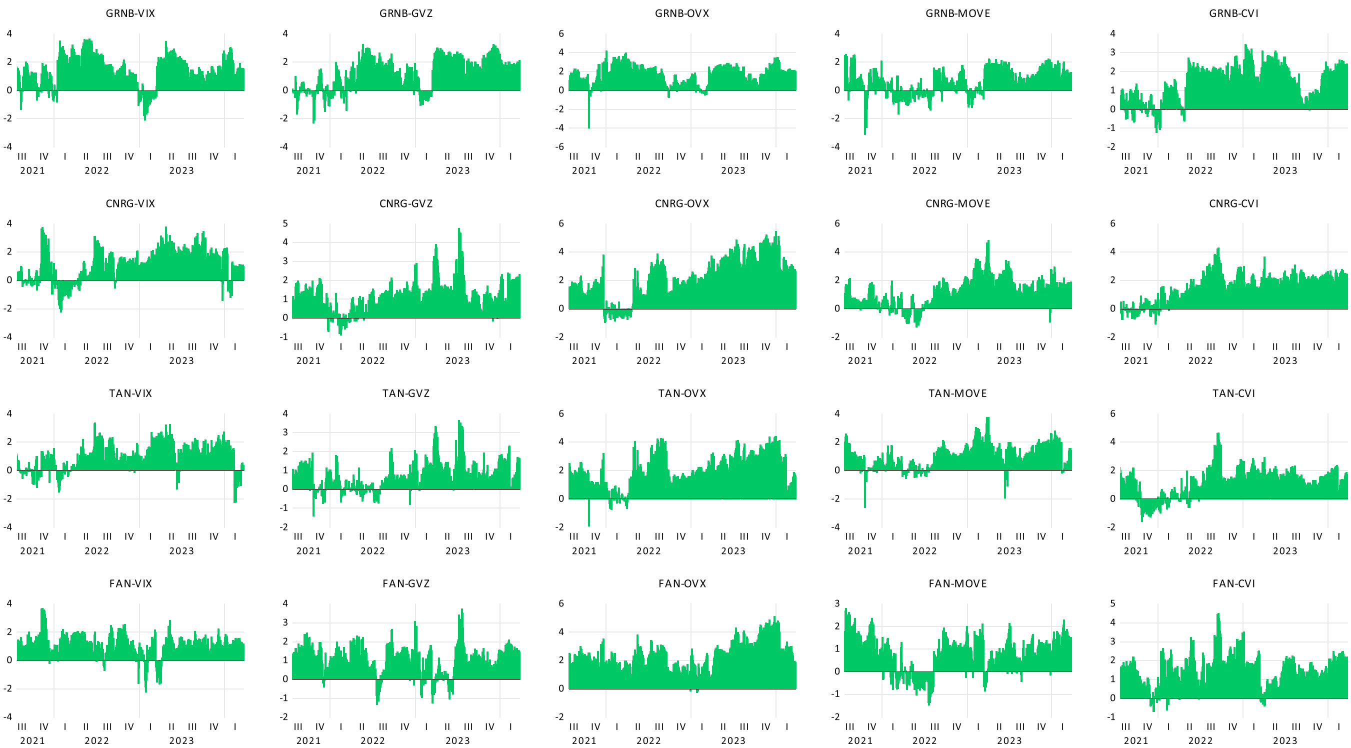


Panel A: NTPDC between Blue ETFs and Volatility Indices at the 0.1 Quantile Level

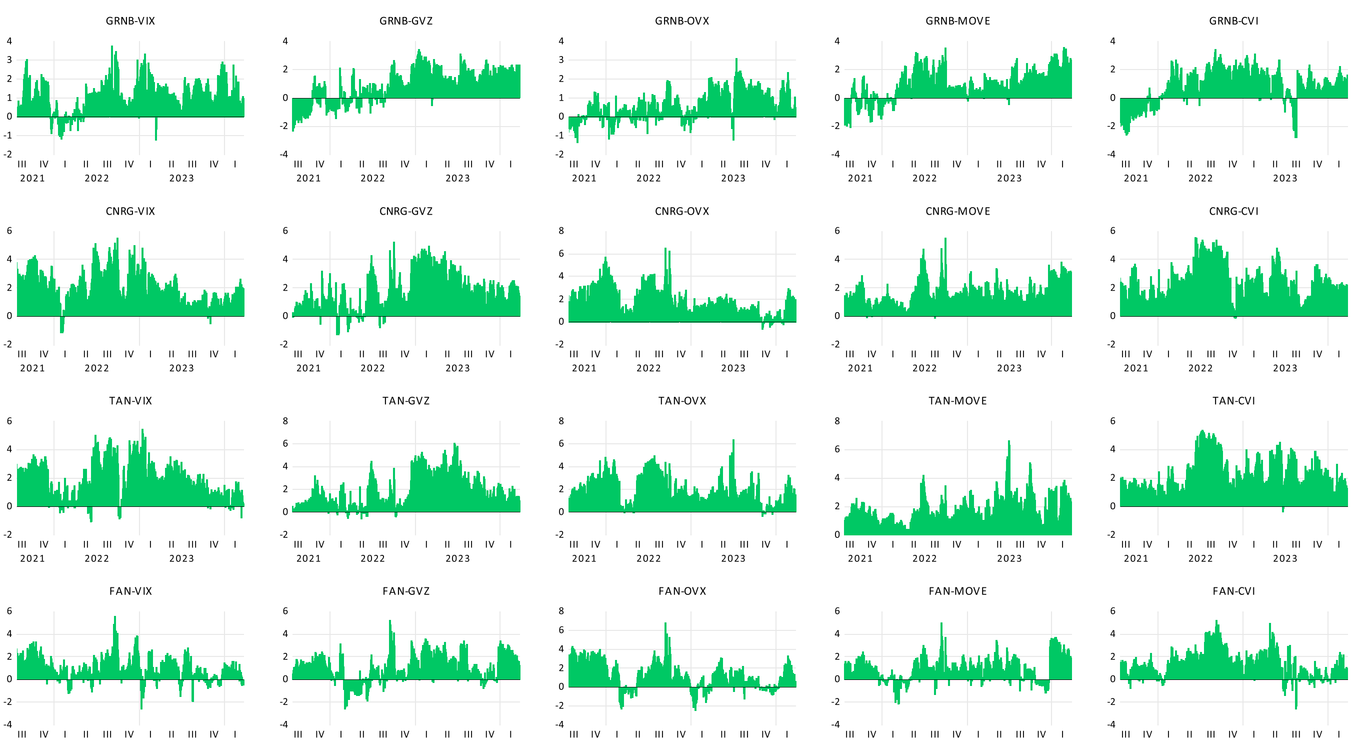


Panel B: NTPDC between Blue ETFs and Volatility Indices at the 0.9 Quantile Level

Fig. A2. NTPDC between blue ETFs and volatility indices at low and high quantile levels.

