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Synergistic Dynamics: The Interplay Between Clean Power, Artificial Intelligence, and Global Assets Across Economic Quantiles¹

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Abstract

This study examines nonlinear, quantile-dependent spillovers among clean power, artificial intelligence (AI), and global financial assets using the quantile-on-quantile VAR connectedness framework with generalised forecast-error generalised variance decomposition. Using daily data from June 1, 2018, to October 18, 2024, the analysis covers clean power, AI, commodities, equities, cryptocurrencies, green bonds, ESG, and alternative investment indices. The results reveal strong state-dependent interconnectedness. The total connectedness index (TCI) is lowest around the median quantiles (0.50–0.50),

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averaging 63–65, but rises sharply in extreme conditions, exceeding 95 at both lower (0.05–0.05) and upper (0.95–0.95) quantiles. Net connectedness estimates show that gold and green bonds are persistent net receivers of shocks, particularly in downside markets, confirming their safe-haven roles. Equities and cryptocurrencies serve as dominant net transmitters in the upper quantiles (0.75–0.95), amplifying systemic risk. Clean power and ESG assets exhibit increasing bidirectional spillovers, indicating deeper financial integration. Rolling-window results show that spillovers intensify during pandemic, geopolitical, and monetary-tightening episodes, with clear implications for tail-risk management and sustainable portfolio design.

Keywords: Financial interconnectedness, spillover effects, systemic risk, clean energy investments

JEL Classification: C22, E44, G11, G15, Q56

1. Introduction

The global transition toward clean energy and the rapid diffusion of artificial intelligence (AI) technologies are increasingly reshaping financial markets. Clean power assets, once largely policy-driven, have become mainstream investment instruments through clean energy indices, green bonds, and ESG-oriented portfolios (Mhadhbi, 2024; Jiang *et al.*, 2023). In parallel, AI-related assets have gained systemic relevance as digitalisation, algorithmic trading, and data-intensive production processes influence market liquidity, pricing efficiency, and risk transmission (Pattnaik *et al.*, 2024; Ambuli *et al.*, 2024). These developments raise an essential yet underexplored question: how do shocks originating in clean power and AI markets spill over to global financial assets under different market conditions?

Several theoretical channels explain why spillovers involving clean energy and AI assets are likely to be nonlinear and state-dependent. First, the liquidity and financialisation channel suggests that growing institutional participation and cross-asset portfolio allocation increase interdependence between clean power, technology-linked assets, equities, and commodities, allowing shocks to propagate more rapidly during stress episodes (Okhrin *et al.*, 2023; Olasehinde-Williams *et al.*, 2023). Second, standard macroeconomic and policy shocks, such as monetary tightening, geopolitical tensions, climate policy uncertainty, and energy price volatility, simultaneously affect AI-intensive firms, clean energy producers, and traditional financial markets (Nasir *et al.*, 2023; Alam *et al.*, 2024). Third, investor sentiment and expectations surrounding technological innovation and the energy transition can amplify synchronised movements during market booms or downturns, particularly in the tails of the return distribution (Ghaemi Asl *et al.*, 2025; Liu *et al.*, 2024). Finally, production and value-chain linkages connect AI and clean power markets to commodities and

equities through energy-intensive digital infrastructure, demand for transition metals, and carbon-adjustment mechanisms (Arfaoui *et al.*, 2025; Madaleno *et al.*, 2023).

Despite rising interest in these issues, much of the existing literature relies on linear or mean-based frameworks such as DCC-GARCH, TVP-VAR, or conventional quantile VAR models (Diebold and Yilmaz, 2014; Baruník and Kocenda, 2019). While these approaches capture time variation and volatility clustering, they are limited in their ability to identify how shocks occurring in one market state (*e.g.*, extreme downside risk) propagate to other assets operating in different states. Recent quantile-based studies provide valuable insights into tail dependence and asymmetric spillovers (Zhang *et al.*, 2023; Shi *et al.*, 2024), yet they typically condition on a single quantile dimension and therefore overlook cross-quantile transmission mechanisms.

The quantile-on-quantile (QQ) connectedness framework introduced by Gabauer and Stenfors (2024) directly addresses these limitations by jointly conditioning on specific quantiles for both shock origin and shock reception. This allows the analysis to capture spillovers, for example, from extreme bearish conditions in one market to bullish conditions in another, dynamics that conventional quantile VAR, TVP-VAR, and DCC-GARCH models cannot detect. This methodological advantage is particularly relevant for AI and clean energy assets, whose spillover effects are inherently nonlinear and sensitive to market regimes (Okhrin *et al.*, 2023; Mhadhbi, 2024). Against this backdrop, this study examines the interconnectedness between clean power, AI, and a broad set of global financial assets using a quantile-on-quantile connectedness approach. Specifically, it investigates whether spillovers are more substantial under extreme market conditions than under normal conditions, whether assets such as gold and green bonds consistently act as shock absorbers, and whether equities and cryptocurrencies function as systemic risk transmitters during market exuberance.

This study contributes to the literature by integrating clean power and AI indices into a QQ-connectedness framework, uncovering cross-quantile spillovers overlooked by existing methods, and providing quantile-specific insights relevant to portfolio diversification, tail-risk management, and macroprudential policy in the context of technological innovation and the global energy transition.

2. Literature Review

The growing intersection of clean energy, artificial intelligence (AI), and global financial markets has generated a rapidly expanding body of empirical research. However, this literature remains fragmented across theoretical explanations, empirical regularities, and

methodological approaches. This section synthesizes prior studies around four core themes: (i) theoretical transmission mechanisms, (ii) empirical evidence on spillovers and tail dependence, (iii) methodological approaches and their limitations, and (iv) unresolved gaps motivating the present study.

2.1 Theoretical Mechanisms Linking Clean Energy, AI, and Financial Spillovers

A first strand of the literature focuses on the theoretical channels through which clean energy and AI-related assets interact with broader financial markets (Tiwari *et al.*, 2023; Zeng *et al.*, 2024). Studies emphasise the role of financialisation and liquidity integration, whereby clean energy and technology assets increasingly co-move with traditional equities and commodities as institutional participation rises (Mhadhbi, 2024; Jiang *et al.*, 2023; Akadiri and Adebayo, 2022). This integration weakens the insulation of green assets from systemic shocks (Baker *et al.*, 2022). A second mechanism involves standard macroeconomic and policy shocks, including monetary tightening, climate policy uncertainty, geopolitical risk, and energy price volatility, which jointly affect clean energy, AI-intensive firms, and conventional markets (Abakah *et al.*, 2023; Nasir *et al.*, 2023; Alam *et al.*, 2024; Sharwa *et al.*, 2024).

Investor sentiment also plays a critical role. Expectations surrounding technological innovation, digital transformation, and energy transition generate synchronised asset price movements, particularly during extreme market conditions (Ghaemi Asl *et al.*, 2025; Liu *et al.*, 2024). Finally, production and value-chain linkages, such as the energy intensity of digital infrastructure and the reliance of clean technologies on transition metals, connect AI and clean power markets to commodities and equities (Arfaoui *et al.*, 2025; Madaleno *et al.*, 2023; Niu and Cao, 2024). These channels jointly imply nonlinear, asymmetric, and state-dependent spillovers.

2.2 Empirical Evidence on Spillovers and Tail Dependence

Empirically, a large body of work documents significant spillovers between clean energy, traditional energy, financial markets, and emerging digital assets. Studies using connectedness and tail-dependence frameworks find that spillovers intensify during crises and geopolitical events (Zhang *et al.*, 2023; Abbas *et al.*, 2024; Cevik *et al.*, 2024; He, 2025). For instance, Aloui *et al.* (2025) and Jiang *et al.* (2023) show that green bonds and ESG assets often act as shock absorbers during downside markets, while equities and energy commodities frequently amplify volatility.

Research on digital assets and AI-related markets suggests increasing integration with conventional financial systems. Bouri *et al.* (2021) and Hasan *et al.* (2022) report that cryptocurrencies transmit shocks during speculative booms, undermining diversification benefits. Similarly, Tiwari *et al.* (2024) and Gubareva *et al.* (2025) show that AI and clean energy markets exhibit strong interdependencies with oil and equity markets. However, empirical findings are mixed regarding whether sustainable assets consistently function as safe havens (Kumar and Paramaiah, 2024), suggesting that their role is contingent on market states and shock origins.

2.3 Methodological Approaches and Their Limitations

Most existing studies rely on DCC-GARCH, wavelet coherence, cross-quantilogram, or time-varying parameter VAR frameworks (Diebold and Yilmaz, 2014; Baruník and Kocenda, 2019; Akadiri and Özkan, 2025; Olasehinde-Williams and Akadiri, 2025; Özkan *et al.*, 2025). While these methods provide valuable insights into dynamic correlations, frequency-domain relationships, and tail dependence, they exhibit notable limitations. DCC-GARCH models focus on conditional correlations and assume symmetric dependence, limiting their ability to capture directional spillovers. Wavelet-based approaches reveal time–frequency co-movement but do not explicitly quantify shock transmission or directionality. Cross-quantilogram and quantile causality methods identify tail dependence but condition on a single quantile dimension, overlooking how shocks at one quantile transmit to different quantiles in other markets.

Moreover, many studies interpret spillovers as causal relationships. However, these frameworks primarily capture predictive dependence or co-movement rather than structural causality. Without explicit identification strategies, spillover measures should be interpreted as indicators of risk transmission rather than causal effects (Diebold and Yilmaz, 2014; Okhrin *et al.*, 2023).

2.4 Advancing the Literature with Quantile-on-Quantile Connectedness

The QQ connectedness framework proposed by Gabauer and Stenfors (2024) addresses several unresolved methodological gaps. By jointly conditioning both shock origin and reception on specific quantiles, QQ connectedness captures cross-quantile transmission mechanisms – for example, how extreme downside shocks in one market affect extreme upside outcomes in another. This feature is absent in standard quantile VAR, DCC-GARCH, and wavelet approaches.

Recent applications demonstrate the effectiveness of QQ-based methods in uncovering nonlinear and asymmetric spillovers across energy and financial markets (Shi *et al.*, 2024; Liu *et al.*, 2024). However, their application to a comprehensive system integrating clean power, AI, sustainable finance, and digital assets remains limited. This study fills this gap by providing a unified QQ connectedness analysis that clarifies when clean energy and AI assets act as shock absorbers or amplifiers across market states, while carefully avoiding causal overinterpretation.

3. Data and Methodology

3.1 Data

This section discusses the study's data description, its source, and the econometric methodology adopted for the empirical analysis. This study explores the interplay between clean power, artificial intelligence, and global assets across economic quantiles from 01.06.2018 to 18.10.2024. For details on data and coding, see Table 1.

