University of Pretoria
Department of Economics Working Paper Series

Multi-Moment and Multilayer Analysis of Connectedness among Clean, Brown, and Technology ETFs: The Role of Climate Risk

Abeeb Olaniran
University of Pretoria
Elie Bouri
Lebanese American University
Rangan Gupta
University of Pretoria
Working Paper: 2025-19
May 2025

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Multi-Moment and Multilayer Analysis of Connectedness among Clean, Brown, and Technology ETFs: The Role of Climate Risk

Abeeb Olaniran[*], Elie Bouri[**] and Rangan Gupta[***]

Abstract

This study adopts a multilayer network approach to investigate the connectedness among clean, brown, and technology ETFs across four moments: returns, volatility, skewness, and kurtosis. Motivated by the non-normality of return distributions and energy transition under intensified climate risk, we demonstrate the importance of incorporating both lower- and higher-order moments to fully capture risk transmission dynamics. Within-layer, cross-layer, and total connectedness analysis reveals generally high interdependence, with notable exceptions during late 2024 (across all layers) and the 2008–2009 period (particularly for skewness and kurtosis). These episodes suggest that investor responses to extreme events differ across statistical moments, stressing the need for a multilayer framework in assessing market behaviour. While the return and volatility layers effectively capture major market shocks, skewness and kurtosis exhibit weaker spillovers, especially prior to the 2008 global financial crisis. Technology ETF plays a central role, exhibiting the highest overlap in both inflows and outflows during crisis periods, particularly between 2008 and 2014, and during COVID-19. Conversely, clean ETF shows limited vulnerability to systemic shocks, suggesting resiliency. Climate risks impact the spillovers across the within- and cross-layers. These findings are particularly relevant to investors, portfolio managers, and policymakers tasked with risk mitigation amid climate change concerns.

Keywords: Clean energy; climate risk; exchange-traded funds (ETFs); spillover and multilayer network; higher-order moments; financial crises

JEL Codes: C32; G10; Q54

---

[*] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa. Email address: olaniranabeeb464@gmail.com.

[**] Corresponding author. School of Business, Lebanese American University, Lebanon. Email address: elie.elbouri@lau.edu.lb.

[***] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa. Email address: rangan.gupta@up.ac.za.

1. Introduction

This study firstly examines multilayer spillovers and risk propagation across clean, brown, and technology exchange-traded funds (ETFs), considering returns and higher-order moments, particularly volatility, kurtosis, and skewness. It highlights the influence of climate risks on spillovers across the within- and cross-layer connectedness measures. The main motivations are threefold. Firstly, the ETF returns examined are not normally distributed, making the analysis of risk propagation based on volatility only somewhat unrealistic and limited as it fails to capture a comprehensive analysis of risk spillovers in the various layers of higher-order moments. Secondly, the energy transition toward a lower carbon economy contributes to significant interlinkages between clean energy sources and technological advancement which are found to be significant under the transition from brown to cleaner energies (Bouri et al., 2025), potentially making the markets of clean, brown, and technology investments interact at higher-order moments of returns affected by climate risk. Thirdly, unlike conventional stock indices which are not directly investable or tradable, ETFs represent an investable vehicle highly accessible to investors and market participants across the globe.

The existing literature is inundated with studies that measure return and volatility spillovers across global markets – spanning emerging and developed stock markets during turbulent periods, often reporting significant uni- and bi-directional effects (Diebold and Yilmaz, 2009; Li and Giles, 2015; Mensi et al., 2016; Jebran et al., 2017; Baumöhl et al., 2018; Gamba-Santamaria et al., 2019). Similar studies have been conducted in credit markets (Diebold and Yilmaz, 2012; Tiwari et al., 2018; McMillan, 2020) and commodity markets, including crude oil and precious metals (Kang et al., 2017; Kang and Yoon, 2019; Mishra et al., 2025), highlighting the interlinkages across various asset classes. These studies mostly cover stock market indices although they are not investable or tradable. Furthermore, issues of global concern such as climate change and geopolitical tension can affect the risk spillovers across these markets (Smales, 2021; Elsayed and Helmi, 2021; Gupta and Pierdzioch, 2022; Balcilar et al., 2023; Bouri et al., 2023; Jin et al., 2023; Sarker et al., 2023; Hao et al., 2024; Oad Rajput et al., 2024; Pham et al., 2024; Cui and Maghyerah, 2025; Xie et al., 2025). The growing concern over these risks, particularly climate change – as witnessed recently in various parts of the world[1]– has undoubtedly influenced risk and volatility transmission between

---

[1] See: https://www.nifc.gov/fire-information/nfn.

carbon-intensive (brown) and clean (green) markets. Instances abound of how these risks, particularly climate-related policy uncertainties, could be propagated across these markets. Carbon pricing or taxation of emission-generating firms such as the EU's Carbon Border Adjustment Mechanism (CBAM) (see Feng et al., 2024; Salisu and Adediran, 2025), aim to reduce global warming to 1.5 degrees Celsius by 2030[2] in consonance with the UN's Intergovernmental Panel on Climate Change goals, and have the potential to suppress trading in the brown market. This occurs through increased production and consumption costs, leading to lower returns on brown assets, while simultaneously amplifying trading and, by extension, volatility in the green market as these assets become more attractive. Similarly, increased investment in eco-friendly assets, as businesses adhere to various climate change agreements, and the adoption of green technologies, could drive a substantial shift in trading activity from brown to green markets[3]. Bouri (2023) attributes this to the substitution effect between products in both markets, as well as financialization and portfolio decarbonization channels. Conversely, brown energy sources, such as crude oil, remain essential inputs in production (Safa, 2017; Salisu et al., 2023) and are often priced lower than green energy alternatives, which command higher costs due to evolving investments in the sector (see also Bouri, 2023). This pricing disparity could reduce the attractiveness of green assets, prompting portfolio diversification from green to brown assets (see also Foglia and Angelini, 2020).

One key reason for examining volatility spillovers is to identify effective hedging strategies to mitigate the risks associated with some markets. However, traditional assets often fall short of providing adequate risk protection (see Wu et al., 2011; Salisu et al., 2025). This limitation contributes to a gradual shift toward financial innovation, particularly ETF-related assets, which have gained prominence as alternative investment vehicles (see Salisu et al. (2025) for a detailed review of the classification of ETFs as financial innovations). In the context of brown and green markets, ETFs could play a pivotal role in managing risk transmission and portfolio adjustment, especially as investors navigate the shifting dynamics driven by climate policies and/or carbon pricing. Furthermore, the role of technology in the transition from brown to green business and

---

[2] See: https://unfccc.int/process-and-meetings/the-paris-agreement.

[3] Shang et al. (2022) show that climate policy uncertainty reduces non-renewable energy demand in the U.S., but positively impacts renewable energy demand in the long-term.

investment models is evident in various developments, such as alternative energy installations and electric vehicles. Overall, the rapid growth of ETFs has significantly transformed financial markets, with their market share exceeding 10 percent of the total US securities market as of the end of 2016. They also represent over 30 percent of daily transactions and nearly 20 percent of aggregate short interest, reshaping the structure of asset management by drawing market share away from conventional investment options such as mutual funds and index futures. Their increasing appeal to both retail and institutional investors is largely attributed to their low transaction costs and intraday tradability. ETF providers issue securities listed on major stock exchanges, with most ETFs designed to track the performance of a specific index (see Ben-Davis et al., 2017). Furthermore, ETFs operate through arbitrage mechanisms that ensure their prices remain aligned with the underlying assets, meaning ETF transactions directly influence the trading of these assets. While ETFs facilitate discovery of price, they are also linked to non-fundamental price volatility and shifts in return correlations. Additionally, ETFs influence the liquidity of the underlying assets, particularly in periods of market distress, further influencing market stability (Ben-Davis et al., 2017; Lettau and Madhavan, 2018).

Given the growing attention paid to clean, brown, and technology ETFs due to their investable nature and easy use in investment strategies, including hedging and asset allocation, it is not unexpected that spillovers – particularly at higher moments including volatility, skewness and kurtosis – may also exist between these ETFs amid the strong deviation of their returns from the normal distribution and increasing concerns about climate change and risk. Accordingly, this study offers novel empirical insights into the multilayer higher-order moments spillovers and risk propagation among clean, brown, and technology ETFs, while considering within-layer, cross-layer, and total connectedness measures and how climate risks can affect these connectedness measures. Such an analysis extends previous studies conducted in this area (Bouri, 2023; Foglia et al., 2024; Addi et al., 2025; Cui and Maghreyeh, 2025; Foglia et al., 2025; Salisu and Gupta, 2025; Xie et al., 2025), which largely overlook the higher-order moments of ETFs, especially in the framework of multilayer connectedness across clean, brown, and technology ETFs, leaving a significant gap in the literature.

In light of this, our current study incorporates technology ETFs into the volatility transmission mechanism between brown and green ETFs (see also Ayinde et al., 2023; Bouri, 2023). To analyse these spillover effects, we employ a multilayer network approach, which captures information spillover dynamics across returns, volatility, skewness, and kurtosis. By integrating intra-market and cross-market spillovers, our framework provides a comprehensive understanding of total and cross-market connectedness between these asset classes (see the methodology section for details). This approach allows a deep examination of risk transmission mechanisms, offering valuable insights into the interdependencies (i.e., connectedness) between clean, brown, and technology markets.

Financial contagion theory provides a framework for understanding how risks spread across various markets (see Forbes and Rigobon, 2002; Rigobon, 2019). In equity markets, it primarily concerns the transmission of shocks in the financial system, often assessed through variations in return correlations during crisis periods (Dungey and Martin, 2001). Forbes and Rigobon (2002) distinguish between contagion and interdependence/spillovers based on changes in cross-market correlations following a shock. In particular, contagion occurs when two markets with moderate correlation during stable periods experience a significant surge in co-movement after a shock, signalling an abnormal transmission of risk. In contrast, if two markets are already highly correlated and continue to be so after a shock, this reflects strong economic and financial linkages, characterizing interdependence rather than contagion. However, Rigobon (2019) downplays this distinction, showing that spillovers can still occur regardless of market conditions.

Relying on this theoretical foundation, this study contributes to the literature in the following ways. Firstly, it extends research on risk contagion/spillovers in financial markets by focusing on clean, brown, and technology ETFs, an area which remains largely unexplored. This enhances our understanding of spillover dynamics in sustainable investments. Secondly, unlike many studies that primarily examine returns and volatility, it incorporates higher-order moments – particularly skewness and kurtosis – to provide a comprehensive view of shock transmission across these asset classes, given that the return distribution is fat-tailed (see Table A1 in the appendix). Thirdly, within a multilayer spillover framework, the study investigates the role of climate risk in influencing cross-market connectedness across the ETFs examined.

The main results show generally high levels of interdependence in the within-layer, cross-layer, and total connectedness measures across various moments and crisis periods, and underline the influence of climate risks on spillovers across the within- and cross-layers, which can be explained by climate change under the transition towards a cleaner economy and decarbonized investment portfolios.

Following this introduction, the rest of the paper is organized as follows. Section 2 describes the datasets. Section 3 outlines the methodological framework guiding our analysis. Section 4 presents and discusses the findings, while Section 5 concludes the paper.