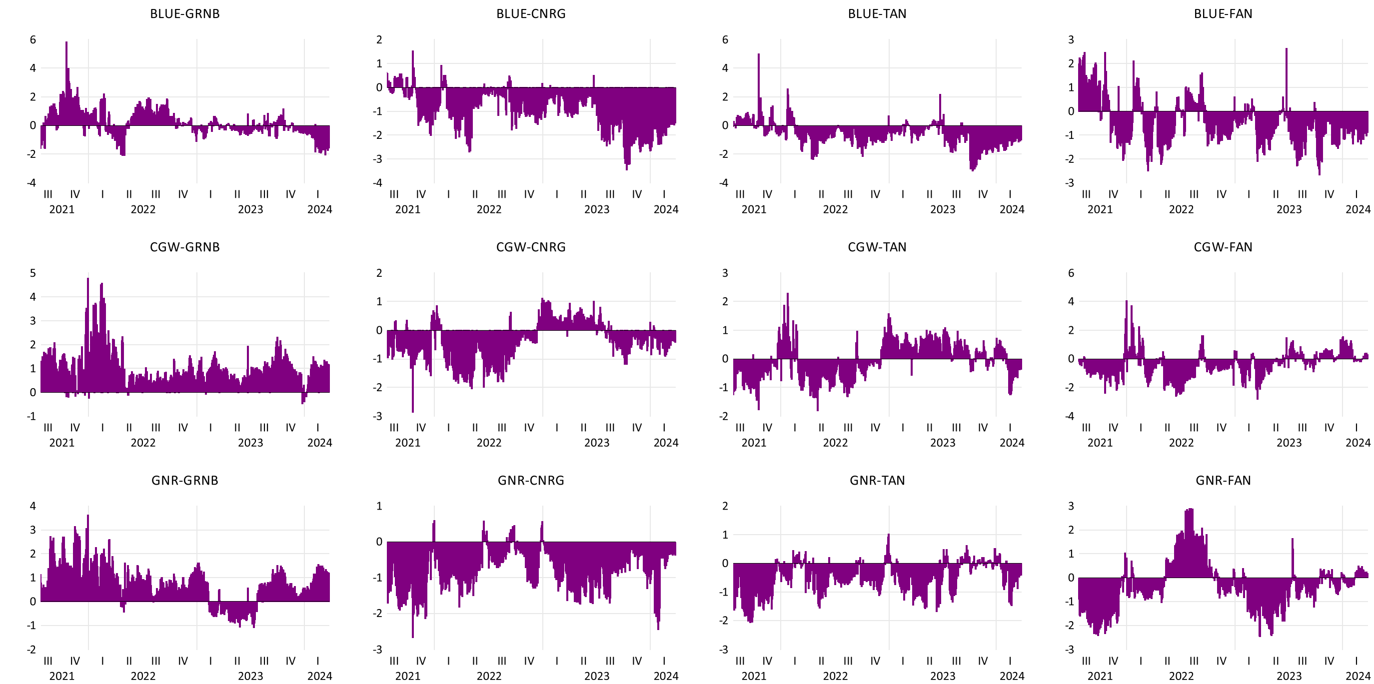


Panel A: NTPDC between Green ETFs and Volatility Indices at the 0.1 Quantile Level

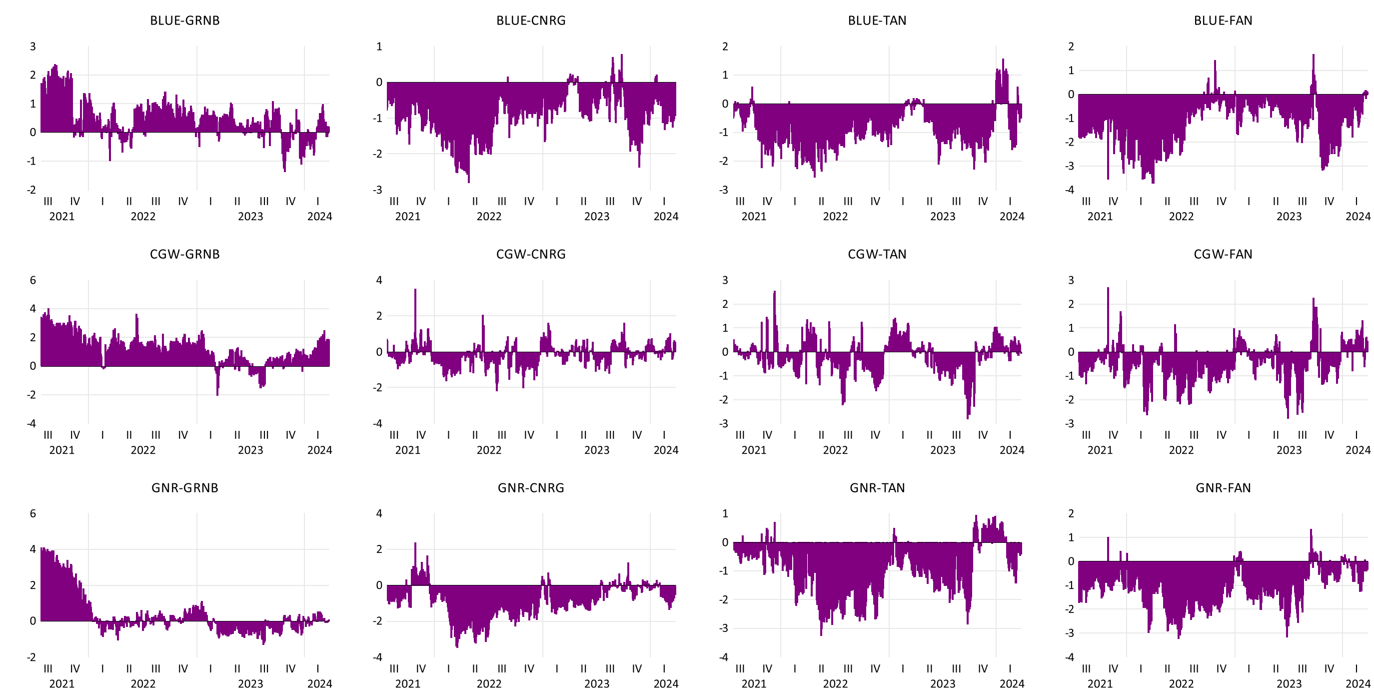


Panel B: NTPDC between Green ETFs and Volatility Indices at the 0.9 Quantile Level

Fig. A3. NTPDC between green ETFs and volatility indices at low and high quantile levels.