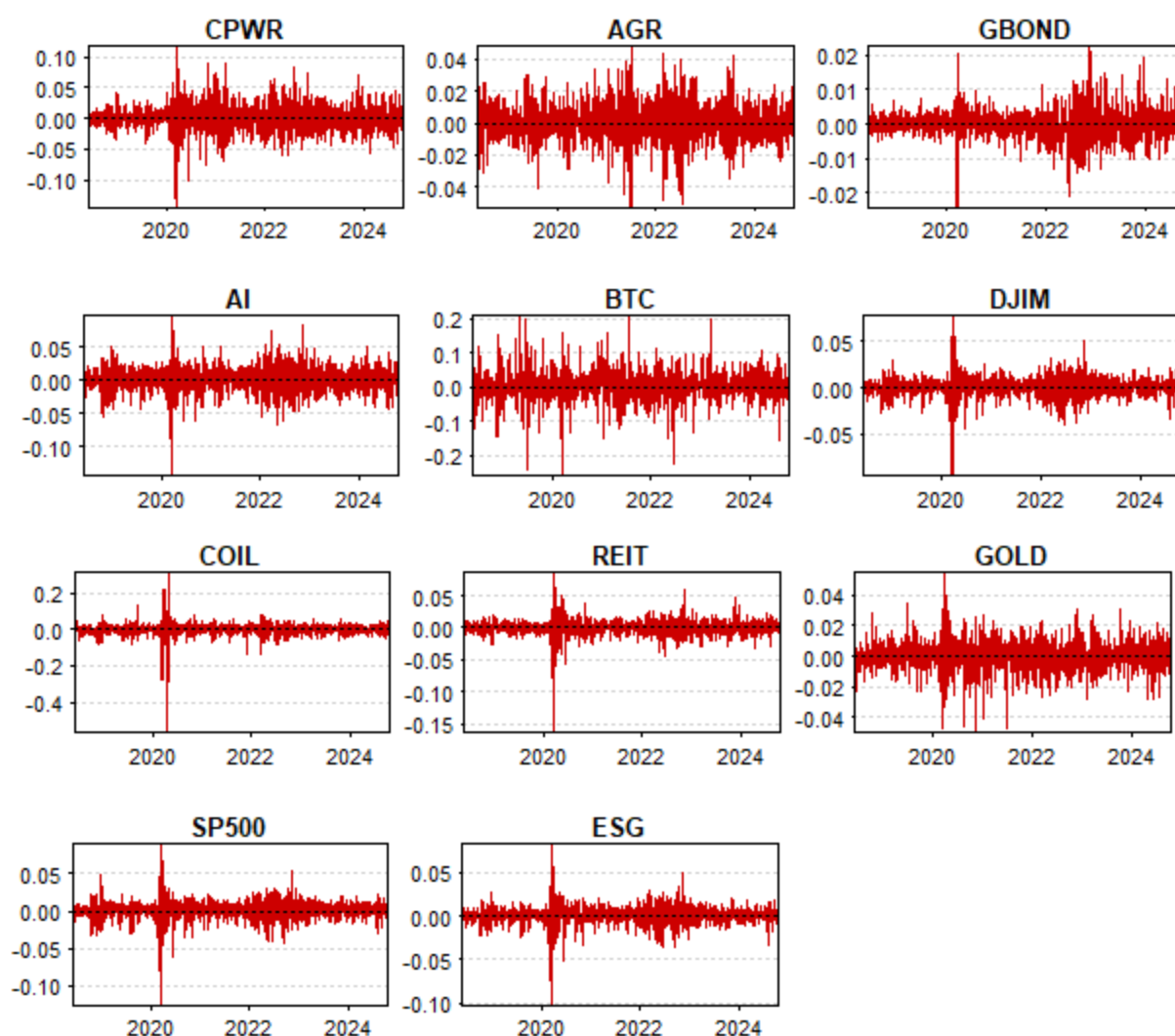
Table 1: Details of the data series

Symbol	Data	Description	Source
CPWR	S&P Kensho Clean Power Index	The index is designed to measure the performance of companies advancing clean technology and clean energy.	SPG (2024)
AI	S&P Kensho Artificial Intelligence Enablers Index	The index seeks to measure the performance of developing companies and of enabling technologies, infrastructure, and services for artificial intelligence.	SPG (2024)
COIL	S&P GSCI Crude Oil	The index provides investors with a reliable, publicly available benchmark for measuring investment performance in the crude oil market.	SPG (2024)
SP500	The S&P 500® Index	The index is widely regarded as the best single gauge of large-cap US equities. It includes 500 leading companies and covers approximately 80% of the available market capitalisation.	SPG (2024)
AGR	S&P GSCI Agriculture Index	The index provides investors with a reliable, publicly available benchmark for investment performance in agricultural commodity markets.	SPG (2024)
BTC	S&P Bitcoin Index	The index is designed to track the performance of the digital asset Bitcoin.	SPG (2024)
REIT	S&P Global REIT Index	The index is a comprehensive benchmark of publicly traded equity REITs listed in developed and emerging markets.	SPG (2024)
ESG	S&P World ESG Index	The index measures the performance of securities meeting sustainability criteria. It is a composite index made up of multiple S&P DJI ESG subindices.	SPG (2024)
GBOND	S&P Green Bond Index	The index is designed to track the global green bond market. It maintains stringent standards, including only bonds whose proceeds are used to finance environmentally friendly projects.	SPG (2024)
DJIM	Dow Jones Islamic Market World Index	The index measures the performance of global stocks that pass rules-based screens for adherence to Shari'ah investment guidelines.	SPG (2024)
GOLD	S&P GSCI Gold Index	The index provides investors with a reliable, publicly available benchmark for tracking the future of COMEX gold. It is designed to be tradable, readily accessible to market participants, and cost-efficient to implement.	SPG (2024)

Source: Authors' own elaboration

Figure 1 presents time-series return plots for various assets, including *CPWR*, *AI*, *BTC*, *GOLD*, *GBOND*, and *DJIM: SP500*. The plots illustrate the volatility dynamics over time, capturing significant fluctuations, particularly during major economic events such as the COVID-19 pandemic (early 2020). *COIL* exhibits the most extreme spikes, indicating high sensitivity to global shocks. *ESG* and *SP500* returns appear relatively stable compared to *BTC* and *COIL*, which display pronounced volatility. Figure 1 highlights the varying risk-return dynamics across asset classes.

Figure 1: Time series of plots of returns



Note: Returns are calculated as $\ln(v_t/v_{t-1})$, where $\ln$ denotes the natural logarithm, and v_t and v_{t-1} represent the values at times t and $t-1$, respectively.

Source: Authors' own elaboration

Table 2 presents descriptive statistics for asset returns, including mean returns, volatility, and higher-order moments such as skewness, kurtosis, and the Jarque–Bera (Jarque and Bera, 1980) test. *BTC* exhibits the highest mean return (0.001374), reflecting its strong growth potential despite high volatility. *AI* and *CPWR* also show positive mean returns, suggesting that technological and clean energy assets offer attractive investment opportunities. In contrast, *GBOND* displays a negative mean return ($-1.08\text{E-}05$), indicating lower profitability than other assets.

Regarding volatility, *COIL* and *BTC* have the highest standard deviations (0.034125 and 0.041352, respectively), reflecting significant price swings and higher risk exposure. On the other hand, *GBOND* and *ESG* assets demonstrate lower volatility (0.004104 and 0.010653), reinforcing their stability as sustainable investment options. The skewness and kurtosis values reveal further insights into the return distributions. Most assets exhibit negative skewness, indicating a tendency toward extreme downside risk, with *COIL* showing the most pronounced left skewness (-3.06639). Additionally, high kurtosis is observed across all assets, particularly in *COIL* (67.0422) and *REIT* (31.96448), suggesting fat-tailed distributions and frequent extreme return events.

Table 2: Descriptive statistics

	Mean	Standard Deviation	Skewness	Kurtosis	JB
<i>CPWR</i>	0.000385	0.021977	−0.30497	7.674154	1,487.797***
<i>AI</i>	0.000657	0.018885	−0.41606	6.95551	1,093.997***
<i>COIL</i>	1.51E-05	0.034125	−3.06639	67.0422	277,141.5***
<i>SP500</i>	0.000481	0.012662	−0.80828	17.73824	14,719.38***
<i>AGR</i>	8.81E-05	0.011636	−0.05088	4.817174	221.7977***
<i>BTC</i>	0.001374	0.041352	−0.23148	7.901858	1,623.24***
<i>REIT</i>	5.32E-05	0.012426	−1.96306	31.96448	57,206.22***
<i>ESG</i>	0.000395	0.010653	−1.02756	18.51934	16,409.71***
<i>GBOND</i>	−1.08E-05	0.004104	−0.07202	7.294	1,235.996***
<i>DJIM</i>	0.000412	0.011005	−0.76293	13.76238	7,911.593***
<i>GOLD</i>	0.000459	0.009515	−0.2406	7.090358	1,135.786***

Note: *** denotes statistical significance at the 1% level.

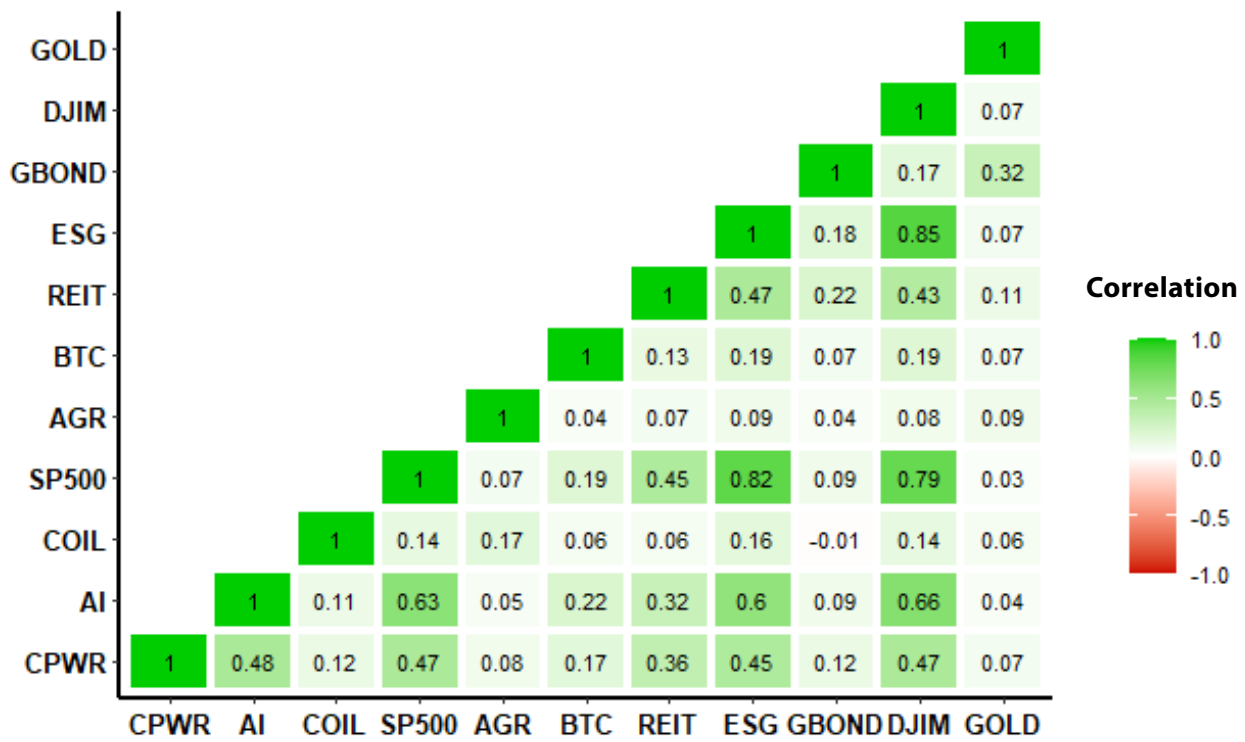
Source: Authors' own calculations

The JB test results confirm non-normality in all asset return distributions ($p < 0.01$), indicating heavy tails and non-Gaussian behaviour. These findings align with the study's focus on risk-return dynamics and asset resilience to unexpected geopolitical and economic shocks. The heightened volatility of *COIL* and *BTC* suggests their vulnerability to extreme market events, while the relatively lower risk of *ESG* and *GBOND* highlights their potential as safe-haven investments.

