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Analyzing the dynamic interactions among environmental finance, energy, and commodity markets using a wavelet coherence approach

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(This article belongs to the *Special Issue: AI Revolutionizing Business Functions: The Digital Transformation of Business Management*)

Abstract

Understanding the evolving interdependencies among environmental finance, technology, energy, and commodity markets is essential for effective portfolio diversification, risk management, and sustainable investment decisions. However, these relationships are dynamic and vary across both time and investment horizons. This paper employs Wavelet Coherence methodology to dissect the dynamic, time- and frequency-dependent linkages between key environmental finance indices (Standard & Poor's [S&P] Global Carbon Efficient Index [CRBN] and S&P Kensho Smart Grids Index [SMOG]) and a comprehensive suite of technology, energy, and commodity assets. Our analysis reveals the distinct economic identities of these indices. We find an exceptionally strong and persistent coherence between CRBN, artificial intelligence, and clean energy across a broad spectrum of frequencies, positioning CRBN as a central node in the modern technology and green investment ecosystem. Furthermore, CRBN exhibits strong long-term coherence with crude oil and copper, indicating its role as a strong proxy for the global business cycle. In contrast, the SMOG index, while also strongly linked to clean energy in the long run, displays a fundamentally different relationship with traditional energy. Its coherence with crude oil is not a long-term phenomenon but manifests as a significant medium-term, crisis-driven linkage, highlighting its sensitivity to cyclical market shocks rather than long-run fundamentals. These findings provide a granular map of the distinct risk exposures and economic drivers of key environmental assets, offering critical insights for horizon-specific asset allocation, thematic investing, and risk management.

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Citation: Monika, Katoch, R. & Khan, S. (2026). Analyzing the dynamic interactions among environmental finance, energy, and commodity markets using a wavelet coherence approach. *Int J Systematic Innovation*, 10(5): 026210109.

[https://doi.org/10.6977/IJoSI.202610_10\(5\).0013](https://doi.org/10.6977/IJoSI.202610_10(5).0013)

Received: May 21, 2026

Revised: June 9, 2026

Accepted: June 29, 2026

Published online: July 15, 2026

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Keywords: Wavelet coherence; Time–frequency analysis; Energy markets; Clean energy; Systemic risk; Commodity prices; Financial contagion

1. Introduction

The global financial ecosystem is characterized by an intricate, ever-evolving web of interconnections, in which shocks originating in one market can rapidly propagate across asset classes and geographic boundaries (Diebold & Yilmaz, 2011; Forbes & Rigobon, 2002). At the heart of this complex network lie the energy markets, with

crude oil historically serving as a critical barometer of global economic health and a primary source of systemic risk (Olabi *et al.*, 2023). The profound influence of oil price fluctuations extends far beyond the energy sector, transmitting significant volatility to international stock markets, exchange rates, and the broader commodity complex (Cadena-Silva *et al.*, 2025; Cui *et al.*, 2025). The financialization of commodities has further amplified these linkages, transforming raw materials from mere physical inputs into a distinct and highly integrated financial asset class (Del Rosario Venegas *et al.*, 2024; Jiang *et al.*, 2026; Li *et al.*, 2026).

In recent years, this established landscape has been fundamentally reshaped by two transformative global megatrends: the imperative of climate change mitigation and the rise of the digital economy. The global push for decarbonization has propelled clean energy and environmental assets to the forefront of financial markets (Babic, 2024). Clean energy stocks, green bonds, and carbon emission allowances (European Union Allowances [EUAs]) now constitute a significant and rapidly growing asset class, creating a new and complex “clean vs. dirty” energy nexus (Gargallo *et al.*, 2024). The relationship between these sectors is multifaceted, exhibiting periods of both competition and co-movement, driven by policy shifts, technological innovation, and macroeconomic undercurrents (Mishra *et al.*, 2023; Rufé & Pidelaserra, 2024). Simultaneously, the emergence of digital assets, particularly cryptocurrencies, has introduced a new, highly volatile, and energy-intensive player into the financial system (Biagi, 2026; Korkusuz, 2025). The well-documented energy consumption of crypto-mining operations creates a direct physical link to energy markets, while their role as a speculative investment vehicle connects them to broader market sentiment and risk appetite (Al-Harbi, 2026; Omrane *et al.*, 2025).

