

Article

Carbon Pricing Uncertainty and the Green Finance Ecosystem: Connectedness, Contagion, and Portfolio Strategies

Bouthaina Ben Othman, Rihab Bedoui Ben Salem and Heni Boubaker * 

Economics, Management and Quantitative Finance Research Laboratory (LaREMFQ), Institute of High Commercial Studies of Sousse, University of Sousse, Sousse 4054, Tunisia

* Correspondence: heni.boubaker@ihesco.u-sousse.tn

Abstract

Carbon price instability within the EU Emissions Trading System (EU ETS) is associated with financial stress that propagates across green finance markets, yet the system-level dynamics linking carbon allowance instruments, clean energy equities, green bonds, and oil volatility remain insufficiently characterized over the turbulent 2021–2026 period. This paper applies the DCC-GARCH R^2 decomposed connectedness framework to five exchange-traded funds and one volatility index spanning the principal channels through which EU ETS regulatory shocks propagate to financial markets, and derives a novel Connectedness-Based Hierarchy Index (CBHI) that translates the transmitter–receiver hierarchy into a time-varying portfolio desirability index. Five key findings emerge. First, the carbon allowance futures ETF (KRBN) and the Paris-aligned equity ETF (CARB) form a near-closed systemic bloc within this asset universe: bilateral connectedness reaches 0.867, with TO and FROM directional connectedness values both approaching 80%. Second, this co-transmitter structure is highly contingent on the joint inclusion of both instruments; excluding CARB raises KRBN's CBHI from 0.251 to 22.204, reclassifying it as a structural diversifier and reducing the mean Total Connectedness Index (TCI) from 52.18% to 30.81%. Third, system-wide connectedness averages 52.18% but surges to nearly 73% during EU ETS regulatory crises. Fourth, connectedness-aware portfolios outperform the minimum-variance benchmark across all risk-adjusted metrics, yielding an annualized Sharpe ratio of 0.148 vs. -1.066 ($T = 1035$ observations, daily rebalancing, zero transaction costs); this improvement is driven by reallocation toward crude oil volatility (OVX), the sole non-ETF and most peripheral instrument ($TO = 5.55\%$, $CBHI = 14.310$), which the CBHI identifies as the system's dominant structural diversifier and whose weight rises from 0.4% in the benchmark to 31.6%. Fifth, the CBHI uncovers a structural tension in Paris-aligned mandates: CARB records the second-lowest CBHI (0.254), indicating that climate alignment and systemic risk minimization are partially conflicting objectives.



Academic Editors: Rashedul Hasan and Mohammad Dulal Miah

Received: 16 June 2026

Revised: 17 July 2026

Accepted: 20 July 2026

Published: 28 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: carbon pricing; EU emissions trading system; DCC-GARCH R^2 connectedness; financial contagion; portfolio optimization; green finance; systemic risk; connectedness hierarchy index; network centrality

1. Introduction

Carbon pricing has emerged as the cornerstone of market-based climate governance, yet its effectiveness depends critically on the stability of the price signal it transmits to investors. The European Union Emissions Trading System (EU ETS), the world's largest cap-and-trade mechanism, has experienced repeated regulatory discontinuities. These range

from structural reforms and Market Stability Reserve interventions to the geopolitical shock of the Russia–Ukraine conflict and, more recently, the early 2026 confluence of geopolitical uncertainty and EU ETS review pressure (ABN AMRO, 2026; Allianz Research, 2026). Each has generated episodes of acute allowance price volatility driven by policy uncertainty rather than by emission fundamentals (Li et al., 2022; Mouffok et al., 2025). At the same time, carbon markets can offer high-integrity crediting pathways and performance-based finance mechanisms capable of mobilizing additional capital for the climate transition (Puerta-Ortega & de Mariz, 2025). The consequences of carbon-price instability extend well beyond the carbon market itself: clean energy equities, green bonds, and renewable energy indices are all sensitive to carbon-price dynamics, and elevated carbon-market volatility is associated with broader stress across this ecosystem through portfolio rebalancing, information transmission, and shared exposure to energy-transition risk (Dogan et al., 2022; Su & Lian, 2025).

Despite growing evidence of cross-market spillovers, the system-level dynamics connecting carbon markets, clean energy equities, green bonds, and oil volatility remain incompletely characterized, particularly over the turbulent 2021–2026 period. These four asset classes are selected because they represent the primary channels through which carbon-pricing risk reaches institutional investors: carbon-pricing instruments provide the direct EU ETS price signal (Li et al., 2022); clean energy equities are the principal beneficiaries or victims of that signal (Dogan et al., 2022); green bonds offer a fixed-income hedge whose insulation properties remain debated (Cao et al., 2024); and oil volatility captures the fossil-fuel uncertainty that continues to shadow the energy transition (Ha & Nham, 2025). This paper applies the DCC-GARCH R^2 decomposed connectedness framework of Cocco et al. (2024) to a system of five green finance assets and one external benchmark: KRBN, CARB, ICLN, IQQH, GRNB, and OVX (the CBOE Crude Oil Volatility Index, included as a fossil-fuel uncertainty benchmark rather than a directly investable green finance instrument). Because the conditional variance dynamics of these series are subject to documented structural breaks, we adopt explicit break-corrected GARCH specifications estimated via the Bai and Perron (2003) procedure (Hillebrand, 2005; Mikosch & Stărică, 2004). From the resulting directional connectedness measures, we derive a Connectedness-Based Hierarchy Index (CBHI) that translates the estimated transmitter–receiver hierarchy into an operationalizable, time-varying portfolio desirability index. We address two research questions. First, which assets act as net transmitters versus net receivers of systemic risk within this green finance system, and how does that hierarchy shift during episodes of acute regulatory uncertainty? Second, does incorporating the estimated connectedness structure into portfolio construction deliver measurable risk-adjusted improvements over a minimum-variance benchmark?

Five main findings emerge from the analysis. First, KRBN and CARB constitute a near-closed systemic bloc at the core of the green finance network. Their bilateral connectedness reaches 0.867, the highest pairwise value in the system, and the TO and FROM values of both instruments approach 80 percent. Their marginal net positions are economically negligible at this scale of bilateral integration (KRBN: NET +1.45 percentage points; CARB: NET +1.00 percentage points, both measured as net connectedness rather than return contributions). Both instruments therefore function as embedded co-transmitters within this six-asset universe, since their joint inclusion introduces structural, near-undiversifiable exposure to EU ETS regulatory shocks. Crucially, this co-transmitter structure is a property of the bilateral KRBN–CARB link rather than of KRBN in isolation: excluding CARB raises KRBN’s CBHI from 0.251 to 22.204 and reduces the mean TCI from 52.18 to 30.81 percent. Within the clean energy equity segment, ICLN acts as a net transmitter (NET = +7.30 percentage points) whereas IQQH is a marginal net receiver

(NET = −2.88 percentage points), reflecting directional propagation from the US-listed to the EU-listed ETF.

Second, system-wide connectedness averages 52.18 percent over the full sample but surges to a peak of nearly 73 percent during episodes of acute regulatory uncertainty. This increase over the structural-interdependence baseline constitutes shift-contagion in the sense of [Forbes and Rigobon \(2002\)](#), consistent with the view that EU ETS discontinuities represent a systemic financial risk factor rather than a localized market disruption. The most pronounced surges coincide with the Russia–Ukraine energy crisis (late 2022–early 2023) and the early 2026 confluence of geopolitical pressure and ETS review, illustrating the extra-territorial reach of European regulatory discontinuities ([Redondo Alamillos & de Mariz, 2022](#)).

Third, OVX and GRNB occupy structurally peripheral positions. OVX records the lowest absolute connectedness in the system (TO = 5.55%, FROM = 6.23%) together with the highest CBHI (14.310), which identifies it as the dominant structural diversifier. Its notional allocation in connectedness-aware portfolios reaches 31.6 percent (MCP), against only 0.4 percent in the minimum-variance benchmark, reflecting its near-total orthogonality to the carbon–clean energy transmission channel. GRNB (TO = 13.84%; CBHI = 5.387) similarly occupies a peripheral position, consistent with a fixed-income coupon structure that insulates green bond returns from short-run carbon market turbulence ([Cao et al., 2024](#); [Ha & Nham, 2025](#)).

Fourth, dynamic hedging within the KRBN/CARB pair achieves a variance reduction of 76.3 percent, whereas OVX-based hedges yield near-zero effectiveness. By exploiting the differential network positions documented above, connectedness-aware portfolios outperform the minimum-variance benchmark across all risk-adjusted metrics (Sharpe ratio: 0.148 vs. −1.066).

Fifth, the CBHI partitions the system into three operationally distinct profiles: structural diversifiers (OVX, GRNB), bidirectionally integrated assets (IQQH, ICLN), and systemic transmitters (KRBN, CARB). The index is orthogonal to individual asset volatility (Kendall $\tau \approx -0.20$). Within this asset universe and over this sample period, it uncovers a structural tension in Paris-aligned mandates: CARB, the instrument most directly aligned with the low-carbon transition, records the second-lowest CBHI in the system (0.254). Climate alignment and systemic risk minimization are thus partially conflicting objectives, and connectedness-aware strategies offer a tractable means of navigating this tension.

These findings carry implications across three domains. For policymakers, the documented association between EU ETS regulatory discontinuities and system-wide connectedness surges suggests that carbon-price volatility may impede the capital reallocation required for the energy transition ([Bartocci et al., 2024](#); [Fornaro et al., 2025](#)); and given the extra-territorial reach of European sustainable finance regulation ([Redondo Alamillos & de Mariz, 2022](#)), these effects may extend beyond the EU. For financial regulators, the variance transmission network reveals a pronounced structural divergence between equity-based and fixed-income green instruments, with FROM values of 66.53 percent for ICLN against 20.04 percent for GRNB, indicating that a single supervisory risk framework is unlikely to be adequate across these instrument classes. For institutional investors, the CBHI introduced in Section 1 provides a time-varying portfolio desirability index that translates the differential connectedness structure into actionable allocation decisions and offers a tractable approach to the trade-off between climate alignment and systemic risk minimization.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 develops the theoretical framework and hypotheses. Section 4 describes the methodology. Section 5 presents the data. Section 6 reports the empirical results. Section 7

discusses the findings against existing evidence and assesses the five hypotheses. Section 8 concludes, and Section 9 sets out the policy implications and limitations.

2. Literature Review

The empirical strategy of this paper rests on a particular reading of the green finance ecosystem: that carbon-price instability operates not as an exogenous environmental parameter but as an endogenous systemic risk factor, whose shocks propagate through a measurable network of directional dependencies and, in doing so, reshape the risk profile of every green asset connected to it. This section assembles the literature that motivates and disciplines that reading, and it does so in five steps. Section 2.1 establishes the economic and financial dependence binding carbon and green markets, isolating the forces—regulatory discontinuity, policy uncertainty, and the transmission of carbon shocks into fiscal, monetary, and asset-pricing outcomes—that render the connection consequential. Section 2.2 reviews the empirical connectedness evidence through which these forces become observable. Section 2.3 traces the methodological lineage that renders directional transmission estimable and motivates the DCC-GARCH R^2 framework adopted here. Section 2.4 develops the network-portfolio literature that converts connectedness structure into allocation decisions. Section 2.5 identifies the resulting gap and states the contribution, which Section 3 formalizes into three theoretical frameworks and five testable hypotheses.

2.1. Carbon–Green Market Dependence

The point of departure for this paper is a reconceptualization of what a carbon market is. Conceived as an environmental instrument—a mechanism for pricing the externality of emissions—the EU Emissions Trading System (EU ETS) has become a financial asset whose price is governed as much by regulatory announcements, geopolitical shocks, and speculative positioning as by the marginal economics of abatement. The instrument's rationale nonetheless remains economic: by raising the relative cost of carbon-intensive production, a credible and rising carbon price improves the competitiveness of low-carbon alternatives and sharpens the incentive for long-horizon capital to finance the transition (Li et al., 2022; Sharma et al., 2022). The EU ETS was designed to transmit precisely this signal. Its realized trajectory, however—punctuated by allowance over-allocation, the Market Stability Reserve, and successive legislative revisions—has been one of acute volatility rather than the smooth ascent that investment theory presupposes (Hinterlang, 2024). It is this divergence between the intended signal and the realized price process that converts carbon-price instability from a question of market design into one of financial stability.

The consequences of that instability do not remain internal to the carbon market. Bartocci et al. (2024) demonstrate that carbon pricing functions as a coordination device for green fiscal policy: a stable price amplifies the fiscal multiplier of green public investment, whereas an erratic one severs the alignment between public commitment and private expectation, and investment retreats. Fornaro et al. (2025) identify an analogous macro-financial channel, in which volatile carbon prices generate stagflationary pressures that narrow the space available to monetary policy for supporting the transition. At the level of asset prices, Mouffok et al. (2025) find that fiscal uncertainty disproportionately depresses clean-energy investment during periods of energy-market stress, while Su and Lian (2025) document that carbon-price innovations transmit substantial volatility to clean-energy equities, with transmission intensifying during EU ETS reform episodes and subsiding as the price stabilizes. The salience of these linkages has grown in step with the scale of green finance itself, which has advanced from a peripheral segment to a systemically consequential asset class (Sun et al., 2023; Tiwari et al., 2025); where the price signal proves unreliable, directed instruments may even substitute for it, as Chitkasame and Pastpipatkul

(2025) show that green bonds can dominate carbon pricing as a mitigation channel under conditions of high carbon-price volatility. The cumulative implication is that the carbon price is a systemic risk factor whose instability is transmitted, rather than absorbed, across the green finance ecosystem.

A final characteristic distinguishes this dependence from a purely domestic phenomenon: its extra-territorial reach. As the deepest and most liquid carbon market in the world, and as the anchor of a regulatory apparatus that increasingly sets the global standard for sustainable finance, the EU ETS exports its shocks well beyond European assets (Redondo Alamillos & de Mariz, 2022). This regulatory externality—formalized in Section 3 as the Brussels Effect—implies that a transmitter–receiver hierarchy estimated for an EU-centred system speaks to the structure of green finance globally, and not merely to its European subset.

2.2. Connectedness and Spillovers in Green Finance

If carbon-price instability is a systemic force, its footprint should be legible in the connectedness structure of green financial markets, and a substantial literature confirms that it is. Dogan et al. (2022) provide an early benchmark, documenting significant and time-varying bidirectional spillovers between green bonds and renewable-energy indices, with system-wide integration intensifying during episodes of global financial stress. The introduction of carbon variables sharpens the picture considerably. Employing a quantile TVP-VAR that spans carbon prices, climate-policy uncertainty, green finance, clean energy, and innovation, Su and Lian (2025) locate carbon markets at a structurally pivotal position: at once receivers of policy uncertainty and transmitters of financial volatility toward the green segments, and most emphatically so at the upper quantiles that characterize stress. This dual role—carbon as both sink and source—is the empirical counterpart to the systemic-risk reading advanced above.

A recurrent theme in this literature is that the connectedness which matters is not the connectedness of the average state. Alomari et al. (2024) show that tail-risk spillovers across green energy and equity markets substantially exceed their mean-based counterparts, particularly during crises, so that estimates calibrated on average co-movement understate systemic risk precisely when it is most consequential. Rahman and Hasan (2025) corroborate this asymmetry across a broader cross-section of sustainable assets and, in a result that anticipates one of the present paper's findings, document that green bonds carry lower tail connectedness than clean-energy equities. The relationship is also horizon-dependent: Uddin et al. (2025) find that policy uncertainty disrupts liquidity at short horizons while reshaping fundamental valuations at longer ones, echoing the frequency-domain evidence of Baruník and Křehlík (2018) that short- and long-run connectedness encode economically distinct mechanisms.