Figure 2 presents the Kendall correlation matrix among the selected assets, offering insights into their interdependencies and co-movements. The colour gradient from green (positive correlation) to red (negative correlation) visually represents the strength and direction of these relationships. Notably, ESG investments exhibit a strong positive correlation with *REIT* (0.47) and *DJIM* (0.85), suggesting that sustainable and ethical investments tend to move with real estate and Islamic market indices; this highlights the growing alignment between sustainability and alternative investment options. Similarly, the S&P 500 (*SP500*) maintains high positive correlations with *ESG* (0.82) and *DJIM* (0.79), reinforcing its close ties to both conventional and ethical investment markets.

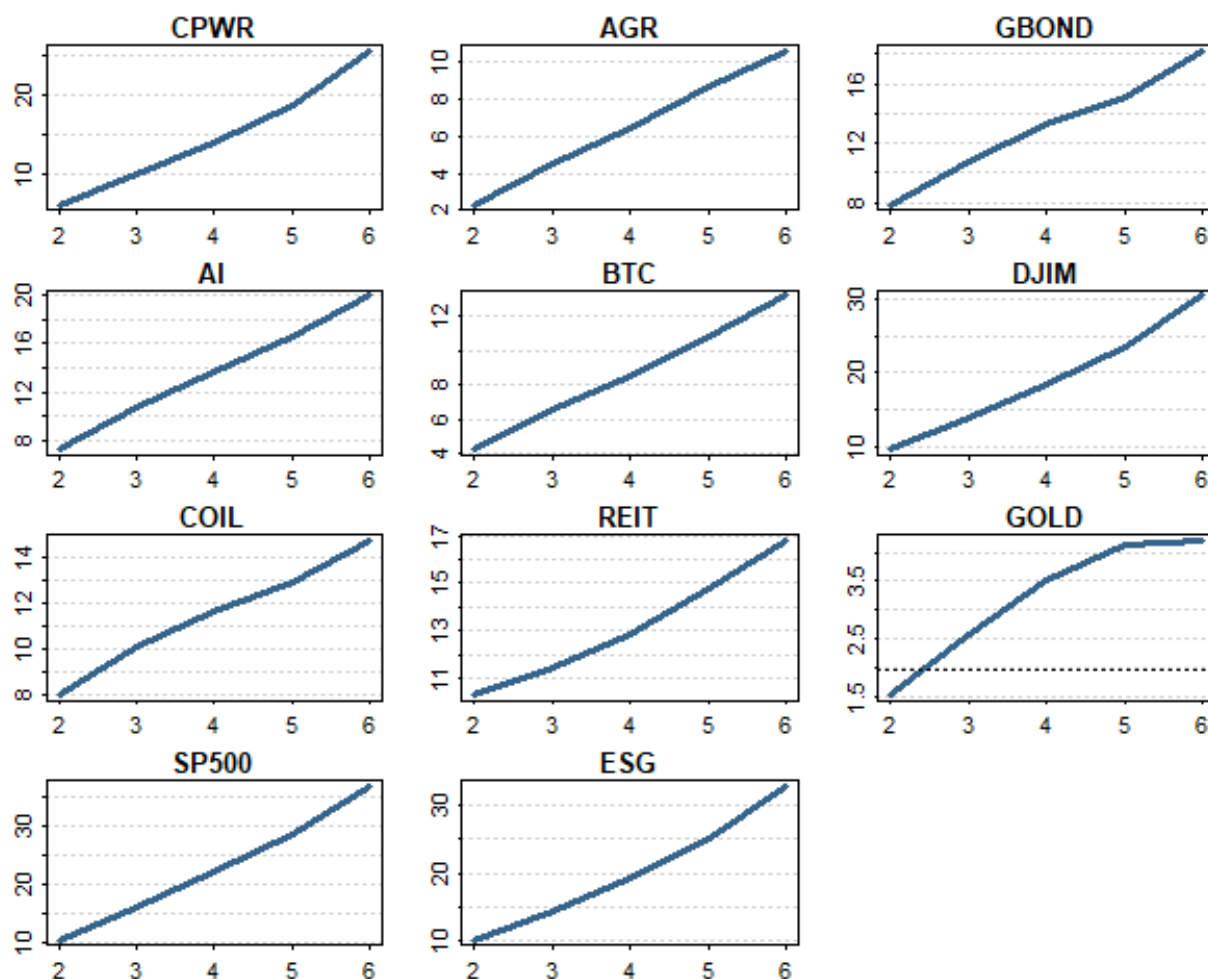
COIL shows moderate correlations with *AI* (0.63) and the S&P 500 (0.17), indicating that technological advancements and market-wide trends influence oil prices. However, *COIL* shows only a weak correlation with other asset classes, reflecting its unique risk-return profile, which is driven by supply-and-demand shocks and geopolitical influences. Despite being a volatile asset, *BTC* shows weak correlations with most traditional assets, with the highest being *AI* (0.22); this underscores *BTC*'s role as a relatively independent asset class that often behaves differently from traditional markets. *GOLD*, known for its safe-haven characteristics, shows weak correlations across the board, with the highest being with *GBOND* (0.32); this suggests that gold may act as a hedging tool against market uncertainties, but its relationship with government bonds is not particularly strong. Figure 2 highlights the varying degrees of co-movement among the selected assets. While specific pairs exhibit strong positive correlations – such as *ESG* and *DJIM*, and *ESG* and *SP500* – other assets, like *BTC* and *COIL*, maintain relatively independent dynamics. These findings provide key insights into portfolio diversification, as assets with low or negative correlations can serve as effective hedging instruments in risk management strategies.

Figure 2: Kendall correlations among the selected assets



Source: Authors’ own elaboration

Figure 3 presents the Brock–Dechert–Scheinkman (Brock, Dechert, Scheinkman (BDS), 1996) test estimates for the selected assets, offering insights into nonlinear dependence within their time series. The results indicate that all assets exhibit BDS estimates exceeding the critical value of 1.96, providing strong evidence of nonlinear dependence in their respective time series. This suggests that these assets do not follow purely random (i.i.d.) processes, highlighting the influence of complex market dynamics, structural shifts, and potential inefficiencies. Given these findings, our analysis employs the quantile-on-quantile connectedness framework introduced by Gabauer and Stenfors (2024) to explore the intricate interdependencies among these assets, as traditional linear models may fail to capture these complexities fully.

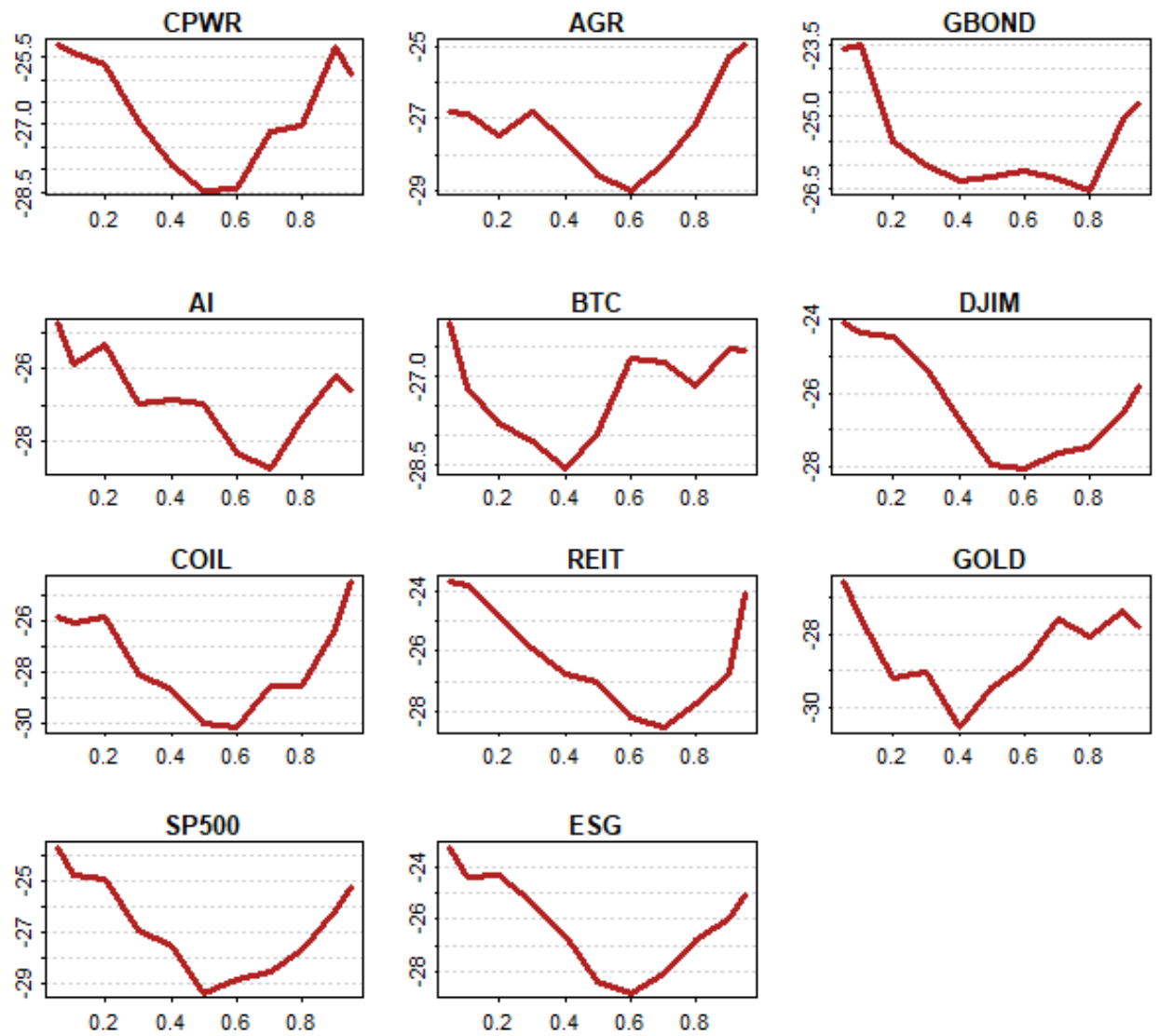
Figure 3: BDS estimates

Note: 5% critical value is 1.96.

Source: Authors' own elaboration

Figure 4 presents the Quantile Augmented Dickey–Fuller (QADF) test estimates for the selected assets, as introduced by Adebayo and Özkan (2024). The QADF test is an extension of the conventional ADF test, designed to assess the stationarity of a time series across different quantiles, thereby capturing potential nonlinear and quantile-dependent unit root properties. The figure shows that the QADF estimates vary across quantiles for all assets, indicating quantile-dependent stationarity dynamics. Most assets exhibit a U-shaped or asymmetric pattern, with stationarity more evident in the mid-range quantiles; this suggests that market conditions, shocks, or structural changes influence the persistence of asset prices differently across quantiles. These findings reinforce the importance of employing nonlinear and quantile-specific approaches when analysing financial time series, as traditional unit root tests may overlook heterogeneous stationarity across different market conditions.

