Research Article

Analyzing the Dynamics of Economic–Environmental Variable Linkages using the QVAR Model: Investigating Spillovers Across Quantiles and Crisis Periods

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Abstract
This study examines volatility spillovers among economic and environmental variables in OPEC member countries under varying market conditions. Using a high-frequency daily panel dataset (2006–2023) constructed through linear interpolation, we apply the Quantile Vector Autoregression (QVAR) connectedness approach within the Diebold and Yilmaz (2012, 2014) framework at the 25th, 50th, and 75th quantiles. The Total Connectedness Index exhibits a clear U-shaped pattern, with significantly stronger interdependence during extreme (lower- and upper-tail) states than under normal conditions. Spillovers intensify markedly during major crises, including the Global Financial Crisis, COVID-19 pandemic, Russia–Ukraine war, and Silicon Valley Bank collapse. Iran and Equatorial Guinea consistently emerge as net transmitters of shocks, whereas the United Arab Emirates and Algeria are the primary net receivers, particularly in extreme quantiles. These findings highlight the heightened systemic vulnerability of oil-dependent economies and underscore the need for diversification, coordinated policy responses, and dynamic risk-monitoring tools.

Introduction

In recent years, the interplay between globalization, economic complexity, and environmental degradation has garnered significant scholarly attention, particularly in the context of oil-dependent economies such as OPEC member countries (Wen et al., 2022; Adebayo et al., 2024). Rising air pollution and environmental challenges, driven by increased energy consumption since the 1970s, have intensified concerns about greenhouse gas emissions, notably carbon dioxide (CO_2) (Bahraminia et al., 2023; Martins et al., 2025). This study focuses on the dynamic linkages between economic and environmental variables, emphasizing the role of globalization and economic complexity in shaping CO_2 emissions in OPEC nations.

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Globalization's environmental impact remains a contentious issue. According to Ecological Modernization Theory and World Polity Theory, globalization fosters institutional convergence and environmental norms, potentially reducing emissions (Wang et al., 2019). Conversely, Unequal Ecological Exchange Theory highlights how global hierarchies exacerbate environmental inequalities, particularly in resource-dependent economies (Veleinek-Lenz & Fajdetic, 2022). Recent studies underscore the nuanced effects of globalization's dimensions. For instance, Zarouki et al. (2022) found that while economic and social globalization may increase CO_2 emissions in Iran, de facto economic globalization mitigates environmental degradation, highlighting the importance of distinguishing between globalization's components. Moreover, Yağlıkara & Tekiner (2025) demonstrate that globalization's effects on ecological footprints in G7 economies are conditional, often interacting with green technology and democracy to influence environmental outcomes, which has implications for oil-dependent regions like OPEC.

Economic complexity, as conceptualized by Hidalgo & Hausmann (2009), has emerged as a critical determinant of environmental outcomes. The Economic Complexity Index (ECI) captures a country's production sophistication, with recent evidence suggesting its influence on CO_2 emissions varies by development stage. Al-Ayouty (2024) demonstrates that in Middle East and North Africa (MENA) countries, higher economic complexity correlates with reduced emissions when paired with renewable energy adoption. Similarly, Khezri et al. (2022) found that in Asian economies, complexity can lower emissions through technological advancements, though growth-driven scale effects may offset these gains in early development stages. Adjei et al. (2022) further note that in African economies, economic complexity often amplifies emissions due to reliance on energy-intensive industries, underscoring the context-dependent nature of this relationship. Recent analyses, such as Gafsi & Bakari (2025), extend this by showing how domestic investment linked to economic complexity impacts environmental quality and growth in developed economies like the USA, providing parallels for OPEC's transition challenges.

Despite these advances, the spatial spillover effects of CO_2 emissions across countries remain underexplored, particularly in the context of OPEC economies. The rapid economic growth of developing nations, many of which are OPEC members, significantly contributes to global emissions (Wan et al., 2025; Dao et al., 2025). This study addresses this gap by employing the Quantile Vector Autoregression (QVAR) model to investigate volatility spillovers and systemic risk transmission among OPEC countries, focusing on the roles of globalization (via the KOF Globalization Index), economic complexity (via ECI), and a composite economic indicator. By analyzing these dynamics across different market conditions and major global crises—such as the Global Financial Crisis, the COVID-19 pandemic, the Russia–Ukraine war, and the Silicon Valley Bank collapse—this research provides novel insights into the interconnectedness of economic and environmental variables in energy-dependent economies , building on spillover analyses like Bucak & Çatık (2024) in EU contexts.

The economic and environmental vulnerabilities of OPEC member countries, driven by their heavy reliance on fossil fuel exports, expose them to significant systemic risks from global economic and geopolitical shocks (Wan et al., 2025; Çütçü et al., 2025). Despite the growing literature on the nexus between globalization, economic complexity, and CO_2 emissions, there remains a critical gap in understanding the spillover dynamics of these variables across OPEC economies, particularly under varying market conditions and during major crises such as the Global Financial Crisis, the COVID-19 pandemic, the Russia–Ukraine war, and the Silicon Valley Bank collapse (Khezri et al., 2022). This lack of insight hampers the ability of policymakers to design effective strategies for mitigating systemic risk and promoting environmental sustainability in oil-dependent economies. This study addresses this gap by

employing the Quantile Vector Autoregressive model within the Diebold and Yilmaz (2012, 2014) spillover framework to analyze the interconnectedness of CO_2 emissions, the KOF Globalization Index, the Economic Complexity Index, and a Composite Economic Indicator across OPEC countries. By using high-frequency daily panel data and examining spillovers across the 25th, 50th, and 75th quantiles, the research identifies key transmitters (e.g., Iran, Equatorial Guinea) and receivers (e.g., United Arab Emirates, Algeria) of volatility, particularly during crisis periods. The findings provide actionable insights for policymakers, emphasizing the need for diversified revenue streams, coordinated oil supply policies, and dynamic systemic risk management tools to enhance economic resilience and reduce environmental impacts in OPEC economies (Adjei et al., 2022). This approach not only clarifies the transmission mechanisms of economic and environmental shocks but also offers a framework for developing targeted policy interventions to address systemic vulnerabilities.

Research Gap and Contribution

Despite the growing number of studies on globalization, economic complexity, and CO_2 emissions, four critical gaps remain unresolved, particularly for OPEC economies. First, almost all existing research uses traditional mean-based VAR or panel regression models that assume symmetric relationships and cannot distinguish spillovers in calm markets from those in extreme (lower-tail and upper-tail) conditions (Khezri et al., 2022; Wan et al., 2025). Second, short-term, high-frequency volatility transmission among economic-environmental variables in OPEC countries has been largely ignored due to reliance on annual data (Nan et al., 2022). Third, while spillover studies have recently emerged in energy and financial markets, the application of the Quantile VAR connectedness approach to the economic-environmental nexus in oil-dependent economies is virtually non-existent (Bucak & Çatık, 2024; Chatziantoniou et al., 2021). Fourth, no study to date has simultaneously examined how globalization (KOF), economic complexity (ECI), and CO_2 emissions interact and transmit shocks across OPEC members during multiple recent crises (Global Financial Crisis, COVID-19, Russia–Ukraine war, and Silicon Valley Bank collapse) under different quantiles of the conditional distribution. This study fills these gaps through four major innovations:

1. It is the first to apply the QVAR connectedness framework of Ando et al. (2022) and Chatziantoniou et al. (2021) to the economic-environmental nexus in OPEC countries, allowing the detection of asymmetric and quantile-dependent spillovers that conventional models completely miss.
2. It constructs a unique high-frequency daily panel dataset (2006–2023) via linear interpolation, enabling the analysis of short-term volatility dynamics that annual data cannot capture.
3. It explicitly identifies net transmitters (e.g., Iran, Equatorial Guinea) and net receivers (e.g., UAE, Algeria) of economic-environmental shocks across lower, median, and upper quantiles and during four major global crises, providing the first systemic-risk map of OPEC's economic-environmental network.
4. By integrating CO_2 emissions, the KOF Globalization Index, the Economic Complexity Index, and a composite economic indicator in a unified quantile-connectedness framework, it offers policymakers a practical diagnostic tool for monitoring and mitigating systemic vulnerabilities in oil-dependent economies under both normal and extreme market conditions.