Crucially for portfolio purposes, the instruments composing the green finance ecosystem do not share a common connectedness profile—a heterogeneity that aggregate indices conceal. Green bonds occupy a central but comparatively inert position: Yuan et al. (2023) find that they impound carbon-market information more slowly and with greater attenuation than equities, and Ringstad and Tselika (2024) confirm in the frequency domain that their linkages with carbon and clean-energy markets concentrate in short-term bands. This insulation is conditional rather than absolute: Cao et al. (2024) document a safe-haven property that survives moderate monetary uncertainty but fails under simultaneous oil-market stress, while Zheng et al. (2024) and Bajra et al. (2025) establish, respectively, that monetary transmission to green bonds is state-dependent across rate-cycle phases and that green bonds attenuate portfolio vulnerability to geopolitical disruption. The monetary channel is itself layered: Fang et al. (2023) show that unconventional monetary policy compresses

green-bond spreads, and [Yin et al. \(2022\)](#) that monetary conditions govern the pace of green innovation. This monetary channel lies outside the present six-asset design—its interaction with green-finance connectedness is the subject of separate work—but it reinforces that green bonds respond to forces distinct from the carbon–equity core. Oil-market volatility introduces a further, structurally distinct force: [Ha and Nham \(2025\)](#) find that extreme volatility episodes in conventional energy markets generate outsized spillovers to green assets, and [Jiang and Chen \(2023\)](#) that the oil–green nexus is predominantly a short-run phenomenon. This division of the system into equity-based transmitters, fixed-income insulators, and an external oil-volatility benchmark is not incidental; it is the empirical regularity that a system-level, instrument-specific connectedness analysis is required to resolve.

2.3. Measuring Connectedness: Methodological Development

The forces described above are only as legible as the methods used to measure them, so the choice of method is substantive rather than merely technical. The governing paradigm descends from the variance-decomposition spillover framework of [Diebold and Yilmaz \(2012\)](#), which apportions each asset’s forecast-error variance among the shocks of every other asset, and from its network formulation ([Diebold & Yilmaz, 2014](#)), in which directional TO and FROM measures render the transmitter–receiver distinction operational. The time-varying-parameter refinement of [Antonakakis et al. \(2020\)](#) freed the framework from arbitrary rolling windows, allowing the connectedness structure to evolve continuously—an indispensable property for a sample dominated by discrete regulatory breaks.

A second, conceptual strand specifies what an increase in connectedness signifies. [Forbes and Rigobon \(2002\)](#) distinguish interdependence—persistently elevated linkages common to all states of the world—from contagion, a shock-conditional intensification of those linkages, and demonstrate that, because conditional correlations rise mechanically with volatility, contagion tests founded on unconditional correlations are biased. [Kaminsky et al. \(2003\)](#) establish that contagion episodes cluster around discrete policy and institutional events rather than gradual macroeconomic drift—a pattern that maps almost exactly onto the regulatory discontinuities of the EU ETS and that supplies the contagion logic formalized in Section 3. Spectral methods ([Baruník & Křehlík, 2018](#)) add a complementary decomposition, separating transient announcement effects from the persistent repricing of transition risk.

The framework adopted here inherits these advances while confronting the heteroskedasticity bias directly. The DCC-GARCH R^2 decomposed connectedness approach of [Cocca et al. \(2024\)](#) models conditional second moments explicitly and decomposes the bilateral variance explained (R^2) across every asset pair, yielding directional measures that are at once more granular and more interpretable than aggregate spillover indices ([Broadstock et al., 2022](#); [Gabauer, 2024](#)). Its rapid diffusion across asset classes—from clean-energy markets to currency–commodity systems ([Huang et al., 2025](#))—attests that bilateral R^2 decomposition recovers transmission pathways that aggregate measures suppress. We adopt it in preference to spectral VAR alternatives ([Baruník & Křehlík, 2018](#)) because its time-varying second-moment estimates map directly onto the dynamic hedging and portfolio problems that motivate the paper, leaving the frequency-domain extension to future work. By rendering conditional variance dynamic, the approach also converts network centrality from a static descriptor into a time-varying, estimable quantity—the object on which the paper’s portfolio results ultimately depend.

2.4. Portfolio Optimization and Connectedness-Aware Construction

The concluding strand concerns the mechanism by which connectedness structure becomes an allocation rule. [Markowitz \(1952\)](#) established the foundational principle that

the relevant risk of an asset is not its own variance but its covariance with the portfolio. Network portfolio theory generalizes this principle to a system of interacting assets: [Peralta and Zareei \(2016\)](#) and [Clemente et al. \(2019\)](#) represent the market as a directed graph whose weighted edges measure bilateral variance transmission, so that an asset's centrality—resolved into the in-degree it absorbs and the out-degree it exports, formally the FROM and TO measures of [Diebold and Yilmaz \(2014\)](#)—becomes the primary determinant of its role in a risk-efficient allocation.

The organizing result of this literature is an inverse relation between optimal weight and centrality: peripheral assets, weakly connected in both directions, systematically dominate risk-efficient portfolios, whereas central transmitters are penalized. [Broadstock et al. \(2022\)](#) render this operational through minimum-connectedness portfolios constructed from variance-decomposition matrices, and [Cocca et al. \(2024\)](#) sharpen it via R^2 -based bilateral decompositions that separate directional transmitters from receivers with greater precision. [Rachev et al. \(2008\)](#) supply the deeper rationale for abandoning variance as the sole criterion, arguing that an adequate risk measure must be asymmetric, heteroskedastic, and responsive to systemic co-movement. This progression—from covariance, to centrality, to a directional and time-varying measure of systemic embeddedness—motivates the Connectedness-Based Hierarchy Index (CBHI) developed in Section 1, which distills the bilateral R^2 decomposition into a single portfolio signal orthogonal to individual asset volatility.

2.5. Research Gap and Contribution of This Paper

Notwithstanding this accumulated evidence, no study has brought the bilateral R^2 framework of [Cocca et al. \(2024\)](#) to bear on a system that jointly comprises carbon-allowance instruments, Paris-aligned equities, clean-energy funds, green bonds, and oil volatility across the 2021–2026 period. The constituent pairwise relationships have been mapped in detail, but the directional architecture of the full system—which instruments originate systemic risk, which absorb it, and how those roles migrate across regulatory regimes—has not been characterized in a manner that separates equity-based from fixed-income green exposures. Nor is the 2021–2026 window merely a more recent sample: the 2022–2023 Russia–Ukraine energy crisis, the REPowerEU reform, and the early 2026 confluence of geopolitical pressure and EU ETS review combined to produce a sequence of structural breaks without precedent in the history of the EU ETS, one that demands a method equipped to track connectedness as it shifts.

The paper makes three contributions. First, it provides the first system-level characterization of the transmitter–receiver hierarchy across the major EU ETS stress episodes of the 2021–2026 period—namely the 2022–2023 Russia–Ukraine energy crisis compounded by the REPowerEU reform, and the early 2026 confluence of geopolitical uncertainty and ETS review pressure—quantifying how carbon allowance instruments, Paris-aligned equities, and clean energy funds differ in their systemic roles despite shared regulatory exposure. Second, it evaluates the risk-adjusted gains from connectedness-aware portfolio construction relative to a minimum-variance benchmark, documenting an annualized Sharpe ratio improvement from -1.066 to 0.148 and establishing that this performance differential is structural rather than sample-specific. Third, it introduces the Connectedness-Based Hierarchy Index (CBHI), a scalar, time-varying portfolio desirability index orthogonal to individual asset volatility (Kendall's $\tau \approx -0.20$) that operationalizes the transmitter–receiver hierarchy into actionable portfolio weights and reveals a structural tension in Paris-aligned mandates: the instrument most directly aligned with the low-carbon transition (CARB, $\text{CBHI} = 0.254$) is simultaneously the most systemically embedded asset in the network.

Section 3 synthesizes the strands reviewed above into a formal theoretical framework from which five testable hypotheses are derived.

3. Theoretical Framework and Hypothesis Development

Building on the literature reviewed in Section 2, the empirical design rests on three complementary theoretical frameworks from which five testable hypotheses are derived. The first is *network portfolio theory* (Clemente et al., 2019; Peralta & Zareei, 2016), developed in Section 2.4, which conceptualizes a financial system as a directed network in which nodes are assets and weighted edges measure bilateral variance transmission. Within this representation, network centrality corresponds to the FROM and TO connectedness measures of Diebold and Yilmaz (2014) estimated below, so that each asset's centrality is directly observable rather than assumed.

Network portfolio theory yields two primary predictions. The first is positional: since carbon prices exert dominant spillover effects on green finance under stress conditions (Su & Lian, 2025), KRBN, as the direct EU ETS allowance futures instrument, should occupy a central transmitter position in the connectedness network (H1). The second is performance-based and follows from the theory's central result that optimal portfolio weights are inversely related to centrality: strategies that underweight central transmitters while overweighting peripheral assets should deliver superior risk-adjusted performance relative to the minimum-variance benchmark (H2) (Broadstock et al., 2022; Cocca et al., 2024).

Financial contagion theory (Forbes & Rigobon, 2002; Kaminsky et al., 2003) distinguishes *interdependence* (persistently high cross-market linkages in all states of the world) from *contagion* (a significant increase in those linkages following a shock), and predicts that system-wide connectedness surges during episodes of acute EU ETS regulatory uncertainty (H3). This prediction is consistent with the empirical regularities reviewed in Section 2.2: overall integration intensifies during episodes of global financial stress (Dogan et al., 2022), tail-risk spillovers exceed mean spillovers during crises (Alomari et al., 2024), and contagion episodes cluster around discrete policy events (Kaminsky et al., 2003). As discussed in Section 2.2, testing H3 credibly requires correcting for the heteroskedasticity bias identified by Forbes and Rigobon (2002), which the break-corrected DCC-GARCH R^2 apparatus of Section 4 is designed to address.

The Brussels Effect (Redondo Alamillos & de Mariz, 2022) supplies the transmission and amplification mechanism behind H3. Because European regulatory and environmental standards propagate globally through capital market linkages and multinational corporate compliance, EU ETS policy discontinuities generate connectedness surges that extend directly to internationally traded assets structurally exposed to carbon-transition risk, including the US-listed ETFs KRBN and ICLN.

Confronting these frameworks with instrument-specific structures yields our remaining two hypotheses. The fixed-income insulation property documented by Cao et al. (2024) and Yuan et al. (2023), and corroborated in the frequency domain by Ringstad and Tselika (2024), predicts that green bonds (GRNB) occupy a peripheral, net receiver position in the system (H4). Finally, Paris-aligned mandates concentrate exposure on precisely the assets most sensitive to EU climate regulation. Given the centrality of carbon-linked instruments under stress (Su & Lian, 2025) and the extra-territorial propagation of EU regulatory shocks (Redondo Alamillos & de Mariz, 2022), the instrument most directly aligned with the low-carbon transition should also be among the most systemically embedded, implying that CARB records a low CBHI despite high regulatory climate alignment (H5). These five hypotheses are assessed jointly in Section 7.2, and the conclusion returns to our three theoretical frameworks to evaluate which predictions the empirical data support and where they require qualification.

4. Methodology

4.1. DCC-GARCH Univariate Stage

Unmodelled structural breaks cause GARCH estimates to absorb level and variance shifts as spurious parameter persistence, systematically overstating volatility half-lives (Hillebrand, 2005; Mikosch & Stărică, 2004). We apply the Bai and Perron (2003) multiple break test to each series twice—once on demeaned returns (mean shifts) and once on squared demeaned returns (variance shifts)—retaining the union of detected dates as step dummy regressors in the GARCH specification (Hamilton, 1994).

Following the structural break detection step described above, each return series is fitted by an ARMA(1, 0)–GARCH specification. Model selection relies on an adjusted Bayesian Information Criterion (BIC) proposed by Antonakakis et al. (2020) and Cocca et al. (2024):

$$\text{BIC}_{\text{adj}} = -2 \ln(\hat{\mathcal{L}}) + k^* \ln(T), \quad k^* = k + n_{\text{insig}} + n_{\text{fail}} \quad (1)$$

where $\hat{\mathcal{L}}$ is the maximized value of the likelihood function and k^* is the penalization term comprising the number of model parameters k , the number of individually insignificant parameters n_{insig} (at the 5% level), and the number of failed misspecification tests n_{fail} (at the 5% level). The misspecification tests entering n_{fail} are the Sign Bias test (R. F. Engle & Ng, 1993), the weighted Li-Mak portmanteau test (Fisher & Gallagher, 2012), the 1% Value-at-Risk coverage test (P. F. Christoffersen, 1998), the 1% Conditional Value-at-Risk test (McNeil & Frey, 2000), and the 1% duration-based VaR test (P. Christoffersen & Pelletier, 2004). The candidate set comprises five variance specifications—sGARCH (Bollerslev, 1986), GJR-GARCH (Glosten et al., 1993), eGARCH (Nelson, 1991), TGARCH, and AVGARCH (Hentschel, 1995)—each nested within the omnibus specification of Hentschel (1995):

$$h_t^{\lambda/2} = \omega + \alpha h_{t-1}^{\lambda/2} (|z_{t-1} - \eta| - \gamma(z_{t-1} - \zeta))^{\delta} + \beta h_{t-1}^{\lambda/2} \quad (2)$$

The nested models correspond to the following parameter restrictions: sGARCH ($\lambda = \delta = 2, \gamma = \eta = \zeta = 0$); GJR-GARCH ($\lambda = \delta = 2, \eta = \zeta = 0, \gamma$ free); TGARCH ($\lambda = \delta = 1, \eta = \zeta = 0, \gamma$ free); AVGARCH ($\lambda = \delta = 1, \gamma, \eta, \zeta$ free); and eGARCH, obtained as the limiting case $\lambda \rightarrow 0$ (logarithmic transformation of the conditional variance) with $\delta = 1$ (Hentschel, 1995). The iGARCH model (R. F. Engle & Bollerslev, 1986) is excluded because it imposes unit persistence by construction ($\alpha_1 + \beta_1 = 1$), which is inconsistent with the covariance-stationarity assumption required by the DCC second stage (R. Engle, 2002). Six error distributions are considered: the Gaussian or normal distribution (Gauss, 1809), the Student- t (Student, 1908), the skewed Student- t (Fernández & Steel, 1998), the Generalized Error Distribution (GED) (Nelson, 1991), the skewed Generalized Error Distribution (sGED) (Fernández & Steel, 1998), and the skewed normal (Azzalini, 1985). All models are estimated by Quasi-Maximum Likelihood (Bollerslev & Wooldridge, 1992) using the rugarch package (Ghalanos, 2024).

4.2. DCC-GARCH and R^2 Connectedness

The second stage estimates time-varying conditional correlations via the DCC model of R. Engle (2002). The conditional covariance matrix is decomposed as $\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$, where $\mathbf{D}_t$ contains the first-stage conditional standard deviations and $\mathbf{R}_t$ follows:

$$\mathbf{Q}_t = (1 - a - b) \bar{\mathbf{Q}} + a \hat{\mathbf{z}}_{t-1} \hat{\mathbf{z}}'_{t-1} + b \mathbf{Q}_{t-1}, \quad \mathbf{R}_t = \text{diag}(\mathbf{Q}_t)^{-1/2} \mathbf{Q}_t \text{diag}(\mathbf{Q}_t)^{-1/2} \quad (3)$$

Following [Cocca et al. \(2024\)](#), we exploit the formal equivalence between the DCC covariance structure and the R^2 of a multivariate linear regression to construct a dynamic conditional R^2 for each series:

$$R_{i,t}^2 = 1 - \frac{[\mathbf{H}_t^{-1}]_{ii}^{-1}}{H_{ii,t}} \quad (4)$$

This measure captures the time-varying proportion of series i 's conditional variance explained by the remaining markets. Pairwise connectedness between series i and j equals the squared dynamic conditional correlation:

$$\text{PCI}_{ij,t} = R_{ij,t}^2 = \frac{H_{ij,t}^2}{H_{ii,t} \cdot H_{jj,t}} \quad (5)$$

From these pairwise measures, FROM, TO, NET, and Total Connectedness Index (TCI) are constructed following [Cocca et al. \(2024\)](#). A series with $\text{NET}_{i,t} > 0$ is a net transmitter; $\text{NET}_{i,t} < 0$ indicates a net receiver. The TCI aggregates system-wide interdependence into a single scalar summarizing the overall strength of cross-market transmission at each point in time.