2. Data and higher-order moments

2.1. Datasets

Two datasets are used in this study. The first consists of three global ETFs, iShares Global Clean (ICLN), iShares Global Energy (IXC), and iShares Global Tech (IXN), covering access to green, brown, and technology stocks, respectively. ICLN tracks the performance of an index comprised of global clean energy firms that produce energy from renewable sources such as sunlight, wind, and water. IXC provides exposure to global energy firms operating in the production and distribution of oil and gas. IXN tracks the performance of an index comprised of global stocks in the technology segment, covering electronics, computer software, computer hardware, and informational technology firms. Interestingly, global ETFs reflect a global view of the three markets, which is necessary under the global transition towards cleaner production and economy. Daily closing prices for each ETF are sourced from DataStream and expressed in USD. Daily logarithmic returns are computed for each ETF examined.

The deviation of the ETF returns from the normal distribution (refer to Table A1 in the appendix) underscores the adoption of a multilayer network approach. The results show evidence of negative skewness across the three ETF returns, while the kurtosis statistics indicate leptokurtic distributions (as the kurtosis values largely exceed 3), suggesting heavy tails in the series. This departure from normality is confirmed by the outright rejection of the normality assumption, as indicated by the statistical significance of the Jarque-Bera test results. The summary statistics in

Appendix A1 are followed by plots of the ETF series both at level and return forms (refer to Figure A1 and Figure A2, respectively, in the appendix).

The second dataset covers climate risks, measured by climate policy uncertainty indices. To capture this, we favour the climate policy uncertainty (CPU) index constructed by Ma et al. (2024)[4]. The index construction follows the Baker et al. (2016) technique, which uses text mining applied to major newspapers from twelve G20 countries across six continents – mostly exposed to climate risks – to construct a global CPU measure. The index is based on 11.27 million news articles published between January 2000 and December 2023, and is adjusted for macroeconomic fundamentals such as GDP (at current prices), purchasing power parity (PPP), and an equally weighted average across the twelve countries. While the index is available at daily, weekly, and monthly frequencies, our study uses the monthly PPP-adjusted measure which accounts for cross-country price differences. Thus, our sample period involving the influence of climate risk on the connectedness between the three ETFs is accordingly limited to the period covered by the PPP-adjusted climate risk measure (i.e., August 2008 to December 2023).

2.2. Higher-order moments' construction

Following Hansen's (1994) autoregressive conditional density (ACD) model, we estimate the time-varying conditional higher-order moments, volatility, skewness, and kurtosis, from the logarithmic return series for the three ETFs, covering clean (ICLN), brown (IXC), and technology (IXN) stocks.

Specifically, the ACD model captures skewness and kurtosis dynamics by incorporating them into a conditional distribution, say *N*, governed by an autoregressive moving average–generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) process, specified as:

$$Ret_t = \propto + \sum_{l=0}^{a} \beta_l Ret_{t-l} + \sum_{k=0}^{b} \gamma_k \mu_{t-k} \text{ ; } \mu_t = \sqrt{var_t}\delta_t \text{ and } \delta_t \sim N(0,1,v_t,\varepsilon_t) \quad (1)$$

---

[4] The data is downloadable at: https://figshare.com/articles/dataset/Global_Climate_Policy_Uncertainty_2000-2023_/24807627?file=49365187.

where Ret_t represents each ETF logarithmic return, $\propto$ is the intercept, and μ_t denotes the residual term with standardized innovation δ_t. The parameters v_t and ε_t represent the time-varying skewness and kurtosis, respectively.

The conditional variance equation is:

$$var_t = \tau + \sum_{i=1}^{c} \pi_i \gamma_{t-i}^2 + \sum_{j=1}^{d} \emptyset_j var_{t-j} \tag{2}$$

where τ is the intercept, and the conditions $\tau > 0$, $\pi_1 \geq 0$, and $\emptyset_1 \geq 0$ ensure the positivity of the variance.

The skewness and kurtosis dynamics are modelled through the transformation functions:

$$\theta(v_t) = \frac{L_{\bar{v}_t} + (U_{\bar{v}_t} - L_{\bar{v}_t})}{1+e^{-v_t}} \tag{3}$$

$$\theta(\varepsilon_t) = L_{\bar{\varepsilon}_t} + U_{\bar{\varepsilon}_t} e^{-t\bar{\varepsilon}_t} \tag{4}$$

where $\theta(v_t)$ and $\theta(\varepsilon_t)$ are bounded transformations ensuring the skewness and shape parameters remain within plausible limits. The skewness parameter v_t captures the asymmetry in the return distribution, while ε_t indicates tail heaviness (kurtosis).

The time-varying structure of the higher-order moments is specified via first-order quadratic autoregressive processes:

$$\bar{v}_t = p_0 + p_1 \mu_{t-1} + p_2 \mu_{t-1}^2 + r_1 \bar{v}_{t-1} \tag{5}$$

$$\bar{\varepsilon}_t = q_0 + q_1 \mu_{t-1} + q_2 \mu_{t-1}^2 + s_1 \bar{\varepsilon}_{t-1} \tag{6}$$

where, $\bar{v}_t$ and $\bar{\varepsilon}_t$ denote the unconstrained skewness and shape parameters, respectively, with their lagged values and lagged residuals (including the lagged squared residuals) μ_{t-1} (μ_{t-1}^2) as regressors. Conditional volatility, conditional skewness, and conditional kurtosis are finally obtained by estimating the ACD model under a normal inverse Gaussian (NIG) innovation structure (see He and Hamori, 2021; Bouri, 2023).

3. Methodology

To empirically establish the interconnectedness between clean, brown, and technology ETFs, in terms of their distributions, particularly return, volatility, kurtosis and skewness, we employ the multilayer network model developed by Wang et al. (2021, 2023). This model integrates the Diebold-Yilmaz (DY) spillover methodology (Diebold and Yilmaz, 2012, 2014) with the LASSO-VAR approach. The DY framework facilitates the analysis of volatility spillovers between green, brown, and technology ETF markets, offering distinct advantages in quantifying spillover effects within (and among) these individual markets. Furthermore, to address the high dimensionality and excessive parameterization of vector autoregressive (VAR) models, we employ the LASSO-VAR model (Nicholson et al., 2017). The LASSO-VAR model introduces penalty terms to the regression parameters, reducing the parameter space and facilitating parameter estimation, albeit when large samples are involved. This is in contrast to the traditional VAR estimation methods which struggle with high dimensions as the number of parameters rises with the number of variables (say, *N*) and lag order (*p*). By shrinking the coefficients of less significant variables towards zero, LASSO enables variable selection while estimating VAR parameters, as demonstrated in previous studies involving large datasets (e.g., Demirer et al., 2018). Our current study adopts the VARX-L framework (see Nicholson et al., 2017), a generalized LASSO-VAR approach, focusing on the VAR-L model (without external variables) to optimize the parameter space and construct informative spillover networks efficiently. Thus, we apply a LASSO-VAR model with a lag order of p=1 and a forecast horizon of *H*=10 to estimate moment-specific spillovers and aggregate block-level transmissions across the ETF markets.

Given that the DY (2012, 2014) framework is built on the stationarity of VAR (p) model, which can be represented as a moving average process, we present both the stationary VAR (p) and its corresponding moving average representation in Equations (7) and (8), respectively, as:

$$G_t = \sum_{i=1}^{p} \theta_i G_{t-1} + \mu_t \tag{7}$$

$$G_t = \sum_{j=0}^{\infty} \vartheta_j \mu_{t-j} \tag{8}$$

where G_t is a vector of endogenous variables at time t, θ_i denotes N x N coefficient matrices for each lag structure, p represents the optimal lag order, and μ_t is a vector of random error with zero mean and a specified covariance structure (i.e., $\mu_t \sim (0, \Sigma)$). We define ϑ_j in Equation (8) as:

$$\vartheta_j = \theta_1 \vartheta_{j-1} + \theta_2 \vartheta_{j-2} + \theta_3 \vartheta_{j-3} + \cdots + \theta_k \vartheta_{j-k} \tag{9}$$

where ϑ_0 is an N x N identity matrix, and $\vartheta_j = 0$ for $j < 0$.

To assess the contribution of each ETF (i.e., green, brown, or technology) to the forecast error variance, the generalized variance decomposition framework is used (see Koop et al., 1996; Pesaran and Shin, 1998). This generalized forecast error variance at an H-step-ahead horizon is calculated as:

$$\Phi_{ij}^{g}(H) = \frac{\varphi_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' B_h \Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i' B_h \Sigma B_h' e_i)}, \tag{10}$$

where:

- Σ is the N x N covariance matrix of the error vector μ,
- φ_{jj} denotes the standard deviation of the j^{th} error term,
- e_i is an N x 1 selection vector for all i equals 1 and 0 otherwise.

This computation results in an N x N generalized variance decomposition matrix, denoted as $[\Phi_{ij}(H)]_{\text{NxN}}$.

To adjust for differences in row sums within the variance decomposition matrix, each element of the H-step-ahead matrix is normalized as:

$$\widetilde{\Phi}_{ij}(H) = \frac{\Phi_{ij}(H)}{\sum_{j=1}^{N}\Phi_{ij}(H)} \tag{11}$$

Using the normalised variance contribution expressed in Equation (10), we compute measures of connectedness to examine spillovers among the three ETFs. In essence, we compute the total connectedness index (TCI), cross connectedness index (CSI), and net directional connectedness index (NSI). The TCI measures the average contribution of spillovers from shocks across the ETF markets to the total forecast error variance. CSI is the pairwise directional spillover among the three ETFs. NSI represents the net spillover effect for green, brown, or technology ETFs.

Given the foregoing, TCI, CSI and NSI are computed as:

$$TCI\ (H) = \frac{\sum_{\substack{i=1 \\ i\neq j}}^{N}\sum_{j=1}^{N}\widetilde{\Phi}_{ij}(H)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\widetilde{\Phi}_{ij}(H)} = \frac{\sum_{\substack{i=1 \\ i\neq j}}^{N}\sum_{j=1}^{N}\widetilde{\Phi}_{ij}(H)}{N}; N = 1,2,3\ and\ i,j \in \{1,2,3\} \tag{12}$$

The cross-spillovers (or connectedness) among the three ETFs are specified as:

$$CSI_{g\to b}^{g\leftarrow b}(H) = \frac{\sum_{\substack{b=1 \\ b\neq g}}^{3}\sum_{g=1}^{3}\widetilde{\Phi}_{bg}(H)}{\sum_{b=1}^{3}\sum_{g=1}^{3}\widetilde{\Phi}_{bg}(H)} = \frac{\sum_{\substack{b=1 \\ b\neq g}}^{3}\sum_{g=1}^{3}\widetilde{\Phi}_{bg}(H)}{N} \tag{13a}$$

$$CSI_{g\to t}^{g\leftarrow t}(H)=\frac{\sum_{\substack{t=1\\t\neq g}}^{3}\sum_{g=1}^{3}\widetilde{\Phi}_{tg}(H)}{\sum_{t=1}^{3}\sum_{g=1}^{3}\widetilde{\Phi}_{tg}(H)}=\frac{\sum_{\substack{t=1\\t\neq g}}^{3}\sum_{g=1}^{3}\widetilde{\Phi}_{tg}(H)}{N} \tag{13b}$$

$$CSI_{b\to g}^{b\leftarrow g}(H)=\frac{\sum_{\substack{g=1\\g\neq b}}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{gb}(H)}{\sum_{g=1}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{gb}(H)}=\frac{\sum_{\substack{g=1\\g\neq b}}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{gb}(H)}{N} \tag{14a}$$

$$CSI_{b\to t}^{b\leftarrow t}(H)=\frac{\sum_{\substack{t=1\\t\neq b}}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{tb}(H)}{\sum_{t=1}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{tb}(H)}=\frac{\sum_{\substack{t=1\\t\neq b}}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{tb}(H)}{N} \tag{14b}$$

$$CSI_{t\to b}^{t\leftarrow b}(H)=\frac{\sum_{\substack{t=1\\t\neq b}}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{tb}(H)}{\sum_{t=1}^{3}\sum_{b=1}^{3}\widetilde{\Phi}_{tb}(H)}=\frac{\sum_{\substack{g=1\\t\neq b}}^{t}\sum_{b=1}^{3}\widetilde{\Phi}_{tb}(H)}{N} \tag{15a}$$

$$CSI_{g\to t}^{t\leftarrow g}(H)=\frac{\sum_{\substack{g=1\\g\neq t}}^{3}\sum_{t=1}^{3}\widetilde{\Phi}_{gt}(H)}{\sum_{g=1}^{3}\sum_{t=1}^{3}\widetilde{\Phi}_{gt}(H)}=\frac{\sum_{\substack{g=1\\g\neq t}}^{3}\sum_{t=1}^{3}\widetilde{\Phi}_{gt}(H)}{N} \tag{15b}$$

where $\widetilde{\Phi}_{ij}(H)$ represents the pairwise directional spillover from asset *j*, say brown ETFs, to asset *i,* say green or technology ETFs, over *H* horizon. The superscript and subscript indicate the direction of spillovers, particularly inflows to and outflows from one ETF to another.