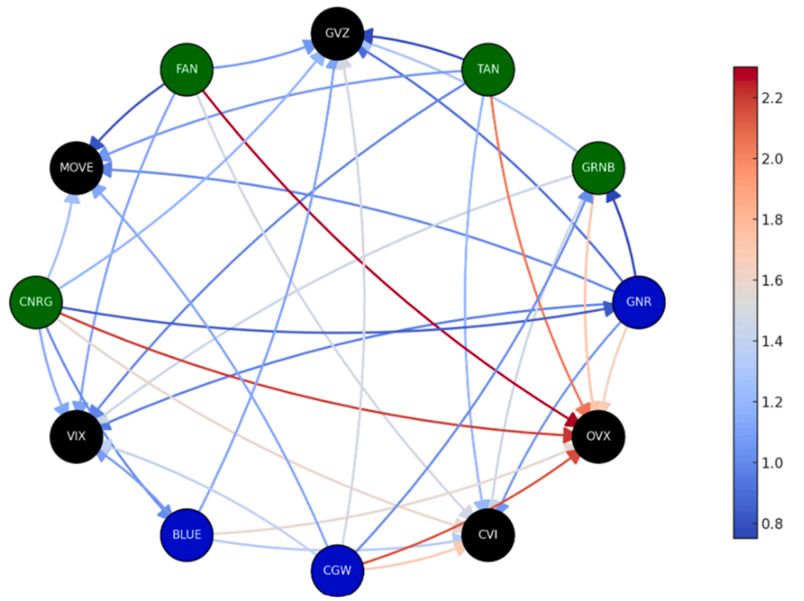


Panel A: NTPDC between Blue ETFs and Greeen ETFs at the 0.1 Quantile Level

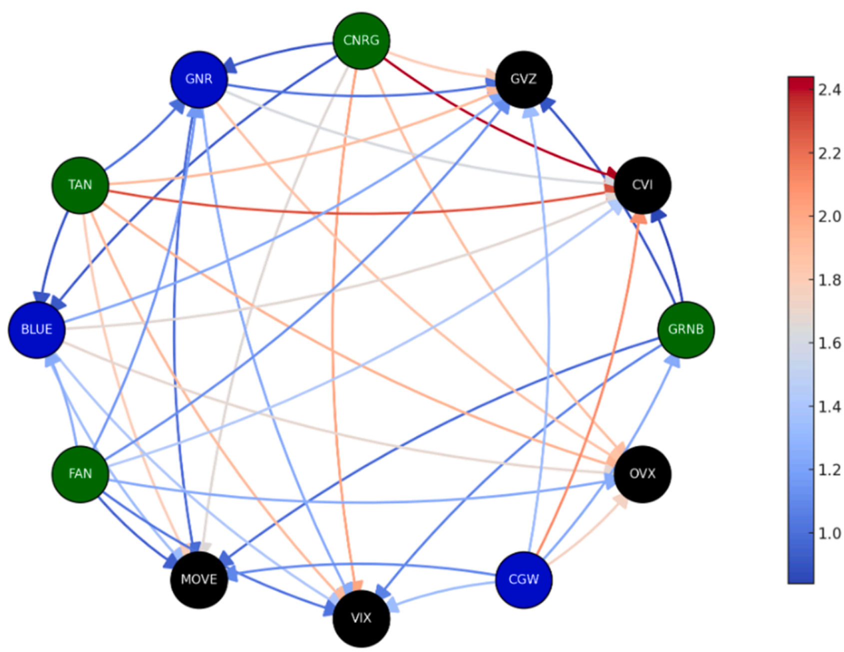


Panel B: NTPDC between Blue ETFs and Greeen ETFs at the 0.9 Quantile Level

Fig. A4. NTPDC between green ETFs and volatility indices at low and high quantile levels.



Panel A: Network Plot of Average Pairwise Connectedness at the 0.1 Quantile Level



Panel B: Network Plot of Average Pairwise Connectedness at the 0.9 Quantile Level

Fig. A5. Network plots of average pairwise connectedness at low and high quantile levels.
Note: The average network connectedness graphs display the net volatility spillovers among the series. Blue nodes represent Blue Economy ETFs, green nodes denote Green Finance ETFs, and black nodes indicate the volatility index series. The arrow's direction indicates the volatility flow from the net transmitter to the net receiver. The intensity of the net spillover increases from dark blue to dark red.

Appendix B Median quantile Q-VAR connectedness for Hamilton-filtered series

In this section, we employ the Hamilton filter (Hamilton, 2018) to create a new series from the data used in this study, applying Q-VAR analysis (tau at 0.5) to the trend series. The findings of the analysis are presented in the following tables and figures. The findings from the analysis with the new series generally show similarities with the return series findings discussed in the main text. Table B1 and Fig. B1 present the descriptive statistics and time-series plots of the Hamilton-filtered trend series. The average connectedness (Table B2 and Fig. B5) exhibits similarities with the findings from the return series, although the coefficients differ. The dynamic findings differ in the trend series created using the Hamilton filter. These trend series dynamic findings (Figs. B2-B4c) reveal higher coefficient changes in connectedness during global economic impact events such as COVID-19, the Ukraine-Russia Conflict, the SVCB Bankruptcy, and the Israel-Palestine War.

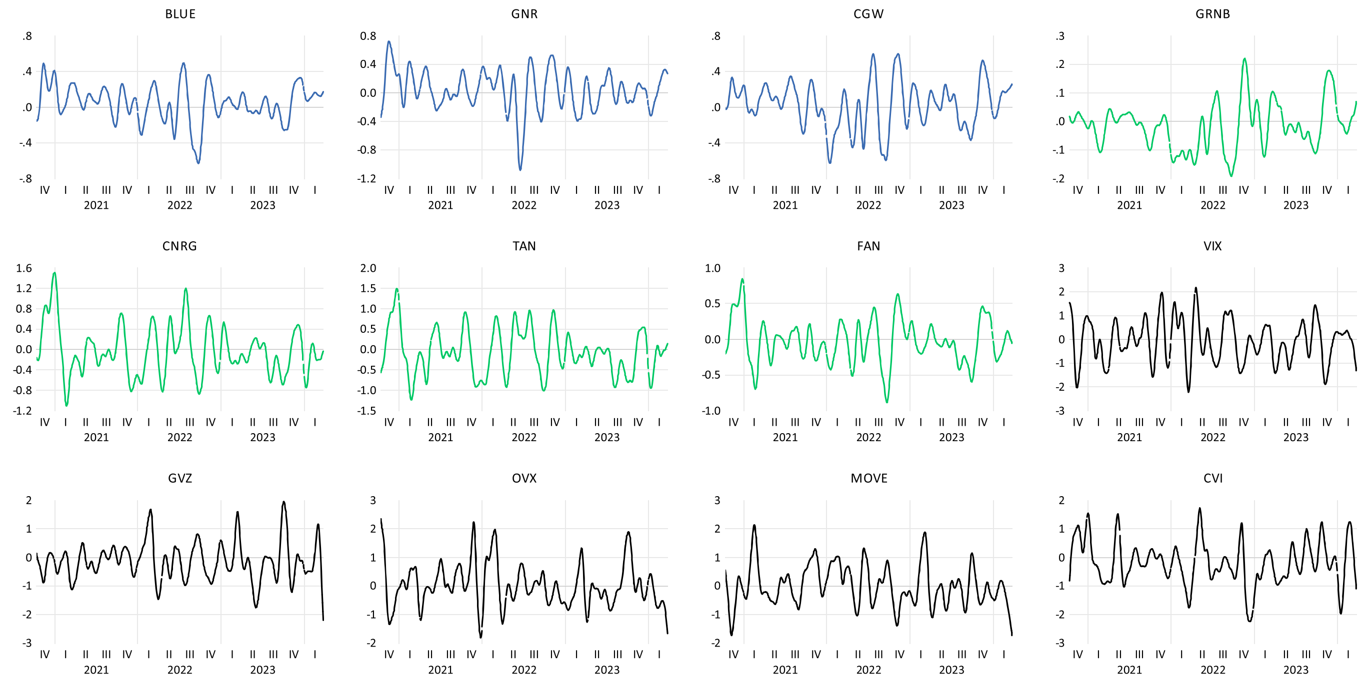


Fig. B1. Time series graphs of series.

Table B1
Descriptive statistics.