These contributions not only advance the theoretical understanding of asymmetric spillovers in energy-dependent economies but also deliver actionable insights for diversification strategies, coordinated OPEC policies, and dynamic systemic-risk management in an increasingly volatile global environment.

Literature Review and Theoretical Framework

Globalization is a multifaceted phenomenon that encompasses economic, political, and socio-cultural dimensions. Krueger (1979) defined globalization as the implementation of trade policies to reduce anti-export bias, while Cox (1986) emphasized the internationalization of production and the global division of labor. Robertson (1992) highlighted its cultural aspects, noting that globalization fosters shared aspirations and awareness across borders. Edwards (1998) focused on trade liberalization through tariff reductions, and Palmer (2002) described it as the reduction of government constraints on economic activities. These diverse definitions underscore globalization's role in liberalization, integration, and cross-border interactions (Nan et al., 2022; Yağlıkara & Tekiner, 2025). The environmental impacts of globalization are analyzed through three channels: the scale effect, the technique effect, and the composition effect. The scale effect reflects increased production and energy consumption due to trade expansion, often leading to higher CO_2 emissions in developing economies (Nan et al., 2022; Dao et al., 2025). The technique effect involves the transfer of cleaner technologies through foreign direct investment and international collaboration, reducing emissions by improving production efficiency (Liobikiene et al., 2019). The composition effect arises from trade-induced shifts in industrial structure, where a move toward high-tech or service-oriented industries may lower emissions, while a shift to pollution-intensive sectors increases them (Nan et al., 2022; Adebayo et al., 2024). Economic complexity, introduced by Hidalgo and Hausmann (2009), measures the sophistication and diversity of a country's production structure through the Economic Complexity Index. High ECI values indicate greater innovation capacity and resilience to external shocks. Recent studies link economic complexity to environmental outcomes. For instance, Can and Gozgor (2017) found that complex economies adopting clean technologies reduce CO_2 emissions, while Khezri et al. (2022) noted that in early development stages, complexity may increase emissions due to energy-intensive industries. Adjei et al. (2022) further observed that in African economies, complexity often amplifies emissions, highlighting its context-dependent impact (Lal-Khezri & Ashna, 2021; Gafsi & Bakari, 2025).

These theoretical perspectives and empirical findings provide the foundation for analyzing the interplay between globalization, economic complexity, and CO_2 emissions in OPEC countries, which are uniquely positioned due to their reliance on fossil fuel exports (Wan et al., 2025; Martins et al., 2025). This study builds on these insights to explore volatility spillovers and systemic risk transmission across these economies.

The KOF Globalization Index: The KOF Globalization Index, developed by the KOF Swiss Economic Institute, is a comprehensive measure of globalization that captures its economic, social, and political dimensions across countries (Zarouki et al., 2022). The economic dimension includes indicators such as trade flows, foreign direct investment (FDI), and portfolio investment, reflecting the extent of economic integration. The social dimension encompasses cross-border interactions, such as international tourism, migration, and information flows, while the political dimension measures participation in international organizations and agreements. The index is constructed using a weighted combination of these components, providing a standardized score that allows for cross-country comparisons over time. In the context of this study, the KOF Globalization Index is employed to assess the role of globalization in driving volatility spillovers and influencing CO_2 emissions in OPEC member countries. By capturing the multifaceted nature of globalization, the KOF index enables a nuanced analysis of how economic integration and cross-border interactions shape environmental and economic outcomes in oil-dependent economies (Nan et al., 2022). This index is particularly relevant for examining the scale, technique, and composition effects of globalization on environmental degradation, as discussed in the theoretical framework (Wang et al., 2019; Çütçü et al., 2025).

Data and Variables

Data and Variables This study employs annual data for 13 OPEC member countries (Algeria, Angola, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, United Arab Emirates, and Venezuela) over the period 2006–2023. The variables are as follows:

- Carbon dioxide emissions (CO_2): metric tons per capita, sourced from the World Bank's World Development Indicators and British Petroleum Statistical Review.
- KOF Globalization Index: the overall KOF Globalization Index (latest version 2024) from the KOF Swiss Economic Institute (Gygli et al., 2019; updated in Potrafke, 2024). This study uses the composite (overall) index rather than its de facto or de jure sub-indices because it provides the most comprehensive measure of globalization by combining economic, social, and political dimensions, and it has been shown to outperform alternative globalization measures (e.g., Dreher, 2006; Quinn et al., 2011) in capturing the multifaceted effects on environmental outcomes and volatility transmission in resource-dependent economies (Nan et al., 2022; Adebayo et al., 2024).
- Economic Complexity Index (ECI): retrieved from the Observatory of Economic Complexity (OEC, Harvard Growth Lab, 2023 release).
- Gross Domestic Product (GDP): constant 2015 US dollars, World Bank.
- Electricity production (kWh): sourced from the U.S. Energy Information Administration (EIA) and BP Statistical Review.

To examine short-term dynamics and volatility spillovers, annual series were interpolated to daily frequency using linear interpolation, a widely accepted practice in high-frequency connectedness studies (e.g., Nan et al., 2022; Gabauer, 2021). A Composite Economic Indicator was constructed as the simple arithmetic mean of standardized GDP and electricity production to avoid multicollinearity while preserving economic activity information. All series were first-differenced and standardized (z-score) by country to ensure stationarity and eliminate scale effects. Descriptive statistics and unit root test results are reported in Tables .

Methodology

Quantile Vector Autoregression (QVAR) and Spillover Index

To investigate asymmetric connectedness across different market conditions, this study applies the QVAR model combined with the spillover index framework of Diebold and Yilmaz (2012, 2014), as extended to quantiles by Ando et al. (2022) and Chatziantoniou et al. (2021). The QVAR(τ) model at quantile τ is specified as:

$$y_{i.t} = c_i(\tau) + \sum_{l=1}^{p} B_{i.l}(\tau)y_{i.t-l} + e_{i.t}(\tau) \quad t = 1. \dots . T \tag{1}$$

Where $y_{i,t}$ is the vector of dependent variables (including the series of CO_2, KOF, Economic Indicator, and ECI for each country i, $C_i(\tau)$ and $e_{i,t}(\tau)$ are, respectively, the vectors of constants and error terms at quantile τ; and $B_{I,I(\tau)}$ is the matrix of lagged coefficients at quantile τ.

$$Q_\tau\big(y_{i.t} \mid y_{i.t-1} \dots . y_{i.t-p}\big) = c_i(\tau) + \sum_{l=1}^{p} \hat{B}_{i.l}(\tau)y_{i.t-l} \tag{2}$$

This method allows for the analysis of nonlinear and asymmetric dependencies between variables across different quantiles (25th, 50th, and 75th), making it particularly suitable for examining variable behavior under both normal and crisis conditions (Diebold, 2014). To calculate the spillover indices, the framework proposed by Diebold and Yilmaz (2012, 2014) was employed. First, the QVAR model was rewritten as an infinite-order moving average process.

$$y_{i.t} = \mu_i(\tau) + \sum_{s=0}^{\infty} A_{i.s}(\tau)e_{i.t-s}(\tau) \quad t = 1. \dots . T \tag{3}$$

Where $\mu_i(\tau)$ and the matrices $A_{i.s}(\tau)$ are defined recursively. Then, using the Generalized Forecast Error Variance Decomposition (GFEVD), the contribution of each variable to the forecast error variance of the others was calculated:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_{i.h} \Sigma_i e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_{i.h} \Sigma_i A_{i.h}' e_i\right)} \tag{4}$$