Furthermore, the net directional connectedness spillover index (NSI) is determined by calculating the difference between the inflow and outflow strengths of the variables. Inflow strength measures the degree to which the green ETF, for instance, is influenced by shocks originating from either the brown or technology ETF, while outflow strength measures the extent to which the green ETF generates shocks that affect the brown or technology ETF. These measures, computed among the three ETFs, are expressed as:

$$NSI\ (H)=CSI_{i\to j}^{outflow}(H)-\ CSI_{i\leftarrow j}^{inflow}(H) \tag{16}$$

where *i,j* denotes the pairwise directional spillover. These connectedness measures offer critical insights into how risks transmitted among the ETFs are analysed. Specifically, they help identify the nature of risk exposure within the ETF markets, revealing whether an ETF acts predominantly as a net recipient or a net contributor to the system of shock spillovers.

Based on the foregoing and as previously espoused, the linkages between green, brown, and technology ETFs are evaluated using the block aggregation technique of Greenwood-Nimmo et al. (2021). In addition, we characterize the cross-market connectedness matrix (see Wang et al., 2023) as:

$$\begin{pmatrix} \theta^h_{g\to g} & \theta^h_{g\to b} & \theta^h_{g\to t} \\ \theta^h_{b\to g} & \theta^h_{b\to b} & \theta^h_{b\to t} \\ \theta^h_{t\to g} & \theta^h_{t\to b} & \theta^h_{t\to t} \end{pmatrix} \tag{17}$$

In Equation (17), $\theta^h_{g\to g}$, $\theta^h_{b\to b}$, and $\theta^h_{t\to t}$ (i.e., the diagonal elements) denote the spillover matrices within the green, brown, and technology ETF markets. Whereas, the off-diagonal elements (such as $\theta^h_{g\to b}$, $\theta^h_{b\to g}$, $\theta^h_{g\to t}$, etc.) indicate cross-market spillover matrices among the three ETFs. With these procedures, we can measure the extent of risk propagated within the same market, the risk transmitted to the other market, and the cross-risk dynamics across the green, brown, and technology ETFs.

In the final set up, a multilayer network is developed using the DY method and cross-spillover matrix to examine connectedness between the three ETFs, with nodes representing stocks from each ETF. This network captures risk transmission through intralayer edges (linking stocks within the same market) and interlayer edges (connecting stocks across markets), thereby allowing for a comprehensive analysis of the risk dynamics in the green and brown ETF markets (see Addi et al., 2024; Foglia et al., 2024). Consistent with the methodology employed by Wang et al. (2021), the daily return series of ETFs is partitioned into rolling windows of length ω, with a step size δ. In particular, we implement a window width (ω) of 240 trading days and a step size (δ) of 20 trading days, which approximately correspond to one trading year and one trading month, respectively, in financial markets.

4. Results and Discussion

This section presents and discusses the findings from our empirical analyses. It is organized into several sub-sections. The first focuses on the total connectedness between the ETFs across four layers: returns, volatility, skewness and kurtosis. Building on the multilayer framework, the analysis is extended to examine cross-spillovers (i.e., cross-layer connectedness) between the three

ETFs, using both the overlap and participation coefficient measures, enabling a comprehensive assessment of the connectedness dynamics in the clean, brown, and technology ETF markets. Finally, we investigate the role of climate risk in shaping these connectedness patterns using both the traditional Granger causality test and the time-varying parameter causality approach of Rossi and Wang (2019).

4.1. Total connectedness analysis

Examining the degree of connectedness between the three ETFs across the layers of returns, volatility, skewness and kurtosis, reveals a high level of connectedness, except during late 2024 (across all layers) and the 2008–2009 period (particularly for skewness and kurtosis). This pattern is evident in the four layers' higher values, as shown in both Figure 1 and Table 1. The lower level of connectedness, particularly observed during 2008–2009, for skewness and kurtosis can be attributed to the global financial crisis (GFC) which characterized this turbulent period. Similarly, the reduced connectedness observed in 2024 may reflect a growing awareness of climate change and its associated risks, which led to intensified calls for the adoption of the green technologies required for green transitions across various markets. The lower connectedness during these high-risk periods, as shown in Figure 1, particularly in the skewness and kurtosis layers, suggests that the three ETF markets become less interdependent during times of heightened uncertainty. This could be due to investors reacting differently and adjusting their positions in divergent ways based on varying risk perceptions and tolerance levels in response to rare or extreme events. Our findings, which indicate lower connectedness among certain layers, suggesting that investors respond differently to rare events, align with the results in the related literature (e.g., Hoffmann et al., 2013; Ameur et al., 2024; García-Monleón et al., 2024).

Before delving into the intricacies of economic and market dynamics shaping ETF connectedness, we direct our attention to the average degree of connectedness (captured by the overlap index) within the multilayer spillover network. Specifically, we investigate whether connectedness among ETFs only occurs within individual layers or spans multiple layers. Evidence of cross-layer connectedness would further justify our adoption of a multilayer network approach to examine the relationships among clean, brown, and technology ETFs. As illustrated in Figure 2, the overlap index hovers between 1.5 and 4, with a mean value of approximately 3. This relatively high index suggests a significant degree of connectivity across the four layers, indicating that all layers contain important information necessary for analysing connectivity, rather than such information being confined to just one or a few layers (see Foglia et al., 2025). These findings highlight the importance of incorporating multilayer structures to gain a comprehensive understanding of the interconnectedness among the three ETFs.

[INSERT FIGURES 1 AND 2]

[INSERT TABLE 1]

Given that all layers analysed contain salient information on spillovers across the three ETF markets, the four layers (see Figure 1) illustrate how these spillovers evolve over time, particularly in the post-GFC period. Various shocks over the past two decades are reflected in the ETF return behaviours shown in Figure 1, while the volatility layer highlights market fluctuations during the same periods. Notably, periods of heightened risk such as the European sovereign debt crisis (2009-2012), the oil price plunge (2014-2016), the COVID-19 pandemic (2020), and the Russia-Ukraine War (post-2022), coincide with increases in ETF returns, possibly due to their resilience during crises (see Salisu et al., 2025). The same periods reveal elevated volatility spillovers, likely driven by high trading volumes.

The skewness and kurtosis layers offer deeper insights into the previously highlighted risk episodes. In contrast to the return and volatility layers, they exhibit relatively lower spillover effects prior to the GFC. This divergence emphasizes the significance of a multilayered approach to examining spillovers and interconnectedness within the ETF markets (see Cui and Maghreyeh, 2025; Foglia et al., 2025).

4.2 Within- and cross-layer spillover analyses

Following Wang et al. (2023), both within- and cross-layer spillovers are examined. As illustrated in Figure 3, there is clear evidence of within-layer spillovers across all four layers. Specifically, within-layer spillover estimates hover between 78 percent and 98 percent for returns to returns, 53 percent to 89 percent for volatility to volatility, 40 percent to 70 percent for skewness to skewness, and 43 percent to 67 percent for kurtosis to kurtosis. These results suggest a substantial degree of internal transmission within each layer, with stronger evidence observed for the return and volatility layers.

In addition, the analysis of cross-layer spillovers – covering twelve directional relationships (i.e., return to volatility, return to skewness, return to kurtosis; volatility to return, volatility to skewness, volatility to kurtosis; skewness to return, skewness to volatility, skewness to kurtosis; kurtosis to return, kurtosis to volatility, and kurtosis to skewness) – reveals varying degrees of risk transmission across layers. Notably, higher returns do not necessarily imply higher volatility or vice versa; instead, they appear to introduce asymmetries into the distribution of both returns and volatility within ETF markets, as evident form the trend of both return to skewness and volatility to skewness. This finding contrasts with the patterns observed in total connectedness and some findings in the existing literature (e.g., Sarker et al., 2023). This asymmetry is plausible, as elevated returns in one ETF market may attract increased investment inflows, which in turn dampen market activity, and consequently, volatility in other ETF markets.

In contrast to the spillover dynamics between the return and volatility layers, we observe that the skewness layer transmits, on average, 30 percent spillovers to the kurtosis layer, while the kurtosis layer transmits approximately 28 percent spillovers back to skewness. These findings highlight a robust bidirectional relationship between the skewness and kurtosis layers, implying that changes in return asymmetry (skewness) can influence the tail behaviour (kurtosis), while variations in kurtosis can, in turn, affect the asymmetry of returns. Similar results are reported by Foglia et al. (2025). The differing results once again underscore the importance of multilayer connectedness analysis, which allows for appreciation of various and diverse dynamics of spillover transmission within and across layers of ETF markets. This approach provides valuable and timely insights for various market players, particularly investors seeking to capitalize on elevated returns during periods of rare and extreme risk events.

[INSERT FIGURE 3]

4.3 Net spillover analysis

Here, we highlight the distinct roles played by each ETF in propagating market shocks. This is illustrated through the overlapping and participation coefficient indices, each further broken down into inflow, outflow, and net components (see Figure 4 and the discussion in the Methodology section). The scaling, represented by red and blue in Figure 4, reveals whether an ETF is a net receiver or transmitter of shocks arising from major events, including the GFC, European sovereign debt crisis, oil price plunge, COVID-19 pandemic, and Russia-Ukraine conflict (as previously highlighted). ETFs are identified as net receivers when inflows exceed outflows, and as net transmitters when outflows surpass inflows.

Given the overlapping dynamics shown in Figure 4, there is a clear increase in overlap between clean, brown, and technology ETFs, as indicated by the predominance of red. This suggests that, during crisis periods, risk transmission or propagation across the ETF markets tend to be strong (see Demirer et al., 2018; Foglia and Angelini, 2020). This highlights the level of connectedness in the ETF markets, where shocks affecting one type of ETF can rapidly spill over to others, an indication of systemic risk transmission. Notably, technology ETF exhibits the highest degree of overlap in both inflows and outflows, particularly between 2008 and 2014, as well as during the COVID-19 period. This underscores its central role in mediating between brown and clean ETFs given its key role in the energy transition. Meanwhile, clean ETFs appear to be only mildly affected by these shocks, indicating a relatively low level of shock propagation over the sample period. This contrasts with the findings of Bouri (2023), which suggest that clean energy is a net transmitter of shocks – specifically volatility and kurtosis shocks – although their focus is not on ETFs but indices.