Understanding the dynamics within this increasingly crowded and complex ecosystem presents a significant analytical challenge. The relationships between these diverse assets are not linear or static; they are characterized by non-stationarity, structural breaks, and time-varying cyclical patterns (Naivasha *et al.*, 2026; Ramos-Requena & Bağcı, 2026). Traditional econometric methods, such as standard correlation and regression analyses, are often inadequate for capturing such complex dynamics, as they tend to average out relationships over time and across different frequencies (Da Matta *et al.*, 2021; Xu *et al.*, 2024). This limitation is particularly acute during periods of market turmoil, where correlations are known to shift dramatically, leading to the breakdown of conventional hedging and diversification strategies (Jouini *et al.*, 2025;

Salhi & Ouakil, 2026).

To overcome these methodological hurdles, this study employs a suite of advanced wavelet analysis techniques. Wavelet analysis serves as a powerful “economic microscope,” capable of decomposing time series into both time and frequency domains simultaneously (Aguar & Soares, 2010; Katoch & Khan, 2026; Percival & Walden, 2000). This dual localization enables a granular examination of how asset relationships evolve over time (e.g., before, during, and after a crisis) and across different investment horizons or frequencies (e.g., short-term vs. long-term) (Ramsey, 2002; Torrence & Compo, 1998). Specifically, we utilize wavelet coherence (WTC) to identify the strength, timing, and lead-lag structure of co-movements (Grinsted *et al.*, 2004); wavelet correlation (WC) to assess how the correlation structure changes from short- to long-term scales (Gençay *et al.*, 2002); and partial WTC (PWC) to isolate direct, intrinsic relationships by controlling for the confounding influence of common market drivers (Almaskati, 2022; Mihanović *et al.*, 2012). These methods have been successfully applied in recent literature to uncover dynamic linkages among oil and stocks, clean energy and financial assets (Kumar *et al.*, 2025), and cryptocurrencies and other markets (Khan *et al.*, 2026).

While the existing literature has applied these methods to various asset pairs, a comprehensive study that simultaneously integrates traditional energy (crude oil, natural gas, coal), new environmental and technological assets (clean energy, Standard & Poor’s [S&P] Global Carbon Efficient Index [CRBN], and S&P Kensho Smart Grids Index [SMOG]), a broad suite of physical commodities, and emergent digital assets within a single, unified analytical framework remains scarce. Most studies focus on bivariate relationships or a limited set of assets, leaving a fragmented understanding of the complete ecosystem (Zander *et al.*, 2025). Furthermore, few have combined the complementary strengths of WTC, PWC, and WC to provide a holistic and robust picture that not only identifies co-movement but also isolates its direct causal channels and maps its evolution across investment horizons. This study seeks to fill this significant research gap.

Consequently, this paper addresses the following key research questions: (i) How have the time–frequency co-movements between traditional energy, environmental assets, commodities, and digital assets evolved, particularly in response to recent global crises such as the COVID-19 pandemic and geopolitical conflicts? (ii) How does the correlation structure between these asset classes change as the investment horizon lengthens from the short term to the

long term? (iii) What are the direct, intrinsic relationships between these assets once the influence of common market drivers is partialled out? By answering these questions, this study makes a significant contribution to the literature by providing a granular, multi-asset, and methodologically robust analysis of the modern financial and commodity landscape. We offer critical insights for investors, portfolio managers, policymakers, and corporate strategists navigating the complexities of portfolio diversification, risk management, and strategic asset allocation amid profound structural change.

The remainder of this paper is organized as follows: Section 2 provides a detailed review of the relevant literature. Section 3 outlines the data and the wavelet methodologies employed. Section 4 presents and discusses the empirical results. Finally, Section 5 concludes with a summary of the key findings and their implications.

2. Literature review

The interconnectedness between energy commodities and financial markets has become a central theme in contemporary economic research, driven by the increasing financialization of commodity markets (Bouri *et al.*, 2022; Mensi *et al.*, 2021). This linkage is not static but evolves dynamically, exhibiting significant instability, particularly during periods of geopolitical tension or global economic crises (Marangoz *et al.*, 2025). Crude oil, in particular, is recognized as a primary source of systemic risk, with its price shocks transmitting rapidly to global equity markets, exchange rates, and other commodities (Escribano *et al.*, 2023). The nature of these spillovers is often asymmetric, with negative shocks exerting a more profound impact than positive ones (Guan *et al.*, 2024).