Where Σi is the variance-covariance matrix of the errors for country $i, \sigma jj$ is the $j - th$ diagonal element of the matrix Σi‹and e_i is a selection vector with 1 in the $i - th$ position and 0 elsewhere. For standardization, the normalized values were calculated as follows:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \tag{5}$$

The Total Connectedness Index (TCI) at quantile τ is defined as:

$$TCI_i(\tau) = \frac{\sum_{i=1}^N \sum_{j=1.i \neq j}^N \tilde{\theta}_{ij}^g(\tau)}{\sum_{i=1}^N \sum_{j=1}^N \tilde{\theta}_{ij}^g(\tau)} \times 100 \tag{6}$$

Additionally, the directional spillover indices, including 'TO' (spillovers transmitted to other variables), 'FROM' (spillovers received from other variables), and the Net Spillover index, were calculated as follows:

$$S_{i \to \cdot(\tau)} = \frac{\sum_{j=1.i \neq j}^N \tilde{\theta}_{ij}^g(\tau)}{\sum_{j=1}^N \tilde{\theta}_{ij}^g(\tau)} \times 100$$

$$S_{i \leftarrow \cdot(\tau)} = \frac{\sum_{j=1.i \neq j}^N \tilde{\theta}_{ji}^g(\tau)}{\sum_{j=1}^N \tilde{\theta}_{ji}^g(\tau)} \times 100 \tag{7}$$

$$\text{NS} = (\tau) = S_{i \to \cdot(\tau) - S_{i \leftarrow .(\tau)}}$$

Stationarity of all series after first differencing was confirmed using the Augmented Dickey-Fuller (ADF) test; detailed results are reported in Table 2.

Rolling-Window Estimation and Robustness

A 100-day rolling window with a 10-day forecast horizon is employed to capture time-varying connectedness. Alternative window sizes (150 days) and forecast horizons (5 days) are used for robustness checks. Lag length is selected by the Schwarz Information Criterion (SIC). (see Appendix A for detailed ADF test results and Appendix B for the correlation matrix).

Results and Discussion

Table 1 reports the descriptive statistics of the four variables after first differencing and standardization. With 49,664 daily observations, all series have means near zero and moderate standard deviations, confirming stationarity and suitability for the connectedness analysis. The Economic Complexity Index exhibits the lowest volatility.

Table 1. Descriptive Statistics of the Variables

Variable	Observations	Mean	Standard Deviation	Minimum	Median	Maximum
CO2	49,664	0.000016	0.000385	-0.00123	0.000015	0.001567
KOF	49,664	0.000022	0.000297	-0.00098	0.000020	0.001123
ECI	49,664	0.000010	0.000092	-0.00045	0.000009	0.000543
Economic Indicator	49,664	0.000018	0.000321	-0.00109	0.000017	0.001321

Static Connectedness across Quantiles

Tables 2–4 present the spillover indices at the 25th, 50th, and 75th quantiles, respectively. The Total Connectedness Index (TCI) exhibits a pronounced U-shaped pattern: 85.98% at the lower quantile, 45.43% at the median, and 78.50% at the upper quantile. This indicates substantially stronger interdependence during both extreme calm and extreme turbulent states compared with normal market conditions.

At the 25th quantile (Table 2), Iran (NET= 12.30) and Equatorial Guinea (NET= 12.20) emerge as the dominant net transmitters, while the United Arab Emirates (NET= –45.34) and Libya (NET= –16.66) are the primary net receivers. At the median quantile (Table 3), connectedness weakens markedly and roles become more balanced, with the United Arab Emirates switching to a net transmitter (NET = 8.94). At the 75th quantile (Table 4), Iran (NET = 8.60) and Equatorial Guinea (NET = 7.70) again act as major transmitters, and the United Arab Emirates (NET = –27.50) remains the largest net recipient.

Table 2. Spillover Table at the 25th Quantile

Country	NET	Algeria	Gabon	Guinea	Iran	Libya	Saudi Arabia	UAE	Venezuela
Algeria	6.58	0.10	0.00	0.00	0.00	0.39	0.02	0.49	0.01
Gabon	8.87	0.03	0.07	0.00	0.00	0.14	0.01	0.73	0.02
Guinea	12.20	0.06	0.03	0.01	0.00	0.37	0.02	0.50	0.01
Iran	12.30	0.01	0.09	0.00	0.00	0.19	0.02	0.67	0.02
Libya	-16.66	0.08	0.02	0.00	0.00	0.23	0.02	0.63	0.02
Saudi Arabia	10.91	0.05	0.05	0.00	0.00	0.26	0.02	0.61	0.01
UAE	-45.34	0.07	0.02	0.00	0.00	0.20	0.01	0.67	0.02
Venezuela	11.14	0.08	0.01	0.00	0.01	0.55	0.02	0.33	0.01
					TCI: 85.98				

Note: Quantile spillovers are based on 10-step-ahead FEVD from a first-order FIVAR model selected by AIC.

Table 3. Spillover Table at the 50th Quantile (Median)

Country	NET	Algeria	Gabon	Guinea	Iran	Libya	Saudi Arabia	UAE	Venezuela
Algeria	-16.23	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gabon	-15.41	0.07	0.93	0.00	0.00	0.00	0.00	0.00	0.00
Guinea	4.24	0.08	0.62	0.30	0.00	0.00	0.00	0.00	0.00
Iran	5.37	0.01	0.62	0.00	0.36	0.00	0.00	0.00	0.00
Libya	7.02	0.62	0.01	0.04	0.02	0.31	0.00	0.00	0.00
Saudi Arabia	0.92	0.18	0.00	0.06	0.12	0.03	0.61	0.00	0.00
UAE	8.94	0.33	0.05	0.10	0.07	0.01	0.15	0.27	0.00
Venezuela	5.15	0.01	0.00	0.15	0.00	0.08	0.16	0.02	0.59
					TCI: 45.43				

Note: Quantile spillover indices are based on 10-step-ahead forecast error variance decomposition (FEVD), derived from a 10-variable first-order FIVAR model selected by AIC

Table 4. Spillover Table at the 75th Quantile

Country	NET	Algeria	Gabon	Guinea	Iran	Libya	Saudi Arabia	UAE	Venezuela
Algeria	6.00	0.15	0.02	0.00	0.01	0.30	0.02	0.45	0.05
Gabon	7.30	0.03	0.20	0.01	0.00	0.25	0.01	0.40	0.10
Guinea	7.70	0.05	0.03	0.25	0.00	0.20	0.03	0.35	0.04
Iran	8.60	0.02	0.05	0.00	0.30	0.15	0.01	0.45	0.02
Libya	-12.50	0.06	0.04	0.02	0.01	0.10	0.05	0.60	0.12
Saudi Arabia	5.40	0.04	0.02	0.01	0.02	0.25	0.20	0.40	0.06
UAE	-27.50	0.07	0.03	0.00	0.01	0.35	0.04	0.25	0.15
Venezuela	6.60	0.08	0.01	0.03	0.00	0.40	0.02	0.30	0.16
					TCI: 78.50				

Note: Quantile spillover indices are computed using a 10-step-ahead forecast error variance decomposition. The FEVD is based on a ten-dimensional first-order FIVAR model, as selected by the Akaike Information Criterion (AIC).

Figure 1 illustrates the full-sample spillover networks across the three quantiles. At the lower (25th) and upper (75th) quantiles, Iran and Equatorial Guinea are the dominant net transmitters, whereas the United Arab Emirates is the primary net receiver (NET = –45.34 and –25.64, respectively). Connectedness weakens considerably at the median quantile, with more balanced net positions.