According to Foglia et al. (2025), the distribution of connections between financial markets across various layers can be assessed using the participation coefficient index. Focusing on the three sub-components, inflow, outflow, and net participation coefficients, a generally balanced concentration across all layers is observed during both turbulent and calm periods. An exception is brown ETFs during the COVID-19 pandemic and the intensified Russia-Ukraine tensions, as reflected in the inflow and outflow components (see Figure 4), buttressing the conclusion previously drawn from Figure 2.

[INSERT FIGURE 4]

4.4 *Climate risk and connectedness among clean, brown, and technology ETFs*

In order to examine the effect of climate risk on the connectedness between the three ETFs, we rely on both traditional and time-varying Granger causality tests to confirm or refute the null hypothesis that climate risk does not Granger-cause connectedness (as well as spillovers) across clean, brown, and technology ETFs. It is worth noting that the tendencies for the delayed influence of the lagged value of an independent variable on the dependent variable inform the time-varying causality by Rossi and Wang (2019).

Thus, we consider the time-varying parameters' VAR model as:

$$Z_t = \sum_{j=1}^{q} \omega_{j,t} Z_{t-j} + \mu_t \qquad (19)$$

where $\omega_{j,t}, j = 1, 2, 3, \dots, q$ are the time-varying coefficient matrices, $Z_t = (Z_{1,t}, Z_{2,t}, Z_{3,t} \dots, Z_{n,t})'$ is an n x1 vector, and the shocks (μ_t) are assumed to be heteroscedastic and serially correlated. Relying on this, we test the null hypothesis that climate risk (measured by CPU) does not Granger-cause connectedness among the three ETFs (i.e., clean, brown, and technology ETFs). This is also tested across both the within-layer and cross-layer connectedness.

Given the foregoing, in Tables 2 and 3, respectively, we highlight the results of the traditional Granger causality test (Ganger 1969) and time-varying robust Granger causality test of Rossi and Wang (2019) which assumes heteroscedastic and serially correlated idiosyncratic shocks. In both cases, we use the PPP-adjusted CPU of Ma et al. (2024) for the analysis.

The results for the traditional Granger causality test (see Table 2) show no sufficient evidence against the null hypothesis that the PPP-adjusted CPU does not Granger-cause connectedness between brown, green, and technology ETFs across the layers, except in a few cases of skewness and kurtosis connectedness (see Panel A of Table 2). However, the results for both within- and cross-layer spillovers indicate that climate risk does not Granger-cause within- and cross-layer spillovers between these assets (see the corresponding Panels B and C).

[INSERT TABLE 2]

Following the above results from the traditional (static) Granger causality test, we examine whether the influence of climate risk on asset connectedness is time-varying using the test of Rossi and Wang (2019). The results are presented in Table 3. Meanwhile, various test statistics, including exponential weighted (ExpW), mean Wald (meanW), Nyblom test (Nyblom) and supremum likelihood ration (SupLR), are reported for robustness because they take account of various statistical features, including gradual and/or abrupt break detection (ExpW and SubLR), parameter instability (Nyblom), and persistence or departure from Granger noncausality (meanW) (see Rossi, 2005). Preliminary tests using the Bai and Perron (2003) global test for multiple structural breaks (UDMax statistic) suggest, for example, the presence of structural break(s)/parameter instability (see Table A2 in the appendix), which represent another justification for adopting the time-varying test of Rossi and Wang (2019).

As shown in Table 3, we find overarching evidence across all the test statistics that climate risks indeed Granger-cause connectedness and spillovers (both within- and cross-layer) between the three ETFs (see Panels A, B, C, and D of Table 3). These results, which contrast with the traditional Granger-causality analysis (see Table 2), indicate that climate risks can indeed predict or Granger-cause connectedness/spillover between these ETFs.[5] We therefore conclude that climate risks influence the behaviour of the three ETFs, leading to both within- and cross-spillovers across returns, volatility, skewness, and kurtosis. The plots showing the array of Wald statistics over various time horizons are also presented (Figures 5, 6, and 7), and offer additional details about the periods when causality occurs across the layers, including within-layers and cross-layers.

Essentially, there exists sufficient and stable evidence that climate risk causes both total and within-layer connectedness, as the Wald statistic trends consistently stretch above the 10 percent and 5 percent critical values across the entire period (except for the kurtosis to kurtosis layer from 2012 to 2014 and 2017 to 2020), indicating a robust causal relationship (see Figures 5 and 6). There are mixed results for the causal relationship between climate risk and cross-layer

---

[5] There are three variants of the uncertainty index by Ma et al. (2024), current price GDP-weighted, equal-weighted CPU, and PPP-adjusted CPU, and the results – although not reported – are consistent across other variants of the climate risk proxies of Ma et al. (2024).

connectedness, with notable sensitivity specific to some periods, particularly around 2012 and 2019 to 2020, with this sensitivity being more pronounced in the kurtosis to volatility layer (see Figure 7). Nonetheless, evidence of stable and robust causal relationships abounds for return to skewness, skewness to return, kurtosis to skewness and vice versa, return to kurtosis, volatility to kurtosis, and volatility to skewness. These results underscore the importance of using a time-varying Granger causality test, which captures the dynamic behaviour of the Wald statistic vis-à-vis the critical values, unlike traditional tests that provide only a single p-value.

[INSERT TABLE 3]

[INSERT FIGURES 5, 6 AND 7]

5. Conclusions and Implication of Findings

The literature on spillovers across global financial markets is growing, with recent attention gradually shifting beyond the first and second moments of stock market returns to cover skewness and kurtosis given the deviation of returns from the normal distribution. However, much of this research overlooks the connectedness among clean, brown, and technology markets under the energy transition and how climate risks affect the dynamics of within-layer, cross-layer, and total connectedness measures. Using data on exchange-traded funds (ETFs) that represent an appealing investable vehicle, unlike non-investable conventional stock indices, we employ a multilayer framework of connectedness based on Wang et al. (2021, 2023). The key findings are summarized as follows.

Firstly, a high degree of connectedness across all four layers (returns, volatility, skewness, and kurtosis) are noted, except during late 2024 and the 2008–2009 period, particularly for skewness and kurtosis. The reduced connectedness during these periods is attributed to the GFC and increased awareness of climate-related risks, which have spurred a shift towards green technology investments. Secondly, a relatively high overlap index (approximately 3) indicates substantial connectivity across all layers. This suggests that each layer contributes unique and important information, supporting the use of a multilayer network approach. Specifically, risk transmission is strongest during crisis periods, with technology ETFs showing the highest degree of overlap. In contrast, clean ETFs appear less affected by shocks from the other ETFs examined, implying limited risk exposure during the sample period. Thirdly, major risk events – such as the European sovereign debt crisis (2009-2012), oil price plunge (2014-2016), COVID-19 pandemic (2020), and Russia-Ukraine War (post-2022) – correspond with increases in ETF returns, underscoring their resilience during crises. Nonetheless, these periods also exhibit elevated volatility spillovers, likely due to surges in trading activity. Fourthly, within- and cross-layer analyses reveal substantial spillovers within each layer, especially for returns and volatility. Importantly, higher ETF returns do not necessarily correspond with higher volatility; rather, they introduce asymmetries into the distributions of both returns and volatility, as reflected in their relationships with skewness. In addition, the skewness layer transmits, on average, 30 percent of spillovers to the kurtosis layer, while the kurtosis layer sends back approximately 28 percent to skewness, highlighting the bidirectional nature of higher-moment connectedness. Finally, climate risks influence the behaviour of all three ETFs across total, within-, and cross-layer connectedness metrics, highlighting the important role played by climate risk in affecting the dynamics of clean, brown, and technology ETF investments under the transition towards a low carbon economy.

Our findings have important implications for various market players, particularly investors, portfolio managers, and policy makers. The multilayer connectedness observed across returns, volatility, skewness, and kurtosis emphasizes the need for investors to move beyond traditional risk measures when making investment decisions in the area of clean, brown, and technology ETFs. The demonstrated resilience of ETFs, especially during systemic crises such as the European sovereign debt crisis, oil price plunge, COVID-19 pandemic, and Russia-Ukraine war, underscores their appeal as stable investment vehicles in turbulent times. Notably, clean ETFs exhibit lower shock propagation, making them attractive for environmentally conscious investors seeking to minimize exposure to extreme market movements. Furthermore, the high overlap index confirms that diversification strategies relying solely on returns or volatility may be inadequate, suggesting the importance of integrating higher-moment metrics to improve asset allocation and hedging strategies, particularly as return-volatility asymmetries become more pronounced during crises. Similarly, including clean ETFs in portfolios may enhance resilience as it mitigates climate-driven shocks and systemic contagion, suggesting that risk and portfolio inferences in the system of clean, brown, and technology ETFs should not be made in isolation of climate risk. For policymakers and sustainability advocates, our findings, which relate climate risk to various multilayer connectedness measures across various dimensions, reinforce the financial relevance of environmental and climate considerations under the global energy transition. Clean ETFs not only align with sustainability goals but also exhibit distinctive risk transmission patterns, making them valuable instruments for reducing climate-related financial exposure while supporting broader environmental transitions.

References

Addi, A., Foglia, M., Wang, G. J., & Miglietta, F. (2025). Crossroads of volatility spillover: Interactions between Islamic and conventional financial systems. *Research in International Business and Finance*, *74*, 102700.

Ameur, H. B., Ftiti, Z., Louhichi, W., & Prigent, J. L. (2024). Financial crisis and investor behavior. *Journal of Economic Behavior & Organization*, *223*, 307-310.

Ayinde, T. O., Olaniran, A. O., Abolade, O. C., & Ogbonna, A. E. (2023). Technology shocks-Gold market connection: Is the effect episodic to business cycle behaviour?. *Resources Policy*, *84*, 103771.

Bai, J., & Perron, P. (2003). Critical values for multiple structural change tests. *The Econometrics Journal*, *6*(1), 72-78.

Balcilar, M., Gabauer, D., Gupta, R., & Pierdzioch, C. (2023). Climate risks and forecasting stock market returns in advanced economies over a century. *Mathematics*, *11*(9), 2077.

Baumöhl, E., Kočenda, E., Lyócsa, Š., & Výrost, T. (2018). Networks of volatility spillovers among stock markets. *Physica A: Statistical Mechanics and its Applications*, *490*, 1555-1574.

Ben-David, I., Franzoni, F., & Moussawi, R. (2017). Exchange-traded funds. *Annual Review of Financial Economics*, *9*(1), 169-189.

Bouri, E. (2023). Spillovers in the joint system of conditional higher-order moments: US evidence from green energy, brown energy, and technology stocks. *Renewable Energy*, *210*, 507-523.

Bouri, E., Rognone, L., Sokhanvar, A., & Wang, Z. (2023). From climate risk to the returns and volatility of energy assets and green bonds: A predictability analysis under various conditions. *Technological Forecasting and Social Change*, *194*, 122682.

Bouri, E., Dudda, T.L., Rognone, L. & Walther, T. (2025). Climate risk and the nexus of clean energy and technology stocks. *Annals of Operations Research*, 347, 445–469.

Cui, J., & Maghyereh, A. (2025). Examining perceived spillovers among climate risk, fossil fuel, renewable energy, and carbon markets: A higher-order moment and quantile analysis. *Journal of Commodity Markets*, *38*, 100470.