Figure 4: QADF estimates



Note: 5% critical value is -2.86 .
Source: Authors' own elaboration

3.2 Methodology

We employ the quantile-on-quantile connectedness introduced by Gabauer and Stenfors (2024)² to examine clean power, artificial intelligence, and global assets. We outline a QVAR(p) model that allows us to estimate the dependencies on different quantiles, as seen in Equation (1).

² For the analyses, please see Gubareva *et al.* (2025) and Arfaoui *et al.* (2025).

$$\mathbf{Y}_t^{(\tau)} = \alpha(\tau) + \sum_{i=1}^P \beta_i(\tau) \mathbf{Y}_{t-i}^{(\tau)} + \mu_t^{(\tau)} \quad (1)$$

where $\mathbf{Y}_t$ and $\mathbf{Y}_{t-i}$ are $K \times 1$ vectors of endogenous variables, $\tau \in [0, 1]$ denotes the quantile level, p represents the QVAR lag length, and $\alpha(\tau)$ is a $K \times 1$ vector of quantile-specific intercepts. Furthermore, $\beta_i(\tau)$ is a $K \times K$ QVAR coefficient matrix for lag i , and $\mu_t^{(\tau)}$ represents the $K \times 1$ vector of error terms at quantile τ with a $K \times K$ variance-covariance matrix $\mathbf{H}(\tau)$. The Wold representation theorem is used to convert the QVAR to a QVMA in order to calculate the generalised forecast error variance decomposition (GFEVD), which was proposed by Koop *et al.* (1996); Pesaran and Shin (1998): $\mathbf{Y}_t^{(\tau)} = \alpha(\tau) + \sum_{i=1}^P \beta_i(\tau) \mathbf{Y}_{t-i}^{(\tau)} + \mu_t^{(\tau)} = \sum_{i=0}^{\infty} \mathbf{A}_i(\tau) \varepsilon_{t-i}(\tau)$. The effect a shock in series t has on series i is thus represented by the F -step ahead GFEVD, expressed in Equation (2):

$$\phi_{i \leftarrow j, \tau}(F) = \frac{\sigma_{jj}^{-1}(\tau) \sum_{f=0}^{F-1} (\mathbf{e}_i' \mathbf{A}_f(\tau) \mathbf{H}(\tau) \mathbf{e}_j)^2}{\sum_{f=0}^{F-1} (\mathbf{e}_i' \mathbf{A}_f(\tau) \mathbf{H}(\tau) \mathbf{A}_f(\tau)' \mathbf{e}_i)} \quad \text{gSOT}_{i \leftarrow j, (\tau)}(F) = \frac{\phi_{i \leftarrow j, \tau}^g(F)}{\sum_{j=1}^K \phi_{i \leftarrow j, \tau}^g(F)} \quad (2)$$

where $\mathbf{e}_i$ is a zero vector with unity on its i -th position that is $K \times 1$ dimensional. Diebold and Yilmaz (2012) proposed normalising $\phi_{i \leftarrow j, \tau}^{gen}(H)$ by dividing it by the row sum to produce the scaled GFEVD, $\text{gSOT}_{i \leftarrow j, (\tau)}(F)$, since the row sum of $\phi_{i \leftarrow j, \tau}^{gen}$ is not equal to unity. The scaled GFEVD, which calculates the overall directional connectivity TO (FROM) others, is the central component of the connectedness approach. The FROM total directional connectedness shows how all series affect series i , whereas the TO total directional connectedness shows how series i affects all others. Equations (3) and (4) can be used to determine these connectivity metrics.

$$S_{i \rightarrow *, \tau}^{\text{gen, to}} = \sum_{j=1, j \neq i}^K \text{gSOT}_{j \leftarrow i, \tau} \quad (3)$$

$$S_{i \leftarrow *, \tau}^{\text{gen, from}} = \sum_{j=1, j \neq i}^K \text{gSOT}_{i \leftarrow j, \tau} \quad (4)$$

A series' NET total directional connectedness is the difference between the TO and FROM total directional connectedness, as seen in Equation (5).

$$S_{i, \tau}^{\text{gen, net}} = S_{i \rightarrow *, \tau}^{\text{gen, to}} - S_{i \leftarrow *, \tau}^{\text{gen, from}} \quad (5)$$

where $S_{i, \tau}^{\text{gen, net}} > 0$ (and $S_{i, \tau}^{\text{gen, net}} < 0$) means that series i is a net transmitter (receiver) of shocks, influencing all other series more (less) than being influenced by them. Lastly, Chatziantoniou *et al.* (2021) adjusted the total connectedness index (TCI), which has a range of $[0, 1]$, as follows:

$$\text{TCI}_{\tau}(F) = \frac{1}{K} \sum_{k=1}^K S_{k \leftarrow *, \tau}^{\text{gen, from}} \equiv \frac{1}{K} \sum_{k=1}^K S_{k \rightarrow *, \tau}^{\text{gen, to}} \quad (6)$$

We use this metric to calculate the degree of network interconnectivity. Therefore, the market risk increases with the TCI.

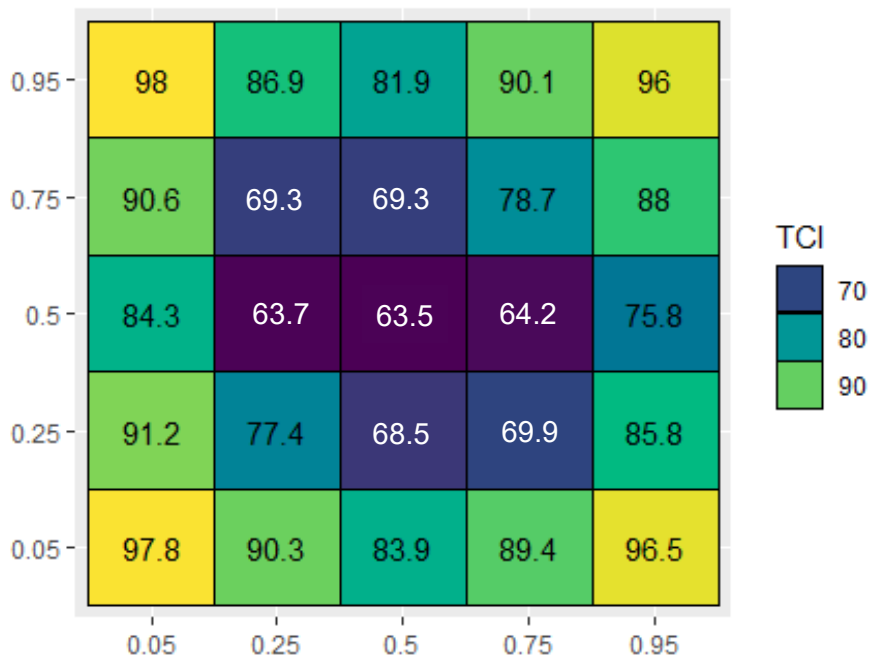
4. Empirical Results and Discussion of Findings³

Figure 5 presents the average total QQ connectedness⁴, illustrating the strength and dynamics of interconnectedness across different quantiles. The heatmap displays the TCI across quantiles from 0.05 to 0.95 on both axes, with lighter colours indicating more substantial spillovers and darker colours indicating weaker transmission. A key observation is the high connectedness in extreme quantiles, particularly at (0.95, 0.95) and (0.05, 0.05), where values exceed 95; this suggests that extreme market conditions, whether bullish or bearish, amplify spillover effects, reinforcing the well-documented phenomenon of heightened interdependence during financial turbulence (Baruník and Křehlík, 2018; Diebold and Yilmaz, 2014). In contrast, the central region (around 0.50, 0.50) exhibits the lowest connectedness values, ranging from 63 to 65, indicating that, under normal market conditions, asset interdependencies weaken. Additionally, an asymmetry in spillover effects is evident, with lower quantiles (associated with bearish conditions) displaying slightly higher total connectedness than mid-quantile values; this suggests that risk contagion is more pronounced during downturns, highlighting the nonlinear nature of market dependencies of interconnectedness over time.

3 It is important to emphasise that the connectedness and spillover measures reported in this study do not imply structural or causal effects. The QQ connectedness framework captures directional risk transmission and predictive dependence across asset returns under different market states. In the absence of an explicit causal identification strategy, the findings should be interpreted as associative measures of systemic risk propagation rather than causal impacts. Observed net transmitter or receiver roles – particularly at extreme quantiles – may reflect underlying mechanisms such as correlated investor behaviour, leverage effects, liquidity conditions, or exposure to standard macroeconomic and policy shocks, rather than direct causal influence.

4 All results are based on a 200-day Rolling Window Quantile-on-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalised forecast error variance decomposition. For the analyses, please see Gubareva et al. (2025) and Arfaoui et al. (2025).

Figure 5: Averaged total QQ connectedness



Source: Authors’ own elaboration

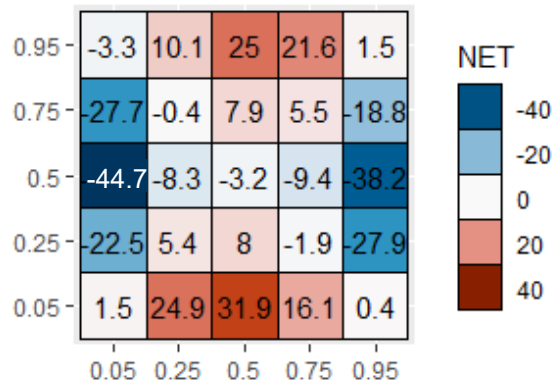
Figure 6 presents the average net QQ-connectedness, illustrating the asymmetric transmission of shocks across quantiles. The eleven heatmaps reveal distinct variations in net spillovers, emphasising the heterogeneous nature of risk propagation across financial and energy markets. This quantile-dependent behaviour underscores the importance of nonlinear modelling approaches in capturing spillover effects that traditional mean-based models might overlook.

Across the eleven subplots, blue-shaded areas represent net receivers of shocks, while red-shaded areas indicate net transmitters. The intensity of connectedness varies significantly across different quantile combinations, reinforcing the non-linearity of spillover dynamics. Extreme quantiles – lower (0.05–0.25) and upper (0.75–0.95) – exhibit the most substantial transmission, suggesting that financial and energy markets are more interconnected under extreme conditions. This finding is consistent with prior research indicating that extreme market scenarios amplify spillover effects (Baruník and Křehlík, 2018).

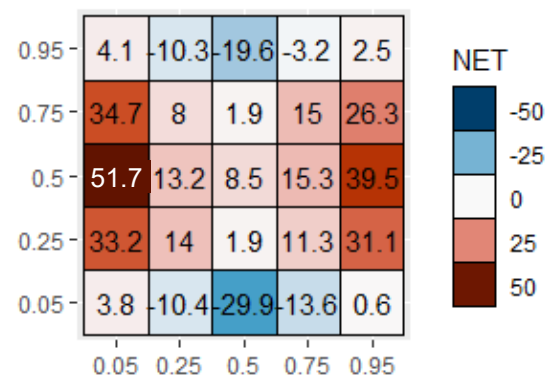
At the lower quantiles (0.05–0.25), the heatmaps predominantly display negative net values (blue), indicating that these quantiles act as net recipients of shocks; this suggests that these markets tend to absorb rather than transmit spillovers during downturns or financial distress. Strong negative connectedness at these levels may reflect capital outflows, liquidity constraints, or policy interventions aimed at stabilising the market.