4.3. Portfolio and Hedging Analysis

Estimating dynamic conditional covariances is not an end in itself. The practical value of the DCC-GARCH framework lies in translating time-varying second moments into actionable portfolio decisions. Before specifying any formula, it is useful to distinguish three roles a financial asset can play in a portfolio context ([Baur & Lucey, 2010](#)). A *diversifier* reduces portfolio variance on average but offers no systematic protection during stress episodes. A *hedge* is negatively correlated—or uncorrelated—with the benchmark asset on average, offsetting losses in normal conditions. A *safe haven* preserves that hedging property precisely when it is most needed, during periods of extreme joint losses. These distinctions matter in the present system because carbon instruments, clean energy equities, and green bonds differ not only in their average return profiles but in the structure of their co-movement with each other.

Two categories of risk are relevant when constructing portfolios from these assets. The first is individual variance: the portion of an asset's return fluctuation attributable to its own idiosyncratic dynamics. The second, and more consequential for system-level investors, is systemic variance propagation: the degree to which an asset imports shocks from the rest of the network or exports its own shocks to other assets. Classical mean-variance optimization addresses only the first category through the covariance matrix. The connectedness-based strategies introduced below address both, exploiting the R^2 decomposition to penalize assets that are structurally embedded in the core of the transmission network.

Bivariate hedge ratios. For an investor holding a long position in asset i and wishing to offset that exposure with a short position in asset j , the optimal hedge ratio of [Kroner and Sultan \(1993\)](#) is:

$$\beta_{ij,t} = \frac{H_{ij,t}}{H_{jj,t}} \quad (6)$$

This ratio measures how many dollars must be shorted in asset j to neutralize one dollar of long exposure in asset i , given the conditional covariance structure at time t . A hedge ratio close to zero signals that asset j provides little offset to movements in asset i ; a ratio close to one signals near-perfect co-movement and thus near-complete hedging potential. Hedging effectiveness is measured by the variance reduction of [Ederington \(1979\)](#):

$$\text{HE}_i = 1 - \frac{\text{var}(r_p)}{\text{var}(r_i)} \quad (7)$$

where r_p is the hedged portfolio return and r_i the unhedged return. A value approaching one indicates near-complete variance elimination; a value near zero indicates no improvement over the unhedged position.

Optimal portfolio weights. Under zero expected returns and no-short-selling constraints, the variance-minimizing weight assigned to asset i in a two-asset portfolio with asset j is (Kroner & Ng, 1998):¹

$$w_{ij,t} = \frac{H_{jj,t} - H_{ij,t}}{H_{ii,t} - 2H_{ij,t} + H_{jj,t}}, \quad w_{ij,t} \in [0, 1] \quad (8)$$

This weight shifts dynamically as the conditional covariance structure evolves. When assets become more correlated, the formula automatically reduces the weight on the higher-variance asset; when correlations fall, it reallocates toward fuller diversification. Sensitivity to this assumption is addressed in Appendix C, which reports Sharpe ratios under proportional round-trip costs of 5, 10, and 25 basis points per daily rebalancing and under monthly rebalancing (zero cost). The MVP–MCP ranking is preserved at every cost level tested. At 25 basis points, the MCP turns marginally negative, reflecting its higher turnover, while the MCCP and MCRP/MR2P retain positive Sharpe ratios under all scenarios; under monthly rebalancing, the MCP records its best performance.

Global minimum risk portfolios. A system of six assets requires a fully multivariate approach. Five portfolio strategies are implemented, each solving the same constrained minimization:

$$\underset{w_t}{\operatorname{argmin}} \quad w_t' P_t w_t \quad \text{subject to} \quad w_t' \mathbf{1} = 1, \quad 0 \leq w_t \leq 1 \quad (9)$$

The strategies differ only in the choice of risk matrix P_t are presented in the Table 1:

Table 1. Portfolio strategies, risk matrices, and minimized risk concepts.

Strategy	Risk Matrix P_t	Risk Concept Minimized
MVP	$\mathbf{H}_t$	Portfolio return variance
MCP	$\mathbf{R}_t$	Average pairwise correlations
MCCP	$\mathbf{PCI}_t^C$	Pairwise connectedness (correlation-based)
MCRP	$\mathbf{PCI}_t^R$	Pairwise connectedness (regression-based)
MR2P	$\mathbf{R}_t^{2,d}$	Decomposed R^2 connectedness

The MVP is the classical benchmark of Markowitz (1952). The MCP substitutes the correlation matrix for the covariance matrix, placing equal weight on the direction of co-movement rather than its magnitude (Broadstock et al., 2022). The three connectedness-based strategies—MCCP, MCRP, and MR2P—replace covariance-based risk matrices with connectedness matrices derived from the variance decomposition framework of Antonakakis et al. (2020), Broadstock et al. (2022), and Cocca et al. (2024), respectively. These strategies penalize not only assets that co-move with others but assets that *propagate* shocks to others—a conceptually distinct and policy-relevant risk dimension. The MR2P strategy, which uses the decomposed R^2 connectedness matrix, is the most direct operationalization of the transmitter–receiver hierarchy documented in Section 6.3. Out-of-sample performance is evaluated via annualized Sharpe ratios computed on standard deviation, VaR, and CVaR bases, with statistical inference using the CUSUM–Fisher method of the ConnectednessApproach package (Gabauer, 2024).

MCRP and MR2P converge to identical allocations in this system by construction; the explanation is provided in the notes to Tables 2 and 3.

Table 2. Portfolio Performance Metrics.

	MVP	MCP	MCCP	MCRP/MR2P
Return (Ann.)	−0.0613	0.0480	0.0358	0.0282
StdDev (Ann.)	0.0576	0.3231	0.2544	0.2436
Sharpe (StdDev)	−1.066	0.148	0.141	0.116
Sharpe (VaR)	−9.722	1.715	1.556	1.277
Sharpe (CVaR)	−7.153	1.085	1.030	0.849
IR vs. GRNB	−0.911	0.254	0.276	0.258

Notes: MVP: Minimum Variance Portfolio (Markowitz, 1952). MCP: Minimum Correlation Portfolio (Broadstock et al., 2022). MCCP: minimizes pairwise PCI^C (Broadstock et al., 2022). MCRP and MR2P: minimize R^2 connectedness (Cocca et al., 2024). IR: Information Ratio vs. GRNB benchmark. Return and volatility are annualised arithmetically ($\times 252$ and $\times \sqrt{252}$), zero risk-free rate. Sharpe (VaR) and Sharpe (CVaR) divide the annualised return by the historical daily 5% Value-at-Risk and Expected Shortfall, respectively. MCRP and MR2P produce identical allocations by construction: in the bivariate DCC-GARCH pipeline adopted here, the regression-based pairwise R^2 coincides with the squared dynamic conditional correlation, so the two risk matrices are not separately identifiable and both strategies are implemented on the same decomposed R^2 connectedness matrix. The two strategies are therefore reported jointly in a single column; the distinction is meaningful in higher-dimensional multivariate systems (Cocca et al., 2024), where the regression of asset i on all remaining assets decomposes into bilateral contributions distinct from squared pairwise correlations.

Table 3. Mean Portfolio Weight Allocations by Strategy (%).

Asset	MVP	MCP	MCCP	MCRP/MR2P
GRNB	88.1	17.8	23.3	21.4
ICLN	0.1	8.9	6.3	13.0
KRBN	3.9	8.9	13.0	13.3
CARB	1.4	16.3	13.6	13.4
IQQH	6.1	16.6	19.2	15.7
OVX	0.4	31.6	24.6	23.2
Total	100.0	100.0	100.0	100.0

Notes: Mean portfolio weights (%) averaged over the rolling estimation window of 252 trading days, rebalanced daily. MVP: Minimum Variance Portfolio (Markowitz, 1952). MCP: Minimum Correlation Portfolio (Broadstock et al., 2022). MCCP: minimizes pairwise PCI^C (Broadstock et al., 2022). MCRP and MR2P: minimize R^2 connectedness (Cocca et al., 2024). Portfolio weights attributed to OVX represent notional allocations to the oil volatility channel. MCRP and MR2P allocations are identical by construction (see the notes to Table 2).

Connectedness-Based Hierarchy Index. The transmitter–receiver hierarchy estimated from the R^2 decomposition is multidimensional by construction: each asset is simultaneously characterized by a FROM measure, a TO measure, and a NET position. Translating this three-dimensional profile into an actionable portfolio signal requires a scalar summary that captures both directional dimensions simultaneously. We introduce the *Connectedness-Based Hierarchy Index* (CBHI), defined for asset i at time t as:

$$CBHI_{i,t} = \frac{1 - FROM_{i,t}}{TO_{i,t} + \varepsilon}, \quad \varepsilon = 0.01 \quad (10)$$

where $FROM_{i,t}$ and $TO_{i,t}$ are expressed as decimals and ε is a regularization constant preventing division by zero during low-connectedness episodes. The numerator $1 - FROM_{i,t}$ measures the share of asset i 's conditional variance that is self-generated rather than imported from the system, rewarding assets insulated from external shocks. The denominator $TO_{i,t}$ penalizes assets that are dominant exporters of systemic variance to others. The ratio is therefore high for structural diversifiers and low for systemic transmitters, providing a scalar that is monotonically consistent with the network-portfolio theory of Peralta and Zareei (2016) and Clemente et al. (2019), who establish that optimal portfolio weights are negatively related to network centrality. The FROM and TO measures correspond formally to the in-degree and out-degree centrality of each node in the variance-decomposition network of Diebold and Yilmaz (2014), grounding the CBHI in the directed-network representation of systemic risk. Unlike the bivariate hedge ratio of Kroner and Sultan (1993) or

the hedging effectiveness of Ederington (1979), which are inherently pairwise, the CBHI captures each asset's systemic position within the full transmission network. Two thresholds partition the CBHI distribution into interpretable regimes. The unit threshold ($CBHI = 1$) is theoretically grounded: above it, self-generated variance exceeds exported variance, identifying structural diversifiers. The lower threshold ($CBHI = 0.40$) corresponds to the 33rd percentile of the empirical distribution, below which assets are classified as dominant systemic transmitters. The CBHI is dynamic by construction: updated at each t from rolling DCC-GARCH estimates, it evolves in real time as the connectedness structure shifts across market regimes, providing a forward-looking diagnostic indicator directly responsive to the regulatory and geopolitical shocks that drive TCI surges. Full empirical application is in Section 6.5.

The empirical analysis proceeds in five stages: Stage 1 fits univariate GARCH models with Bai–Perron dummies; Stage 2 estimates bivariate DCC-GARCH models; Stage 3 applies the R^2 bilateral decomposition; Stage 4 constructs the five portfolio strategies; and Stage 5 computes the CBHI (Equation (10)).

5. Data and Variables

5.1. Sample Construction and Variable Definitions

The empirical analysis draws on daily closing price data for six financial instruments spanning carbon allowance instruments, Paris-aligned equities, clean energy funds, green bonds, and oil volatility, all of which carry significant exposure to European carbon-pricing regulation. All data are sourced from Yahoo Finance. The sample runs from 2 September 2021 to 13 March 2026, yielding 1035 trading-day observations. The sample start date is determined by the availability of KRBN, the most recently launched instrument. KRBN was listed on 22 July 2020; the sample begins on 2 September 2021, providing at least one year of price history and average daily trading volume consistently exceeding one million shares—the liquidity threshold applied. All price series are converted to continuously compounded daily log returns:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \quad (11)$$

where $P_{i,t}$ denotes the closing price of series i on day t . The six instruments are selected to cover the four channels through which European carbon-pricing risk propagates to financial markets. KRBN and CARB represent the carbon-pricing channel directly—the former through allowance futures, the latter through the equity valuations of carbon-transition firms—and together capture both the regulatory and corporate dimensions of EU ETS price dynamics. ICLN and IQQH represent the clean energy equity channel: they are the primary beneficiaries or victims of the carbon price signal (Dogan et al., 2022), and including both the US-listed and EU-listed variants allows the analysis to examine whether geographic listing generates meaningful differences in how clean energy equities absorb carbon market shocks. GRNB represents the green fixed-income channel, whose insulation properties relative to carbon and equity markets remain debated in the literature (Cao et al., 2024). Finally, OVX captures the fossil-fuel uncertainty channel: elevated oil volatility dampens renewable investment sentiment even when carbon prices are simultaneously rising (Ha & Nham, 2025; Yuan et al., 2023); its direction of transmission within the system is an empirical question this study is designed to answer.² Table 4 summarizes the six instruments.

Table 4. Sample Instruments and Market Segments.

Ticker	Instrument Name	Exchange	Market Segment
<i>Green Finance</i>			
GRNB	VanEck Green Bond ETF	NYSE Arca	Green fixed income
ICLN	iShares Global Clean Energy ETF	NASDAQ	Clean energy equity (US)
IQQH	iShares Global Clean Energy UCITS ETF	Frankfurt	Clean energy equity (EU)
<i>Carbon Markets</i>			
KRBN	KraneShares Global Carbon Strategy ETF	NYSE Arca	Carbon allowance futures
CARB	iShares MSCI Carbon All Sectors PA UCITS ETF	LSE	Carbon-transition equity (Paris-Aligned)
<i>Energy Uncertainty</i>			
OVX	CBOE Crude Oil Volatility Index	CBOE	Oil market uncertainty

Notes: PA: Paris-Aligned. LSE: London Stock Exchange. CARB is an MSCI Paris-Aligned equity ETF tracking firms with reduced carbon footprints; it is not a direct carbon allowance or futures instrument. Its inclusion captures firm-level exposure to carbon repricing risk alongside the allowance-futures-based KRBN. CARB (ticker: CARB.L) is downloaded in GBP and IQQH (ticker: IQQH.DE) in EUR; the remaining four instruments are in USD. Returns are computed in local listing currencies, consistent with standard practice in the volatility connectedness literature (Cocca et al., 2024; Diebold & Yilmaz, 2012). On a daily horizon, EUR/USD and GBP/USD fluctuations average 0.3–0.5 percent (measured from daily EUR/USD and GBP/USD returns over the sample period), substantially smaller than the annualized volatilities of the assets themselves (CARB: 0.44; IQQH: 0.26); the currency component is therefore unlikely to materially distort the estimated connectedness structure (Diebold & Yilmaz, 2015).

5.2. Preliminary Data Analysis and Statistical Tests

Table 5 presents descriptive statistics and serial dependence diagnostics for the six return series. Mean daily returns shown as 0.000 are rounded to three decimal places. Annualised values are GRNB = −3.4%, ICLN = −6.5%, KRBN = −7.6%, CARB = +1.0%, IQQH = −5.6%, OVX = +25.8%, consistent with weak-form efficiency at daily frequency. Variance differs considerably across instruments: OVX records the highest daily variance (0.004), reflecting elevated oil market uncertainty, while GRNB exhibits near-zero variance, consistent with the stable behavior of green bond returns.

Table 5. Descriptive Statistics and Serial Dependence Diagnostics.

	GRNB	ICLN	KRBN	CARB	IQQH	OVX
Mean	0.000 (0.177)	0.000 (0.630)	0.000 (0.676)	0.000 (0.924)	0.000 (0.635)	0.001 (0.693)
Variance	0.000	0.000	0.000	0.001	0.000	0.004
Skewness	−0.116 * (0.091)	0.235 *** (0.003)	−1.966 *** (0.000)	−0.619 *** (0.000)	0.161 * (0.029)	1.088 *** (0.000)
Ex.Kurtosis	1.554 *** (0.000)	1.388 *** (0.000)	19.204 *** (0.000)	5.237 *** (0.000)	1.957 *** (0.000)	11.481 *** (0.000)
JB	106.492 *** (0.000)	92.602 *** (0.000)	16,571.806 *** (0.000)	1248.786 *** (0.000)	169.582 *** (0.000)	5888.809 *** (0.000)
ERS	−10.254 *** (0.000)	−4.921 *** (0.000)	−4.889 *** (0.000)	−4.109 *** (0.000)	−4.663 *** (0.000)	−1.736 [†] (0.007)
Q(20)	29.879 (0.072)	33.885 * (0.027)	29.101 (0.086)	22.997 (0.289)	23.176 (0.280)	53.866 *** (0.000)
Q ² (20)	174.812 *** (0.000)	62.693 *** (0.000)	33.195 *** (0.001)	232.239 *** (0.000)	79.120 *** (0.000)	126.094 *** (0.000)
<i>Kendall rank correlation matrix</i>						
GRNB	1.000	0.229 ***	0.043 **	0.025	0.122 ***	−0.013
ICLN	0.229 ***	1.000	0.086 ***	0.060 ***	0.567 ***	−0.154 ***
KRBN	0.043 **	0.086 ***	1.000	0.731 ***	0.072 ***	−0.081 ***
CARB	0.025	0.060 ***	0.731 ***	1.000	0.068 ***	−0.069 ***
IQQH	0.122 ***	0.567 ***	0.072 ***	0.068 ***	1.000	−0.126 ***
OVX	−0.013	−0.154 ***	−0.081 ***	−0.069 ***	−0.126 ***	1.000

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels. *p*-values in parentheses. [†] OVX statistic (−1.736) rejects at 10% but not 5%.