Demirer, M., Diebold, F. X., Liu, L., & Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, *33*(1), 1-15.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of econometrics*, *182*(1), 119-134.

Dungey, M., & Martin, V. L. (2001). *Contagion across financial markets: An empirical assessment* (pp. 16-17). Cleveland: Econometric Society.

Elsayed, A. H., & Helmi, M. H. (2021). Volatility transmission and spillover dynamics across financial markets: the role of geopolitical risk. *Annals of Operations Research*, *305*(1), 1-22.

Feng, K., Yang, Z., Zhuo, Y., Jiao, L., Wang, B., & Liu, Z. (2024). Impact of Carbon Tax on Renewable Energy Development and Environmental–Economic Synergies. *Energies*, *17*(21), 5347.

Foglia, M., & Angelini, E. (2020). Volatility connectedness between clean energy firms and crude oil in the COVID-19 era. *Sustainability*, *12*(23), 9863.

Foglia, M., Di Tommaso, C., Wang, G. J., & Pacelli, V. (2024). Interconnectedness between stock and credit markets: The role of European G-SIBs in a multilayer perspective. *Journal of International Financial Markets, Institutions and Money*, *91*, 101942.

Foglia, M., Plakandaras, V., Gupta, R., & Ji, Q. (2025). Long-span multi-layer spillovers between moments of advanced equity markets: The role of climate risks. *Research in International Business and Finance*, *74*, 102667.

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, *57*(5), 2223-2261.

Gamba-Santamaria, S., Gomez-Gonzalez, J. E., Hurtado-Guarin, J. L., & Melo-Velandia, L. F. (2019). Volatility spillovers among global stock markets: measuring total and directional effects. *Empirical Economics*, *56*, 1581-1599.

García-Monleón, F., González-Rodrigo, E., & Bordonado-Bermejo, M. J. (2024). Investor behavior in crisis: a comparative study of fear-driven downtrends and confidence-led recoveries. *The Journal of Risk Finance*, *25*(5), 894-914.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

Greenwood-Nimmo, M., Nguyen, V. H., & Shin, Y. (2021). Measuring the connectedness of the global economy. *International Journal of Forecasting*, *37*(2), 899-919.

Gupta, R., & Pierdzioch, C. (2022). Forecasting the realized variance of oil-price returns: a disaggregated analysis of the role of uncertainty and geopolitical risk. *Environmental Science and Pollution Research*, *29*(34), 52070-52082.

Hansen, B. E. (1994). Autoregressive conditional density estimation. *International Economic Review*, 705-730.

Hao, X., Ma, Y., & Pan, D. (2024). Geopolitical risk and the predictability of spillovers between exchange, commodity and stock markets. *Journal of Multinational Financial Management*, *73*, 100843.

He, X., & Hamori, S. (2021). Is volatility spillover enough for investor decisions? A new viewpoint from higher moments. *Journal of International Money and Finance*, *116*, 102412.

Hoffmann, A. O., Post, T., & Pennings, J. M. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, *37*(1), 60-74.

Jebran, K., Chen, S., Ullah, I., & Mirza, S. S. (2017). Does volatility spillover among stock markets varies from normal to turbulent periods? Evidence from emerging markets of Asia. *The Journal of Finance and Data Science*, *3*(1-4), 20-30.

Jin, Y., Zhao, H., Bu, L., & Zhang, D. (2023). Geopolitical risk, climate risk and energy markets: A dynamic spillover analysis. *International Review of Financial Analysis*, *87*, 102597.

Kang, S. H., McIver, R., & Yoon, S. M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics*, *62*, 19-32.

Kang, S. H., & Yoon, S. M. (2019). Financial crises and dynamic spillovers among Chinese stock and commodity futures markets. *Physica A: Statistical Mechanics and its Applications*, *531*, 121776.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, *74*(1), 119-147.

Lettau, M., & Madhavan, A. (2018). Exchange-traded funds 101 for economists. *Journal of Economic Perspectives*, *32*(1), 135-154.

Li, Y., & Giles, D. E. (2015). Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. *International Journal of Finance & Economics*, *20*(2), 155-177.

Ma, D., Zhang, D., Guo, K., & Ji, Q. (2024). Coupling between global climate policy uncertainty and economic policy uncertainty. *Finance Research Letters*, *69*, 106180.

McMillan, D. G. (2020). Interrelation and spillover effects between stocks and bonds: cross-market and cross-asset evidence. *Studies in Economics and Finance*, *37*(3), 561-582.

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Kang, S. H. (2016). Global financial crisis and spillover effects among the US and BRICS stock markets. *International Review of Economics & Finance*, *42*, 257-276.

Mishra, A. K., Mishra, A. K., Anand, K., & Ranjan, S. (2025). Risk spillovers between crude oil and agricultural commodities in India: Insights from two major global disruptions. *European Review of Agricultural Economics*, jbaf011.

Nicholson, W. B., Matteson, D. S., & Bien, J. (2017). VARX-L: Structured regularization for large vector autoregressions with exogenous variables. *International Journal of Forecasting*, *33*(3), 627-651.

Oad Rajput, S. K., Memon, A. A., Siyal, T. A., & Bajaj, N. K. (2024). Volatility spillovers among Islamic countries and geopolitical risk. *Journal of Islamic Accounting and Business Research*, *15*(5), 729-745.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17-29.

Pham, S. D., Nguyen, T. T., & Do, H. X. (2024). Impact of climate policy uncertainty on return spillover among green assets and portfolio implications. *Energy Economics*, *134*, 107631.

Rigobon, R. (2019). Contagion, spillover, and interdependence. *Economía*, *19*(2), 69-100.

Rossi, B. (2005). Optimal tests for nested model selection with underlying parameter instability. *Econometric theory*, *21*(5), 962-990.

Rossi, B., & Wang, Y. (2019). Vector autoregressive-based Granger causality test in the presence of instabilities. *The Stata Journal*, *19*(4), 883-899.

Safa, H. (2017). The impact of energy on global economy. *International Journal of Energy Economics and Policy*, *7*(2), 287-295.

Salisu, A. A., Adediran, A. I. (2025), A GVAR analysis of the macroeconomic effects of the Carbon Border Adjustment Mechanism in the Global South. SPES Focus - Work Package #7, SPES project - Sustainability Performances, Evidence and Scenarios. Florence: University of Florence. Available at: https://www.sustainabilityperformances.eu /publications-deliverables

Salisu, A. A., Gupta, R., & Olaniran, A. (2023). The effect of oil uncertainty shock on real GDP of 33 countries: a global VAR approach. *Applied Economics Letters*, *30*(3), 269-274.

Salisu, A. A., & Gupta, R. (2025). Commodity Risk and Forecastability of International Stock Returns: The Role of Oil Returns Skewness. *Risks,* 13(3), 49.

Salisu, A. A., Olaniran, A. O., & Vo, X. V. (2025). Geopolitical risk, climate risk and financial innovation in the energy market. *Energy*, *315*, 134365.

Sarker, P. K., Bouri, E., & Marco, C. K. L. (2023). Asymmetric effects of climate policy uncertainty, geopolitical risk, and crude oil prices on clean energy prices. *Environmental Science and Pollution Research*, *30*(6), 15797-15807.

Shang, Y., Han, D., Gozgor, G., Mahalik, M. K., & Sahoo, B. K. (2022). The impact of climate policy uncertainty on renewable and non-renewable energy demand in the United States. *Renewable Energy*, 197, 654-667.

Smales, L. A. (2021). Geopolitical risk and volatility spillovers in oil and stock markets. *The Quarterly Review of Economics and Finance*, *80*, 358-366.

Tiwari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance*, *70*, 194-202.

Wang, G. J., Chen, Y. Y., Si, H. B., Xie, C., & Chevallier, J. (2021). Multilayer information spillover networks analysis of China's financial institutions based on variance decompositions. *International Review of Economics & Finance*, *73*, 325-347.

Wang, G. J., Wan, L., Feng, Y., Xie, C., Uddin, G. S., & Zhu, Y. (2023). Interconnected multilayer networks: Quantifying connectedness among global stock and foreign exchange markets. *International Review of Financial Analysis*, *86*, 102518.

Wu, F., Guan, Z., & Myers, R. J. (2011). Volatility spillover effects and cross hedging in corn and crude oil futures. *Journal of Futures Markets*, *31*(11), 1052-1075.

Xie, Q., Bi, Y., Xi, Y., & Xu, X. (2025). The impact of geopolitical risk on higher-order moment risk spillovers in global energy markets. *Energy Economics*, *144*, 108292.

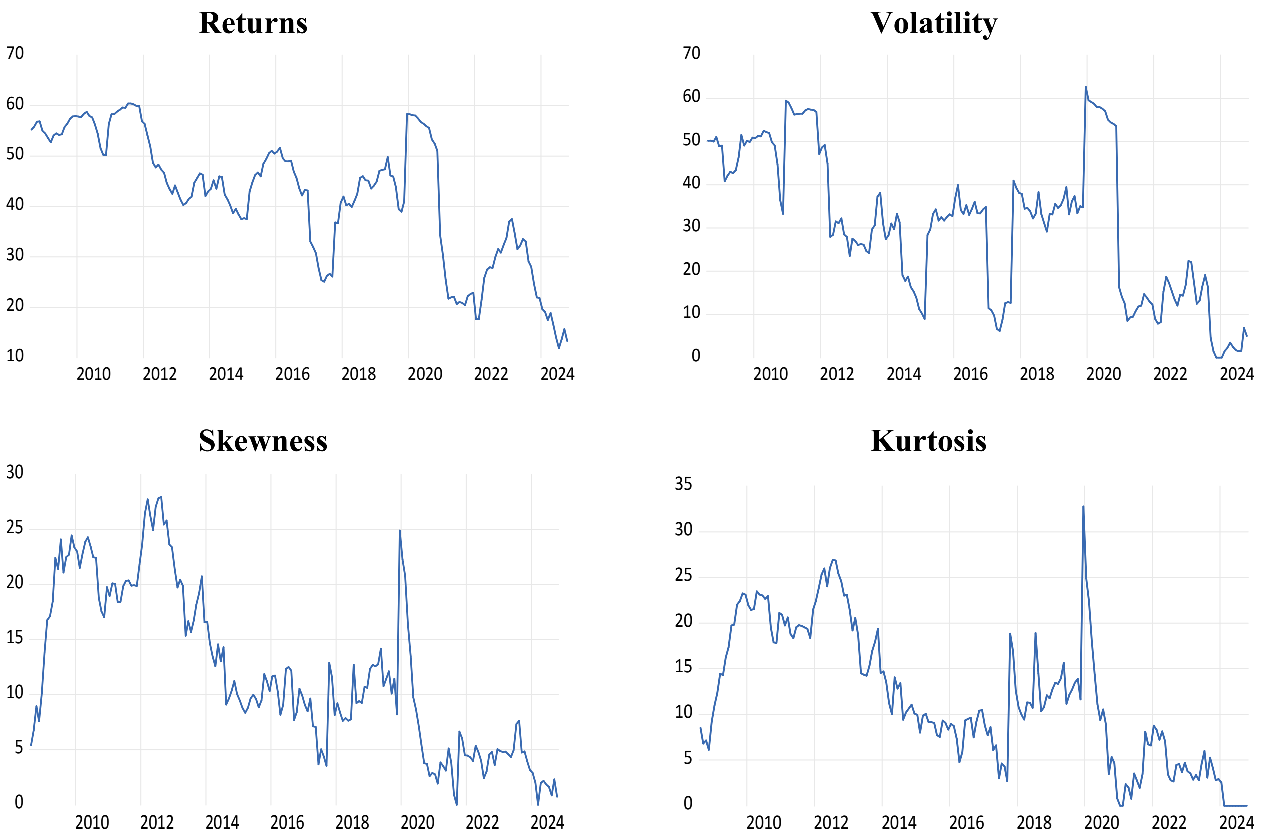


Figure 1: Extent of connectedness for each layer of returns, volatility, skewness, and kurtosis