Concurrently, the global push for decarbonization has elevated the importance of environmental assets in financial analysis (Xu *et al.*, 2026). Clean energy stocks and carbon emission prices (e.g., EUAs) have emerged as a distinct asset class, creating a new and complex set of interactions with traditional energy markets (Katoch & Khan, 2026; Yadav *et al.*, 2025). The relationship between clean and dirty energy sources is often competitive, with shocks in one sector directly influencing investment and performance in the other (Mahadeo, 2024). Furthermore, the rise of the digital economy has introduced cryptocurrencies as a new variable, linked to energy markets through their significant electricity consumption for mining operations and as a potential, albeit volatile, investment alternative (Jafari *et al.*, 2025).

Investigating these intricate relationships requires methodologies that can transcend the limitations of traditional linear models (Torres & Akbaritabar, 2025).

Financial and commodity time series are characterized by non-stationarity, structural breaks, and cyclical patterns that standard correlation coefficients fail to capture (Torres & Akbaritabar, 2025). To address this, wavelet analysis has become a powerful and widely adopted tool in the finance and energy economics literature (Percival & Walden, 2000). The WTC methodology decomposes time series into both time and frequency domains simultaneously, allowing for the identification of localized co-movements and lead-lag relationships across different time horizons (Torrence & Compo, 1998). This approach can reveal, for instance, that two assets are decoupled in the short term but strongly linked in the long term, offering critical insights for horizon-specific investment and hedging strategies (Jouini *et al.*, 2025).

A vast body of literature has used wavelet analysis to confirm crude oil's central role in the financial system. Studies consistently show strong, time-varying coherence between oil prices and global stock markets, which intensifies significantly during crisis periods such as the Global Financial Crisis and the COVID-19 pandemic (Mensi *et al.*, 2024). The co-movement is also frequency-dependent, with long-term linkages being more pronounced than short-term ones (Wadud *et al.*, 2023). This coherence extends to other commodities, where oil serves as a primary cost input, leading to strong positive correlations with industrial metals over medium- to long-term investment horizons (Khalfaoui *et al.*, 2021).

Wavelet analysis has been instrumental in understanding the dynamics of the clean energy transition. Research shows a complex, time- and frequency-dependent relationship between clean energy stocks and oil prices (Marín-Rodríguez *et al.*, 2023). While they often move in tandem in the long run due to shared economic drivers, they can decouple or even exhibit negative coherence in the short run, particularly in response to policy news or technological breakthroughs (Lei *et al.*, 2026). Similarly, the link between carbon emission prices (EUAs) and energy prices is highly dynamic, with WTC revealing that EUAs are increasingly driven by natural gas prices, especially in the long run (Leone *et al.*, 2025).

The scale-dependent nature of asset relationships, as revealed by WC, is critical for assessing hedging effectiveness. Gold is widely regarded as a safe-haven asset against volatility in energy markets (Ameur *et al.*, 2024). Wavelet studies confirm that gold's hedging properties are strongest in the long term, while its effectiveness in the short term can be unreliable (Maghyreh *et al.*, 2018; Nasreddine & Zouari, 2024; Qin *et al.*, 2025). Natural gas has also been identified as a potential long-term diversifier for broad commodity portfolios due to its unique, localized

drivers, which cause it to decouple from other assets over longer horizons (Al-Maadid *et al.*, 2026; Malhotra *et al.*, 2025).

More recent studies have applied WTC to the nascent field of digital assets. A significant bidirectional relationship has been found between energy prices and the returns of major cryptocurrencies like Bitcoin (Sapra *et al.*, 2024; Sapra *et al.*, 2026). This coherence is particularly strong in the short- to medium-term, reflecting both the energy-intensive nature of crypto mining and the role of cryptocurrencies as speculative assets sensitive to broader market sentiment (Alabi, 2025).