Figure 6: Averaged net QQ connectedness

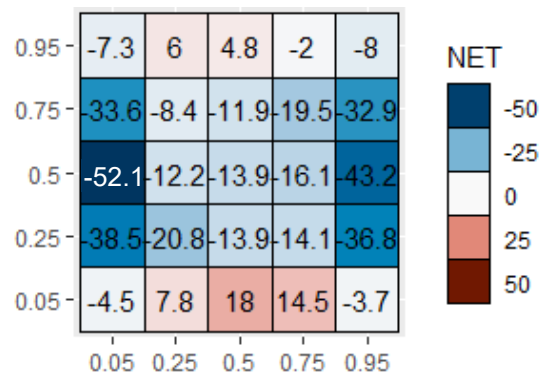
(a) CPWR



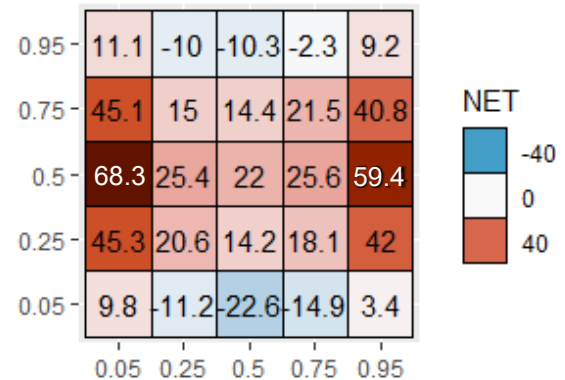
(b) AI



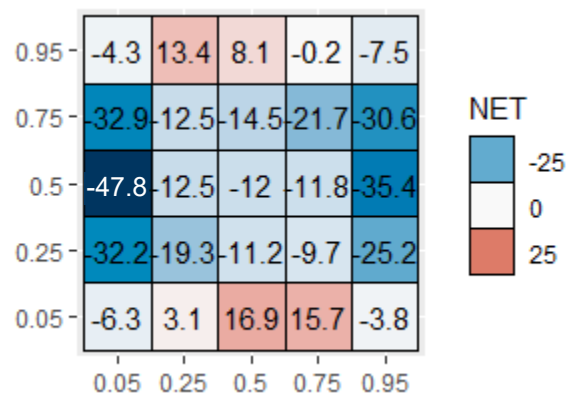
(c) COIL



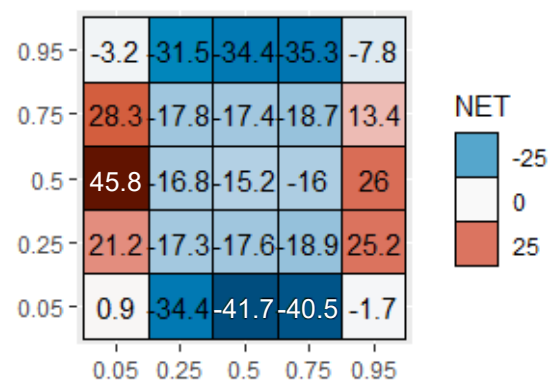
(d) SP500

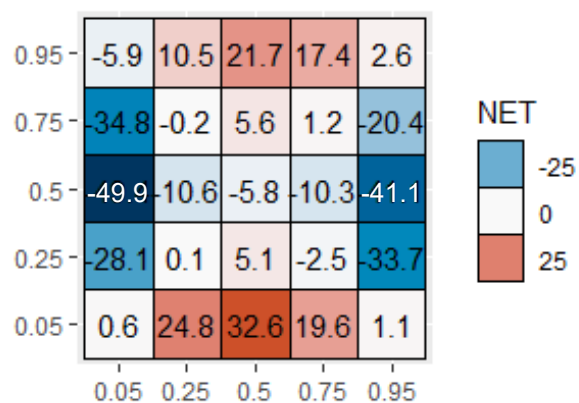
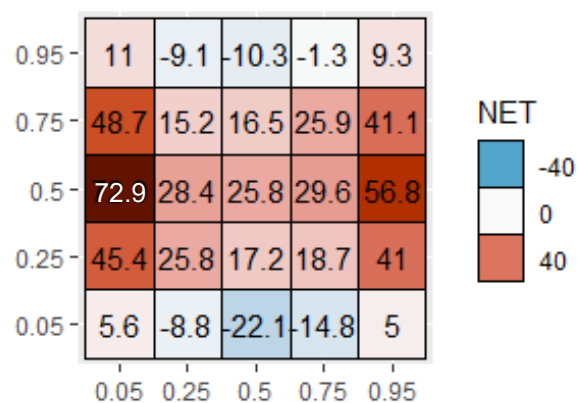
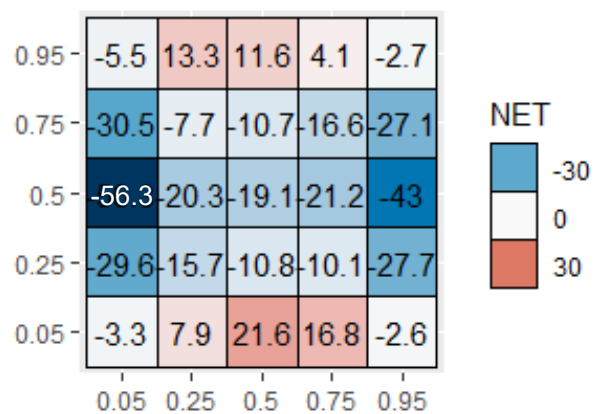
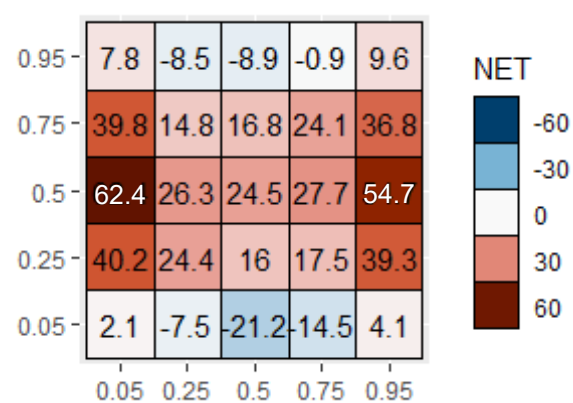
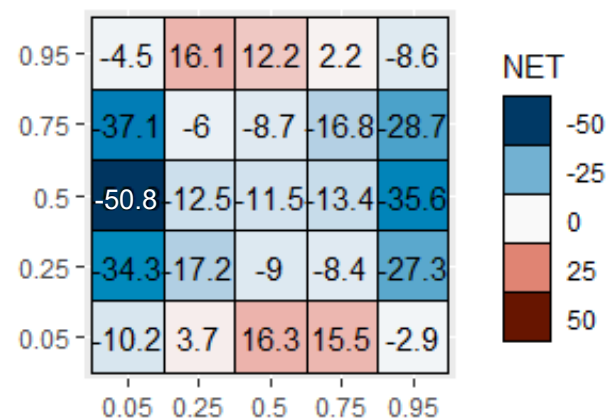


(e) AGR



(f) BTC



(g) REIT**(h) ESG****(i) GBOND****(j) DJIM****(k) GOLD**

Source: Authors' own elaboration

Conversely, the upper quantiles (0.75–0.95) display strong positive net values (red shading), indicating they are dominant net transmitters of shocks, particularly during periods of high volatility or speculative activity. This result corroborates previous studies that have found stronger co-movement and contagion during market booms or speculative bubbles (Bouri *et al.*, 2021). The amplification of spillovers at these quantiles implies heightened systemic risk, which is critical for policymakers and investors monitoring crisis propagation.

The mid-range quantiles (around 0.50) exhibit relatively neutral dynamics, in which markets neither strongly receive nor transmit shocks; this suggests that, under normal market conditions, spillover effects remain balanced, with limited directional risk transmission. The neutral behaviour in these quantiles highlights market stability during moderate economic fluctuations.

A key takeaway from the eleven heatmaps is the asymmetric nature of spillovers across different quantiles (0.05–0.95). The variation in net connectedness across the heatmaps indicates that different economic indicators or asset classes respond differently to shocks. While some panels balance positive and negative net connectedness, others exhibit pronounced asymmetries, implying that external shocks – such as geopolitical tensions, oil price fluctuations, or financial crises – affect markets in ways that depend on their structural characteristics.

The intensity of spillovers is highest at extreme quantiles, particularly at 0.95. Several heatmaps indicate strong positive spillovers in the upper quantiles, suggesting that shock transmission is significantly amplified during periods of speculative activity or excessive risk-taking. This finding aligns with previous literature on financial contagion, which shows that risk propagation is heightened in bullish markets (*e.g.*, Baruník and Křehlík, 2018). Conversely, strong negative spillovers are observed in the lower quantiles (0.05–0.25), reflecting periods of financial distress in which markets act as shock absorbers rather than transmitters.

The quantile-dependent nature of spillovers reinforces the need for tailored risk management strategies. At lower quantiles, policies should focus on stabilising markets and mitigating negative spillovers. Regulatory measures should curb excessive speculation and financial contagion at higher quantiles. Policymakers should dynamically monitor spillover dynamics, particularly during extreme market conditions, to mitigate financial instability and systemic risk; these results confirm that financial and economic spillovers are not uniform but depend on market conditions and quantile levels. Strong positive spillovers at high quantiles and negative spillovers at low quantiles suggest asymmetric risk transmission. These findings are crucial for theoretical modelling and practical policy considerations,

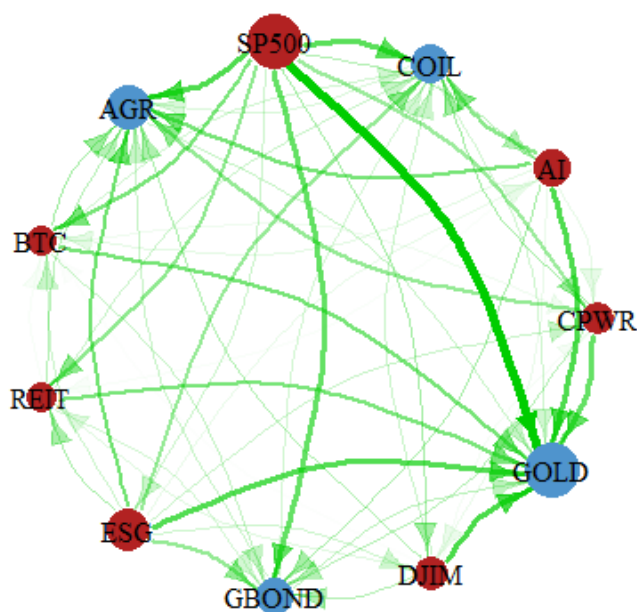
highlighting the importance of using quantile-based methodologies to assess risk transmission in global markets.

Figure 7 presents two network graphs illustrating the average net QQ connectedness among financial assets, commodities, and sustainability-related investments. Each node represents a financial instrument, with red nodes indicating net transmitters of shocks and blue nodes representing net receivers. The green directional edges indicate the strength and direction of spillover effects, with thicker lines signifying stronger connections. Analysing spillover dynamics across quantiles provides deeper insights into how financial contagion propagates under different market conditions.