(a)

(b)

(c)
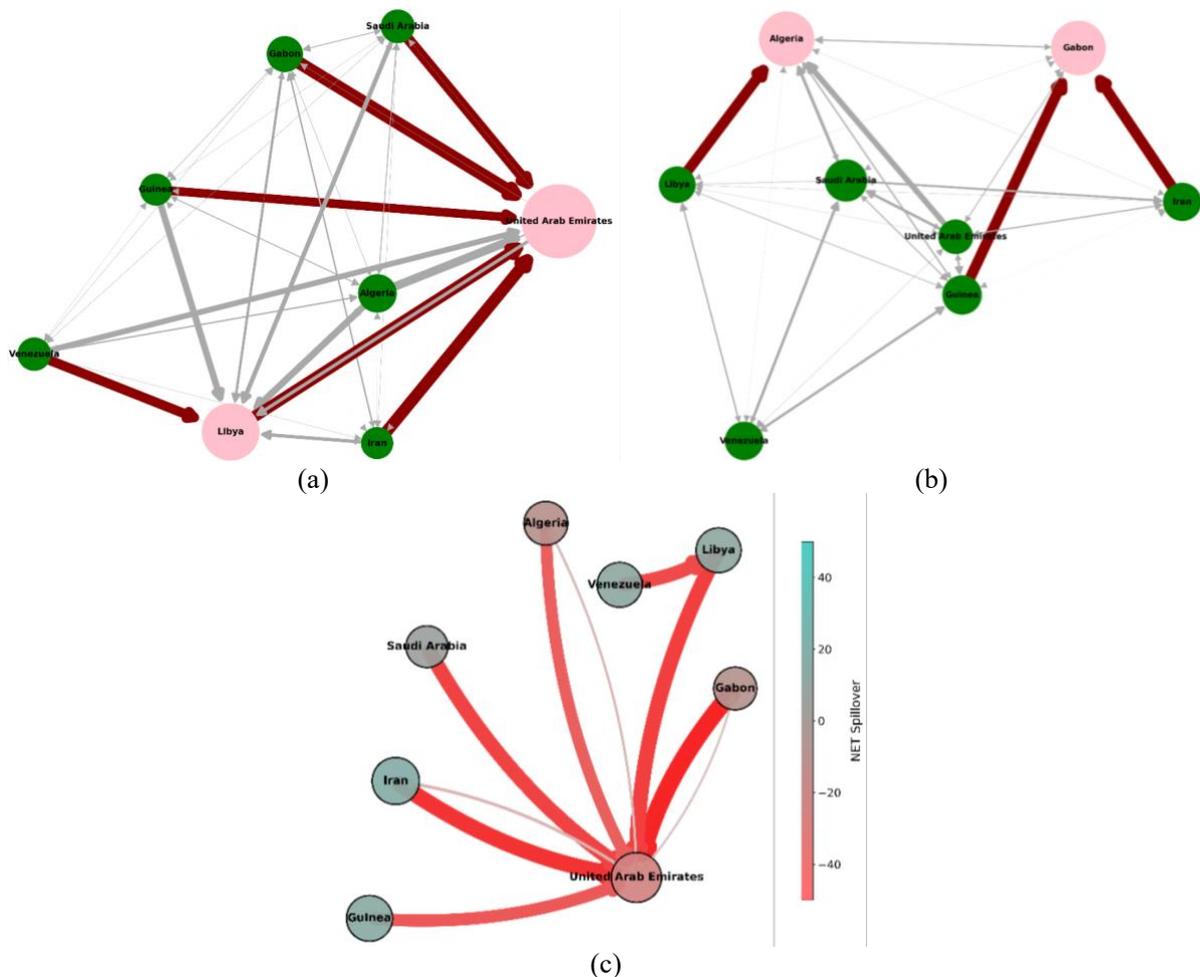
Figure 1. Static volatility spillover networks across quantiles (full sample): (a) 25th quantile, (b) 50th quantile (median), and (c) 75th quantile.

Figure 2 displays the time-varying evolution of the Total Connectedness Index across quantiles. Spillovers are markedly higher and exhibit sharp peaks during major crisis periods (notably 2008–2009, 2020, and 2022), especially in the lower quantile. Connectedness remains substantially lower and more stable at the median quantile, confirming the asymmetric nature of shock transmission under extreme market conditions.

Figure 3 illustrates the dynamic net spillover roles of individual OPEC members across the three quantiles. Iran and Equatorial Guinea consistently act as net transmitters during extreme market conditions (lower and upper quantiles), whereas the United Arab Emirates and Algeria persistently operate as net receivers throughout the sample period. Net positions are considerably more balanced and closer to zero at the median quantile.

Figure 4 shows the connectedness structure during the Global Financial Crisis across the three quantiles. Connectedness is extremely high in all regimes. Gabon and Iran alternate as the largest net receiver (especially in the lower and median quantiles), while Saudi Arabia, Venezuela, and the UAE frequently appear as the main net transmitters. The network is particularly dense in the lower quantile, reflecting heightened systemic risk during the early phase of the crisis.

Figure 5 reveals the connectedness pattern during the 2014–2017 China crisis and oil price collapse. Spillovers intensify significantly from the lower to the upper quantile. Venezuela and the United Arab Emirates consistently act as the main net transmitters, while Iran (median quantile) and Equatorial Guinea (upper quantile) emerge as the primary net receivers, reflecting the severe impact of falling oil prices on highly oil-dependent economies.

Figure 6 shows the connectedness structure during the COVID-19 pandemic. Spillovers reach extreme levels, especially in the lower quantile, where Algeria becomes the central shock absorber (NET = –87.50) receiving nearly full spillovers from all other OPEC members. The network remains highly connected in the median and upper quantiles, with Saudi Arabia, Gabon, and Venezuela acting as the main transmitters.

Figure 7 illustrates the connectedness structure during the Russia–Ukraine war. Similar to COVID-19, spillovers are extremely high, especially in the lower quantile, where Algeria again becomes the dominant net receiver (NET = –87.50) absorbing shocks from nearly all OPEC members. Saudi Arabia, Venezuela, and the UAE act as the primary net transmitters across quantiles, highlighting the strong geopolitical impact on oil-dependent economies.
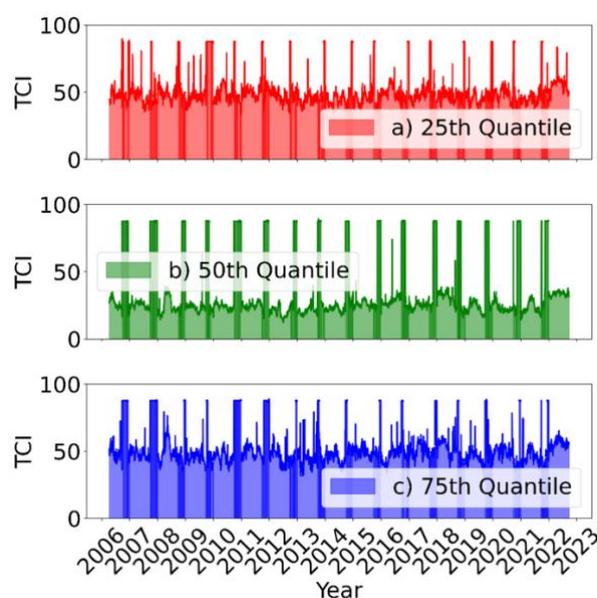