While WTC is powerful, it cannot distinguish between direct and indirect relationships, where a third variable may be driving two assets simultaneously (Anwer *et al.*, 2026). PWC addresses this limitation by measuring the coherence between two time series after controlling for the influence of a third, confounding variable (Ng & Chan, 2012). PWC has been used to demonstrate that the apparent coherence among some assets is merely a spurious reflection of their common dependence on a major market driver, such as the S&P 500 or oil prices (Qureshi *et al.*, 2020). This technique provides a cleaner, more accurate map of the true channels of financial contagion and risk transmission (Paltalidis *et al.*, 2015).

The existing literature has successfully applied wavelet techniques to various asset pairs, confirming the time- and frequency-dependent nature of their relationships. However, a comprehensive analysis that simultaneously investigates the dynamic linkages between traditional energy (oil, gas, coal), new environmental assets (clean energy, SMOG, CRBN), key commodities, and emerging digital assets within a unified framework remains lacking. Furthermore, few studies have combined WTC, PWC, and WC to provide a holistic picture that not only identifies co-movement and its evolution across scales but also isolates the direct, intrinsic connections from spurious, indirect ones. This study aims to fill this gap by providing a multi-asset, multi-methodology analysis, focusing particularly on how these complex relationships are reshaped during recent global crises, thereby offering a more granular and robust understanding of the modern financial ecosystem.

3. Research methodology

This study investigates the dynamic, time- and frequency-dependent interrelationships between a diverse set of energy, environmental, commodity, and digital assets. To capture the non-stationary and complex nature of these linkages, which traditional time-invariant methods fail to adequately model, we employed a suite of advanced

wavelet analysis techniques. This section details the data acquisition process, provides a robust rationale for the chosen methodology, and offers a technical exposition of the WTC, PWC, and WC frameworks.

3.1. Data and sample period

The empirical analysis used daily price series (converted to continuously compounded returns) for a comprehensive set of market indices covering traditional energy, clean energy/environmental indices, and broad commodity benchmarks. Specifically, the environmental indices were: CRBN and SMOG. Clean energy was proxied by the S&P Global Clean Energy Index, while traditional energy benchmarks included the S&P Goldman Sachs Commodity Index [GSCI] Crude Oil, S&P GSCI Natural Gas, and S&P GSCI Coal series. The commodity basket comprised major S&P GSCI constituents (gold, silver, platinum, palladium, aluminum, copper, nickel, zinc). All price data were retrieved from the Bloomberg Terminal. The sample period was from January 1, 2015, to December 31, 2024.

To isolate intrinsic pairwise relationships in PWC, we included a small set of well-justified control variables that capture global risk and macroenergy conditions: Chicago Board Options Exchange Volatility Index (VIX) to capture market risk/uncertainty; West Texas Intermediate (WTI) front-month futures (CL1) to control for the global oil price benchmark; and the US 10-year treasury yield to capture global interest-rate and macroeconomic stance. We also tested robustness by including the S&P 500 index as an alternative common market driver. These controls were selected because they represented (i) market fear (VIX), (ii) the primary energy price channel that drove many commodity production costs (WTI), and (iii) the global macro-financial environment that affected discount rates and broad risk premia (US 10-Year Treasury Note). In PWC plots, the above series were partialled out sequentially and jointly to ensure detected coherence was direct rather than driven by common global drivers.

To ensure stationarity and for the results to be interpretable as continuously compounded returns, all daily price series (P_t) were transformed into logarithmic returns using the formula: $r_t = \ln(P_t) - \ln(P_{t-1})$. The analysis was conducted on these return series.

Wavelet analysis is uniquely suited for this purpose. It serves as a powerful mathematical microscope that simultaneously decomposes a time series into its constituent components in both the time and frequency domains. This dual localization allows us to answer not only when relationships change (e.g., during a crisis) but also at which frequencies (investment horizons) these

changes are most pronounced. This is a critical advantage for deriving practical implications for horizon-specific portfolio diversification and hedging strategies.