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	JB	ADF
BLUE	0.046682	0.062028	0.493941	−0.630955	0.202009	−0.582596	3.904008	80.0182*	−5.8754*
GNR	0.039057	0.050592	0.723186	−1.084613	0.280031	−0.6496	4.769159	177.2564*	−6.8471*
CGW	0.02574	0.0535	0.598726	−0.630222	0.255058	−0.260701	2.948426	10.10004*	−5.8566*
GRNB	−0.015773	−0.010893	0.220126	−0.191771	0.07956	0.387623	3.285263	25.10593*	−4.4774*
CNRG	−0.030402	−0.105393	1.510401	−1.111188	0.487874	0.575937	3.339177	53.04826*	−5.9012*
TAN	−0.063023	−0.097761	1.496322	−1.23177	0.557859	0.285014	2.581925	18.38552*	−6.1694*
FAN	−0.030903	−0.04132	0.845745	−0.885895	0.306284	0.087518	3.141902	1.868061*	−6.1354*
VIX	−0.077149	−0.046042	2.166635	−2.229818	0.880112	−0.025736	2.518596	8.623945*	−7.2245*
GVZ	−0.127814	−0.12787	1.958055	−2.196336	0.650527	0.463327	4.026205	70.3377*	−5.9772*
OVX	0.021907	−0.073279	2.351381	−1.812534	0.749617	0.6341	3.624284	73.51198*	−6.2072*
MOVE	0.010421	−0.059208	2.140818	−1.737628	0.710282	0.407592	3.136808	25.13762*	−5.2001*
CVI	−0.168118	−0.226288	1.735061	−2.242666	0.758177	−0.042017	3.276586	3.074366	−6.2527*

Table B2
Avarage of quantile connectedness.

	BLUE	GNR	CGW	GRNB	CNRG	TAN	FAN	VIX	GVZ	OVX	MOVE	CVI	FROM
BLUE	19.37	6.03	9.86	4.42	10.6	10.18	13.79	9.09	2.34	5.16	3.45	5.71	80.63
GNR	8.13	24.36	9.87	6.35	6.94	7.32	7.78	8.43	4.74	4.84	5.35	5.88	75.64
CGW	8.74	6.96	21.79	5.32	9.47	6.05	10.41	10.77	4.3	4.03	3.82	8.33	78.21
GRNB	4.62	6.38	6.6	31.24	4.66	6.83	8.23	3.95	8.37	5.99	7.29	5.83	68.76
CNRG	9.61	4.78	8.74	3.6	20.86	15.77	12.27	6.63	4.15	4.4	3.89	5.31	79.14
TAN	9.34	5	5.95	4.08	17.19	21.62	13.45	6.16	3.98	4.38	4.65	4.21	78.38
FAN	8.29	6.55	8.72	6.97	9.9	10.73	27.06	6.58	2.52	3.37	3.88	5.42	72.94
VIX	5.89	5.51	8.44	4.02	7.04	6.97	8.18	28.61	6.29	7.45	6.79	4.83	71.39
GVZ	4.35	5.52	6.4	3.83	5.1	6.49	3.99	9.4	28.1	7.08	14.73	4.97	71.86
OVX	6.87	5.8	6.25	3.91	4.76	4.43	5.22	16.67	7.32	27.63	8.25	2.89	72.37
MOVE	4.06	6.36	5.05	4.09	2.86	3.45	5.85	10.09	14.8	7.6	30.8	5.05	69.2
CVI	7.48	5.79	6.86	5.84	6.74	6.12	4.33	3.03	4.51	5.63	4.17	39.5	60.49
TO	77.38	64.68	82.73	52.43	85.26	84.32	93.49	90.8	63.3	59.93	66.27	58.4	879
Inc.Own	96.76	89.05	104.5	83.68	106.13	105.9	120.6	119.4	91.4	87.56	97.07	98	TCI
NET	-3.24	-11	4.53	-16.32	6.13	5.94	20.55	19.41	-8.61	-12.4	-2.93	-2.05	73.25

Note: This table displays the average connectedness among our series consisting of Blue and Green ETFs and Volatility Indices, which have been transformed into new trend series using the Hamilton filter. The connectedness averages are at the median quantile level (0.5).The colour gradient from light yellow to dark green indicates increasing values of connectedness.

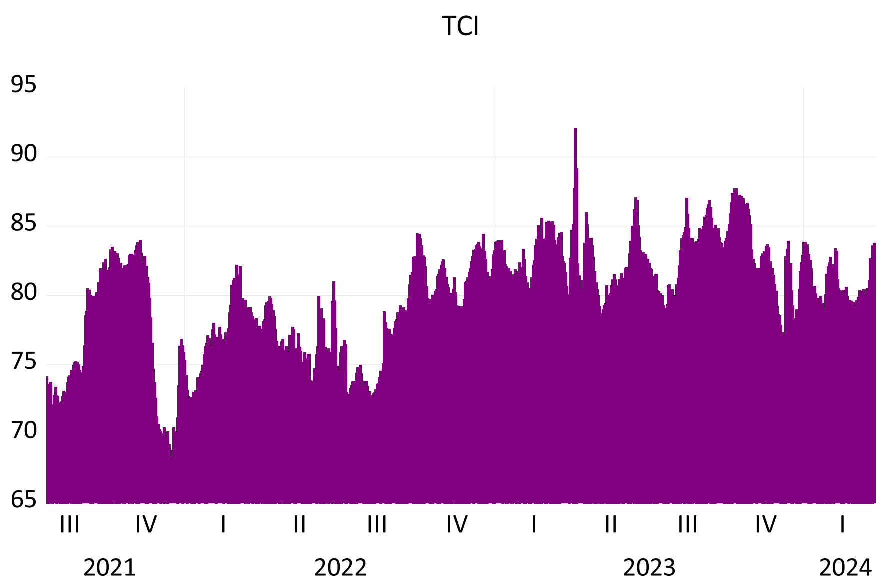


Fig. B2. TCI.