All six series deviate strongly from normality. Excess kurtosis is statistically significant across all assets, ranging from 1.388 (ICLN) to 19.204 (KRBN), and the Jarque–Bera (JB) test rejects normality at the 1% level for every series. The skewness estimates are economically meaningful: OVX exhibits strong positive skewness (1.088), capturing the tendency of oil volatility to spike during stress episodes, while KRBN (−1.966) and CARB (−0.619) display pronounced negative skewness. These distributional features justify the use of non-Gaussian error distributions in the GARCH estimation stage. All series are confirmed stationary by the Elliott–Rothenberg–Stock (ERS) test. The $Q^2(20)$ statistics are highly significant for all six series (ranging from 33.195 for KRBN to 232.239 for CARB), providing strong evidence of volatility clustering and supporting the use of GARCH-family models.

The Kendall rank correlation matrix reveals a clear two-bloc dependence structure. Within the carbon bloc, KRBN and CARB are the most tightly linked pair in the system ($\tau = 0.731$, significant at 1%), reflecting their near-perfect co-movement under the common EU ETS discipline. Within the clean energy equity bloc, ICLN and IQQH share similarly strong dependence ($\tau = 0.562$). GRNB stands apart from both groups, showing only moderate correlations with clean energy equities ($\tau = 0.235$ with ICLN; $\tau = 0.122$ with IQQH) and no significant relationship with carbon assets, consistent with green bond returns being driven primarily by credit and interest rate dynamics. OVX exhibits negative and statistically significant rank correlations with all other assets—including ICLN ($\tau = -0.158$), KRBN ($\tau = -0.081$), and CARB ($\tau = -0.067$)—indicating that increases in oil market uncertainty are systematically associated with declines across the clean energy and carbon market spectrum. However, the negative rank correlations reflect a contemporaneous statistical pattern consistent with common macro-financial exposures rather than directional variance transmission within the carbon–clean energy network.

6. Empirical Results

The empirical results are organized in five steps. Section 6.1.1 identifies structural break dates across all six return series and reports the selected univariate GARCH specifications with their parameter estimates and diagnostic tests. Section 6.2 presents the bivariate DCC-GARCH parameter estimates and dynamic conditional correlations. Section 6.3 develops the R^2 decomposed connectedness analysis, documenting the transmitter–receiver hierarchy and its time-varying dynamics across EU ETS stress episodes. Section 6.4 evaluates bivariate hedge ratios—distilling the most economically informative bilateral pairs, with the full thirty-pair panel reported in Appendix A—optimal portfolio weights, and the risk-adjusted performance of the five minimum connectedness strategies relative to the minimum-variance benchmark. Section 6.5 introduces the Connectedness-Based Hierarchy Index (CBHI) and assesses the robustness of the resulting hierarchy.

6.1. Univariate GARCH Estimation Results

6.1.1. Structural Break Detection

Before estimating the time-varying risk matrices, we first test for the presence of structural breaks in the variance of each return series. The presence of such breaks can significantly affect the stability of portfolio weights and the interpretation of connectedness measures. To this end, we employ the Bai and Perron (2003) sequential testing procedure, which allows for multiple breakpoints in a univariate time series. The method selects the optimal number of breaks using the Bayesian Information Criterion (BIC) and sequentially tests for structural changes in the mean and variance of the series.

Table 6 reports the number and timing of the identified structural breaks for each of the six series under consideration. The results indicate that the green bond index (GRNB) exhibits the highest number of breaks (four), with the earliest break occurring in early 2022,

coinciding with the onset of the geopolitical turmoil in Eastern Europe. For most other series, a single significant break is detected around the fourth quarter of 2022, which aligns with the tightening of global monetary policy and the subsequent repricing of carbon and energy markets. Notably, the OVX series shows two breaks, with the second occurring in late September 2024, reflecting recent spikes in oil price uncertainty.

Table 6. Structural Break Detection Results: Bai–Perron Procedure.

Series	No. Breaks	Break Date(s)
GRNB	4	25 February 2022; 20 October 2022; 10 November 2022; 14 December 2023
ICLN	1	10 November 2022
KRBN	1	4 January 2023
CARB	1	27 October 2022
IQQH	1	28 July 2022
OVX	2	10 February 2022; 25 September 2024

Notes: Break dates are detected via the Bai–Perron procedure (Bai & Perron, 2003) applied separately to demeaned returns (mean shifts) and squared demeaned returns (variance shifts). The February 2022 breaks in GRNB and OVX coincide with the outbreak of the Russia–Ukraine conflict, which triggered an energy price shock that propagated across carbon, clean energy, and bond markets simultaneously. The October–November 2022 cluster of breaks across GRNB, CARB, and ICLN reflects the peak of European energy supply stress and the EU emergency response interventions in energy markets. The January 2023 break in KRBN corresponds to the first EU ETS auction suspension and the announcement of the REPowerEU initiative, which materially altered the trajectory of carbon allowance prices. The July 2022 break in IQQH coincides with the European heatwave and drought episode that reduced hydropower output and temporarily elevated clean energy equity uncertainty. The December 2023 break in GRNB reflects the ECB pivot away from quantitative tightening, which altered the discount rate environment for fixed-income instruments. The September 2024 break in OVX captures partial energy market stabilization following the normalization of European gas storage levels.

6.1.2. Model Selection and Specification

Table 7 presents the selected univariate GARCH specifications. Results reflect fundamentally different volatility dynamics across the six series. The symmetric sGARCH is retained only for GRNB, consistent with its fixed-income nature and lower sensitivity to directional sentiment shocks. The eGARCH governs ICLN, KRBN, and CARB, consistent with leverage effects whereby negative shocks generate disproportionately larger volatility responses, while GJR-GARCH is selected for IQQH and OVX, capturing the same asymmetric pattern through a threshold mechanism better suited to equity indices and implied volatility series. The skewed Student-*t* distribution is preferred for four series; GED is selected for GRNB and CARB. Structural break dummies are incorporated into all final specifications, with GRNB requiring four breaks—the highest in the system—reflecting the multiple regulatory and geopolitical discontinuities affecting the green bond market.

Table 7. Univariate GARCH Model Selection.

Series	Model	Distribution	BIC _{adj}	Breaks
GRNB	sGARCH	GED	−8.6691 *	4
ICLN	eGARCH	sstd	−5.1840 *	1
KRBN	eGARCH	sstd	−5.2879 *	1
CARB	eGARCH	GED	−4.5310 *	1
IQQH	gjrGARCH	sstd	−5.4150 *	1
OVX	gjrGARCH	sstd	−2.9925 *	2

Notes: Selected via the adjusted BIC of Antonakakis et al. (2020) and Cocca et al. (2024). * denotes the BIC value of the selected model. sstd: skewed Student-*t* distribution of Fernández and Steel (1998). GED: Generalized Error Distribution (Nelson, 1991).

6.1.3. Parameter Estimates and Diagnostic Tests

Table 8 presents the full diagnostic battery including the residual diagnostics and misspecification tests. All six models record zero failures, confirming that the conditional

distribution and risk forecasts are correctly specified across the full system. For CARB, the serial dependence tests $LB^2(20)$ and ARCH-LM reject, an outcome that is mechanically explained by the October 2022 structural break: as shown by Mikosch and Stărică (2004) and Bollerslev and Wooldridge (1992), portmanteau tests on squared residuals over-reject when step dummies have absorbed part of the volatility clustering without fully eliminating short-run serial dependence at a 20-lag horizon. Since none of the five misspecification tests reject for CARB, this outcome does not constitute a model failure and has no bearing on the adjusted BIC selection criterion.

Table 8. Univariate GARCH Residual Diagnostics and Misspecification Tests.

Series	LB(20)	LB ² (20)	ARCH-LM	Sign Bias	WARCH(20)	VaR 1%	CVaR 1%	VaR Dur	Fails	Pers.
GRNB	0.818	0.182	0.179	0.720	0.966	0.870	0.664	0.975	0	0.9973
ICLN	0.393	0.868	0.888	0.782	0.999	0.870	0.314	0.620	0	0.9466
KRBN	0.791	1.000	1.000	0.625	1.000	0.870	0.131	0.851	0	0.9466
CARB	0.860	0.005	0.003	0.413	0.142	0.870	0.612	0.944	0	0.9429
IQQH	0.498	0.639	0.621	0.620	0.993	0.870	0.594	0.750	0	0.9870
OVX	0.185	1.000	1.000	0.887	1.000	0.870	0.246	0.478	0	0.9200

Notes: The residual diagnostic tests: LB(20) and LB²(20) denote the Ljung–Box test (Ljung & Box, 1978) on standardized residuals and squared standardized residuals at lag 20, respectively. ARCH-LM is the R. F. Engle (1982) LM test for autoregressive conditional heteroskedasticity. LB(20), LB²(20), and ARCH-LM are not included in n_{fail} and do not affect model selection; they are reported as supplementary checks on residual serial dependence. The misspecification tests: the Sign Bias test of R. F. Engle and Ng (1993); the weighted Li-Mak portmanteau test of Fisher and Gallagher (2012); the 1% Value-at-Risk coverage test of P. F. Christoffersen (1998); the 1% Conditional Value-at-Risk test of McNeil and Frey (2000); and the 1% duration-based VaR test of P. Christoffersen and Pelletier (2004). Fails denotes the number of misspecification tests rejected at the 5% significance level following Antonakakis et al. (2020) and Cocca et al. (2024). A value of zero confirms model adequacy, indicating that no misspecification is detected in the estimated conditional variance specification. Pers.: GARCH persistence. For sGARCH, Pers. = $\hat{\alpha}_1 + \hat{\beta}_1$; for eGARCH, Pers. = $\hat{\beta}_1$; and for GJR-GARCH, Pers. = $\hat{\alpha}_1 + \hat{\beta}_1 + \hat{\gamma}_1\kappa$, where κ is the probability weight of negative shocks implied by the fitted conditional distribution.

Table 9 reports parameter estimates. Three findings stand out. First, volatility persistence is uniformly high ($\hat{\beta}_1 \in [0.863, 0.956]$), indicating that shocks remain embedded in conditional volatility for extended periods. Second, leverage effects are pervasive. For the three eGARCH series, CARB ($\hat{\gamma}_1 = +0.202$), KRBN ($\hat{\gamma}_1 = +0.159$), and ICLN ($\hat{\gamma}_1 = +0.049$) all record positive and significant asymmetry coefficients, indicating that negative shocks generate disproportionately larger volatility responses than positive shocks of the same magnitude—the canonical leverage effect (Nelson, 1991). OVX, estimated as gjrGARCH, exhibits a negative asymmetry coefficient ($\hat{\gamma}_1 = -0.232$), capturing the inverse pattern whereby positive shocks (spikes in oil market fear) amplify volatility more than negative shocks. IQQH shows no statistically significant asymmetry. Third, all series exhibit fat tails (GED: $\hat{\nu} \in [1.460, 1.655]$; Student- t : $\hat{\nu} \in [5.069, 8.416]$) and non-unity skewness ($\hat{\xi} \in [0.922, 1.297]$), indicating that a Gaussian specification would substantially underestimate tail risk across the system.

6.2. Bivariate DCC-GARCH Estimation Results

DCC Parameter Estimates

The bivariate DCC parameter estimates in Table 10 reveal substantial heterogeneity in conditional correlation dynamics. Most pairs exhibit high persistence ($\hat{\alpha} + \hat{\beta} > 0.95$), with near-zero $\hat{\alpha}$ coefficients. The ICLN/IQQH pair shows low persistence (0.184), with $\hat{\alpha} = 0.124$, implying rapid correlation adjustment. The KRBN/CARB pair displays moderate persistence (0.883), reflecting the near-simultaneous but not identical response of KRBN and CARB to EU ETS regulatory shocks. Estimated degrees of freedom approaching 50 for GRNB/CARB and CARB/IQQH suggest near-Gaussian co-movements, whereas

lower values for ICLN/IQQH (6.013) and KRBN/CARB (7.997) point to heavy-tailed joint behavior.

Table 9. GARCH Parameter Estimates.

	GRNB	ICLN	KRBN	CARB	IQQH	OVX
Model	sGARCH	eGARCH	eGARCH	eGARCH	gjrGARCH	gjrGARCH
Dist.	GED	sstd	sstd	GED	sstd	sstd
μ	−0.0001 **	−0.0002	0.0015 ***	0.0002	0.0004	0.0022
SE	[0.0001]	[0.0013]	[0.0005]	[0.0007]	[0.0014]	[0.0049]
α_1	−0.0435	−0.0345	−0.0172	−0.0170	−0.0168	−0.0581 *
SE	[0.0320]	[0.0306]	[0.0305]	[0.0155]	[0.0309]	[0.0319]
ω	0.0000	−0.4038 ***	−0.3964 ***	−0.3757 ***	0.0000	0.0002
SE	[0.0000]	[0.0058]	[0.0582]	[0.1209]	[0.0000]	[0.0001]
α_1	0.0410 ***	−0.0208	−0.0019	−0.0156	0.0239 **	0.1839 ***
SE	[0.0103]	[0.0195]	[0.0294]	[0.0248]	[0.0120]	[0.0480]
β_1	0.9563 ***	0.9466 ***	0.9466 ***	0.9429 ***	0.9536 ***	0.8632 ***
SE	[0.0099]	[0.0010]	[0.0073]	[0.0164]	[0.0109]	[0.0390]
γ_1	—	0.0492 ***	0.1585 ***	0.2019 ***	0.0192	−0.2317 ***
SE	—	[0.0151]	[0.0446]	[0.0418]	[0.0187]	[0.0525]
Shape (ν)	1.6552 ***	8.4157 ***	5.0687 ***	1.4598 ***	6.4988 ***	5.5342 ***
SE	[0.0639]	[2.0114]	[0.8049]	[0.0905]	[1.3172]	[0.9393]
Skew (ξ)	—	1.0620 ***	0.9219 ***	—	0.9830 ***	1.2968 ***
SE	—	[0.0491]	[0.0413]	—	[0.0418]	[0.0583]

Notes: Standard errors in brackets. Significance: *** 1%, ** 5%, * 10%. All specifications include Bai–Perron structural break dummies (Bai & Perron, 2003). Estimation by QML (Bollerslev & Wooldridge, 1992) using rugarch (Ghalanos, 2024).

Table 10. Bivariate DCC-GARCH Parameter Estimates.

Pair	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha} + \hat{\beta}$	$\hat{\nu}$	AIC	BIC
<i>GRNB pairs</i>						
GRNB/ICLN	0.0474	0.9104	0.9578	11.662	−14.113	−14.004
GRNB/KRBN	0.0105	0.9603	0.9708	30.523	−14.055	−13.946
GRNB/CARB	0.0041	0.9715	0.9756	50.000	−13.282	−13.183
GRNB/IQQH	0.0230	0.9437	0.9667	11.928	−14.220	−14.116
GRNB/OVX	0.0000	0.9319	0.9319	14.683	−11.767	−11.648
<i>ICLN pairs</i>						
ICLN/KRBN	0.0000	0.9683	0.9683	48.307	−10.583	−10.475
ICLN/CARB	0.0032	0.9883	0.9915	28.833	−9.810	−9.711
ICLN/IQQH	0.1236	0.0608	0.1844	6.013	−11.667	−11.563
ICLN/OVX	0.0000	0.9881	0.9881	49.999	−8.329	−8.211
<i>KRBN pairs</i>						
KRBN/CARB	0.0976	0.7850	0.8826	7.997	−11.611	−11.512
KRBN/IQQH	0.0020	0.8595	0.8615	50.000	−10.802	−10.700
KRBN/OVX	0.0000	0.8837	0.8837	21.063	−8.395	−8.276
<i>CARB pairs</i>						
CARB/IQQH	0.0030	0.9939	0.9969	49.999	−10.036	−9.941
CARB/OVX	0.0000	0.9236	0.9236	33.650	−7.624	−7.515
<i>IQQH pairs</i>						
IQQH/OVX	0.0000	0.9708	0.9708	16.348	−8.539	−8.426

Notes: $\hat{\alpha}$: DCC shock parameter. $\hat{\beta}$: DCC persistence parameter (R. Engle, 2002). $\hat{\alpha} + \hat{\beta} < 1$ confirms covariance stationarity. $\hat{\nu}$: degrees of freedom of the multivariate Student- t copula; lower values indicate stronger tail dependence. Estimated by QML (Bollerslev & Wooldridge, 1992).