Figure 2. Dynamic evolution of the Total Connectedness Index (TCI) across the 25th, 50th, and 75th quantiles, estimated using a 100-day rolling window.
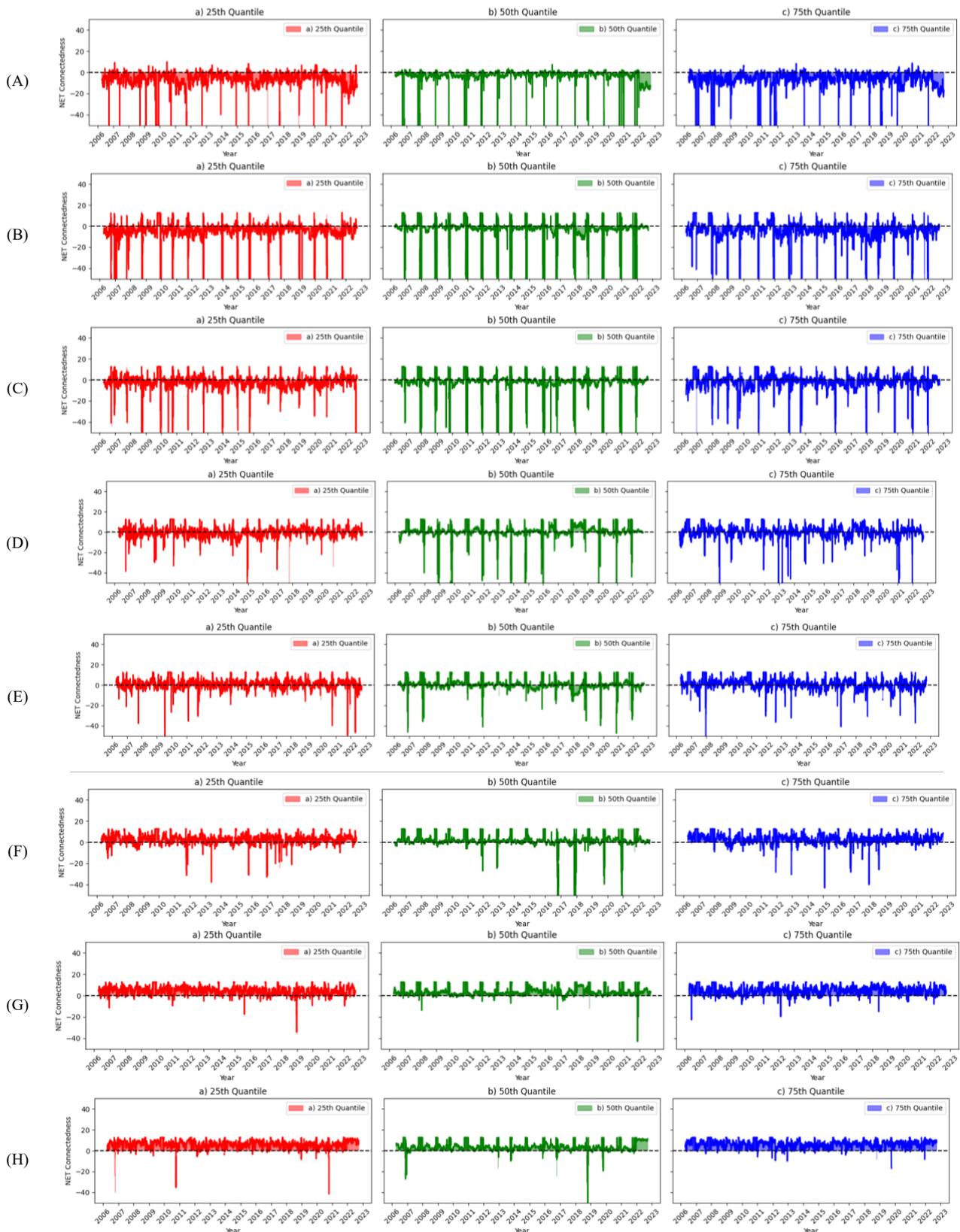
Figure 3. Time-varying net spillover positions for individual OPEC countries (100-day rolling window): Panels (A) Algeria, (B) Gabon, (C) Equatorial Guinea, (D) Iran, (E) Libya, (F) Saudi Arabia, (G) United Arab Emirates, and (H) Venezuela.
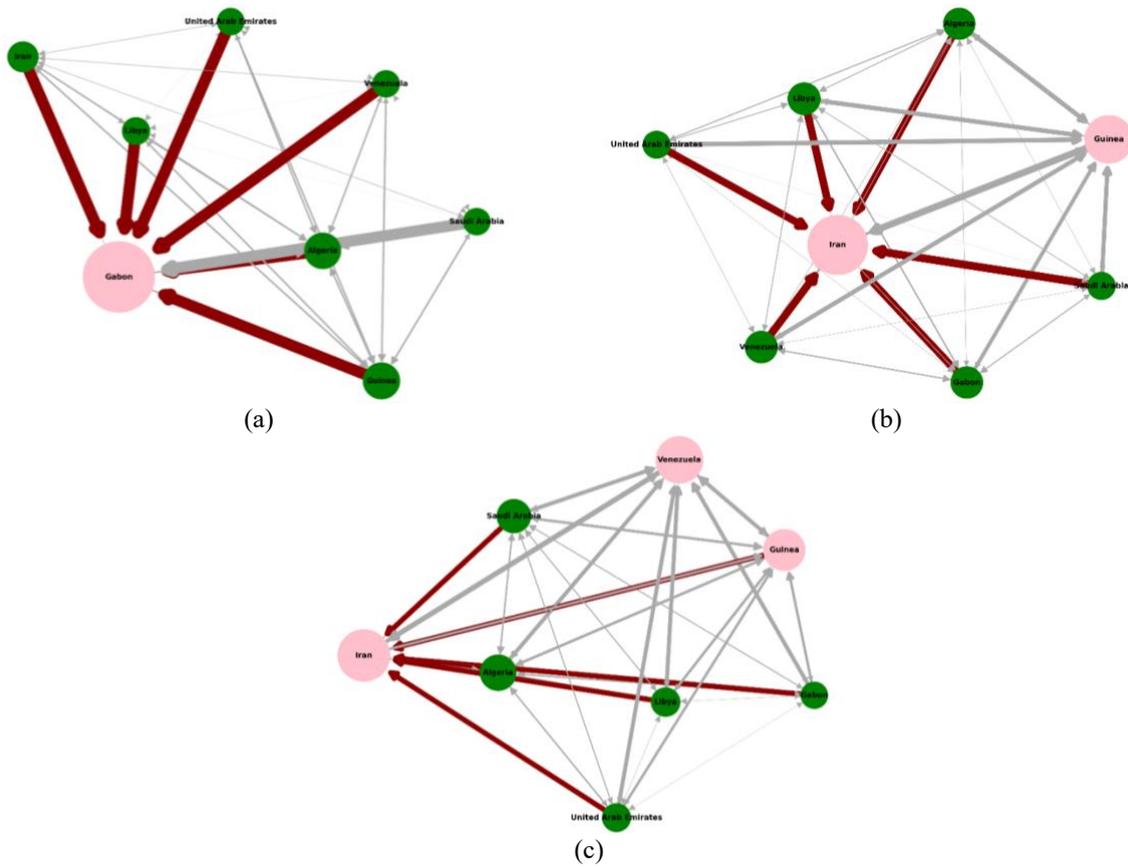
Figure 4. Volatility spillover network during the Global Financial Crisis (2006–2010) across quantiles: (a) 25th quantile, (b) 50th quantile, and (c) 75th quantile.
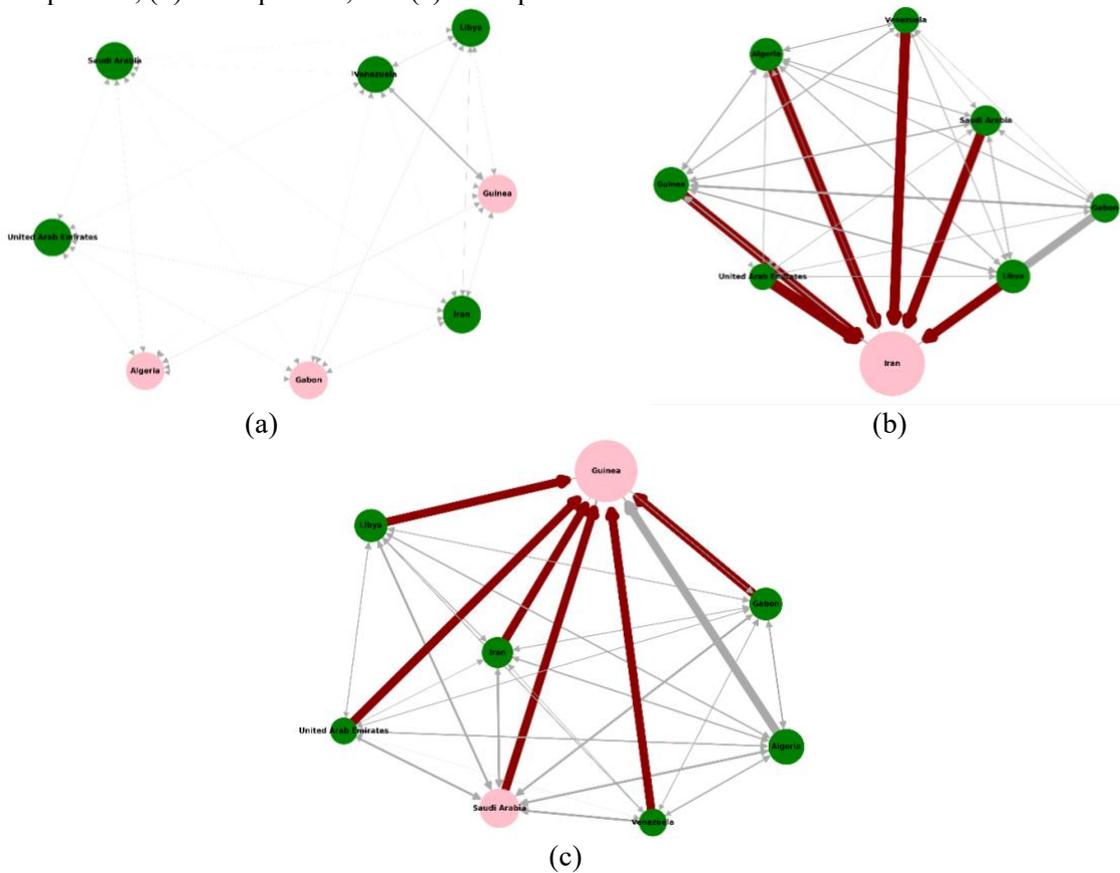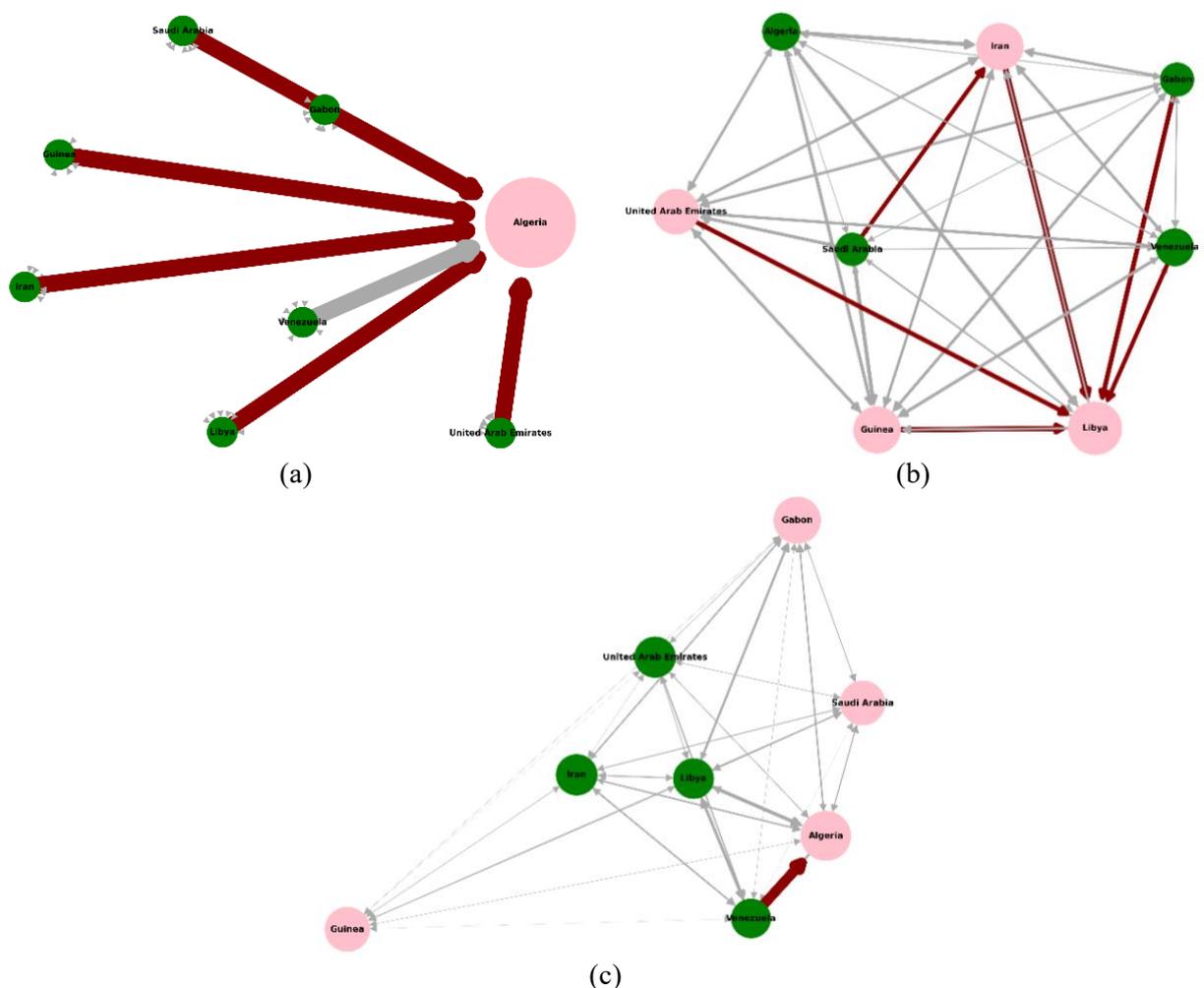