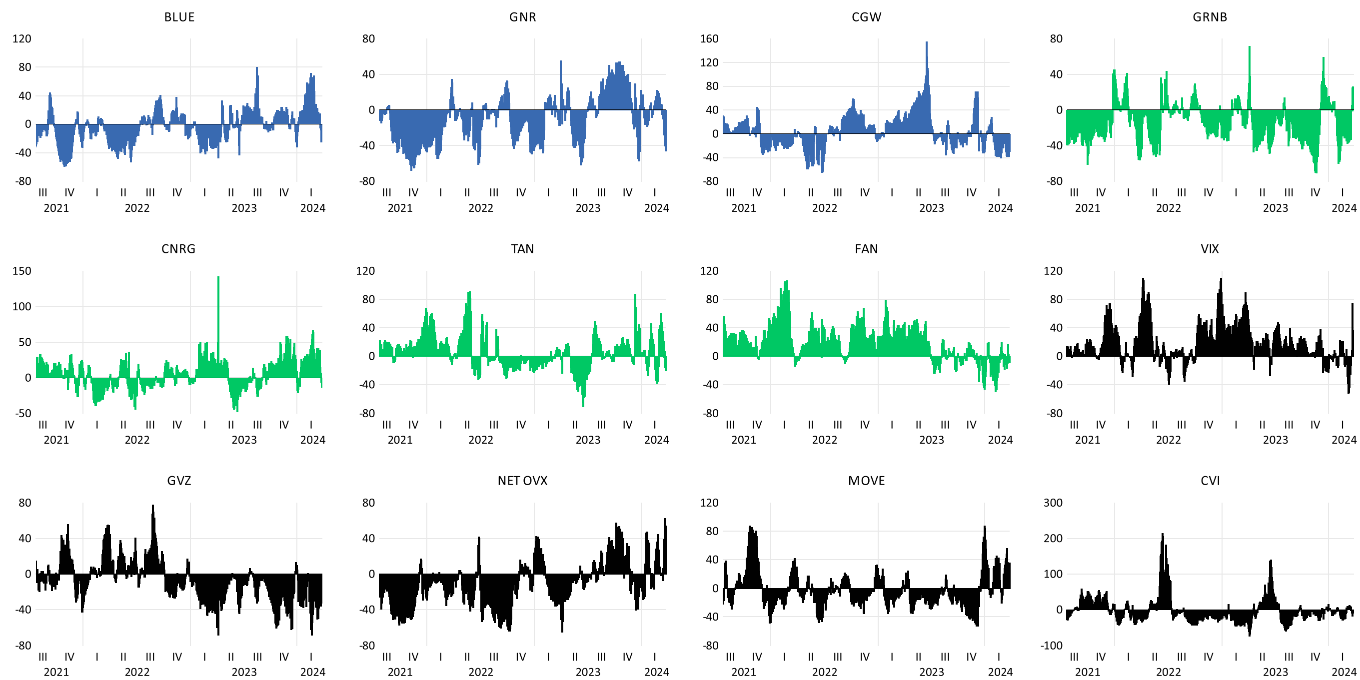


Fig. B3. Net directional connectedness.

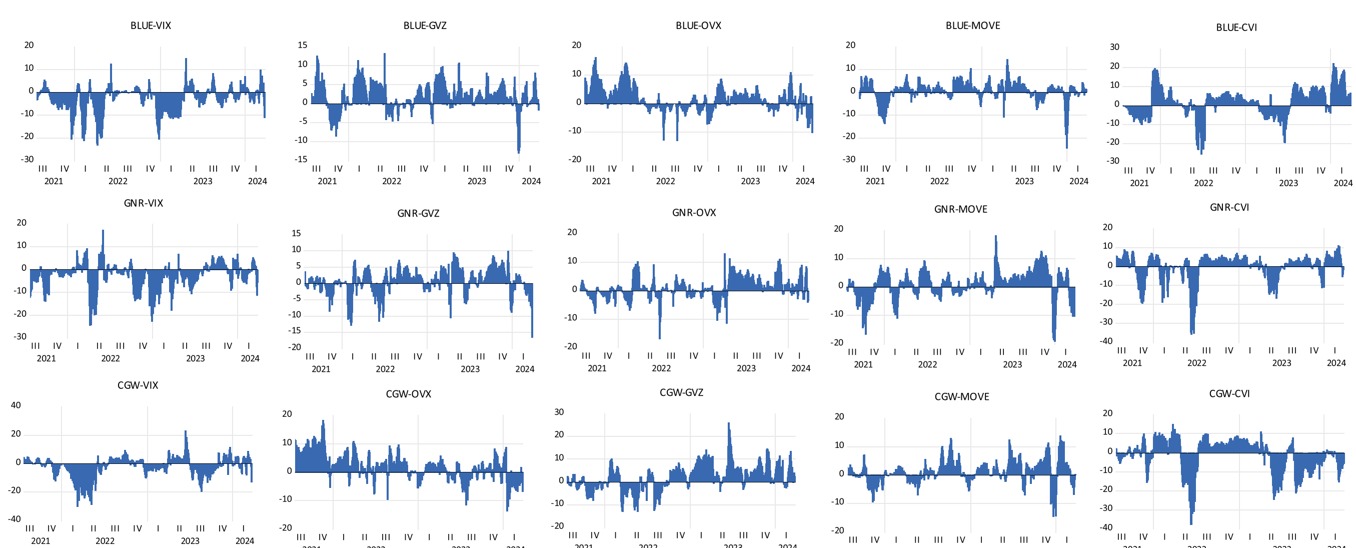


Fig. B4a. Net pairwise directional connectedness “BLUE ETF-volatility index.

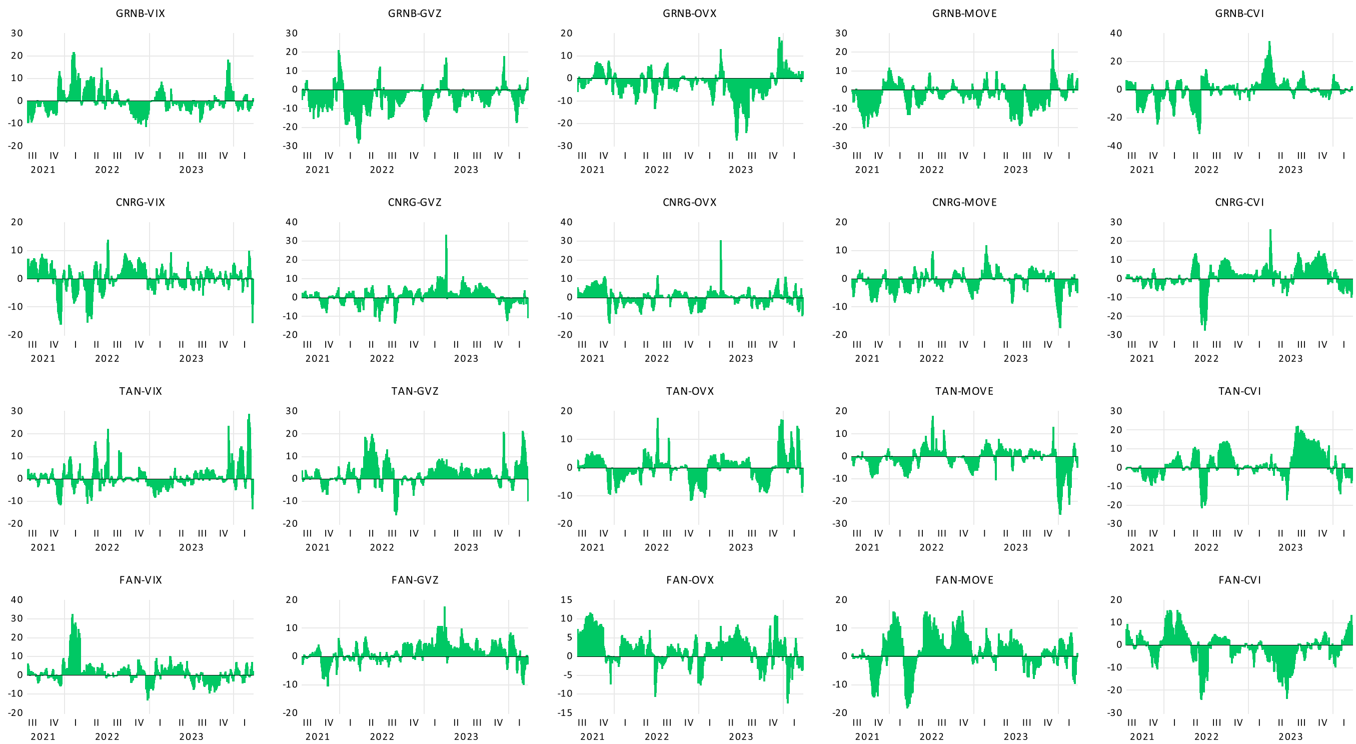


Fig. B4b. Net pairwise directional connectedness "GREEN ETF-volatility index.