6.3. R^2 Decomposed Connectedness Analysis

Average Connectedness Measures

Table 11 yields three key findings. First, KRBN (carbon allowance) and CARB (Paris-aligned equity) dominate the system as the primary sources of systemic variance propagation. KRBN records the highest TO value (80.90 percent; NET = +1.45 percentage points), identifying it as the dominant net transmitter. CARB records a near-equivalent TO of 80.34 percent and is likewise a marginal net transmitter (NET = +1.00 percent), positioning it as a core bidirectional hub: it exports and absorbs systemic variance in near-equal measure. Their bilateral cross-contributions exceed 76 percent in both directions (KRBN→CARB: 76.81 percent; CARB→KRBN: 76.97 percent)—the strongest pairwise link in the system—reflecting their shared exposure to EU ETS allowance price dynamics. From a portfolio management perspective, a connectedness-aware investor would treat these elevated TO values as a signal to underweight both instruments during high-TCI episodes. By contrast, peripheral assets such as OVX and GRNB, with TO values of 5.55 and 13.84 percent, respectively, are natural candidates for overweight allocations.

Table 11. Average R^2 Decomposed Connectedness Measures.

	GRNB	ICLN	KRBN	CARB	IQQH	OVX	FROM
GRNB	100.00	13.09	1.65	1.68	3.41	0.21	20.04
ICLN	9.60	100.00	1.03	0.74	52.48	2.68	66.53
KRBN	0.64	0.89	100.00	76.81	0.54	0.57	79.45
CARB	0.64	0.67	76.97	100.00	0.59	0.48	79.34
IQQH	2.76	55.86	0.64	0.65	100.00	1.62	61.52
OVX	0.21	3.32	0.61	0.46	1.63	100.00	6.23
TO	13.84	73.83	80.90	80.34	58.64	5.55	313.11
Inc.Own	113.84	173.83	180.90	180.34	158.64	105.55	
NET	−6.19	+7.30	+1.45	+1.00	−2.88	−0.67	TCI = 52.18

Notes: R^2 decomposed connectedness measures following [Cocca et al. \(2024\)](#). Rows: transmitting markets; columns: receiving markets. FROM: total variance received. TO: total variance transmitted. NET = TO − FROM. TCI reported in the bottom-right cell. The mean TCI summarizes a dynamic series ranging between approximately 34 and 73 percent over the sample (Figure 1); the CUSUM–Fisher inference of Section 4.3 applies to portfolio Sharpe comparisons rather than to the TCI itself.

Second, within the clean energy equity bloc, ICLN and IQQH display strong but asymmetric bilateral integration: ICLN transmits 52.48 percent of its variance toward IQQH while IQQH transmits 55.86 percent in return, yielding NET = +7.30 percentage points for ICLN (net transmitter) and NET = −2.88 percentage points for IQQH (marginal net receiver). GRNB records FROM of only 20.04 percent and TO of only 13.84 percent—both the second lowest after OVX—consistent with insulation from the carbon–clean energy channel in both directions ([Cao et al., 2024](#); [Yuan et al., 2023](#)). Third, OVX stands apart with a total spillover contribution of just 5.55 percent—the lowest in the system—consistent with the finding that oil market uncertainty does not systematically drive carbon or clean energy markets at daily frequency. The TCI of 52.18 percent reflects moderate-to-high system-wide integration, with a clear two-bloc architecture.

This structural isolation is directly exploitable in portfolio construction. OVX’s CBHI of 14.310—the highest in the system and nearly three times that of GRNB (5.387)—identifies it as the dominant structural diversifier. Minimum-connectedness strategies systematically overweight OVX: the MCP assigns it 31.6 percent versus 0.4 percent in the minimum-variance benchmark. This roughly 79-fold reallocation away from KRBN/CARB and toward OVX is the primary driver of the Sharpe improvement from −1.066 to 0.148 (MCP).

The dynamic total and pairwise connectedness indices are displayed in Figures 1–3 below. The TCI oscillates between approximately 34 and 73 percent, with the most sus-

tained surge occurring in late 2022 through early 2023, coinciding with the peak of the Russia–Ukraine energy crisis. A second sharp spike appears in early 2026, coinciding with the simultaneous onset of multiple destabilizing factors: geopolitical uncertainty stemming from US trade tariffs and Middle East tensions, growing political pressure from EU member states on the pace of free allowance phase-out, and the European Commission’s announced review of the ETS mechanism scheduled for July 2026.³ EUA prices surged above €92/tCO₂ in January 2026 before correcting sharply by more than 20 percent within two months as market sentiment shifted under the combined weight of these regulatory and geopolitical pressures. Each of these episodes illustrates the extra-territorial reach of EU regulatory discontinuities: as documented by Redondo Alamillos and de Mariz (2022) in the context of the Brussels effect, European sustainable finance regulation tends to set standards that propagate globally, amplifying the systemic relevance of EU ETS disruptions beyond European markets. KRBN and CARB remain in positive net territory throughout most of the sample. ICLN also occupies predominantly positive net territory (full-sample NET = +7.30 percentage points), fluctuating between approximately −15 and +40 percent, consistent with its role as the primary net transmitter within the clean energy equity bloc. GRNB records the most persistently negative net values among peripheral assets (full-sample NET = −6.19 percentage points), identifying it as the dominant net receiver within the structurally decoupled segment of the system; note that ICLN (FROM = 66.53 percent) and IQQH (FROM = 61.52 percent) absorb substantially larger absolute volumes of systemic variance, but as bidirectional integrated assets rather than peripheral ones. The KRBN/CARB pair records the highest average PCI (0.867), structurally invariant to external shocks; the ICLN/IQQH pair is the second strongest (mean PCI = 0.700) but documents meaningful time variation.

6.4. Portfolio Optimization and Risk Management

Before evaluating portfolio-level strategies, it is instructive to characterize the standalone risk-return profile of each asset in the system. Table 12 reports annualized mean returns, annualized volatility, Sharpe ratios, and historical and filtered Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) at the 5% level for each of the six assets over the full sample period. These metrics establish the baseline against which the diversification gains from connectedness-aware portfolio construction are subsequently assessed.

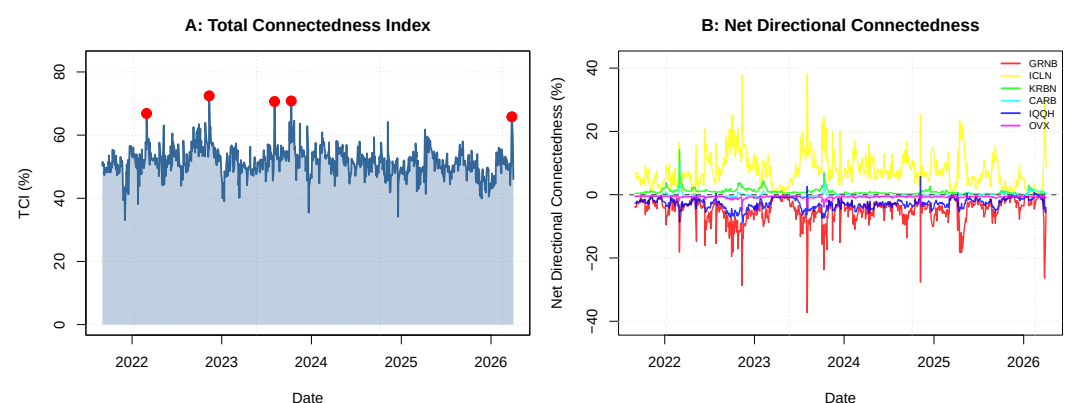


Figure 1. Dynamic Total Connectedness Index and Net Directional Connectedness across Clean Energy, Carbon, and Oil Markets. *Notes:* Panel (A): dynamic TCI from Cocca et al. (2024); red dots mark the five highest TCI observations. Panel (B): net directional connectedness; positive (negative) values identify net transmitters (receivers); dashed line at zero.

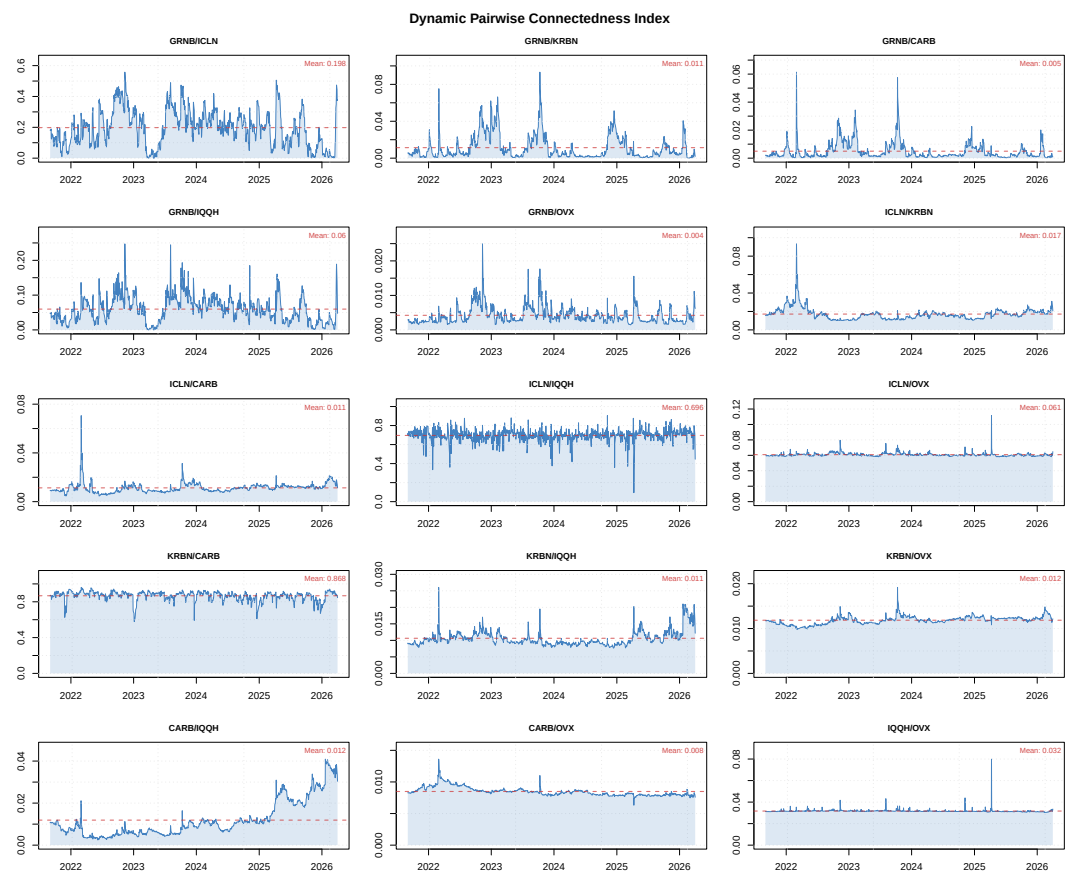


Figure 2. Dynamic Pairwise Connectedness Index across Clean Energy, Carbon, and Oil Markets. *Notes:* Symmetric average of bilateral R^2 measures (Cocca et al., 2024); red dashed line marks the full-sample mean.

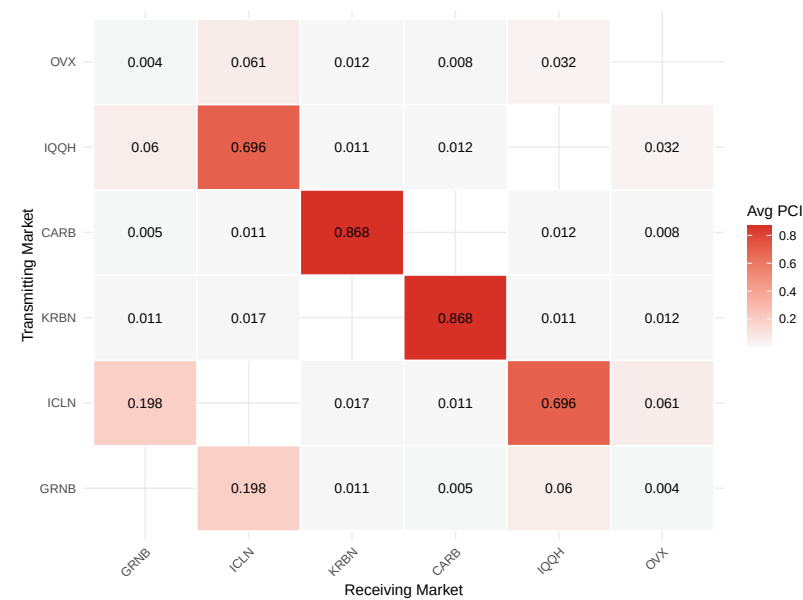


Figure 3. Average Pairwise Connectedness Index: Full-Sample Heatmap. *Notes:* Blue (red) cells indicate low (high) bilateral integration.

Table 12. Portfolio Risk Metrics: Sharpe Ratio, VaR and CVaR at 5% Level.

Series	Mean (Ann.)	Vol (Ann.)	Sharpe	VaR 5%	VaR 5% (F)	CVaR 5%	CVaR 5% (F)
GRNB	−0.0343	0.0524	−0.6537	−0.0056	−0.0056	−0.0076	−0.0073
ICLN	−0.0648	0.2881	−0.2250	−0.0285	−0.0288	−0.0384	−0.0382
KRBN	−0.0762	0.3237	−0.2353	−0.0287	−0.0296	−0.0523	−0.0530
CARB	0.0103	0.4362	0.0237	−0.0429	−0.0428	−0.0679	−0.0680
IQQH	−0.0563	0.2608	−0.2157	−0.0265	−0.0263	−0.0364	−0.0363
OVX	0.2584	1.0119	0.2554	−0.0892	−0.0922	−0.1377	−0.1417

Notes: Mean (Ann.) and Vol (Ann.): annualized mean return and volatility computed as daily mean $\times 252$ and daily SD $\times \sqrt{252}$. Sharpe Ratio: annualized return per unit of annualized volatility. VaR 5%: historical Value-at-Risk at the 5% quantile level. VaR 5% (F): filtered VaR using GARCH-scaled residuals. CVaR 5%: Conditional Value-at-Risk (Expected Shortfall). CVaR 5% (F): filtered CVaR.

6.4.1. Individual Asset Risk Metrics

Among green finance instruments, GRNB records negative annualized return (−0.034) with the lowest volatility (0.053) and a strongly negative Sharpe ratio (−0.654), reflecting the adverse impact of the 2022–2023 interest rate tightening cycle on fixed-income valuations. CARB is the sole green finance asset with a positive annualized return (0.010), though at the cost of the second highest volatility (0.436) and substantial tail risk. OVX records the highest return (0.259) and the highest volatility (1.012), with the highest Sharpe ratio (0.255) in the sample, but also the largest tail exposure (CVaR = −0.138).

The full set of bivariate hedge ratios and hedging effectiveness measures across all thirty asset pairs is reported in Table A1 (Appendix A); the discussion here concentrates on its economically informative content. Optimal time-varying bivariate hedge ratios are estimated following Kroner and Sultan (1993), and hedging effectiveness is measured as the percentage reduction in portfolio variance relative to the unhedged benchmark (Ederington, 1979). The KRBN/CARB pair achieves the highest hedging effectiveness (HE = 0.763), reducing KRBN portfolio variance by 76.3 percent, consistent with their near-unity bilateral PCI. Pairs involving OVX consistently produce negative hedge ratios (e.g., ICLN/OVX: −0.080), indicating that a long OVX position is required to hedge green and carbon asset exposure, reflecting the inverse co-movement between oil market uncertainty and clean energy valuations. OVX-hedged positions achieve near-zero effectiveness (GRNB/OVX: 0.001; KRBN/OVX: 0.015), consistent with oil volatility moving in the correct direction but with insufficient magnitude to reduce portfolio variance materially.