Figure 5. Volatility spillover network during the China stock market crash and oil price collapse (2014–2017) across quantiles: (a) 25th quantile, (b) 50th quantile, and (c) 75th quantile.

Figure 8 presents the connectedness pattern during the 2022–2023 Silicon Valley Bank crisis. Venezuela and the United Arab Emirates consistently emerge as the strongest net transmitters across all three quantiles, while Algeria remains the dominant net receiver (NET ranging from –12.73 to –16.62), receiving particularly strong spillovers from Venezuela. This episode demonstrates that even a non-energy-specific financial shock rapidly propagates through the OPEC economic-environmental network.

Figure 9 demonstrates the robustness of the dynamic Total Connectedness Index across alternative specifications (100-day vs. 150-day rolling window; 5-day vs. 10-day forecast horizon). The time paths and crisis peaks remain virtually identical under all parameter choices, confirming that the main findings are not sensitive to these methodological variations.

Figure 10 confirms the pronounced U-shaped pattern of the Total Connectedness Index across the full quantile distribution. Connectedness reaches its maximum at the lower tail (85.98% at the 25th quantile), drops to a minimum near the median (45.43%), and rises again in the upper tail (78.50% at the 75th quantile). This pattern underscores significantly stronger interdependence and shock transmission during extreme market conditions compared with normal states.