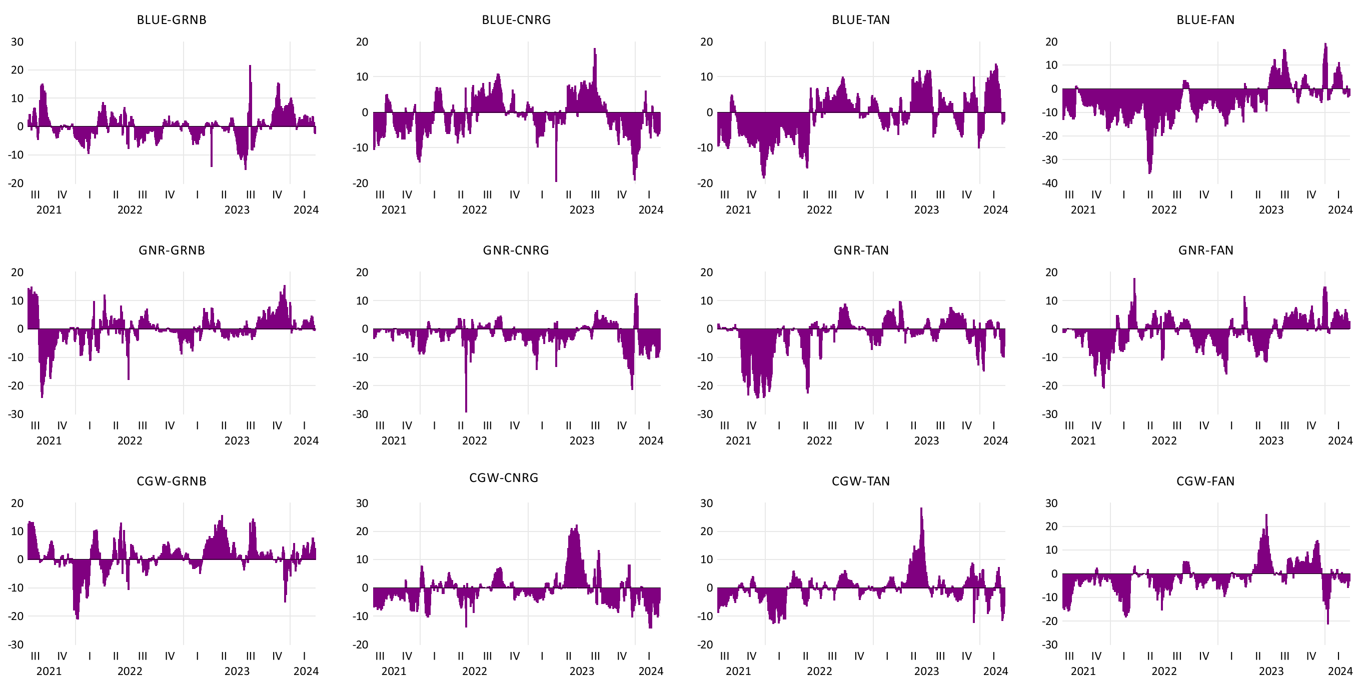


Fig. B4c. Net pairwise directional connectedness "BLUE ETF-GREEN ETF.

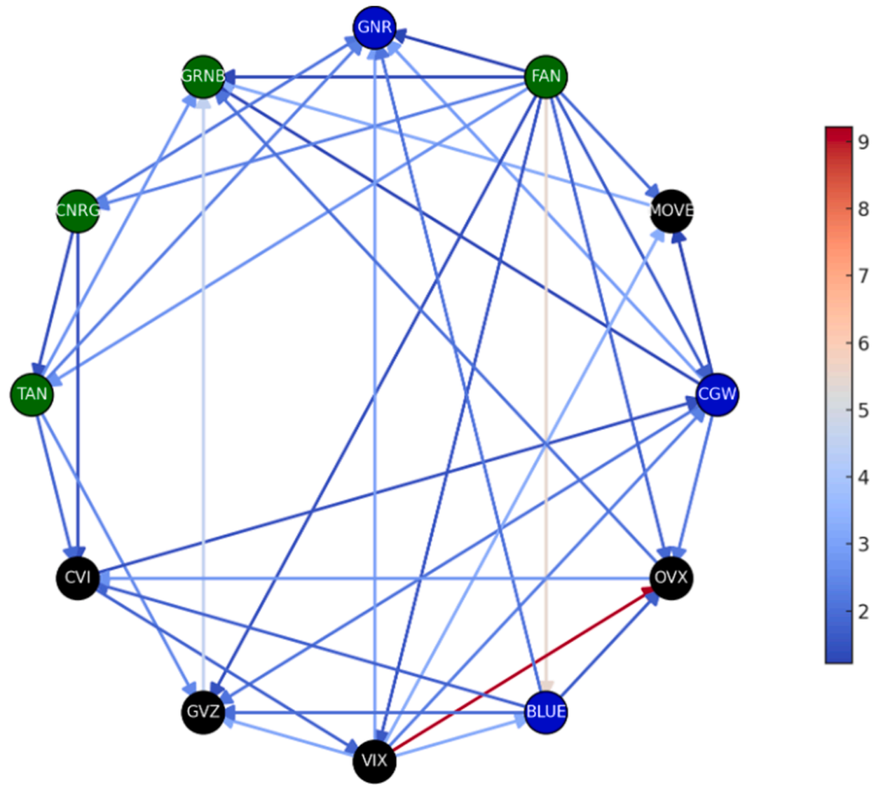


Fig. B5. Network plot of avarage pairwise connectedness.
Note: The average network connectedness graphs display the net volatility spillovers among the series. Blue nodes represent Blue Economy ETFs, green nodes denote Green Finance ETFs, and black nodes indicate the volatility index series. The arrow's direction indicates the volatility flow from the net transmitter to the net receiver. The intensity of the net spillover increases from dark blue to dark red.

Data availability

Data is public and accessible (investing.com).

References

Ahmad, N., Rehman, M. U., Vo, X. V., & Kang, S. H. (2022). Does inter-region portfolio diversification pay more than the international diversification? *The Quarterly Review of Economics and Finance, 83*, 26–35. https://doi.org/10.1016/j.qref.2021.10.004

Al Janabi, M. A., Ferrer, R., & Shahzad, S. J. H (2019). Liquidity-adjusted value-at-risk optimiza tion of a multi-asset portfolio using a vine copula approach. *Physica A: Statistical Mechanics and Its Applications, 536*, Article 122579. https://doi.org/10.1016/j.physa.2019.122579

Alexopoulos, T. A. (2018). To trust or not to trust? A comparative study of conventional and clean energy exchange-traded funds. *Energy Economics, 72*, 97–107. https://doi.org/10.1016/j.eneco.2018.03.013

AlGhazali, A., Belghouthi, H., Mensi, W., McIver, R., & Kang, S. H. (2024). Oil price shocks, sustainability index, and green bond market spillovers and connectedness during bear and bull market conditions. *Economic Analysis and Policy, 84*(C), 1470–1489.