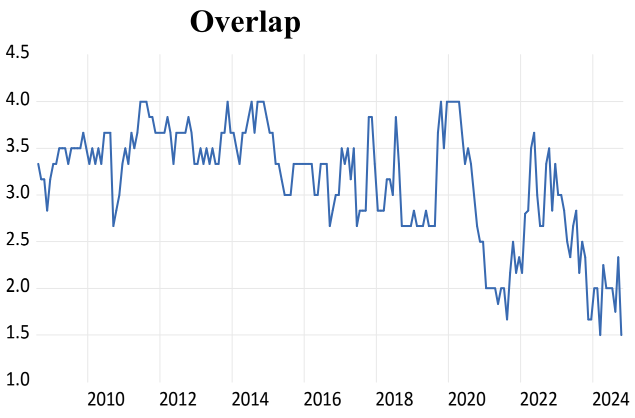
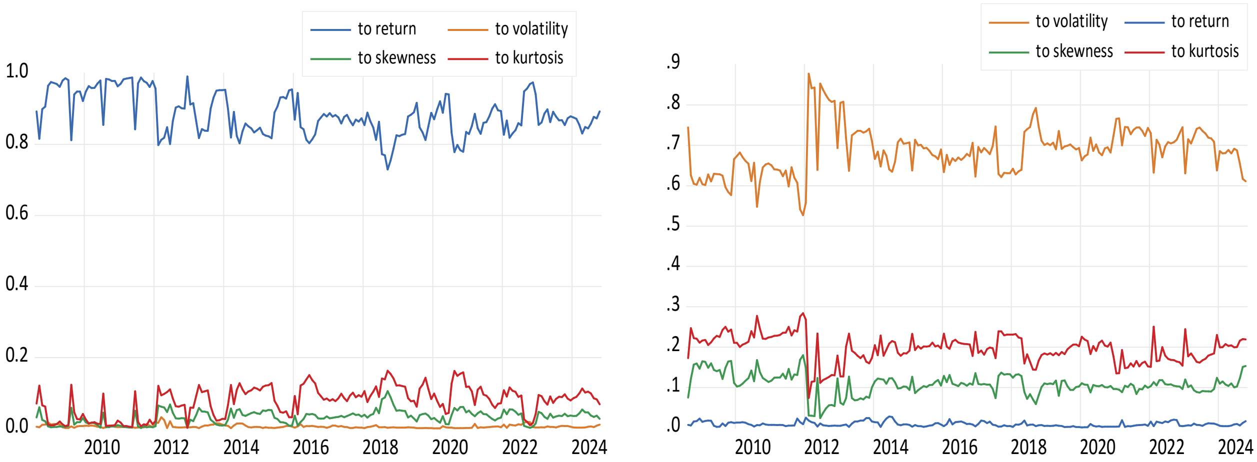


Figure 2: Trend in overlap index

Table 1: Descriptive statistics of the connectedness index

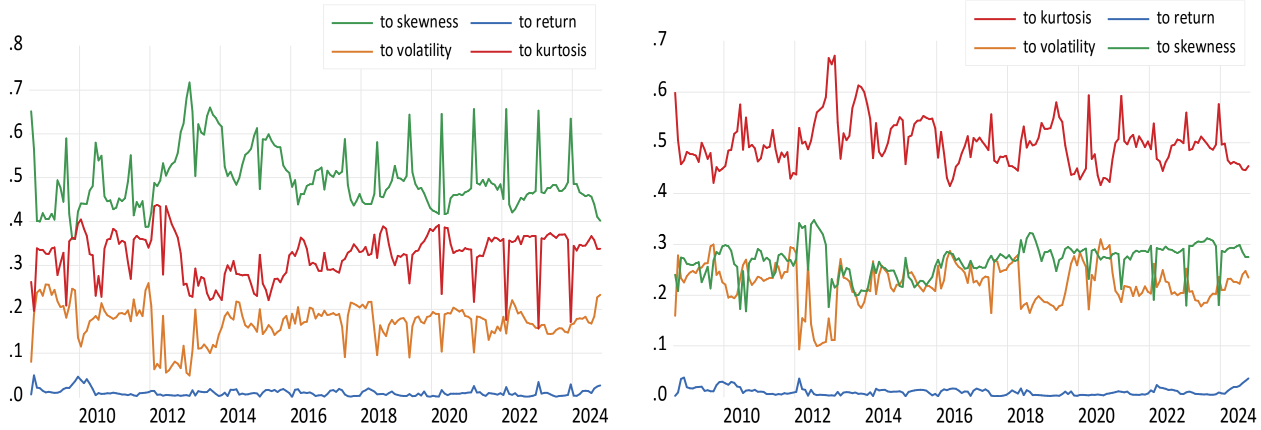
	Layer			
	Return	Volatility	Skewness	Kurtosis
Mean	42.2221	30.9265	12.0219	11.8274
Maximum	60.4468	62.6934	27.9558	32.7788
Minimum	11.8759	0.0000	0.0000	0.0000
Std. Dev.	12.7769	16.9334	7.4185	7.4319

Note: Std. Dev. denotes standard deviation.



Spillover from return layer

Spillover from volatility layer

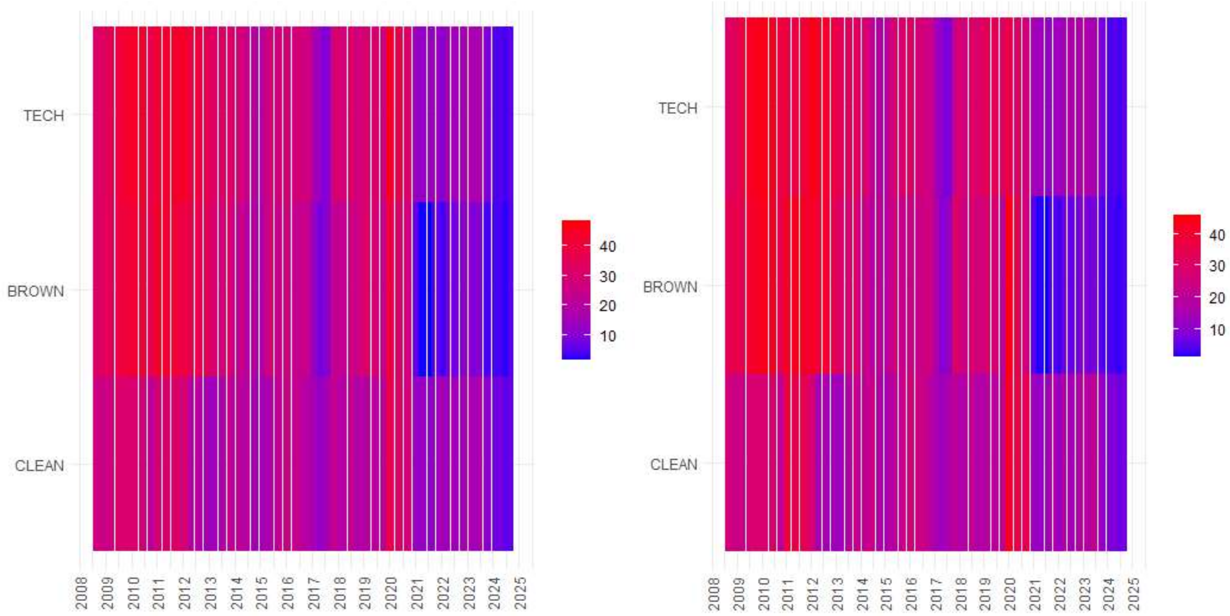


Spillover from skewness layer

Spillover from kurtosis layer

Figure 3: Cross-spillover among layers

Note: The blue line is spillover to return layers, the orange line is spillover to volatility layers, the green line is spillover to skewness layers, and the pink line is spillover to kurtosis layers.


Overlapping strength (inflow)

Overlapping strength (outflow)

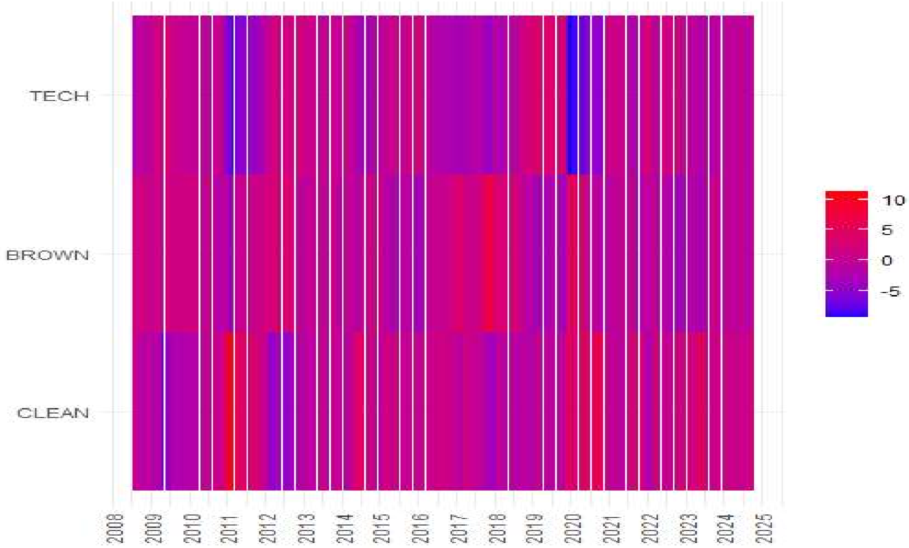
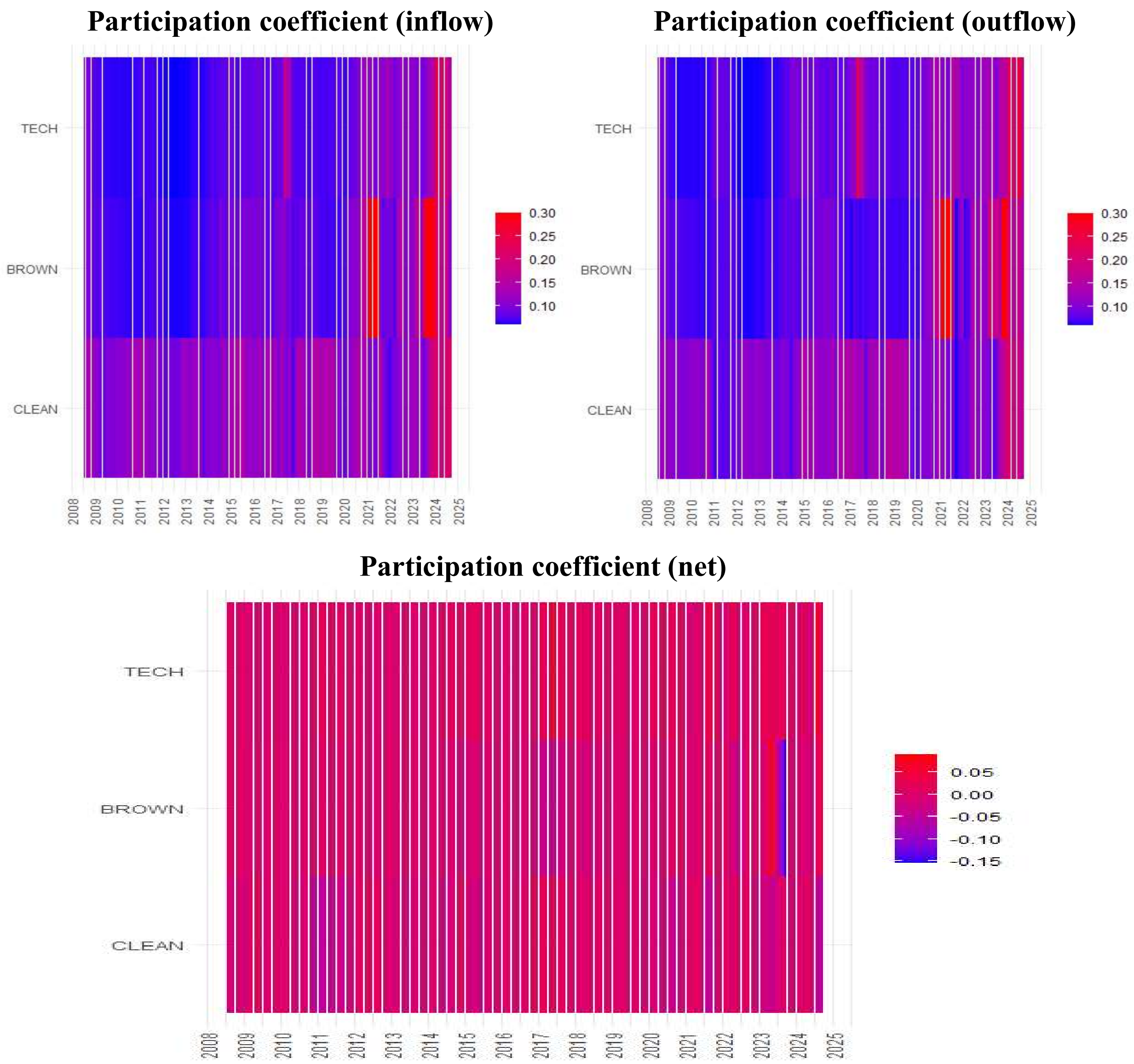