(a)

(b)

(c)

Figure 6. Volatility spillover network during the COVID-19 pandemic (2019–2022) across quantiles: (a) 25th quantile, (b) 50th quantile, and (c) 75th quantile.
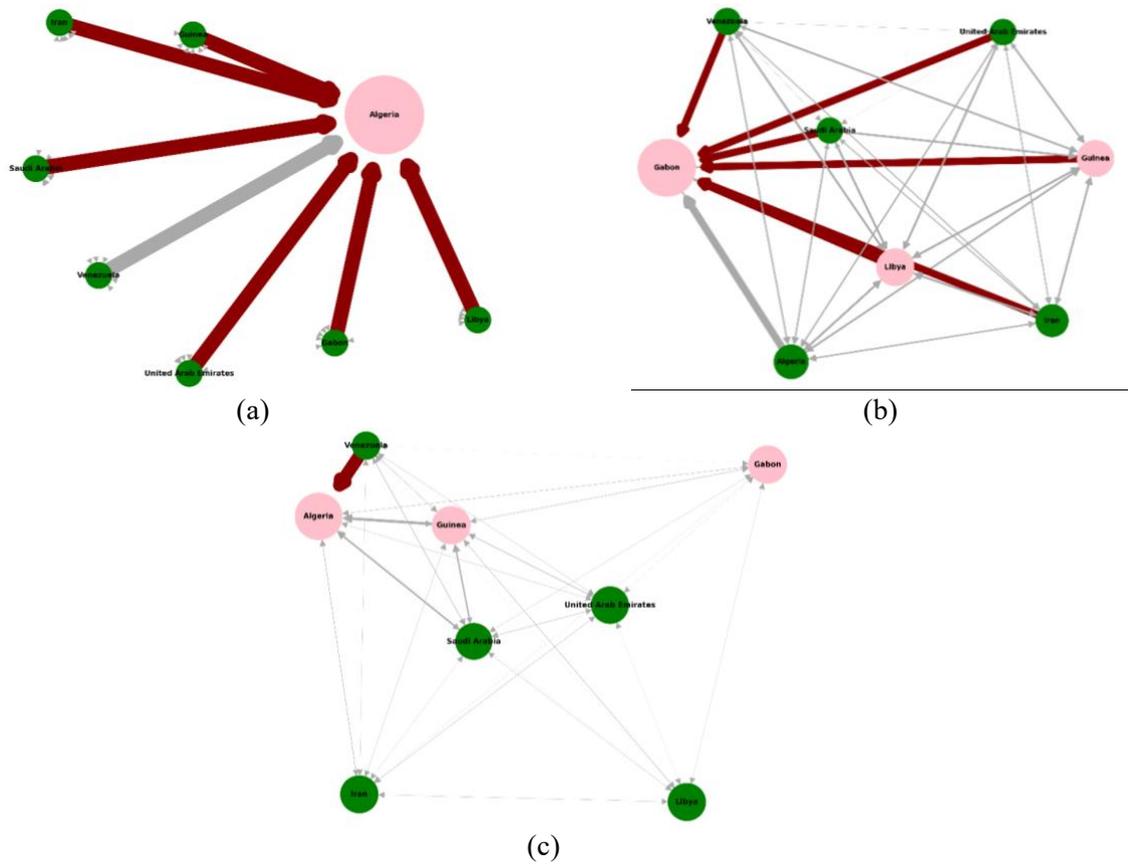
Figure 7. Volatility spillover network during the Russia–Ukraine war (2021–2023) across quantiles: (a) 25th quantile, (b) 50th quantile, and (c) 75th quantile.
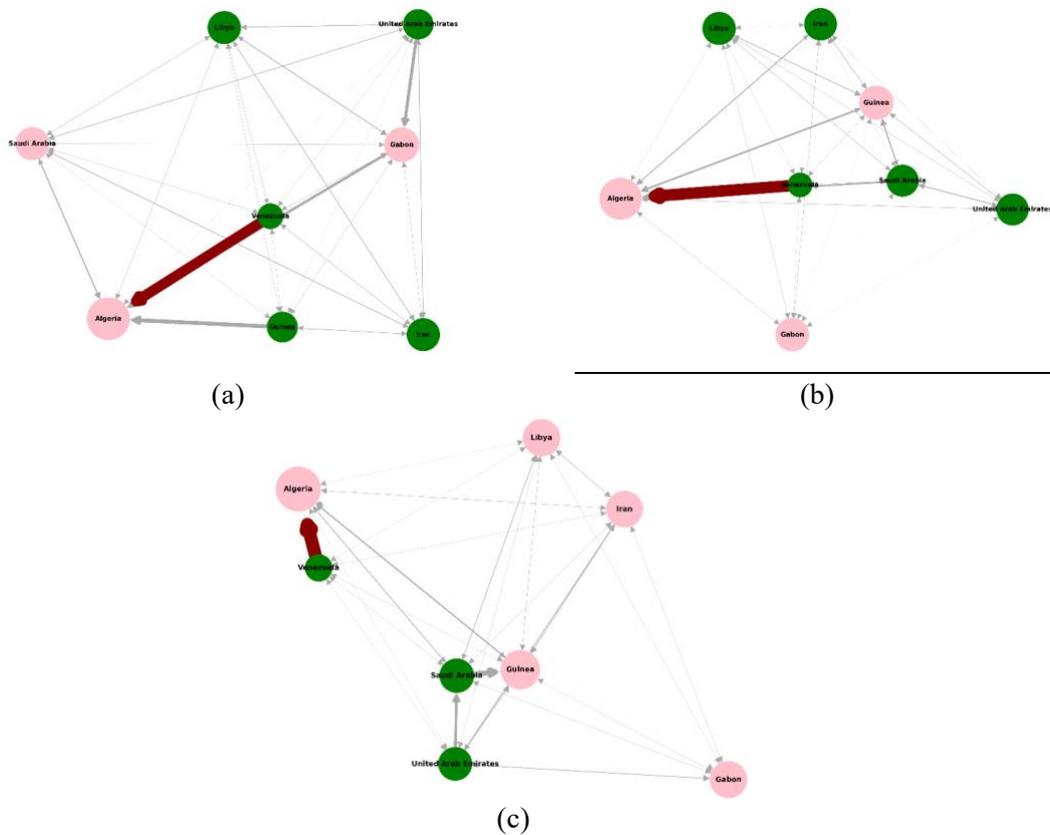
Figure 8. Volatility spillover network during the Silicon Valley Bank crisis (2022–2023) across quantiles: (a) 25th quantile, (b) 50th quantile, and (c) 75th quantile.
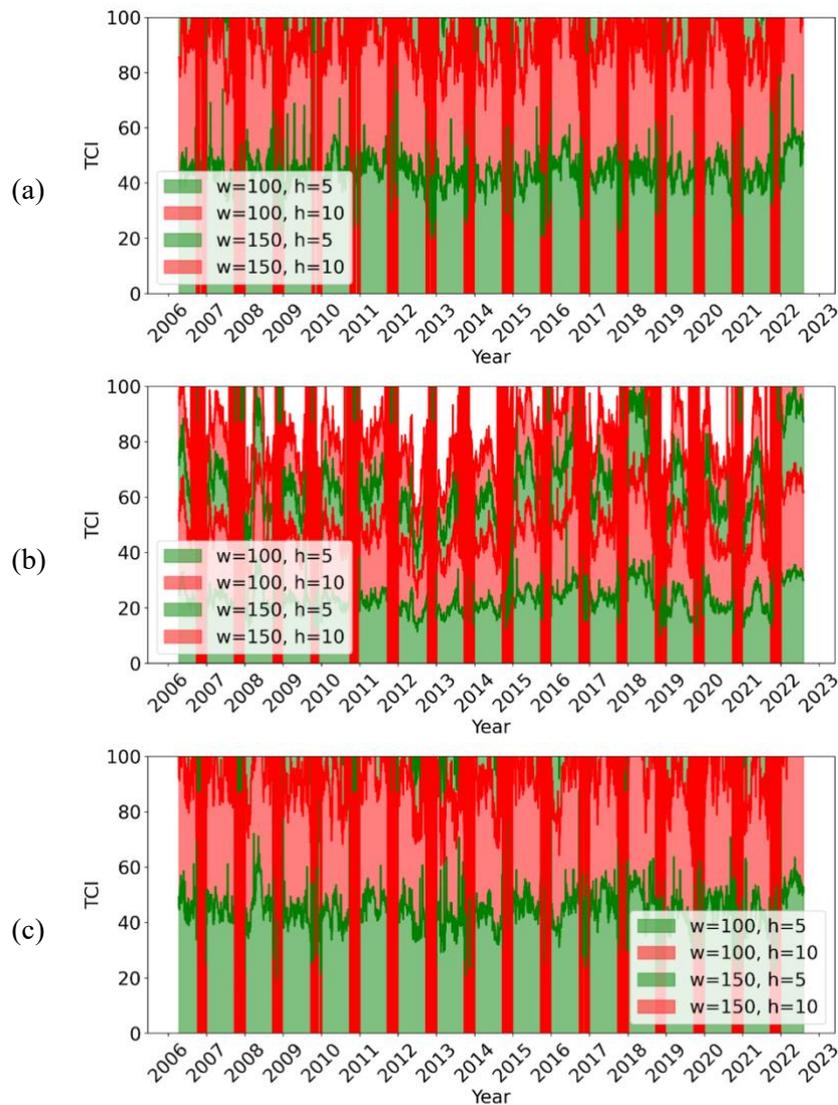
Figure 9. Robustness check: Dynamic Total Connectedness Index under alternative specifications: (a) 100-day window, 10-day horizon vs. 150-day window, 10-day horizon; (b) 100-day window, 5-day horizon vs. 100-day window, 10-day horizon; (c) 150-day window, 5-day horizon vs. 150-day window, 10-day horizon.
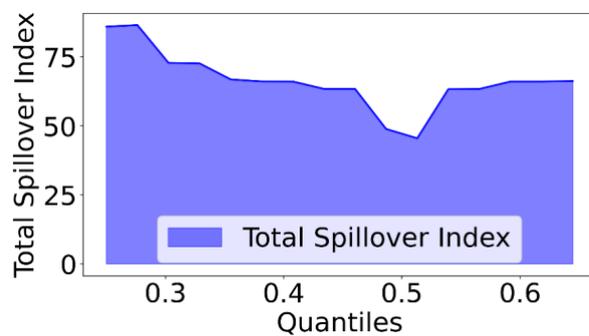
Figure 10. Total Connectedness Index across the quantile distribution (0.05 to 0.95), illustrating the U-shaped pattern of spillover intensity.