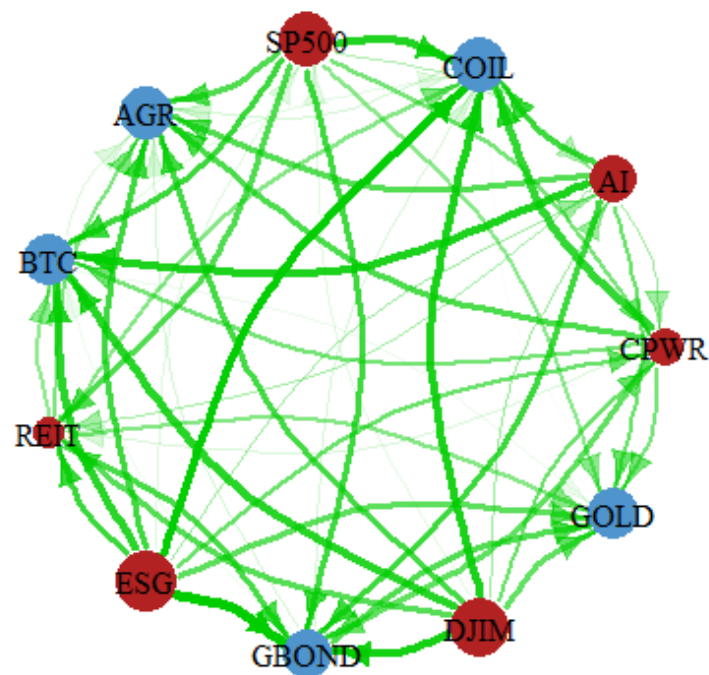
At the lower quantiles (5th-5th), representing extreme bearish market conditions, spillovers are relatively weak, with the SP500 remaining a primary shock transmitter but transmitting to other assets only to a limited extent. At low quantile levels, traditional safe-haven assets such as *GOLD* and *GBOND* act as strong net recipients, reinforcing their defensive role during market downturns. *BTC* and *REIT* exhibit weak connectivity at these lower quantiles, suggesting their responses to extreme downside risks are subdued; this aligns with the existing literature indicating that gold and bonds provide stability during financial distress (Baur and Lucey, 2010; He, 2025).

Figure 7: Average network QQ connectedness

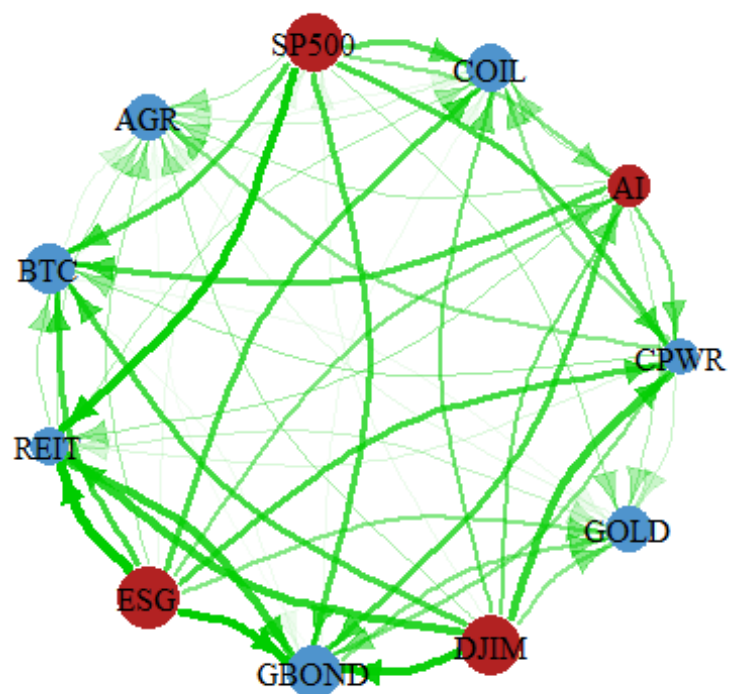
(a) 5th–5th quantile



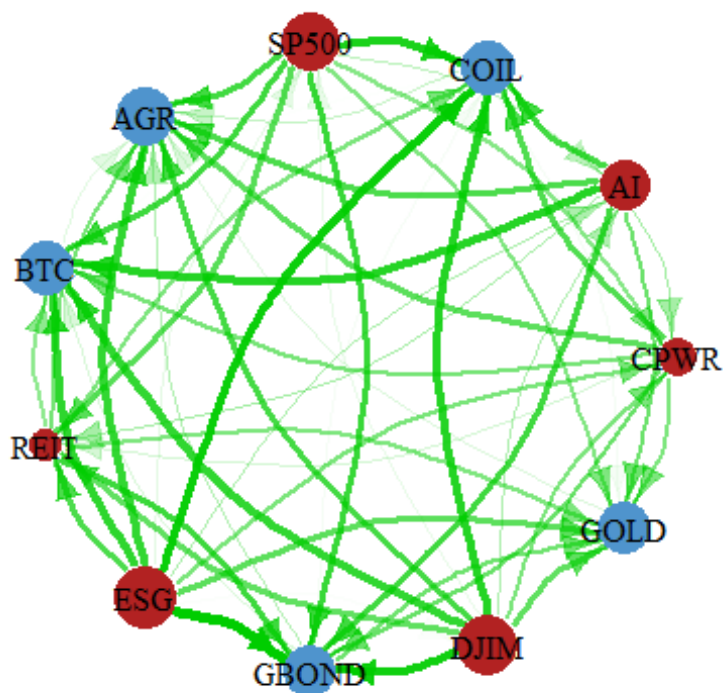
(b) 25th–25th quantile



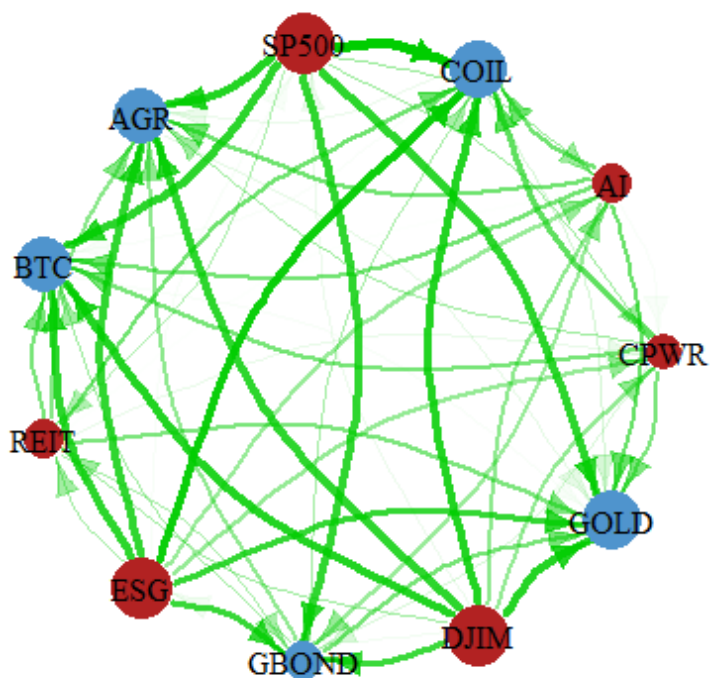
(c) 50th–50th quantile



(d) 75th–75th quantile



(e) 95th–95th quantile



Source: Authors' own elaboration

Moving towards the mid-quantiles (25th–50th), spillover intensity increases, particularly from *SP500*, *ESG*, and *AI*. ESG investments show excellent transmission effects, reflecting their growing integration into global financial markets. Notably, *CPWR* and *COIL* exhibit stronger bidirectional relationships, highlighting the role of energy markets in financial contagion. Gold remains a significant net receiver, though its spillover absorption is lower than at extreme quantiles, suggesting that its role as a safe-haven asset becomes more pronounced during periods of higher market uncertainty.

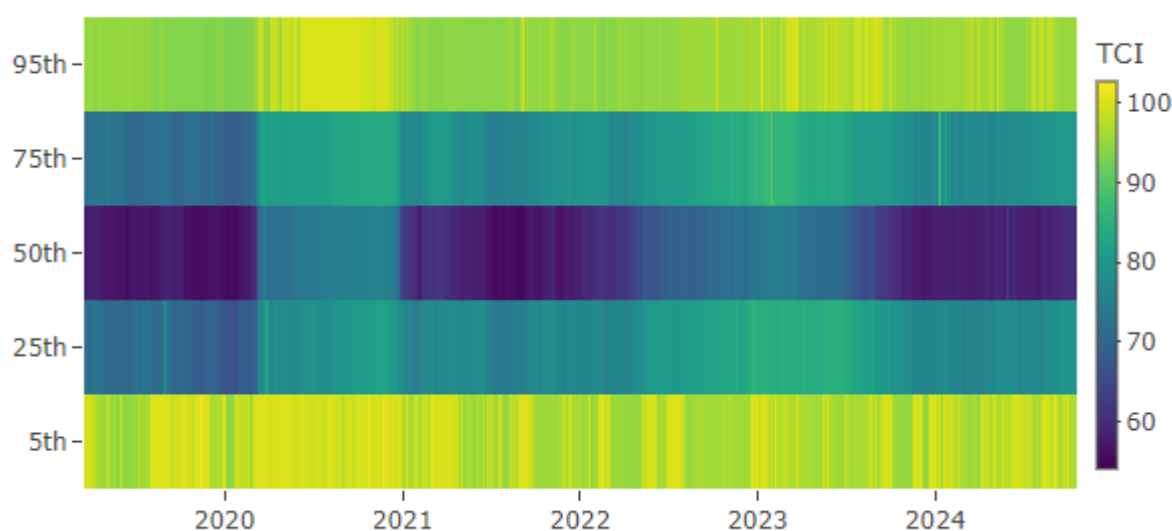
At higher quantiles (75th–95th), corresponding to bullish market conditions and speculative periods, the overall network density increases, indicating more substantial interconnectedness. *BTC* and *REIT* have become more prominent as net receivers, reflecting their heightened sensitivity to market exuberance. The transmission effects of ESG investments and AI-related assets are intensifying, suggesting that sustainability-driven and technology-based investments are playing an increasingly important role in financial market dynamics. The persistent strong linkage between *SP500* and *GOLD* across all quantiles underscores gold's asymmetric response to equity market fluctuations, reinforcing its hedging role in volatile conditions (Hasan *et al.*, 2022).

This transition highlights an evolution from a concentrated transmission structure dominated by *SP500* and *GOLD* to a more interconnected system where multiple asset classes exhibit significant spillover effects. The findings underscore the asymmetric and evolving nature of financial contagion, in which risk transmission varies across market conditions. The increasing role of *ESG* and *BTC* in higher quantiles suggests that these markets are becoming more embedded in global financial dynamics, aligning with studies emphasising the role of sustainability-focused and digital assets in modern portfolio strategies (Baker *et al.*, 2018; Rubbaniy *et al.*, 2022).

Figure 8 presents the dynamic TCI over time, capturing the spillover effects across different quantiles (5th–95th) from 2020 to 2024. The colour gradient represents the intensity of connectedness, with darker shades indicating lower connectedness and lighter shades signifying stronger connectedness. The heatmap reveals a distinct pattern across quantiles, highlighting variations in spillover effects over time. Notably, the central quantile (50th) exhibits the lowest levels of connectedness, as indicated by the deep purple regions; this suggests that shocks are relatively contained at the median quantile level and that spillover effects are minimised. Conversely, the tails (5th and 95th quantiles) display higher connectedness, as indicated by the yellow-green hues, suggesting that extreme market conditions or shocks lead to greater spillover effects.