Overlapping strength (net)

Figure 4: Multilayer information spillover measures


Participation coefficient (inflow)

Participation coefficient (outflow)

Participation coefficient (net)

Figure 4: Continued

Table 2: Traditional Granger causality test

Panel A		Panel B		Panel C			
Connectedness	**F-Stat.**	**Within**	**F-Stat.**	**Cross**			
					F-Stat.		**F-Stat.**
Full	2.83*	k-to-k	0.01	k-to-r	1.18	r-to-k	2.34
Ret	9.16***	r-to-r	2.42	k-to-v	0.26	v-to-k	3.66*
Vol	4.88**	s-to-s	0.07	k-to-s	1.56	s-to-k	0.69
Skew	0.42	v-to-v	2.02	r-to-v	0.00	v-to-r	0.00
Kurt	1.48			r-to-s	1.68	s-to-r	0.91
				v-to-s	0.70	s-to-v	0.04

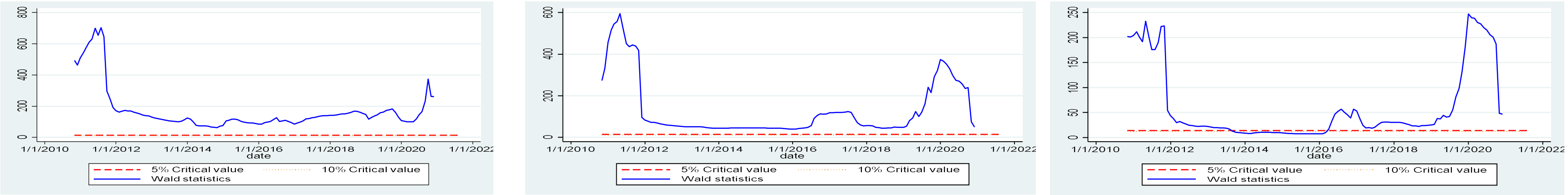
Note: Within’ and ‘Cross’ in Panels B and C denote within-layer and cross-layer spillovers, respectively. The PPP-adjusted CPU of Ma et al. (2024) is used to proxy climate risk. ‘Full’ denotes connectedness across the entire layers (see Panel A), while ‘Kurt’ (and k), ‘Ret’ (and r), ‘Skew’ (and s) and ‘Vol’ (and v) indicate connectedness/spillovers along the layers of kurtosis, return, skewness, and volatility, respectively. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively. H$_0$: Climate risk does not cause connectedness/spillovers among brown, green, and technology ETFs.

Table 3: Time-varying Granger causality from climate risk to connectedness and spillovers across multiple layers

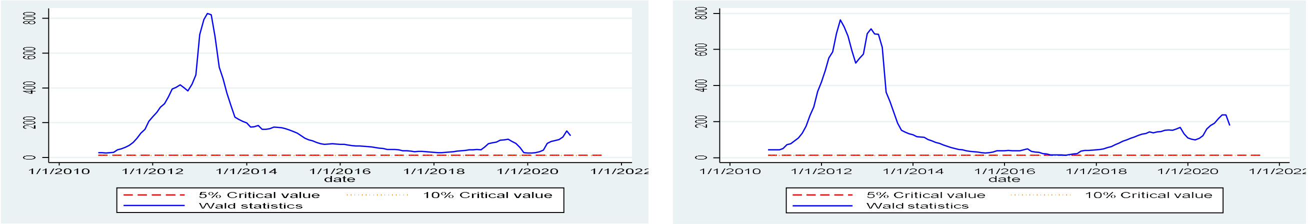
	Panel A: ExpW							Panel B: MeanW						
Connectedness		**Within**		**Cross**				**Connectedness**	**Within**		**Cross**			
Full	347.08***	k-to-k	36.19***	k-to-r	44.50***	r-to-k	299.32***	178.46***	k-to-k	14.00***	k-to-r	28.08***	r-to-k	57.95***
Ret	292.70***	r-to-r	189.30***	k-to-v	42.44***	v-to-k	113.31***	138.07***	r-to-r	70.43***	k-to-v	13.20***	v-to-k	64.62***
Vol	139.79***	s-to-s	121.64***	k-to-s	104.18***	s-to-k	47.36***	66.35***	s-to-s	47.69***	k-to-s	78.63***	s-to-k	43.33***
Skew	409.06***	v-to-v	232.64***	r-to-v	58.19***	v-to-r	39.81***	150.53***	v-to-v	83.98***	r-to-v	23.93***	v-to-r	22.25***
Kurt	376.81***			r-to-s	322.39***	s-to-r	74.80***	169.63***			r-to-s	56.80***	s-to-r	36.90***
				v-to-s	187.71***	s-to-v	79.60***				v-to-s	37.39***	s-to-v	16.63***

	Panel C: Nyblom							Panel D:SupLR						
Connectedness		**Within**		**Cross**				**Connectedness**	**Within**		**Cross**			
Full	24.05***	k-to-k	22.79***	k-to-r	17.73***	r-to-k	13.87***	703.55***	k-to-k	81.95***	k-to-r	97.01***	r-to-k	608.24***
Ret	77.61***	r-to-r	6.77***	k-to-v	2.82***	v-to-k	18.76***	595.02***	r-to-r	388.22***	k-to-v	93.53***	v-to-k	236.14***
Vol	11.58***	s-to-s	46.88***	k-to-s	75.09***	s-to-k	69.02***	289.20***	s-to-s	252.36***	k-to-s	217.37***	s-to-k	103.58***
Skew	9.05***	v-to-v	18.71***	r-to-v	51.43***	v-to-r	24.65***	827.71***	v-to-v	474.66***	r-to-v	125.85***	v-to-r	88.16***
Kurt	6.77***			r-to-s	18.44***	s-to-r	38.07***	763.23***			r-to-s	654.17***	s-to-r	159.21***
				v-to-s	14.06***	s-to-v	2.14***				v-to-s	385.02***	s-to-v	168.82***

Note: The Table reports the results of the various test statistics of the Granger causality robustness test, with *** denoting statistical significance at 1% level. ‘Within’ and ‘Cross’ denote within-layer and cross-layer spillovers, respectively. The PPP-adjusted CPU of Ma et al. (2024) is used to proxy climate risk. ‘Full’ denotes connectedness across the entire layers, while ‘Kurt’ (and k), ‘Ret’ (and r), ‘Skew’ (and s) and ‘Vol’ (and v) indicate connectedness/spillovers along the layers of kurtosis, return, skewness, and volatility, respectively. The optimal lag is 1, and heteroscedastic and serially correlated idiosyncratic shocks are assumed (see Rossi and Wang, 2019).

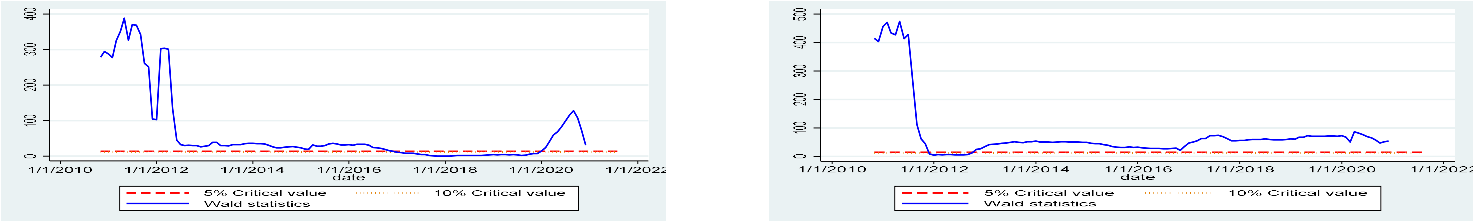


Full **Returns** **Volatility**

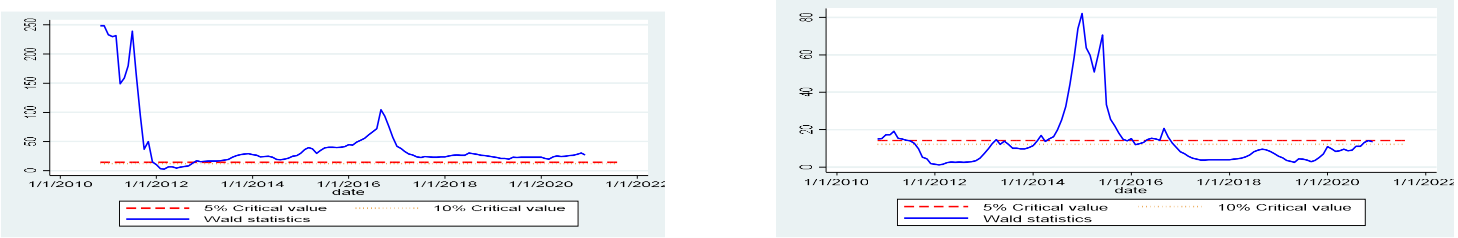


Skewness **Kurtosis**

Figure 5: Time-varying Wald test for Granger causality between CPU and total connectedness