Alnafisah, H., Almansour, B. Y., Elabed, W., & Jeribi, A. (2025). Spillover dynamics of digital assets during economic and political crises. *Research in International Business and Finance, 75*, Article 102770. https://doi.org/10.1016/j.ribaf.2025.102770

Alnafisah, H., Loukil, S., Bejaoui, A., & Jeribi, A. (2024). Co-movements and spillovers in GCC financial and commodity markets during turbulent periods: A quantile VAR connectedness approach. *International Journal of Islamic and Middle Eastern Finance and Management.* https://doi.org/10.1108/IMEFM-02-2024-0083

Alomari, M., Selmi, R., Mensi, W., Ko, H., & Kang, S. H. (2024). Dynamic spillovers in higher moments and jumps across ETFs and economic and financial uncertainty factors in the context of successive shocks. *The Quarterly Review of Economics and Finance, 93*, 210–228. https://doi.org/10.1016/j.qref.2023.12.009

Amoako, G., Boateng, E., Asafo-Adjei, E., Amoanyi, D., & Adam, A. M. (2022). Contagion and interdependencies: A dynamic connectedness approach among implied volatilities. *Cogent Economics and Finance, 10*(1), Article 2148366. https://doi.org/10.1080/23322039.2022.2148366

Ando T., Greenwood-Nimmo M. & Shin Y. (2018). Quantile Connectedness: Modelling tail behaviour in the topology of financial networks. Available at SSRN, 3164772. doi: 10.2139/ssrn.3164772.

K Banerjee, A., Özer, Z. S., Rahman, M. R., & Sensoy, A. (2024). How does the time-varying dynamics of spillover between clean and brown energy ETFs change with the intervention of climate risk and climate policy uncertainty?. *International Review of Economics & Finance, 93*(Part A), 442–468. https://doi.org/10.1016/j.iref.2024.03.046.

Banerjee, A. K. (2024). Environmental sustainability and the time-varying changing dynamics of green and brown energy ETFs. *Finance Research Letters, 62*(Part B), Article 105148. https://doi.org/10.1016/j.frl.2024.105148

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a haven? An analysis of stocks, bonds and gold. *Financial Review, 45*(2), 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

, Jr Boateng, E., Owusu Junior, P., Adam, A. M., Abeka, M., Qabhobho, T., & Asafo-Adjei, E. (2022). Quantifying information flows among developed and emerging equity markets. In *Mathematical Problems in Engineering, 2022*. https://doi.org/10.1155/2022/2462077.

Bouoiyour, J., & Selmi, R. (2015). What does bitcoin look like? *Annals of Economics and Finance, 16*(2), 449–492.

Bouri, E., Gök, R., Gemici, E., & Kara, E. (2024). Do geopolitical risk, economic policy uncertainty, and oil implied volatility drive assets across quantiles and time-horizons? *The Quarterly Review of Economics and Finance, 93*, 137–154. https://doi.org/10.1016/j.qref.2023.12.004

Bouri, E., Jalkh, N., Molnár, P., & Roubaud, D. (2017). Bitcoin for energy commodities before and after the december 2013 crash: Diversifier, hedge or safe haven? *Applied Economics, 49*(50), 5063–5073. https://doi.org/10.1080/00036846.2017.1299102

Buckle, M., Chen, J., Guo, Q., & Tong, C. (2018). Do ETFs lead the price moves? Evidence from the major US markets. *International Review of Financial Analysis, 58*, 91–103. https://doi.org/10.1016/j.irfa.2017.12.005

Chatziantoniou, I., Gabauer, D., & Stenfors, A. (2021). Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach. *Economics Letters*, (204)https://doi.org/10.1016/j.econlet.2021.109891

Çelik, I., Sak, A. F., Höl, A., & Vergili, G. (2022). The dynamic connectedness and hedging opportunities of implied and realized volatility: Evidence from clean energy ETFs. *The North American Journal of Economics and Finance, 60*, Article 101670. https://doi.org/10.1016/j.najef.2022.101670

Deng, Y., & Zhang, Z. (2025). The spillover effects of green bond issuance in peer firms' financial performance. *Research in International Business and Finance, 77*(PA).

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics, 182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Dong, X., Xiong, Y., Nie, S., & Yoon, S. (2023). Can bonds hedge stock market risks? Green bonds vs conventional bonds. *Finance Research Letters, 52*, Article 103367. https://doi.org/10.1016/j.frl.2022.103367

Duan, K., Zhao, Y., Wang, Z., & Chang, Y. (2023). Asymmetric spillover from bitcoin to green and traditional assets: A comparison with gold. *International Review of Economics & Finance, 88*, 1397–1417. https://doi.org/10.1016/j.iref.2023.06.036

Dutta, A., Bouri, E., Saeed, T., & Vo, X. V. (2020). Impact of energy sector volatility on clean energy assets. *Energy, 212*, Article 118657. https://doi.org/10.1016/j.energy.2020.118657

Fang, T., Sub, Z., & Yin, L. (2020). Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis, 71*, Article 101566. https://doi.org/10.1016/j.irfa.2020.101566

Ferrer, R., Shahzad, S., & Soriano, P. (2021). Are green bonds a different asset class? Evidence from time-frequency connectedness analysis. *Journal of Cleaner Production, 292*, Article 125988. https://doi.org/10.1016/j.jclepro.2021.125988

Goodell, J. W., Corbet, S., Yadav, M. P., Kumar, S., Sharma, S., & Malik, K. (2022). Time and frequency connectedness of green equity indices: Uncovering a socially important link to Bitcoin. *International Review of Financial Analysis, 84*, Article 102379. https://doi.org/10.1016/j.irfa.2022.102379

Gökgöz, H., Arifoğlu, A., & Kandemir, T. (2024). Stochastic and dynamic interaction between islamic volatility index and volatility indices. *Turkish Journal of Islamic Economics, 11*(2), 59–83. https://doi.org/10.26414/A4106

Gyamerah, S. A., & Asare, C. (2024). The impacts of global economic policy uncertainty on green bond returns: A systematic literature review. *Heliyon, 10*(3), Article e25076. https://doi.org/10.1016/j.heliyon.2024.e25076

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *The Review of Economics and Statistics, 100*(5), 831–843. https://doi.org/10.1162/rest_a_00706

Hanif, W., Teplova, T., Rodina, V., Alomari, M., & Mensi, W. (2023). Volatility spillovers and frequency dependence between oil price shocks and green stock markets. *Resources Policy, 85*(Part B), Article 103860. https://doi.org/10.1016/j.resourpol.2023.103860

Henriques, I., & Sadorsky, P. (2018). Investor implications of divesting from fossil fuels. *Global Finance Journal, 38*, 30–44. https://doi.org/10.1016/j.gfj.2017.10.004

Hsu, S. H., Sheu, C., & Yoon, J. (2021). Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. *North American Journal of Economics and Finance, 57*, Article 101443. https://doi.org/10.1016/j.najef.2021.101443

Kandemir, T., & Gökgöz, H. (2022). Is Bitcoin more than a diversifier for commodities? Range-based analysis via cDCC-GARCH. *Research of Financial Economic and Social Studies, 7*(2), 227–240. https://doi.org/10.29106/fesa.1092764

Kang, S., Hernandez, J., Sadorsky, P., & McIver, R. (2021). Frequency spillovers, connectedness, and the hedging effectiveness of oil and gold for US sector ETFs. *Energy Economics, 99*, Article 105278. https://doi.org/10.1016/j.eneco.2021.105278

Kayahan, C., Gökgöz, H., & Murat, T. (2022). Quantile connectedness between cryptocurrencies and stablecoins. *International Journal of Economics and Administrative Studies, 37*, 143–156. https://doi.org/10.18092/ulikidince.1146239

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the new gold – a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis, 59*, 105–116. https://doi.org/10.1016/j.irfa.2018.07.010

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74*(1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4

Le, T., Abakah, E., & Tiwari, A. (2021). Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change, 162*, Article 120382. https://doi.org/10.1016/j.techfore.2020.120382

Lee, S., Lee, J., & Jung, S. (2019). *The Impact of Geopolitical Risk on Stock Returns: Evidence from Inter-Korea Geopolitics*. Available at: https://doi.org/10.2139/ssrn.4329355.