From a temporal perspective, total connectedness appears relatively stable, with periodic fluctuations. However, an observable increase in spillover intensity occurs intermittently, particularly during specific periods in 2021 and 2023, which may correspond to external shocks such as geopolitical risks, financial crises, or macroeconomic uncertainties. The persistence of high connectedness in extreme quantiles suggests that systemic risks propagate more intensively across the network during market stress or exuberance. This figure underscores the asymmetric nature of spillovers across quantiles, reinforcing the importance of considering nonlinear interdependencies when analysing financial contagion, volatility transmission, and risk dynamics.

Figure 8: Dynamic total QQ connectedness

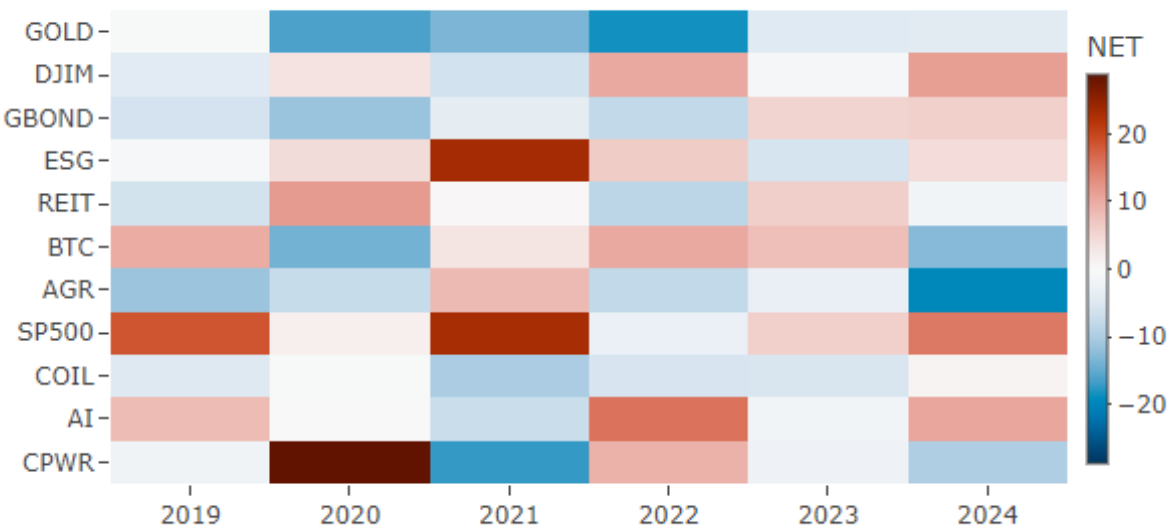


Source: Authors' own elaboration

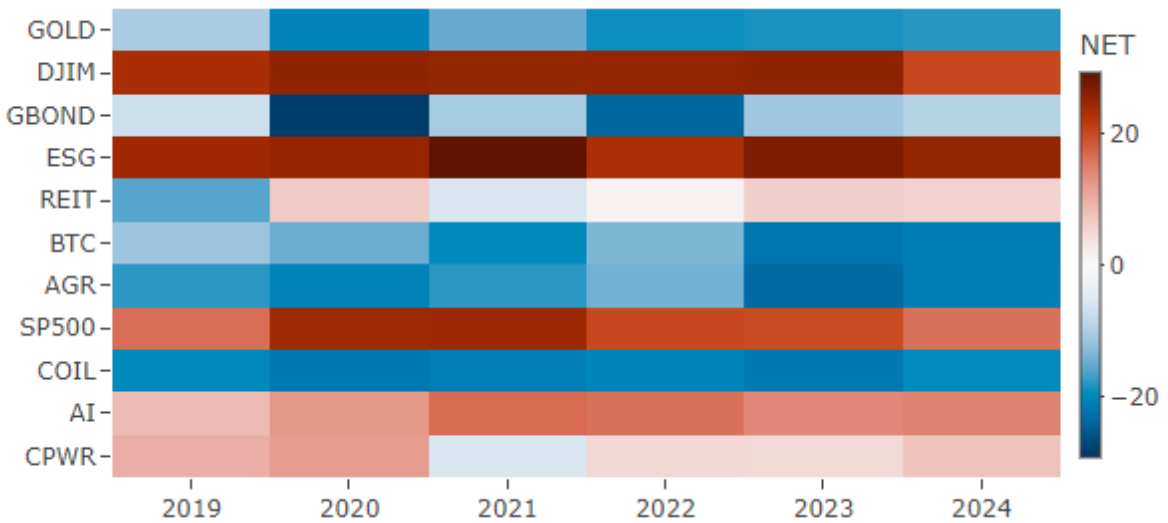
Figure 9 illustrates the dynamic net QQ connectedness across various asset classes from 2019 to 2024. The heatmaps capture the evolution of net spillover effects, where red (positive values) indicates a net transmitter of shocks, while blue (negative values) represents a net receiver. The variation in intensity highlights the asymmetric spillover dynamics across different periods and financial instruments.

Figure 9: Dynamic net QQ connectedness

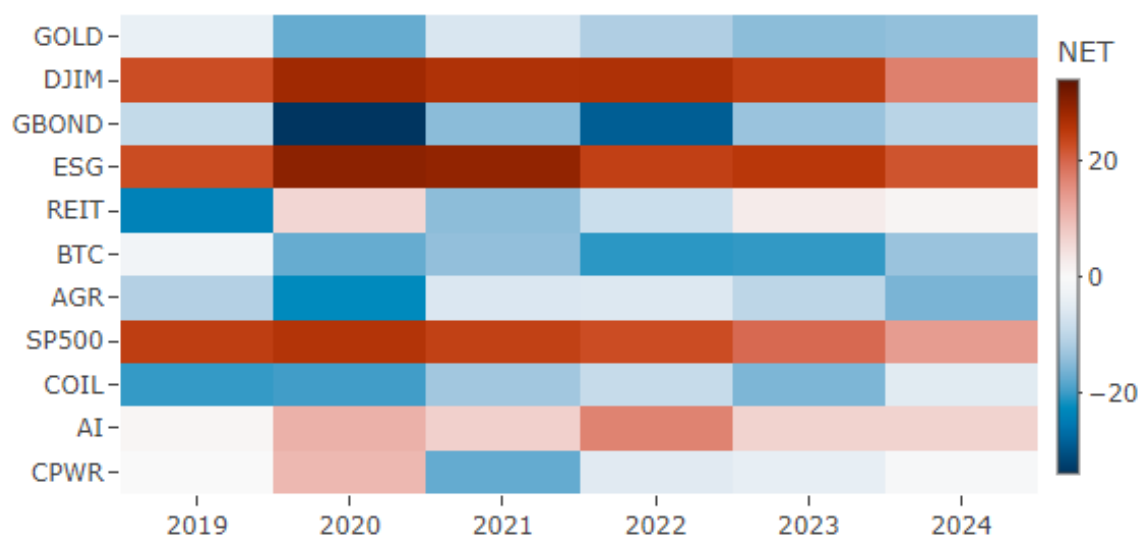
(a) 5th–5th quantile



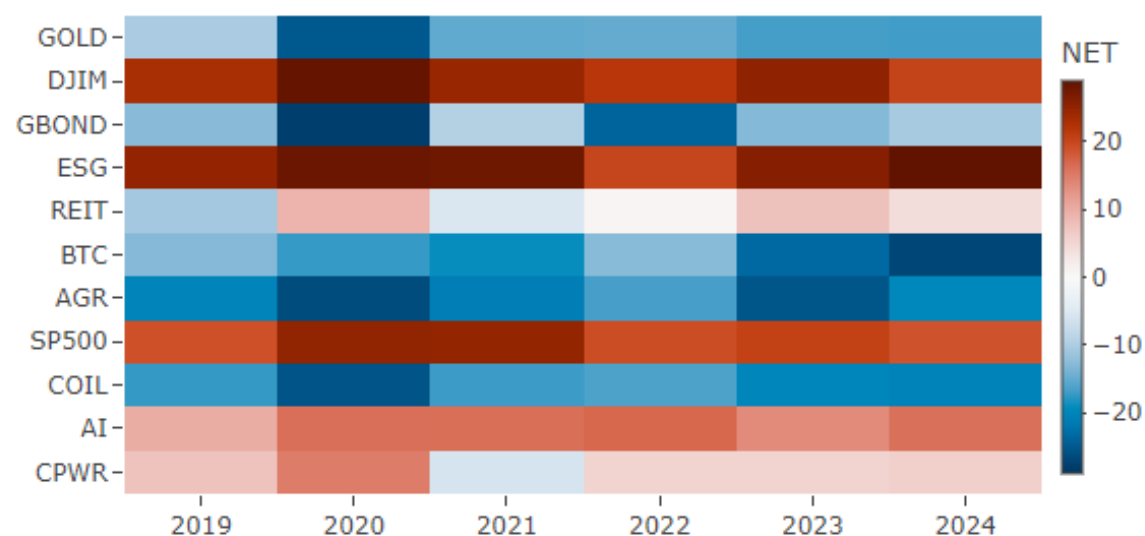
(b) 25th–25th quantile



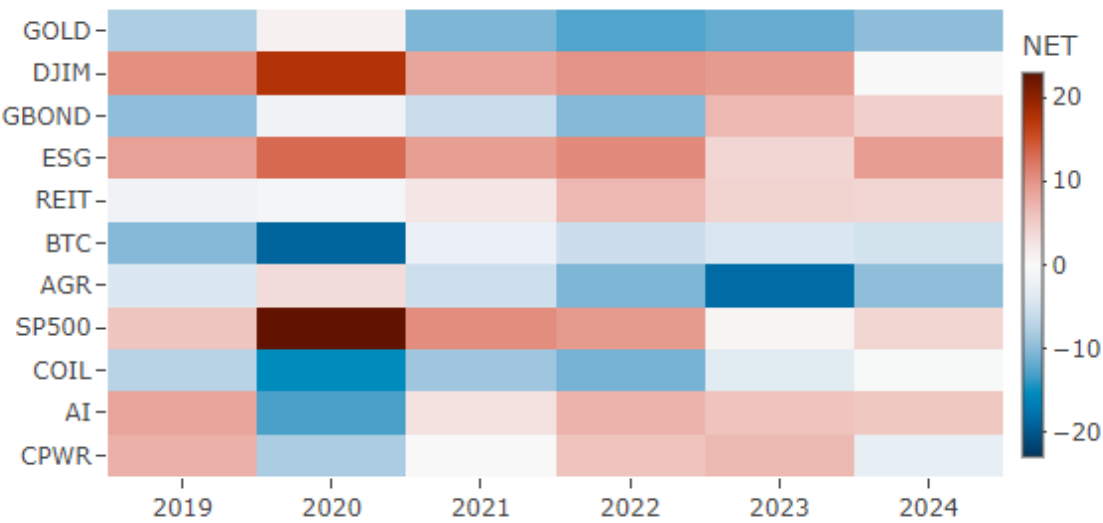
(c) 50th–50th quantile



(d) 75th–75th quantile



(e) 95th–95th quantile



Source: Authors’ own elaboration

The dynamic nature of network connectedness suggests that different assets shift between roles as shock transmitters or receivers over time. *GOLD*, *GBOND*, and digital infrastructure investment markets (*DIIM*) frequently emerge as net transmitters, especially during heightened market uncertainties such as the COVID-19 pandemic and geopolitical crises. These findings align with prior studies (e.g., Bouri *et al.*, 2020) that emphasise the role of gold and government bonds as safe-haven assets, particularly during financial turmoil.