3.2. Preliminary statistical analysis

Prior to wavelet estimation, we confirmed that all return series were stationary using the Augmented Dickey–Fuller and Phillips–Perron unit root tests. Descriptive statistics, including mean, standard deviation, skewness, and excess kurtosis, were computed for each return series. All series exhibited leptokurtic distributions (excess kurtosis > 3) and non-zero skewness, confirming the non-Gaussian character of financial returns that motivated a time–frequency rather than a standard linear framework. Pairwise Pearson correlations across the full sample were also reported as a baseline, providing context against which the time- and scale-varying coherence patterns uncovered by wavelet analysis were interpreted.

3.3. The wavelet transform framework

3.3.1. The continuous wavelet transform

The foundation of our analysis was the continuous wavelet transform (CWT), which transformed a time series $x(t)$ into a two-dimensional time–frequency space. The CWT of a time series is defined as the convolution of the series with a set of “daughter” wavelets, which are scaled and translated versions of a “mother” wavelet (Equation 1):

$$\Psi(t): W_x(s, \tau) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \Psi^* \left(\frac{t - \tau}{s} \right) dt \quad (1)$$

where Ψ^* is the complex conjugate of the mother wavelet, s is the scale parameter (inversely related to frequency) that dilates or compresses the wavelet to capture different cyclical periods, and τ is the translation parameter that localizes the analysis to a specific point in time.

Following the standard in financial economics, we employed the Morlet wavelet as our mother wavelet. It is a complex-valued wavelet defined as Equation 2:

$$\Psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \quad (2)$$

where ω_0 is the central frequency (set to 6). The Morlet wavelet provides an optimal trade-off between time and frequency localization, making it highly suitable for analyzing financial and economic time series.

3.3.2. Wavelet coherence

The WTC extends the CWT to a bivariate setting, providing a localized measure of the co-movement between two time series, $x(t)$ and $y(t)$, in the time–frequency space.

The squared WTC is defined as (Equation 3):

$$R^2(s, \tau) = \frac{|S(s^{-1} W_{xy}(s, \tau))|^2}{S(s^{-1} |W_x(s, \tau)|^2) \cdot S(s^{-1} |W_y(s, \tau)|^2)} \quad (3)$$

where $W_{xy}(s, \tau) = W_x(s, \tau) W_y^*(s, \tau)$ is the cross-wavelet spectrum, and S is a smoothing operator in both time and scale. The value of $R^2(s, \tau)$ ranges from 0 to 1, representing the squared correlation between the two series at a specific time (τ) and scale (s). A value close to 1 indicates strong co-movement.

Statistical significance was determined using Monte Carlo simulations, in which the coherence of the original series was compared with that of a large ensemble of surrogate data pairs generated from a first-order autoregressive process. The phase difference, ϕ_{xy} , provides information on the lead-lag relationship, visualized by arrows on the coherence plot:

- (In-phase): The series move in tandem; positive correlation.
- ← (Anti-phase): The series move in opposite directions; negative correlation.
- ↗ (X leads Y) / ↖ (Y leads X): In-phase relationship with a lead-lag structure.
- ↘ (Y leads X) / ↙ (X leads Y): Anti-phase relationship with a lead-lag structure.

3.3.3. Partial wavelet coherence

To isolate the direct relationship between two time series, $x(t)$ and $y(t)$, while controlling for the confounding influence of a third series, $z(t)$, we employed PWC. PWC measures the residual coherence between x and y after their common coherence with z has been partialled out. The squared PWC is calculated as Equation 4:

$$R_p^2(x, y|z) = \frac{|R(x, y) - R(x, z) \cdot R^*(z, y)|^2}{(1 - |R(x, z)|^2)(1 - |R(y, z)|^2)} \quad (4)$$

where $R(x, y)$, $R(x, z)$, and $R(y, z)$ are the complex WTC coefficients between the respective pairs. A high and significant PWC value indicates a robust, direct linkage between x and y that is not merely a spurious reflection of their shared dependence on z .