López, R. (2018). The behaviour of energy-related volatility indices around scheduled news announcements: Implications for variance swap investments. *Energy Economics, 72*, 356–364. https://doi.org/10.1016/j.eneco.2018.04.040

Mand, A., Ghafoor, A., & Sifat, I. (2023). Time-varying price dynamics of clean and dirty energy portfolios. *Journal of Environmental Management, 337*, Article 117687. https://doi.org/10.1016/j.jenvman.2023.117687

Mensi, W., Vo, X., & Kang, S. (2021). Upside-downside multifractality and efficiency of green bonds: The roles of global factors and COVID-19. *Finance Research Letters, 43*, 101995. https://doi.org/10.1016/j.frl.2021.101995

Mensi, W., Aslan, A., Vo, X. V., & Kang, S. H. (2023). Time-frequency spillovers and connectedness between precious metals, oil futures and financial markets: Hedge and safe haven implications. *International Review of Economics & Finance, 83*(C), 219–232.

Naeem, M., Ashraf, S., Karim, S., & Moussa, F. (2024). Green finance under stress: Unraveling the spillover effects of tail risk. *International Review of Economics & Finance, 93*, 225–236. https://doi.org/10.1016/j.iref.2024.03.026

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

Naeem, N., Nguyen, T., Karim, S., & Lucey, B. (2023). Extreme downside risk transmission between green cryptocurrencies and energy markets: The diversification benefits. *Finance Research Letters, 58*, Article 104263. https://doi.org/10.1016/j.frl.2023.104263

Naqvi, B., Rizvi, S., Hasnaoui, A., & Shao, X. (2022). Going beyond sustainability: The diversification benefits of green energy financial products. *Energy Economics, 111*, Article 106111. https://doi.org/10.1016/j.eneco.2022.106111

Ozcelebi, O., Pérez-Montiel, J., & Izgi, M. T. (2023). The connectivity of financial stress, green bonds, conventional bonds, stocks, and commodities: Empirical evidence from quantile-based analysis. *Reference Module in Social Sciences*. https://doi.org/10.1016/B978-0-44-313776-1.00127-6

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis In linear multivariate models. *Economics Letters, 58*(1), 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0

Pham, L., & Do, H. (2022a). Green bonds and implied volatilities: Dynamic causality, spillovers, and implications for portfolio management. *Energy Economics, 112*, Article 106106. https://doi.org/10.1016/j.eneco.2022.106106

Pham, L., & Do, H. X. (2022b). Green bonds and implied volatilities: Dynamic causality, spillovers, and implications for portfolio management. *Energy Economics, 112*, Article 106106. https://doi.org/10.1016/j.eneco.2022.106106

Pham, L., & Nguyen, C. (2021). Asymmetric tail dependence between green bonds and other asset classes. *Global Finance Journal, 50*, Article 100669. https://doi.org/10.1016/j.gfj.2021.100669

Reboredo, J. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics, 74*, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030

Reboredo, J., & Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling, 88*, 25–38. https://doi.org/10.1016/j.econmod.2019.09.004

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

Shahid, M., Azmi, W., Ali, M., Islam, M., & Rizvi, S. (2023). Uncovering risk transmission between socially responsible investments, alternative energy investments and the implied volatility of major commodities. *Energy Economics, 120*, Article 106634. https://doi.org/10.1016/j.eneco.2023.106634

Sheikh, S., Jamil, S., Aysan, A., Atif, M., Rabbani, M., & Kayani, U. (2023). Do implied volatilities of stock and commodity markets affect conventional & shariah indices differently? An evidence by OVX, GVZ and VIX. *Heliyon.* , Article e21094. https://doi.org/10.1016/j.heliyon.2023.e21094

Snene Manzli, Y., Alnafisah, H., & Jeribi, A. (2024). Safe Haven ability of energy and agricultural commodities against G7 stock markets and banking indices during COVID-19, Russia–Ukraine war, and SVB collapse: Evidence from the wavelet coherence approach. *Discrete Dynamics in Nature and Society*. , Article 2587000. https://doi.org/10.1155/ddns/2587000

Sohag, K., Hassan, M. K., Bakhteyev, S., & Mariev, O. (2023). Do green and dirty investments hedge each other? *Energy Economics, 120*, Article 106573. https://doi.org/10.1016/j.eneco.2023.106573

Tian, H., Long, S., & Li, Z. (2022). Asymmetric effects of climate policy uncertainty, infectious diseases-related uncertainty, crude oil volatility, and geopolitical risks on green bond prices. *Finance Research Letters, 48*, Article 103008. https://doi.org/10.1016/j.frl.2022.103008

Urom, C., & Ndubuisi, G. (2023). Do geopolitical risks and global market factors influence the dynamic dependence among regional sustainable investments and major commodities? *The Quarterly Review of Economics and Finance, 91*, 94–111. https://doi.org/10.1016/j.qref.2023.07.007

Wang, C., Wu, Y., Hsieh, H., Huang, P., & Lin, M. (2022a). Does green bond issuance have an impact on climate risk concerns? *Energy Economics, 111*, Article 106066. https://doi.org/10.1016/j.eneco.2022.106066

Wang, X., Li, J., & Ren, X. (2022b). Asymmetric causality of economic policy uncertainty and oil volatility index on time-varying nexus of the clean energy, carbon and green bond. *International Review of Financial Analysis, 83*, Article 102306. https://doi.org/10.1016/j.irfa.2022.102306

Xu, D., Hu, Y., Oxley, L., Lin, B., & He, Y. (2025). Exploring the connectedness between major volatility indexes and worldwide sustainable investments. *International Review of Financial Analysis, 97*, Article 103862. https://doi.org/10.1016/j.irfa.2024.103862

Xu, D., Hu, Y., Corbet, S., & Lang, C. (2024). Return connectedness of green bonds and financial investment channels in China: Implications for hedging and regulation. *Research in International Business and Finance, 70*(Part A), Article 102329. https://doi.org/10.1016/j.ribaf.2024.102329

Yousaf, I., Hunjra, A., Alshater, M., Bouri, E., & Li, Y. (2023). Multidimensional connectedness among the volatility of global financial markets around the Russian-Ukrainian conflict. *Pacific Basin Finance Journal, 82*, Article 102163. https://doi.org/10.1016/j.pacfin.2023.102163

Yousefi, H., & Najand, M. (2022). Geographical diversification using ETFs: Multinational evidence from COVID-19 pandemic. *International Review of Financial Analysis, 83*, Article 102261. https://doi.org/10.1016/j.irfa.2022.102261