Table 13 distills the four most economically informative pairs from the full thirty-pair panel of Table A1 (Appendix A), summarizing the bilateral structure that the portfolio strategies evaluated below exploit.

Table 13. Key Pairwise Connectedness and Hedge Effectiveness: Selected Pairs.

Pair	Interpretation	PCI (Mean)	HE	SR (Hedged)
KRBN/CARB	Carbon systemic bloc	0.867	0.763	−0.528
ICLN/IQQH	Clean energy integration	0.700	0.586	−0.061
ICLN/OVX	Oil–clean energy hedge	—	0.039	−0.206
GRNB/OVX	Bond–oil decoupling	0.004	0.000	−0.649

Notes: PCI: full-sample average Pairwise Connectedness Index (Cocca et al., 2024). HE: hedging effectiveness (Ederington, 1979). SR: annualised Sharpe ratio. Zero risk-free rate. Values extracted from Tables 11 and A1.

6.4.2. Optimal Portfolio Strategies

Five portfolio strategies are evaluated: the Minimum Variance Portfolio (MVP), the Minimum Correlation Portfolio (MCP), the Minimum Pairwise Connectedness Portfolio (MCCP), the Minimum Connectedness Risk Portfolio (MCRP), and the Minimum R^2 Portfolio (MR2P). The MVP serves as the conventional benchmark (Markowitz, 1952); the four

connectedness-aware strategies progressively incorporate information from the DCC-GARCH R^2 decomposition into the objective function (Broadstock et al., 2022; Cocca et al., 2024).

Tables 2 and 3 jointly support connectedness-aware portfolio construction over variance minimization. The MVP concentrates 88.1 percent of its weight in GRNB—the lowest-volatility instrument in the system—yet delivers a Sharpe ratio of -1.066 and an Information Ratio of -0.911 , reflecting the limitation of variance minimization as a portfolio criterion when the lowest-volatility asset generates negative average returns (Rachev et al., 2008). By contrast, all connectedness-aware strategies produce positive Sharpe ratios and Information Ratios, with the MCP achieving the highest Sharpe ratio (0.148) and the MCCP the highest Information Ratio (0.276); the MCP attains its performance through a diversified allocation that assigns 31.6 percent to OVX and spreads the remainder across the five green finance instruments. In economic terms, the MCP delivers a positive annualised return of 4.8 percent at 32.3 percent annualised volatility, against -6.1 percent at 5.8 percent volatility for the MVP: the performance differential is visible in raw returns, not only in risk-adjusted ratios. The three R^2 -based strategies—MCCP, MCRP, and MR2P—converge on similar allocations: the peripheral assets OVX and GRNB systematically receive the two highest weights, while the dominant systemic transmitters identified in Section 6.3—KRBN and CARB—are confined to weights of roughly 13–14 percent, well below their share under naive equal weighting of the transmission core, an outcome directly consistent with the network portfolio theory of Peralta and Zareei (2016) and Clemente et al. (2019) establishing that peripheral assets dominate risk-efficient allocations.

6.5. A Connectedness-Based Hierarchy Index

Table 14 presents the full-sample CBHI values computed from the directional connectedness measures of Table 11. The index partitions the system into three structural profiles.

Table 14. Connectedness-Based Hierarchy Index: Full-Sample Values.

Rank	Asset	FROM (%)	TO (%)	NET (%)	Vol (Ann.)	CBHI	Systemic Profile
<i>Structurally decoupled (CBHI > 1): low FROM and low TO</i>							
1	OVX	6.23	5.55	-0.67	1.012	14.310	Orthogonal diversifier
2	GRNB	20.04	13.84	-6.19	0.052	5.387	Insulated diversifier
<i>Bidirectional integrated (CBHI $\in [0.40, 1.00]$): high FROM and TO</i>							
3	IQQH	61.52	58.64	-2.88	0.261	0.645	Net receiver, partial diversification
4	ICLN	66.53	73.83	$+7.30$	0.288	0.447	Net transmitter, limited diversification
<i>Systemic transmitters (CBHI < 0.40): high FROM and TO</i>							
5	CARB	79.34	80.34	$+1.00$	0.436	0.254	Core transmitter, hedge target
6	KRBN	79.45	80.90	$+1.45$	0.324	0.251	Dominant transmitter, hedge target

Notes: $CBHI_i = (1 - FROM_i) / (TO_i + \varepsilon)$, $\varepsilon = 0.01$, FROM and TO expressed as decimals. Full-sample averages from Table 11. $NET = TO - FROM$. Assets with $CBHI > 1$ generate more variance internally than they import while transmitting little to others; assets with $CBHI < 0.40$ are dominant systemic transmitters. The CBHI ranking is broadly consistent with the weight allocations of the three R^2 -based strategies (MCCP, MCRP, MR2P) in Table 3; the MCP, which minimizes pairwise correlations rather than R^2 connectedness, departs from this pattern for ICLN and CARB, consistent with minimum R^2 connectedness portfolios implicitly maximizing CBHI-weighted exposure (Broadstock et al., 2022). Kendall $\tau \approx -0.20$ between CBHI and individual asset volatility is consistent with orthogonality to conventional variance measures (Rachev et al., 2008).

Structural diversifiers ($CBHI > 1$): OVX (14.310) and GRNB (5.387) both exceed the unit threshold. OVX's FROM of only 6.23 percent and TO of 5.55 percent are consistent with near-total insulation from the carbon–clean energy transmission channel; GRNB's fixed-income coupon structure and project-linked use of proceeds insulate green bond returns from short-run carbon market turbulence (Cao et al., 2024). Both assets are natural overweight candidates during high-TCI episodes, consistent with the peripheral-node optimality result of Peralta and Zareei (2016).

Intermediate assets ($CBHI \in [0.40, 1.00]$): IQQH (0.645) and ICLN (0.447) absorb substantial systemic variance from the carbon channel—FROM values above 60 percent—but

their TO contribution falls short of full dominance, warranting neutral to moderate portfolio weights depending on the TCI regime. ICLN's net positive position ($NET = +7.30$ percentage points) places it closer to the transmitter boundary, consistent with its role as the primary conduit through which US clean energy equity dynamics propagate to the EU-listed counterpart.

Systemic transmitters ($CBHI < 0.40$): KRBN (0.251) and CARB (0.254) record FROM and TO values both approaching 80 percent. Importantly, KRBN is a marginal net transmitter ($NET = +1.45$ percentage points) while CARB is likewise a marginal net transmitter ($NET = +1.00$ percentage points); their low CBHI values reflect not their NET direction but the exceptional magnitude of their bilateral connectedness in both directions simultaneously. The CBHI captures this correctly where the NET measure cannot: both instruments are embedded at the core of the transmission network and should be treated as hedging targets regardless of their marginal NET sign. Their near-identical CBHI values reflect the symmetric bilateral link documented in Table 11 and signal that both instruments should be underweighted or treated as active hedging targets when the TCI is elevated.

6.5.1. Sensitivity to ε

Table 15 shows that the three-tier CBHI partition is robust across $\varepsilon \in \{0.001, 0.005, 0.01, 0.05\}$. Cardinal values for OVX vary (16.59 to 8.89) but tier membership is unchanged under all choices.

Table 15. CBHI Sensitivity to ε .

Asset	0.001	0.005	0.01	0.05	Tier
OVX	16.589	15.492	14.310	8.886	>1 ✓
GRNB	5.735	5.575	5.387	4.244	>1 ✓
IQQH	0.655	0.651	0.645	0.605	[0.40, 1] ✓
ICLN	0.453	0.450	0.447	0.425	[0.40, 1] ✓
CARB	0.257	0.256	0.254	0.242	<0.40 ✓
KRBN	0.254	0.252	0.251	0.239	<0.40 ✓

Notes: ✓ = tier unchanged. $CBHI_i = (1 - FROM_i) / (TO_i + \varepsilon)$.

The CBHI ranking—OVX > GRNB > IQQH > ICLN > CARB > KRBN—is broadly consistent with the weight allocations of the three R^2 -based strategies (MCCP, MCRP, MR2P) in Table 3. The MCP, which minimizes pairwise correlations rather than R^2 connectedness, departs from this pattern for ICLN and CARB: despite ICLN recording a higher CBHI (0.447) than CARB (0.254), the MCP assigns CARB a higher mean weight (16.3 percent vs. 8.9 percent), reflecting the distinct objective functions of correlation-based versus R^2 -based minimization. For the three R^2 -based strategies, however, this consistency is not mechanical: the CBHI is derived from the full connectedness matrix while portfolio weights are optimized from the PCI matrix independently. This coherence is consistent with the network portfolio theory of Peralta and Zareei (2016) and indicates that the CBHI captures a dimension of portfolio desirability orthogonal to individual variance (Kendall $\tau \approx -0.20$, Rachev et al. 2008). As a dynamic measure updated in real time from rolling DCC-GARCH estimates, the CBHI provides a forward-looking diagnostic (Figure 4). KRBN and CARB remain pinned below the 0.40 transmitter threshold throughout virtually the entire sample, indicating that their systemic embeddedness is structural rather than episodic. The informative dynamics occur in the diversifier tier: during both the 2022–2023 energy-crisis episode and the early-2026 ETS review episode, GRNB's CBHI collapses from diversifier territory toward the transmitter zone, signalling that the green bond segment temporarily loses part of its insulation precisely when the TCI approaches its nearly 73 percent peak, whereas OVX's CBHI remains stable near 14 across both episodes—the only asset whose

diversification capacity survives systemic stress intact. This differential behavior generates an actionable trigger directly computable from the existing estimation framework without additional model requirements.

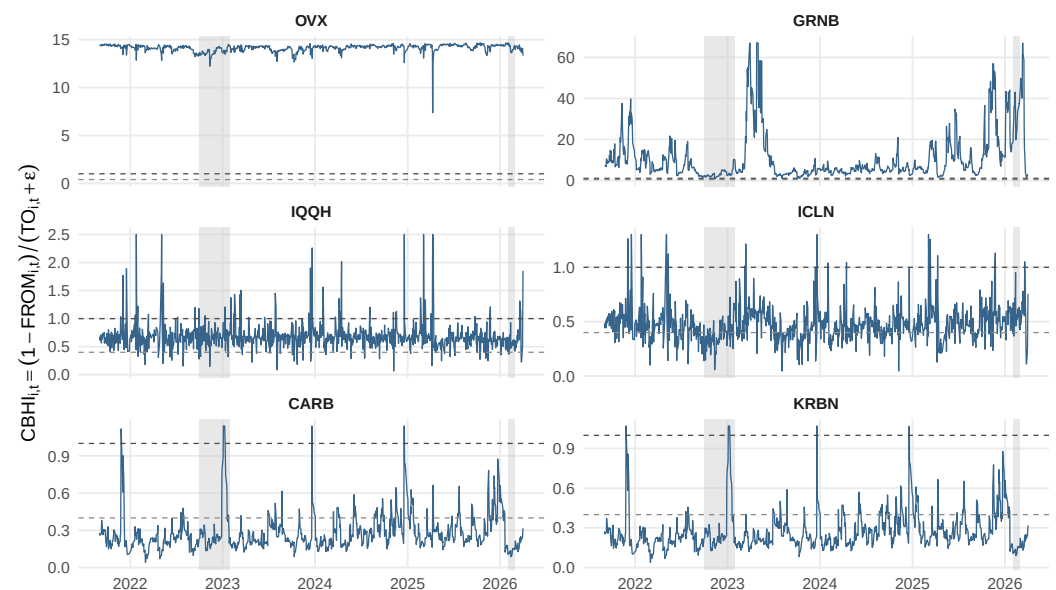


Figure 4. Dynamic Connectedness-Based Hierarchy Index (CBHI) by Asset, September 2021–March 2026. *Notes:* $CBHI_{i,t} = (1 - FROM_{i,t}) / (TO_{i,t} + \epsilon)$, $\epsilon = 0.01$. Horizontal dashed lines at $CBHI = 1$ (diversifier threshold) and $CBHI = 0.40$ (33rd-percentile transmitter threshold). Grey shaded areas mark EU ETS stress episodes (October 2022–January 2023; February 2026). Assets above $CBHI = 1$ (OVX, GRNB) are structural diversifiers; assets below $CBHI = 0.40$ (KRBN, CARB) are systemic transmitters.

6.5.2. Robustness of the Hierarchy

Table 16 reports the connectedness measures for a five-asset system excluding CARB alongside the six-asset baseline, allowing direct comparison of the CBHI partition across asset universes. The three-tier hierarchy is preserved among the remaining assets—OVX and GRNB as structural diversifiers, ICLN and IQQH as intermediate—while mean TCI falls from 52.18 to 30.81 percent. KRBN, by contrast, is reclassified from systemic transmitter to structural diversifier (CBHI rising from 0.251 to 22.204), because 76.81 percent of its baseline TO was directed toward CARB. The KRBN–CARB bilateral link therefore constitutes the dominant transmission channel of the six-asset system; the implications of this contingency for H1 and H5 are assessed in Section 7.2.

Table 16. Connectedness Measures: Five-Asset System Excluding CARB.

Asset	TO (%)	FROM (%)	NET (ppts)	CBHI	Tier
<i>Six-asset baseline (Mean TCI = 52.18%)</i>					
GRNB	13.84	20.04	−6.19	5.387	Structural diversifier
ICLN	73.83	66.53	+7.30	0.447	Intermediate
KRBN	80.90	79.45	+1.45	0.251	Systemic transmitter
IQQH	58.64	61.52	−2.88	0.645	Intermediate
OVX	5.55	6.23	−0.67	14.310	Structural diversifier

Table 16. Cont.

Asset	TO (%)	FROM (%)	NET (ppts)	CBHI	Tier
<i>Five-asset system excl. CARB (Mean TCI = 30.81%)</i>					
GRNB	13.13	17.31	−4.18	5.853	Structural diversifier
ICLN	72.65	65.39	+7.26	0.470	Intermediate
KRBN	3.35	3.48	−0.13	22.204	Structural diversifier [†]
IQQH	58.15	60.67	−2.52	0.665	Intermediate
OVX	5.10	5.55	−0.46	15.495	Structural diversifier

Notes: Five-asset system obtained by dropping CARB; pipeline identical to the main analysis (bivariate DCC-GARCH(1,1)–mvt on all ten pairs, followed by the R^2 connectedness decomposition of [Cocca et al. 2024](#)). $CBHI_i = (1 - FROM_i) / (TO_i + \varepsilon)$, $\varepsilon = 0.01$, FROM/TO expressed as decimals. Tier thresholds are held fixed at their six-asset values (CBHI = 1 and CBHI = 0.40) to ensure comparability. [†] KRBN is reclassified from systemic transmitter (CBHI = 0.251) to structural diversifier (CBHI = 22.204), with its NET sign flipping from +1.45 to −0.13 ppts, because 76.81% of its baseline TO was directed toward CARB; mean TCI falls from 52.18% to 30.81%. KRBN's transmitter role is therefore contingent on CARB's presence: the KRBN–CARB bilateral link constitutes the dominant transmission channel of the six-asset system. The remaining four assets preserve their baseline tiers and NET signs.

7. Discussion

7.1. Comparison with Existing Evidence

Our finding that the carbon allowance futures ETF (KRBN) and the Paris-aligned equity ETF (CARB) constitute a near-closed systemic bloc, characterized by a bilateral Pairwise Connectedness Index (PCI) of 0.867, significantly extends the empirical evidence of [Su and Lian \(2025\)](#), while [Su and Lian \(2025\)](#) document strong carbon-to-green-finance connectedness at upper quantiles during the 2022–2024 period, our framework identifies the specific bilateral channel, running from EU ETS allowance futures to Paris-aligned equity, as the dominant transmission link within the system. Notably, the magnitude of this link exceeds previously documented pairwise values in this asset class.