Conversely, assets such as *BTC* and the S&P 500 (*SP500*) demonstrate fluctuating behaviour, alternating between net receivers and transmitters depending on market conditions; this aligns with the literature on cryptocurrency spillovers (e.g., Hasan *et al.*, 2022), highlighting the increasing integration of digital assets with traditional financial markets. Notably, ESG-linked investments and green bonds exhibit substantial spillover effects, reinforcing findings from Jiang *et al.* (2023) on the rising systemic importance of sustainable finance.

Examining the temporal dimension, distinct periods exhibit shifts in net connectedness: **2020–2021:** The pandemic-induced economic uncertainty resulted in increased net connectedness, with safe-haven assets transmitting shocks while equities and high-risk assets acted as receivers. **2022–2023:** The post-pandemic recovery, inflationary pressures, and tightening monetary policies contributed to an evolving connectedness structure, in which riskier assets, such as *BTC*, became more influential in transmitting shocks. **2024:** The latest trends suggest a stabilisation phase, with a more balanced transmission-reception dynamic

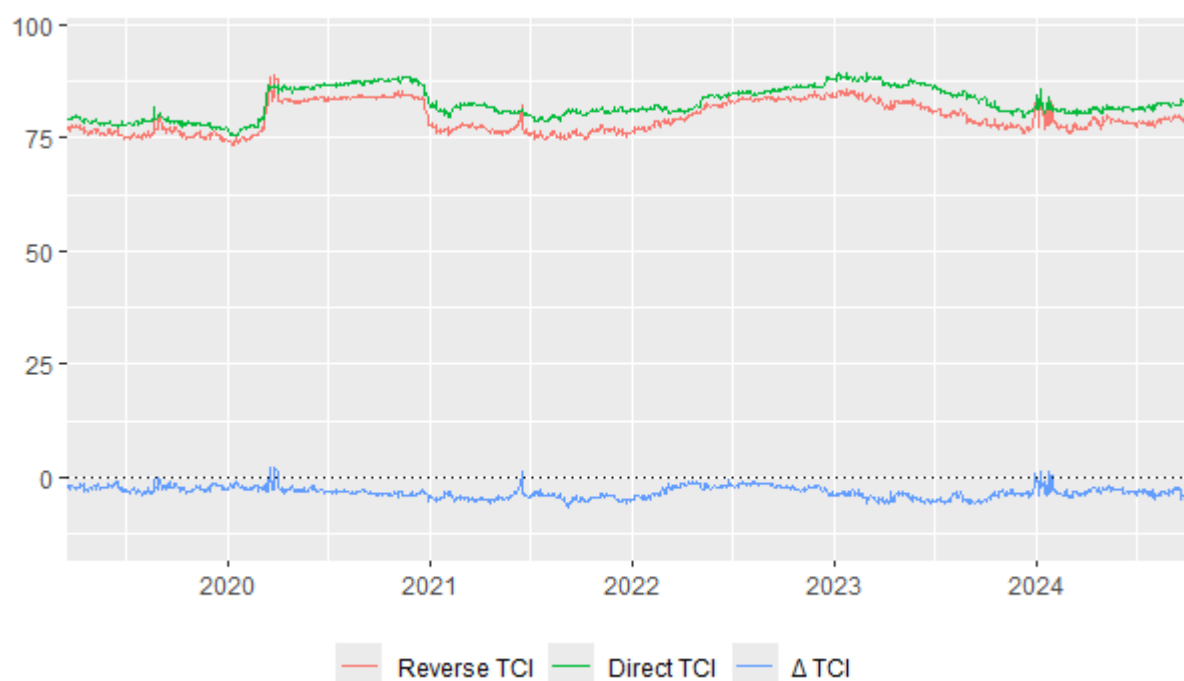
across asset classes. However, certain assets, such as *AI* and *COIL*, continue to experience volatility-driven shifts in connectedness.

These findings align with the growing body of literature on financial market connectedness. Diebold and Yilmaz (2014) emphasise the dynamic, spillover-driven nature of global asset dynamics, while Barunik and Kocenda (2019) highlight quantile-specific risk transmission patterns. Additionally, our results support He (2025), who investigated tail-dependent spillovers in financial markets and found that extreme quantile shocks exhibit stronger connectedness effects. Figure 9 provides empirical evidence of the dynamic nature of net QQ connectedness, reinforcing the need for a quantile-based approach to understand risk transmission across financial markets. The results underscore the role of macroeconomic shocks, policy uncertainty, and investor sentiment in shaping the evolving spillover structure across asset classes.

Figure 10 illustrates the dynamic evolution of the reverse TCI and direct TCI, along with their differential component (ΔTCI) from 2019 to 2024. The green line represents direct TCI, while the red line corresponds to reverse TCI. Both indices exhibit high synchronisation, indicating that spillovers are largely bidirectional, though minor variations exist. Notably, the direct TCI consistently exceeds the reverse TCI, implying that shock transmission from the system to specific assets is stronger than the feedback effects received from those assets.

A sharp rise in both direct and reverse TCI is evident in early 2020, coinciding with the onset of the COVID-19 pandemic, reflecting heightened financial market spillovers. Another notable increase is observed around early 2024, possibly linked to geopolitical risks or policy-induced financial stress, which momentarily disturbs the stability of connectedness dynamics. The ΔTCI , representing the difference between direct and reverse TCI, fluctuates around zero with occasional spikes, suggesting intermittent periods where direct or reverse connectedness dominates. Minor deviations indicate a relatively balanced transmission-reception mechanism, with external shocks stably propagating through financial networks. However, notable spikes in 2020 and 2024 suggest asymmetric spillovers, where direct connectedness temporarily dominates, likely due to crisis-induced market dependencies.

Figure 10: Dynamic reverse and direct QQ connectedness



Source: Authors' own elaboration

The persistent gap between direct and reverse TCI reinforces findings in the connectedness literature (*e.g.*, Diebold and Yilmaz, 2014), which show that systemic factors significantly influence individual asset spillovers more than vice versa. The spikes in the Δ TCI signal episodes of financial stress, supporting previous studies (*e.g.*, Barunik and Kocenda, 2019) that highlight tail risk transmission in global markets. The findings align with the literature on risk transmission during turbulent periods (*e.g.*, He, 2025), which shows that financial contagion intensifies asymmetrically during crises. Figure 10 underscores the dynamic interplay between reverse and direct connectedness, demonstrating how financial spillovers fluctuate. The dominance of direct TCI over reverse TCI suggests that systemic risks exert a greater influence on asset-level spillovers than the reverse. Additionally, market distress amplifies connectedness asymmetries, reinforcing the need for tail-risk-sensitive policy measures to mitigate systemic vulnerabilities.

5. Conclusion and Policy Ideas

5.1 Conclusion

The dynamic net and directional QQ connectedness analyses reveal crucial insights into the evolving nature of financial market interlinkages. Spillover effects are highly time-varying, intensifying during economic uncertainty, geopolitical tensions, and financial distress. The dominance of direct over reverse connectedness suggests that systemic shocks affect individual assets more than the feedback effects they generate. This asymmetric transmission highlights the influence of external shocks on financial contagion. Periodic spikes in connectedness underscore the importance of monitoring cross-asset linkages, particularly during crisis periods.

The average net and directional QQ connectedness analysis further shows persistent interdependencies across asset classes. Gold and government bonds consistently act as net recipients of shocks, reinforcing their roles as safe-haven assets. In contrast, cryptocurrencies and equity indices often serve as net transmitters, indicating their significant role in amplifying market volatility. Clean energy, ESG assets, and alternative investments are increasingly integrated into mainstream markets. At the same time, agricultural commodities and industrial metals also exhibit notable spillover effects, reflecting their sensitivity to macroeconomic and geopolitical disruptions. In general, the results confirm that financial interconnectedness is dynamic and shaped by external shocks, necessitating diversified investment strategies and robust risk management frameworks to navigate volatility and contagion risks effectively.

5.2 Policy Ideas

The findings underscore the need for macroprudential frameworks that explicitly account for asymmetric and state-dependent spillovers across financial markets. Because interconnectedness intensifies during extreme market conditions, policymakers should move beyond average-risk assessments and incorporate tail-sensitive monitoring tools into financial stability surveillance. Strengthening macroprudential oversight, through regular stress testing and enhanced supervision of cross-market exposures, can help reduce systemic vulnerabilities, particularly in periods of heightened uncertainty.

From an operational standpoint, the QQ connectedness measures developed in this study can serve as complementary risk-monitoring indicators, rather than mechanical policy triggers. In particular, supervisory authorities could track the total connectedness index (TCI) and net directional connectedness at extreme quantiles (*e.g.*, 0.05 and 0.95) to iden-

tify the buildup of tail risks and potential contagion channels. Persistent elevations in upper-quantile TCI, or repeated episodes in which specific assets – such as equities, cryptocurrencies, or AI-related indices – emerge as net transmitters, may signal rising systemic fragility during speculative or high-volatility regimes. Conversely, sustained net receiver roles of gold and green bonds at lower quantiles highlight their continued importance as shock absorbers during stress, underscoring the need to preserve liquidity and market functioning in these segments during crises.

These QQ-based indicators can be integrated into early-warning systems alongside conventional stress measures such as volatility indices, credit spreads, and liquidity indicators. Rather than relying on fixed regulatory thresholds, supervisory responses could be guided by relative deviations from historical benchmarks, for example, when tail connectedness persistently exceeds its long-run percentile distribution or when sharp regime shifts occur in transmitter–receiver roles. This flexible, benchmark-based approach allows for adaptation across market structures and avoids overly rigid, rule-based interventions.

Given the prominent role of high-transmission assets, closer monitoring of cryptocurrencies, equity markets, and digital finance instruments is warranted. Risk-based regulation of digital assets and derivatives, focusing on leverage, liquidity, and interconnected exposures, can help contain spillover amplification. At the same time, policies supporting sustainable finance, such as green bond incentives, transparent ESG standards, and carbon-pricing mechanisms, can strengthen the resilience of clean energy and ESG assets as they become more deeply integrated into global financial systems.

Finally, spillovers observed in commodities and alternative assets highlight the importance of sector-specific risk assessments, supply-chain resilience, and trade diversification strategies. Because financial contagion increasingly transcends national boundaries, international policy coordination among central banks, regulators, and financial institutions remains essential for managing cross-asset spillovers during geopolitical and macroeconomic turbulence.

5.3 Limitations and Future Research Directions

It is important to acknowledge several limitations. First, the magnitude and direction of spillovers are likely to vary across geographical settings, reflecting differences in financial depth, regulatory frameworks, and exposure to global shocks. Second, alternative index constructions (*e.g.*, sector-specific clean energy or AI indices) may yield different connectedness patterns. Third, results may be sensitive to sample length and frequency, particularly when significant structural breaks or crisis episodes are included or excluded. According-

ly, the findings should be interpreted as evidence of quantile-dependent risk transmission within the studied market configuration, rather than universal constants. Extending the QQ framework to other regions, asset definitions, and rolling estimation windows represents a promising avenue for future research.

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AI usage statement: The authors confirm that no artificial intelligence (AI) or AI-assisted tools were used in the creation of this manuscript.

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