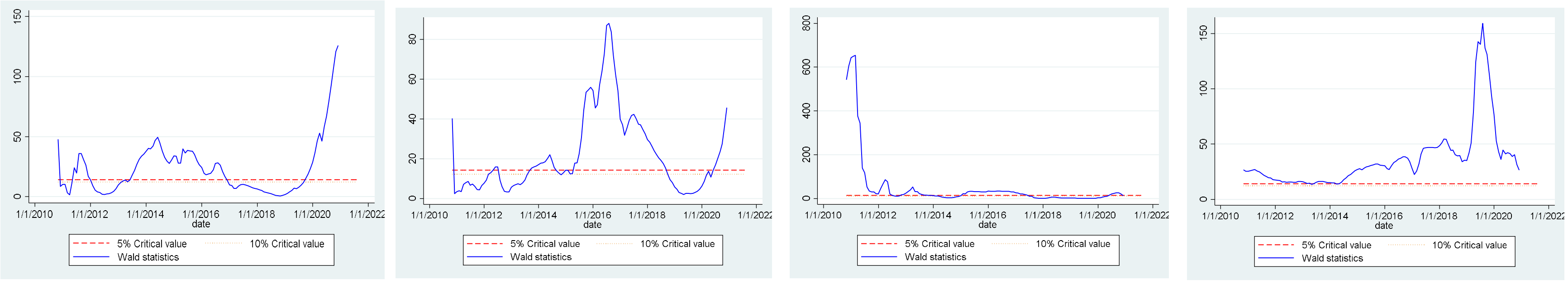


Return-to-Return **Volatility-to-Volatility**

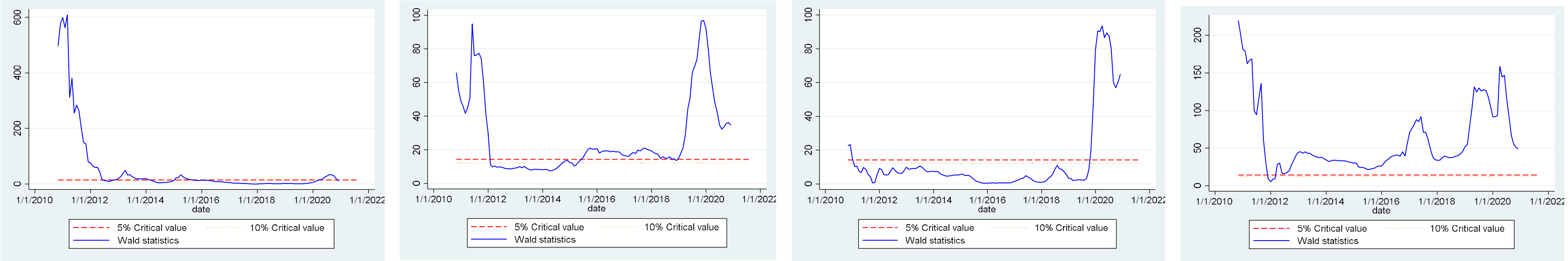


Skewness-to-Skewness **Kurtosis-to-Kurtosis**

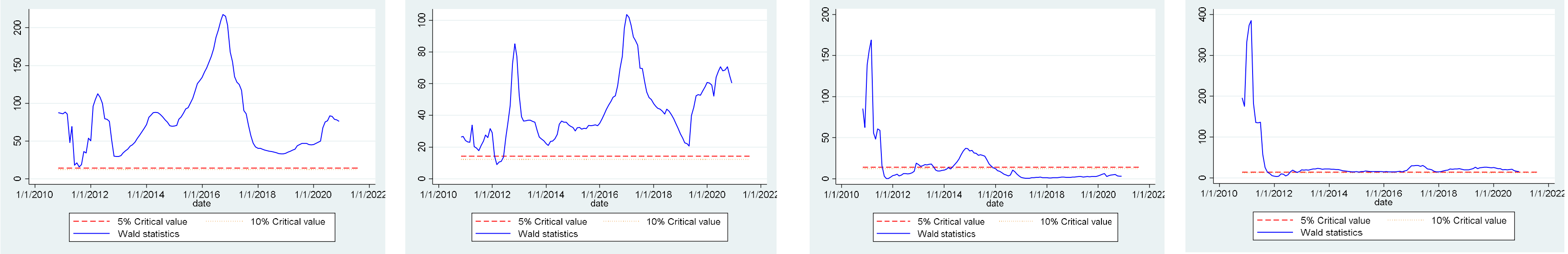
Figure 6: Time-varying Wald test for Granger causality between CPU and within-layer connectedness



Return-to-Volatility **Volatility-to-Return** **Return-to-Skewness** **Skewness–to-Return**



Return-to-Kurtosis **Kurtosis-to-Return** **Kurtosis-to-Volatility** **Volatility-to-Kurtosis**



Kurtosis-to-Skewness **Skewness-to-Kurtosis** **Skewness-to-Volatility** **Volatility-to-Skewness**

Figure 7: Time-varying Wald test for Granger causality between CPU and cross-layer connectedness

Appendix

Table A1: Summary statistics

	BROWN ETF	**CLEAN ETF**	**TECH ETF**
Mean	-0.0042	-0.0347	0.0496
Std. Dev.	1.8032	2.0571	1.4428
Skewness	-0.7395	-0.5412	-0.4378
Kurtosis	18.4974	13.676	11.4991
Jarque-Bera	43169.9***	20512.03***	13003.4***

Note: The returns of the three ETFs are used.

Table A2: Stability tests

TC	**No of breaks**	**break dates**	**Within-layer**	**No of breaks**	**break dates**
Full	2	2017M10, 2020M01	**k-to-k**	1	2011M10
Kurtosis	1	2020M01	**r-to-r**	1	2012M02
Return	1	2020M12	**s-to-s**	1	2018M06
Skewness	2	2017M10, 2020M01	**v-to-v**	1	2012M02
Volatility	1	2020M12			
			Cross-layer		
	No of breaks	**break dates**	**Within-layer**	**No of breaks**	**break dates**
k-to-r	-	-	**s-to-k**	1	2020M04
k-to-s	3	2012M12, 2015M11, 2020M04	**s-to-r**	-	-
k-to-v	-	-	**s-to-v**	2	2012M02, 2014M05
r-to-k	1	2012M02	**v-to-k**	1	2012M02
r-to-s	1	201M09	**v-to-r**	2	2017M06, 2021M09
r-to-v	4	2012M05, 2014M09, 2017M06, 2021M09	**v-to-s**	1	2012M01

Note: TC means total connectedness. We apply the Bai-Perron multiple breakpoint test with the 'global L-breaks vs. none' (using UDMax determined breaks) option and allow for differing error distributions across regimes. This is to relax the assumption of no homoscedasticity and serial correlation in line with the time-varying causality analysis conducted.

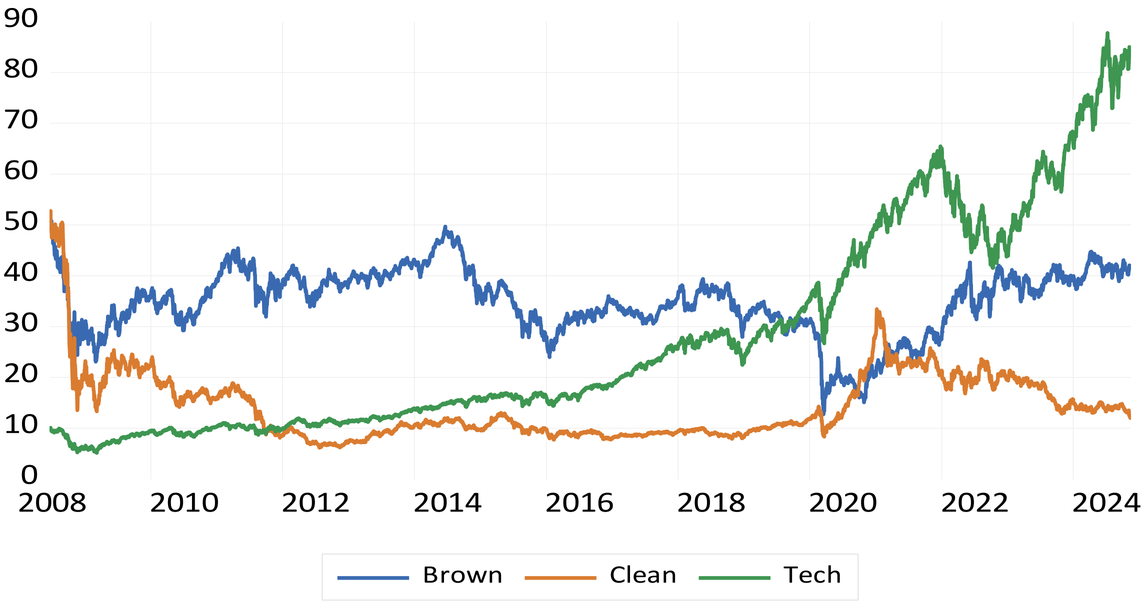


Figure A1: Brown, clean, and technology ETF price trends

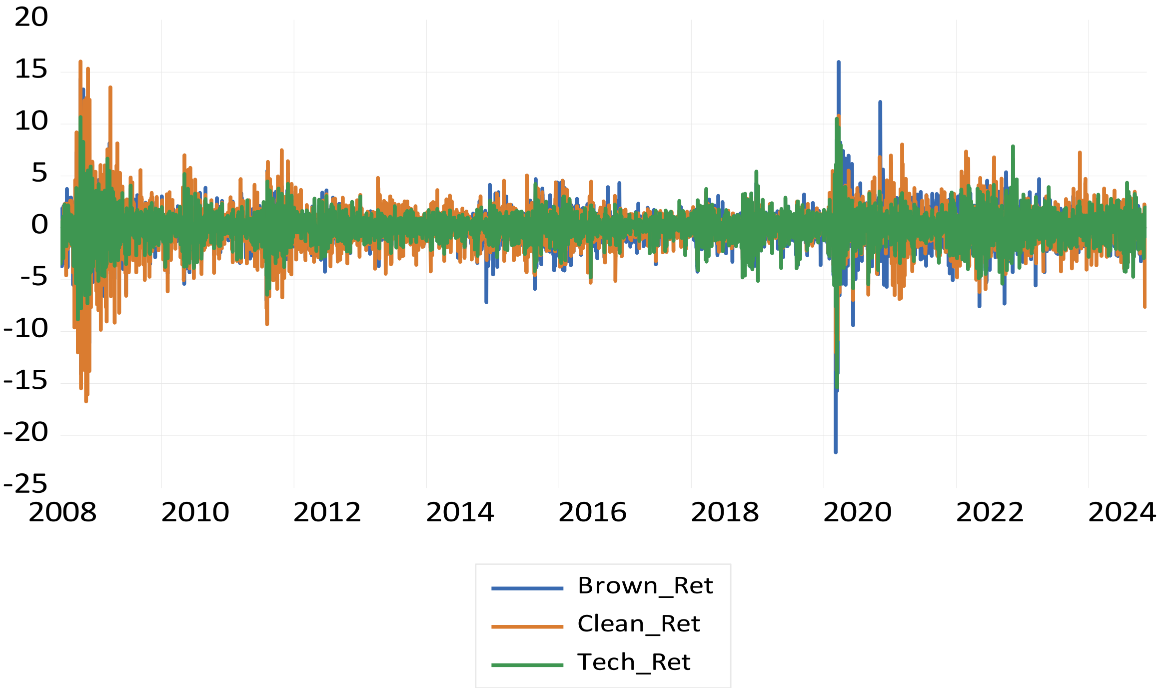


Figure A2: Brown, clean, and technology ETF return trends