Conclusion

This study presents the first quantile-connectedness analysis of the economic-environmental nexus in OPEC countries using high-frequency daily panel data and the QVAR connectedness

framework of Chatziantoniou et al. (2021) and Ando et al. (2022). The results reveal a robust U-shaped pattern in the Total Connectedness Index, with significantly stronger interdependence during extreme market conditions (lower and upper quantiles) than under normal conditions. Iran and Equatorial Guinea systematically emerge as the primary net transmitters of economic-environmental shocks across quantiles and crises, whereas the United Arab Emirates and Algeria consistently act as the dominant net receivers. Spillovers intensify dramatically during major exogenous shocks, most notably during the COVID-19 pandemic and the Russia–Ukraine war, highlighting the acute systemic vulnerability of oil-dependent economies.

These findings extend the existing literature in several important directions. While previous studies (e.g., Khezri et al., 2022; Wan et al., 2025; Zarouki et al., 2022) have documented linkages between globalization, economic complexity, and environmental outcomes using traditional mean-based or annual-frequency models, this research is the first to uncover short-term asymmetric and quantile-dependent volatility transmission mechanisms within OPEC using high-frequency data and the QVAR connectedness approach. The observed U-shaped connectedness corroborates the presence of tail-risk contagion documented in financial and energy markets (Chatziantoniou et al., 2021; Bucak & Çatık, 2024), but extends it to the multidimensional economic-environmental nexus in resource-dependent economies. Moreover, the persistent net transmitter role of Iran and Equatorial Guinea, even during non-energy-specific crises such as the Silicon Valley Bank collapse, underscores the critical influence of geopolitical and structural factors beyond oil price fluctuations.

The results carry three major policy implications for OPEC members and similar oil-dependent economies:

1. Net receiver countries (particularly the UAE and Algeria) should accelerate economic diversification and reduce fiscal dependence on hydrocarbon exports to lower their shock-absorption capacity and enhance resilience against both energy-specific and global financial shocks.

2. Net transmitter countries (Iran and Equatorial Guinea) can play a stabilizing role by pursuing more predictable and coordinated production and export policies, thereby helping to dampen regional volatility transmission.

3. OPEC as an organization would benefit from establishing real-time quantile-connectedness monitoring systems that track systemic risk across extreme market states. Such early-warning tools would enable proactive, coordinated responses during crises and support more effective risk management in an increasingly volatile global environment.

Finally, the moderate positive correlation between CO_2 emissions and the Economic Complexity Index suggests that diversification strategies must be designed with environmental sustainability in mind. Future research could fruitfully extend the present framework by incorporating green finance indices, renewable energy penetration rates, or climate policy uncertainty measures to better inform the transition toward low-carbon, resilient economic structures in hydrocarbon-reliant nations.

Declarations

This study did not involve human participants or animals, and therefore ethical approval was not required.
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.
The authors declare that they have no conflicts of interest or competing interests.

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Appendix A. Unit Root Tests

Table 1a. Augmented Dickey-Fuller (ADF) Test Results for Stationarity

Country	CO2	KOF	ECI	Economic Indicator
Algeria	0.137(Non-stationary)	0.0247 (Stationary)	0.0000 (Stationary)	0.0081 (Stationary)
Gabon	0.0062(Stationary)	0.0142 (Stationary)	0.0000 (Stationary)	0.1546 (Non-stationary)
Iran	0.0370 (Stationary)	0.0187 (Stationary)	0.0000 (Stationary)	0.0320 (Stationary)
Libya	0.0100 (Stationary)	0.0943 (Non-stationary)	0.0000 (Stationary)	0.0066 (Stationary)
Guinea	0.2389 (Non-stationary)	0.0490 (Stationary)	0.0000 (Stationary)	0.0625 (Non-stationary)
Saudi Arabia	0.3457 (Non-stationary)	0.0400 (Stationary)	0.0000 (Stationary)	0.0771 (Non-stationary)
United Arab Emirates	0.0765 (Non-stationary)	0.0783 (Non-stationary)	0.0000 (Stationary)	0.2728(Non-stationary)
Venezuela	0.1494 (Non-stationary	0.0143 (Stationary)	0.0000 (Stationary)	0.0423(Stationary)

Stationarity of the series was confirmed using the Augmented Dickey-Fuller (ADF) test after first differencing . All variables are stationary at the 5% significance level in first differences, satisfying the requirements for the QVAR connectedness analysis.

Appendix B. Pairwise Correlation Matrix

Figure 1a presents the pairwise correlation matrix of the four variables (CO_2 emissions, KOF Globalization Index, Economic Complexity Index, and Composite Economic Indicator). CO_2 emissions exhibit a moderate positive correlation with ECI (0.46) and a weak negative correlation with the KOF Globalization Index (−0.29). The KOF Index and ECI are both moderately positively correlated with the Composite Economic Indicator (0.34 and 0.32, respectively). These preliminary correlations provide initial evidence of the interrelationships among the variables and support the subsequent connectedness analysis.
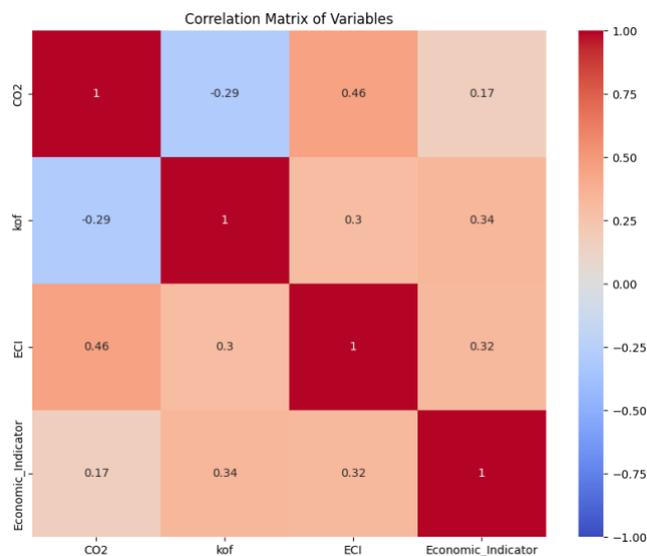
Figure 1a. Pairwise Correlation Matrix of Variables (CO_2 Emissions, KOF Globalization Index, Economic Complexity Index, Composite Economic Indicator)