Meanwhile, the peripheral position of green bonds (GRNB, with a FROM connectedness of 20.04%) aligns closely with the work of [Ringstad and Tselika \(2024\)](#), who observe that green bond connectedness with carbon markets attenuates structurally at longer horizons. Our results indicate that this insulation holds at a daily frequency over a post-2021 sample encompassing multiple EU ETS stress episodes. This pattern is highly consistent with the safe-haven characterization offered by [Cao et al. \(2024\)](#) under conditions of moderate monetary uncertainty.

Finally, the near-total independence of crude oil volatility (OVX) from the carbon–clean energy core (TO = 5.55%) is consistent with [Jiang and Chen \(2023\)](#), who find that the oil–green energy nexus is predominantly a short-run, high-frequency phenomenon. At a daily frequency, fossil-fuel uncertainty operates through channels that are structurally distinct from those of the carbon transition system, positioning OVX as a natural diversifier despite its negative rank correlations with green assets.

7.2. Hypothesis Assessment

The five hypotheses formulated in this study receive differentiated support, and their joint assessment sharpens the paper's central message.

First, *H1* (carbon centrality) is supported with key qualifications, while KRBN records the highest out-degree centrality in the system (TO = 80.90%) and the lowest Connectedness-Based Hierarchy Index (CBHI of 0.251), this support rests on gross centrality rather than its net direction. KRBN's net position (NET = +1.45 percentage points) is economically negligible, suggesting that the instrument is more accurately characterized as a dominant gross co-transmitter rather than a one-directional net transmitter. Furthermore, the robustness check in Table 16 shows that this centrality is highly contingent on the joint inclusion of CARB in the asset universe.

Second, *H2* (portfolio dominance) is partially supported. The Minimum Correlation Portfolio (MCP) achieves an annualized Sharpe ratio of 0.148 compared to -1.066 for the Minimum Variance Portfolio (MVP) under zero transaction costs. As shown in Appendix C, this performance ranking is preserved across all transaction cost scenarios tested (0.109 vs. -1.210 at 5 basis points; 0.070 vs. -1.355 at 10 basis points; and -0.047 vs. -1.788 at 25 basis points). However, the dominance of the full suite of connectedness-aware strategies does not fully survive the highest cost scenario; the high-turnover MCP turns marginally negative at 25 basis points, whereas the Minimum Pairwise Connectedness Portfolio (MCCP, $+0.034$) and the Minimum Connectedness-Risk Portfolios (MCRP/MR2P, $+0.072$) remain positive. Under monthly rebalancing, the MCP achieves its optimal Sharpe ratio of 0.163, suggesting that the daily turnover penalty is an implementation artifact rather than a structural deficit. The outperformance claim therefore holds fully for institutional investors operating under low execution costs or utilizing lower-frequency rebalancing.

Third, *H3* (crisis amplification) is strongly supported. The Total Connectedness Index (TCI) surges from a full-sample average of 52.18% to nearly 73% during the 2022–2023 EU ETS stress episode and the early 2026 ETS review period. This spike of approximately 21 percentage points above the structural interdependence baseline constitutes shift-contagion in the sense of Forbes and Rigobon (2002), amplified by Brussels Effect dynamics (Redondo Alamillos & de Mariz, 2022). Because our underlying correlations are conditional on GARCH-filtered variances with structural break corrections, this surge is unlikely to reflect the heteroskedasticity bias identified by Forbes and Rigobon (2002) in traditional contagion tests.

Fourth, *H4* (green bond insulation) is supported. GRNB's FROM value of 20.04% is the second lowest in the system, and its bilateral PCI of 0.022 with KRBN and 0.004 with OVX confirms the structural insulation of fixed-income green assets from the carbon-clean energy transmission channel.

Finally, *H5* (CBHI–climate tension) is supported within this asset universe. CARB records the second-lowest CBHI (0.254), illustrating that climate alignment and systemic risk minimization are partially conflicting objectives. The five-asset robustness check (Table 16) confirms that this tension, much like KRBN's centrality, is an emergent property of this joint instrument universe rather than of any single asset in isolation. Taken together, these assessments corroborate the centrality–weight predictions of network portfolio theory and the contagion-based reading of TCI dynamics, while clearly delimiting the transaction-cost boundaries of *H2* and the universe-specificity of *H1* and *H5*.

8. Conclusions

This study examines the dynamic connectedness and portfolio implications of carbon-market volatility among six key assets with significant exposure to European carbon-pricing regulation over the 2021–2026 period. By applying the DCC-GARCH R^2 decomposed connectedness framework of Cocca et al. (2024) to KRBN, CARB, ICLN, IQQH, GRNB, and OVX, five principal findings emerge.

First, KRBN and CARB constitute a near-closed systemic bloc within this asset universe, characterized by bilateral connectedness of 0.867 and TO/FROM values approaching 80%. This co-transmitter structure is highly contingent on their joint inclusion; excluding CARB raises KRBN's CBHI from 0.251 to 22.204 and reduces the mean TCI by 21 percentage points (Table 16). Their marginal net positions ($NET = +1.45$ percentage points for KRBN, $NET = +1.00$ percentage points for CARB) are economically negligible, indicating that both instruments act as highly integrated co-transmitters. Consequently, their inclusion in any portfolio introduces structural exposure to EU ETS regulatory risk, irrespective of net direction. System-wide integration surges from a baseline of 52.18% to nearly 73% dur-

ing regulatory crises, suggesting that carbon pricing discontinuities constitute a systemic financial risk factor rather than a localized market disruption.

Second, dynamic hedging within the KRBN/CARB pair achieves a variance reduction of 76.3%, the highest in the system, consistent with their near-unit bilateral connectedness. Conversely, OVX-based hedges yield near-zero effectiveness; although oil market uncertainty moves in the correct direction relative to green assets, its transmission magnitude is insufficient to reduce portfolio variance materially.

Third, the system exhibits a clear three-tier connectivity architecture. The peripheral tier, consisting of OVX (TO = 5.55%) and GRNB (TO = 13.84%), is structurally decoupled from the carbon–clean energy transmission channel. The intermediate tier, containing IQQH (NET = −2.88 percentage points) and ICLN (NET = +7.30 percentage points), is bidirectionally integrated with the carbon bloc yet retains partial insulation. Finally, the systemic core, dominated by KRBN and CARB, concentrates variance transmission with near-zero residual idiosyncratic risk.

Fourth, connectedness-aware portfolio strategies consistently outperform minimum-variance optimization across all risk-adjusted metrics. The MCP achieves a Sharpe ratio of 0.148 and an Information Ratio of 0.254 (with the MCCP recording the highest Information Ratio at 0.276), compared to −1.066 and −0.911 for the MVP. This performance advantage is robust across various Sharpe variants (including VaR and CVaR measures), and the MVP–MCP ranking survives every transaction cost scenario tested (Appendix C). This performance differential is highly structural: while the MVP concentrates 88% of its weight in GRNB (the lowest-volatility instrument) and generates negative returns because it ignores the direction of systemic transmission, connectedness-aware strategies address this by systematically shifting weight to peripheral assets (allocating 23–32% to OVX, compared to 0.4% in the MVP) and underweighting embedded transmitters.

Fifth, the CBHI successfully translates the three-tier architecture into a scalar, time-varying portfolio desirability index that is orthogonal to individual asset volatility (Kendall's $\tau \approx -0.20$; Rachev et al., 2008). It reveals a structural tension that variance-based measures cannot detect: within this asset universe and sample period, CARB, the instrument most directly aligned with the low-carbon transition, records the second-lowest CBHI (0.254). This indicates that climate alignment and systemic risk minimization are partially conflicting objectives. Connectedness-aware strategies offer a tractable mathematical approach to mitigating this tension, delivering positive risk-adjusted performance (Broadstock et al., 2022; Cocca et al., 2024) through the CBHI portfolio desirability framework (Peralta & Zareei, 2016; Rachev et al., 2008).

9. Policy Implications and Limitations

These findings carry critical implications across three distinct domains.

For policymakers, the surge in system-wide connectedness from a baseline of 52.18% to nearly 73% during EU ETS regulatory crises suggests that carbon price instability may elevate the cost of green capital precisely when the transition price signal is most needed. Given the extra-territorial reach of European sustainable finance regulation (Redondo Alamillos & de Mariz, 2022), these systemic disruptions are likely to extend beyond EU borders. This reinforces the case for robust regulatory continuity and predictability in carbon pricing structures (Bartocci et al., 2024; Fornaro et al., 2025).

For financial regulators, the structural divergence between equity-based and fixed-income green instruments in the variance transmission network is highly pronounced: GRNB records a FROM value of 20.04%, compared to 66.53% for ICLN. This disparity indicates that prudential stress-testing frameworks must explicitly incorporate connectedness-

based network scenarios, as a unified risk-management paradigm is unlikely to be adequate across these distinct asset classes.

For institutional investors, our results document a fundamental structural trade-off in Paris-aligned mandates. Within this asset universe and sample period, CARB, the instrument most directly reflecting the low-carbon transition, is also the most systemically embedded asset. Minimum connectedness strategies provide a mathematically sound and tractable approach to managing this trade-off (Broadstock et al., 2022; Cocca et al., 2024). Specifically, the CBHI operationalizes this approach into a time-varying portfolio desirability index that is directly computable from the DCC-GARCH framework (Peralta & Zareei, 2016; Rachev et al., 2008).

Returning to the three theoretical frameworks developed in Section 3, our empirical evidence supports their joint predictions with one important qualification. The inverse relationship between network centrality and portfolio desirability predicted by network portfolio theory (Clemente et al., 2019; Peralta & Zareei, 2016) is borne out twice over: the highest-centrality assets (KRBN, CARB) receive the lowest weights in every connectedness-aware allocation, and the CBHI successfully orders the system consistently with realized risk-adjusted performance (H1, H2). The contagion–interdependence distinction of Forbes and Rigobon (2002) organizes the temporal dynamics: the 52.18% baseline reflects structural interdependence, whereas the surges toward nearly 73% during EU-specific regulatory episodes constitute shift-contagion (H3). Green bond insulation (H4) and the CBHI–climate tension (H5) likewise hold as predicted. The qualification concerns H1: excluding CARB reclassifies KRBN as a structural diversifier (CBHI rising from 0.251 to 22.204; mean TCI falling from 52.18% to 30.81%, Table 16), establishing that KRBN’s centrality is a property of the bilateral KRBN–CARB link rather than of the allowance instrument in isolation. Furthermore, DCC lag structure sensitivity tests ($\text{dccOrder} = (1, 2)$ and $(2, 1)$) yield a mean TCI within ± 0.9 percentage points of 52.18%, with the ordinal NET ranking preserved and all NET signs stable across specifications: CARB remains a marginal net transmitter throughout ($+0.72$ ppts under DCC(1,2); $+1.89$ ppts under DCC(2,1)), consistent with its bidirectional-hub characterization (Table A2).

Finally, five key limitations of this study highlight productive avenues for future research. First, the empirical analysis is primarily European in focus and may not generalize to other emerging carbon pricing jurisdictions. Second, the portfolio strategies assume daily rebalancing, which imposes a turnover penalty under high-cost scenarios. Third, the 2021–2026 window, while rich in identifying variation and regulatory shifts, is relatively short for characterizing long-run structural transition dynamics. Fourth, the cardinal CBHI values of low-connectedness assets depend to some degree on the chosen regularization constant ϵ , although the three-tier partition itself remains highly stable across all values tested (Table 15). Fifth, the MCRP and MR2P strategies converge to identical allocations in this system (Tables 2 and 3), a redundancy that arises by construction in the bivariate implementation adopted here, where the regression-based pairwise R^2 coincides with the squared dynamic conditional correlation.

Extending this framework to a multi-jurisdictional carbon market system, incorporating realistic transaction cost models, decomposing connectedness across frequency bands (Baruník & Křehlík, 2018), and backtesting the dynamic CBHI as a real-time rebalancing rule represent the most valuable avenues for subsequent research.

Author Contributions: Conceptualization, B.B.O.; methodology, B.B.O.; software, B.B.O.; validation, B.B.O., R.B.B.S., and H.B.; formal analysis, B.B.O. and H.B.; investigation, B.B.O. and H.B.; resources, B.B.O.; data curation, B.B.O.; writing—original draft preparation, B.B.O.; writing—review and editing, H.B.; visualization, B.B.O. and H.B.; supervision, R.B.B.S.; project administration, R.B.B.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting the findings of this study are publicly available. Daily closing prices for all six assets—KRBN, CARB, ICLN, IQQH, GRNB, and OVX—were retrieved from Yahoo Finance (<https://finance.yahoo.com>) for the period September 2021 to March 2026. No proprietary or restricted datasets were used.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Bivariate Hedge Ratios and Hedging Effectiveness

Table A1 reports the full set of time-varying bivariate hedge ratios and hedging effectiveness measures across all thirty asset pairs, organized in six panels by base asset. The economically informative pairs are distilled in Table 13 and discussed in Section 6.4.

Table A1. Time-Varying Bivariate Hedge Ratios and Hedging Effectiveness.

Pair	Mean	Std.Dev.	5%	95%	HE	<i>p</i> -Value	Return	Std.Dev.	SR
<i>Panel A: GRNB as base asset</i>									
GRNB/ICLN	0.065	0.036	0.007	0.123	0.171	0.519	−0.027	0.048	−0.561
GRNB/KRBN	0.016	0.011	0.000	0.038	0.018	0.802	−0.033	0.052	−0.643
GRNB/CARB	0.007	0.010	−0.008	0.023	0.003	0.863	−0.034	0.052	−0.650
GRNB/IQQH	0.040	0.024	0.005	0.076	0.047	0.617	−0.029	0.051	−0.561
GRNB/OVX	−0.003	0.001	−0.005	−0.001	0.000	0.000	−0.034	0.052	−0.649
<i>Panel B: ICLN as base asset</i>									
ICLN/GRNB	1.943	0.798	0.306	2.974	0.145	1.000	−0.011	0.266	−0.042
ICLN/KRBN	0.158	0.031	0.113	0.211	0.021	0.802	−0.090	0.285	−0.315
ICLN/CARB	0.089	0.033	0.035	0.140	0.012	0.863	−0.100	0.286	−0.350
ICLN/IQQH	0.856	0.097	0.709	1.030	0.586	0.617	−0.011	0.185	−0.061
ICLN/OVX	−0.078	0.030	−0.135	−0.037	0.039	0.000	−0.058	0.282	−0.206
<i>Panel C: KRBN as base asset</i>									
KRBN/GRNB	0.447	0.349	−0.005	1.036	0.008	1.000	−0.113	0.322	−0.349
KRBN/ICLN	0.154	0.035	0.111	0.207	0.021	0.519	−0.111	0.320	−0.346
KRBN/CARB	0.628	0.082	0.524	0.743	0.763	0.863	−0.083	0.158	−0.528
KRBN/IQQH	0.141	0.037	0.089	0.205	0.008	0.617	−0.111	0.322	−0.343
KRBN/OVX	−0.041	0.019	−0.076	−0.018	0.015	0.000	−0.103	0.321	−0.320
<i>Panel D: CARB as base asset</i>									
CARB/GRNB	0.380	0.707	−0.596	1.375	0.003	1.000	−0.057	0.436	−0.131
CARB/ICLN	0.169	0.055	0.074	0.259	0.007	0.519	−0.071	0.435	−0.163
CARB/KRBN	1.265	0.177	0.988	1.546	0.788	0.802	0.132	0.201	0.657
CARB/IQQH	0.171	0.059	0.085	0.269	0.004	0.617	−0.075	0.435	−0.173
CARB/OVX	−0.052	0.023	−0.093	−0.023	0.011	0.000	−0.054	0.434	−0.125
<i>Panel E: IQQH as base asset</i>									
IQQH/GRNB	0.992	0.447	0.161	1.733	0.034	1.000	−0.040	0.256	−0.158
IQQH/ICLN	0.703	0.083	0.576	0.836	0.586	0.519	−0.038	0.168	−0.226
IQQH/KRBN	0.118	0.029	0.076	0.176	0.011	0.802	−0.078	0.259	−0.300
IQQH/CARB	0.076	0.038	0.029	0.144	0.012	0.863	−0.086	0.259	−0.333
IQQH/OVX	−0.058	0.021	−0.091	−0.027	0.031	0.000	−0.057	0.257	−0.221
<i>Panel F: OVX as base asset</i>									
OVX/GRNB	−0.917	0.575	−1.958	−0.366	0.002	1.000	−0.246	1.011	−0.244
OVX/ICLN	−0.766	0.346	−1.384	−0.377	0.086	0.519	−0.227	0.967	−0.235
OVX/KRBN	−0.412	0.208	−0.751	−0.179	0.010	0.802	−0.210	1.007	−0.209
OVX/CARB	−0.260	0.127	−0.472	−0.117	0.011	0.863	−0.190	1.006	−0.189
OVX/IQQH	−0.689	0.318	−1.276	−0.373	0.023	0.617	−0.275	1.000	−0.275

Notes: Hedge ratios estimated following Kroner and Sultan (1993). HE: hedging effectiveness (Ederington, 1979), measured as the percentage reduction in portfolio variance relative to the unhedged position. Return and Std.Dev. are annualized. SR: Sharpe ratio of the hedged portfolio. *p*-value: significance of the DCC correlation coefficient. Negative hedge ratios indicate that a long position in the hedging instrument is required. All estimates based on a rolling 252-day window.

Appendix B. Robustness Checks

Table A2. DCC Lag Structure Sensitivity: Mean TCI and NET Rankings.

Statistic	DCC(1,1)	DCC(1,2)	DCC(2,1)
Mean TCI (%)	52.18	51.19	52.01
NET ICLN (ppts)	+7.30	+6.86	+6.44
NET KRBN (ppts)	+1.45	+1.63	+2.61
NET CARB (ppts)	+1.00	+0.72	+1.89
NET OVX (ppts)	−0.67	−0.70	−0.59
NET IQQH (ppts)	−2.88	−2.77	−3.02
NET GRNB (ppts)	−6.19	−5.74	−7.32

Notes: All 15 bivariate DCC-GARCH pairs re-estimated under alternative lag orders, with univariate specifications, the multivariate Student-*t* distribution, and Bai–Perron break dummies held fixed. Mean TCI remains within ± 0.90 percentage points of the DCC(1,1) baseline. The ordinal NET ranking (ICLN > KRBN > CARB > OVX > IQQH > GRNB) is preserved under both alternative specifications. NET signs are preserved for all assets under all three specifications; CARB remains a marginal net transmitter throughout (+1.00 ppts under DCC(1,1); +0.72 under DCC(1,2); +1.89 under DCC(2,1)), consistent with its characterization as a bidirectional hub (Section 6.3).

Appendix C. Portfolio Performance Under Transaction Costs

Table A3 reports annualised Sharpe ratios for all five portfolio strategies under proportional round-trip transaction costs of 5, 10, and 25 basis points per daily rebalancing, and under monthly rebalancing with zero cost. Costs apply to the five ETF instruments; OVX weights are treated as notional and excluded from cost calculations.

Table A3. Portfolio Sharpe Ratios Under Alternative Transaction Cost Assumptions.

Cost Assumption	MVP	MCP	MCCP	MCRP/MR2P
Zero costs (baseline)	−1.066	0.148	0.141	0.116
5 bps daily	−1.210	0.109	0.119	0.107
10 bps daily	−1.355	0.070	0.098	0.098
25 bps daily	−1.788	−0.047	0.034	0.072
Monthly rebalancing	−0.710	0.163	0.124	0.106

Notes: Sharpe ratios annualised ($\times \sqrt{252}$) under the convention of Table 2, zero risk-free rate. Proportional round-trip costs are applied to realized daily turnover on the ETF legs only (KRBN, CARB, ICLN, IQQH, GRNB); OVX weights are notional and excluded from cost calculations. The MVP–MCP ranking is preserved at every cost level. At 25 bps, the MCP turns marginally negative (−0.047)—reflecting its higher turnover—while the MCCP (+0.034) and MCRP/MR2P (+0.072) remain positive, so at least one connectedness-aware strategy retains a positive Sharpe ratio at every cost level tested. Under monthly rebalancing, the MCP records its best performance (0.163), indicating that lower-frequency implementations mitigate the turnover penalty. Practical replication of OVX exposure would require instruments such as volatility-linked ETFs or options on crude oil futures, which carry additional transaction and roll costs not modelled here; the reported figures therefore provide an upper bound on realizable performance for strategies that assign positive weight to OVX.

Notes

- Transaction costs are set to zero. For the five exchange-traded fund instruments—KRBN, CARB, ICLN, IQQH, and GRNB—this assumption is a realistic approximation for institutional investors: liquid equity and bond ETFs typically carry bid–ask spreads of 1–5 basis points (Broadstock et al., 2022; Cocca et al., 2024). OVX is not directly investable; see the notes to Tables 3 and A3. Sensitivity to the zero-cost assumption is reported in Appendix C.
- OVX is a CBOE implied volatility index; equivalent exposure is replicable via options on USO or WTI volatility derivatives. Its inclusion follows standard practice in the connectedness literature (Alomari et al., 2024; Ha & Nham, 2025). Portfolio weights attributed to OVX represent notional allocations to the oil volatility channel.
- These market developments are documented in contemporaneous institutional research reports and EU ETS price data available from the European Energy Exchange (EEX) and Refinitiv.

References

- ABN AMRO. (2026). *European carbon market review: EUA price dynamics and ETS reform prospects*. ABN AMRO Bank N.V. Available online: <https://www.abnamro.com/research> (accessed on 12 December 2025).
- Allianz Research. (2026). *EU ETS under pressure: Carbon market outlook amid regulatory and geopolitical uncertainty*. Allianz SE.

- Alomari, M., El Khoury, R., Mensi, W., Vo, X. V., & Kang, S. H. (2024). Extreme downside risk connectedness between green energy and stock markets. *Energy*, 312, 133477. [\[CrossRef\]](#)
- Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84. [\[CrossRef\]](#)
- Azzalini, A. (1985). A class of distributions which includes the normal ones. *Scandinavian Journal of Statistics*, 12, 171–178.
- Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1–22. [\[CrossRef\]](#)
- Bajra, U. Q., Aliu, F., & Prenaj, V. (2025). Connectivity of green financial assets under geopolitical risks and market-implied volatility. *Finance Research Letters*, 76, 107037. [\[CrossRef\]](#)
- Bartocci, A., Notarpietro, A., & Pisani, M. (2024). “Green” fiscal policy measures and nonstandard monetary policy in the euro area. *Economic Modelling*, 136, 106743. [\[CrossRef\]](#)
- Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271–296. [\[CrossRef\]](#)
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217–229. [\[CrossRef\]](#)
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327. [\[CrossRef\]](#)
- Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews*, 11(2), 143–172. [\[CrossRef\]](#)
- Broadstock, D. C., Chatziantoniou, I., & Gabauer, D. (2022). Minimum connectedness portfolios and the market for green bonds: Advocating sustainable investment. *Energy Economics*, 112, 106129. [\[CrossRef\]](#)
- Cao, Y., Cheng, S., & Li, X. (2024). Investment value of green bonds under oil market uncertainty: A safe haven perspective. *International Review of Financial Analysis*, 91, 103001. [\[CrossRef\]](#)
- Chitkasame, T., & Pastpipatkul, P. (2025). Comparative effectiveness of carbon pricing and green finance in promoting carbon mitigation in the Eurozone. In V.-N. Huynh, K. Honda, B. Le, M. Inuiguchi, & H.-T. Huynh (Eds.), *Integrated uncertainty in knowledge modelling and decision making (IUKM 2025)* (Vol. 15586, pp. 309–320). Springer Nature. [\[CrossRef\]](#)
- Christoffersen, P., & Pelletier, D. (2004). Backtesting value-at-risk: A duration-based approach. *Journal of Financial Econometrics*, 2(1), 84–108. [\[CrossRef\]](#)
- Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review*, 39(4), 841–862. [\[CrossRef\]](#)
- Clemente, G. P., Grassi, R., & Hitaj, A. (2019). Asset allocation: New evidence through network approaches. *Annals of Operations Research*, 299, 61–80. [\[CrossRef\]](#)
- Cocca, T., Gabauer, D., & Pomberger, S. (2024). Clean energy market connectedness and investment strategies: New evidence from DCC-GARCH R^2 decomposed connectedness measures. *Energy Economics*, 136, 107680. [\[CrossRef\]](#)
- 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. [\[CrossRef\]](#)
- 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. [\[CrossRef\]](#)
- Diebold, F. X., & Yilmaz, K. (2015). *Financial and macroeconomic connectedness: A network approach to measurement and monitoring*. Oxford University Press.
- Dogan, E., Luni, T. S., Bekun, F. V., & Sarkodie, S. A. (2022). Investigating the spillovers and connectedness between green finance and renewable energy sources. *Renewable and Sustainable Energy Reviews*, 157, 112007. [\[CrossRef\]](#)
- Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, 34(1), 157–170. [\[CrossRef\]](#)
- Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339–350. [\[CrossRef\]](#)
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987–1007. [\[CrossRef\]](#)
- Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews*, 5(1), 1–50. [\[CrossRef\]](#)
- Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance*, 48(5), 1749–1778. [\[CrossRef\]](#)
- Fang, F., Si, D.-K., & Hu, D. (2023). Green bond spread effect of unconventional monetary policy: Evidence from China. *Economic Analysis and Policy*, 80, 398–413. [\[CrossRef\]](#)
- Fernández, C., & Steel, M. F. J. (1998). On Bayesian modeling of fat tails and skewness. *Journal of the American Statistical Association*, 93(441), 359–371. [\[CrossRef\]](#)
- Fisher, T. J., & Gallagher, C. M. (2012). New weighted portmanteau statistics for time series goodness of fit testing. *Journal of the American Statistical Association*, 107(498), 777–787. [\[CrossRef\]](#)

- Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance*, 57(5), 2223–2261. [CrossRef]
- Fornaro, L., Guerrieri, V., & Reichlin, L. (2025). *Monetary policy for the green transition*. BIS Papers No. 160. BIS.
- Gabauer, D. (2024). *ConnectednessApproach: Connectedness approach* (R package version 1.0.2). CRAN. Available online: <https://CRAN.R-project.org/package=ConnectednessApproach> (accessed on 12 December 2025).
- Gauss, C. F. (1809). *Theoria motus corporum coelestium in sectionibus conicis solem ambientium*. Perthes et Besser.
- Ghalanos, A. (2024). *rugarch: Univariate GARCH models* (R package version 1.5-3). CRAN. Available online: <https://CRAN.R-project.org/package=rugarch> (accessed on 12 December 2025).
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5), 1779–1801. [CrossRef]
- Ha, L. T., & Nham, N. T. H. (2025). Interlinkages between fossil fuel uncertainty and green assets: New evidence from rare disaster events. *Energy Economics*, 141, 107983. [CrossRef]
- Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press.
- Hentschel, L. (1995). All in the family: Nesting symmetric and asymmetric GARCH models. *Journal of Financial Economics*, 39(1), 71–104. [CrossRef]
- Hillebrand, E. (2005). Neglecting parameter changes in GARCH models. *Journal of Econometrics*, 129(1–2), 121–138. [CrossRef]
- Hinterlang, N. (2024). Different effects of carbon pricing and border adjustment in Germany and Spain. *Economic Modelling*, 141, 106840. [CrossRef]
- Huang, J., Li, H., Chen, B., Liu, M., An, C., & Xia, X. (2025). Revisiting the currency-commodity nexus: New insights into the R² decomposed connectedness and the role of global shocks. *International Review of Economics & Finance*, 98, 103852. [CrossRef]
- Jiang, W., & Chen, Y. (2023). Time-frequency connectedness among traditional/new energy, green finance, and ESG in pre- and post-Russia-Ukraine war periods. *Resources Policy*, 83, 103618. [CrossRef]
- Kaminsky, G. L., Reinhart, C. M., & Végh, C. A. (2003). The unholy trinity of financial contagion. *Journal of Economic Perspectives*, 17(4), 51–74. [CrossRef]
- Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies*, 11(4), 817–844. [CrossRef]
- Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(4), 535–551. [CrossRef]
- Li, W., Lu, X., & Yin, L. (2022). Exploring the asymmetric effect of economic policy uncertainty on carbon emission trading market. *Finance Research Letters*, 46, 102378. [CrossRef]
- Ljung, G. M., & Box, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2), 297–303. [CrossRef]
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91. [CrossRef]
- McNeil, A. J., & Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. *Journal of Empirical Finance*, 7(3–4), 271–300. [CrossRef]
- Mikosch, T., & Stărică, C. (2004). Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. *Review of Economics and Statistics*, 86(1), 378–390. [CrossRef]
- Mouffok, M. A., Mouffok, O., Bouabdallah, W., & Souar, Y. (2025). Asymmetric effect of monetary and fiscal policy uncertainty on the energy transition: Evidence from the United States. *Globalization and Business*, 10, 23–40. [CrossRef]
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347–370. [CrossRef]
- Peralta, G., & Zareei, A. (2016). A network approach to portfolio selection. *Journal of Empirical Finance*, 38, 157–180. [CrossRef]
- Puerta-Ortega, C., & de Mariz, F. (2025). *Climate change integrating policy, carbon markets with sovereign debt relief: The carbon participation debt-for-climate swaps (CP-DFCS) approach*. (SSRN Working Paper 6207379). SSRN. [CrossRef]
- Rachev, S., Ortobelli, S., Stoyanov, S., Fabozzi, F. J., & Biglova, A. (2008). Desirable properties of an ideal risk measure in portfolio theory. *International Journal of Theoretical and Applied Finance*, 11(1), 19–54. [CrossRef]
- Rahman, M. A., & Hasan, M. B. (2025). Quantifying dynamic connectedness among diverse green and sustainable financial assets: Evidence from quantile-base VAR technique. *Finance Research Open*, 1(2), 100007. [CrossRef]
- Redondo Alamillos, R., & de Mariz, F. (2022). How can European regulation on ESG impact business globally? *Journal of Risk and Financial Management*, 15(7), 291. [CrossRef]
- Ringstad, I. E. F., & Tselika, K. (2024). Connectedness between green bonds, clean energy markets and carbon quota prices: Time and frequency dynamics. *Journal of Commodity Markets*, 36, 100442. [CrossRef]
- Sharma, G. D., Verma, M., Shahbaz, M., Gupta, M., & Chopra, R. (2022). Transitioning green finance from theory to practice for renewable energy development. *Renewable Energy*, 195, 554–565. [CrossRef]
- Student. (1908). The Probable Error of a Mean. *Biometrika*, 6(1), 1–25. [CrossRef]
- Su, X., & Lian, Y. (2025). Dynamic connectedness between carbon markets, clean energy, climate policy uncertainty and green innovation. *Energy Economics*, 138, 107826. [CrossRef]

- Sun, G., Li, G., Dilanchiev, A., & Kazimova, A. (2023). Promotion of green financing: Role of renewable energy and energy transition in China. *Renewable Energy*, 210, 769–775. [\[CrossRef\]](#)
- Tiwari, S., Mohammed, K. S., & Balsalobre-Lorente, D. (2025). Green finance: A pathway to achieving carbon neutrality and sustainable development. *Sustainable Development*, 33(S1), 988–1002. [\[CrossRef\]](#)
- Uddin, M. A., Chang, B. H., Aldawsari, S. H., & Li, R. (2025). The interplay between green finance, policy uncertainty and carbon market volatility: A time frequency approach. *Sustainability*, 17(3), 1198. [\[CrossRef\]](#)
- Yin, H.-T., Chang, C.-P., & Wang, H. (2022). The impact of monetary policy on green innovation: Global evidence. *Technological and Economic Development of Economy*, 28(6), 1933–1953. [\[CrossRef\]](#)
- Yuan, X., Li, J., Shang, Y., & Xiang, L. (2023). Financial connectedness between green bonds and carbon markets: New evidence from time-frequency domain. *Pacific-Basin Finance Journal*, 80, 102093. [\[CrossRef\]](#)
- Zheng, T., Zhang, H., & Ye, S. (2024). Monetary policies on green financial markets: Evidence from a multi-moment connectedness network. *Energy Economics*, 136, 107739. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.