3.3.4. Wavelet correlation

While WTC provides a localized, point-by-point measure of co-movement, WC offers a global measure of correlation for each distinct scale (frequency band). It computes the correlation of the wavelet coefficients of two series, $x(t)$ and $y(t)$, across the entire time domain for a given scale s_j . The WC at scale s_j is defined as Equation 5:

$$\rho_{xy}(s_j) = \frac{\text{Cov}(W_x(s_j, \cdot), W_y(s_j, \cdot))}{\sqrt{\text{Var}(W_x(s_j, \cdot)) \text{Var}(W_y(s_j, \cdot))}} \quad (5)$$

This provides a single correlation value for each investment horizon, allowing us to plot the evolution of correlation from short-term to long-term scales. The output is a line graph with the x-axis representing the scale and the y-axis representing the correlation coefficient, complete with 95% confidence intervals to assess statistical significance. This technique is ideal for determining whether assets are short-term diversifiers but long-term complements, or vice versa.

4. Results

4.1. Analysis of wavelet coherence

This analysis revealed how crude oil's price dynamics were interconnected with other key commodities during major global events (Figure 1):

- Oil Crisis 2018: Crude oil exhibited medium-term coherence with S&P GSCI Platinum and short-term coherence with S&P GSCI Aluminum. This suggests that the immediate shock of the crisis, coupled with aluminum prices and oil, had a more sustained impact on platinum.
- COVID-19 (505–757): The pandemic period fostered deeper connections. A significant long-term coherence emerged between crude oil and S&P GSCI Aluminum. Furthermore, medium-term co-movements were identified with S&P GSCI Zinc and S&P GSCI Copper, reflecting a synchronized response to the global economic slowdown and subsequent recovery in the industrial sector.
- Russia–Ukraine War (1,031–1,260): During this period, no significant coherence was observed between crude oil and the listed commodities across any time horizon.
- Iran–Israel Tensions (1,261–1,571): This conflict saw a re-emergence of significant relationships. A long-term coherence with S&P GSCI Aluminum persisted. Medium-term co-movement was observed with S&P GSCI Platinum and S&P GSCI Nickel, while a short-term link was observed with S&P GSCI Copper.

Figure 2 shows the spillover effects of natural gas price movements into the broader commodities market

- Oil Crisis 2018: Natural gas displayed broad and significant coherence with several metals. It was linked with S&P GSCI Platinum in both the short- and medium-term and with S&P GSCI Zinc across the same time frames. Short-term coherence was also observed with S&P GSCI Palladium.

- COVID-19 (505–757): The pandemic's initial economic shock created a strong short-term linkage between natural gas and key industrial metals, including S&P GSCI Aluminum, S&P GSCI Zinc, and S&P GSCI Copper.
- Russia–Ukraine War (1,031–1,260): No significant coherence was identified between natural gas and the other commodities during this timeframe.
- Iran–Israel Tensions (2,261–2,608): A medium-term coherence was established between natural gas and S&P GSCI Aluminum, indicating a moderately sustained connection during this period of geopolitical tension.

This analysis examined the relationship between the clean energy sector and commodities, highlighting potential dependencies and shared market drivers (Figure 3):

- Oil Crisis 2018: No significant coherence was found, suggesting that the clean energy sector was decoupled from commodity markets during this event.
- COVID-19 (505–757): The clean energy index showed medium-term coherence with S&P GSCI Silver and short-term coherence with S&P GSCI Copper. This highlights the connection between the sector and key metals essential for its technologies.
- Russia–Ukraine War (1,031–1,260): A short-term co-movement was observed between the clean energy index and S&P GSCI Gold, suggesting a brief, shared reaction to the initial market shock of the conflict.
- Iran–Israel Tensions (2,261–2,608): No significant coherence was noted during this period.

Figure 4 details the interconnections between coal and other commodities, reflecting its role as a primary industrial energy source:

- Oil Crisis 2018: Coal demonstrated extensive coherence with industrial and precious metals. Short-term links were found with S&P GSCI Silver, S&P GSCI Aluminum, and S&P GSCI Copper. S&P GSCI Zinc showed both short- and medium-term coherence, while a medium-term link was observed with S&P GSCI Platinum.
- COVID-19 (505–757): This period was characterized by longer-term linkages. Coal developed a long-term coherence with S&P GSCI Gold and S&P GSCI Silver. Simultaneously, it showed both medium- and long-term co-movement with S&P GSCI Palladium. Short-term links were also noted with S&P GSCI Aluminum and S&P GSCI Nickel.
- Russia–Ukraine War (1,031–1,260): The only significant relationship was a medium-term coherence with S&P GSCI Copper.

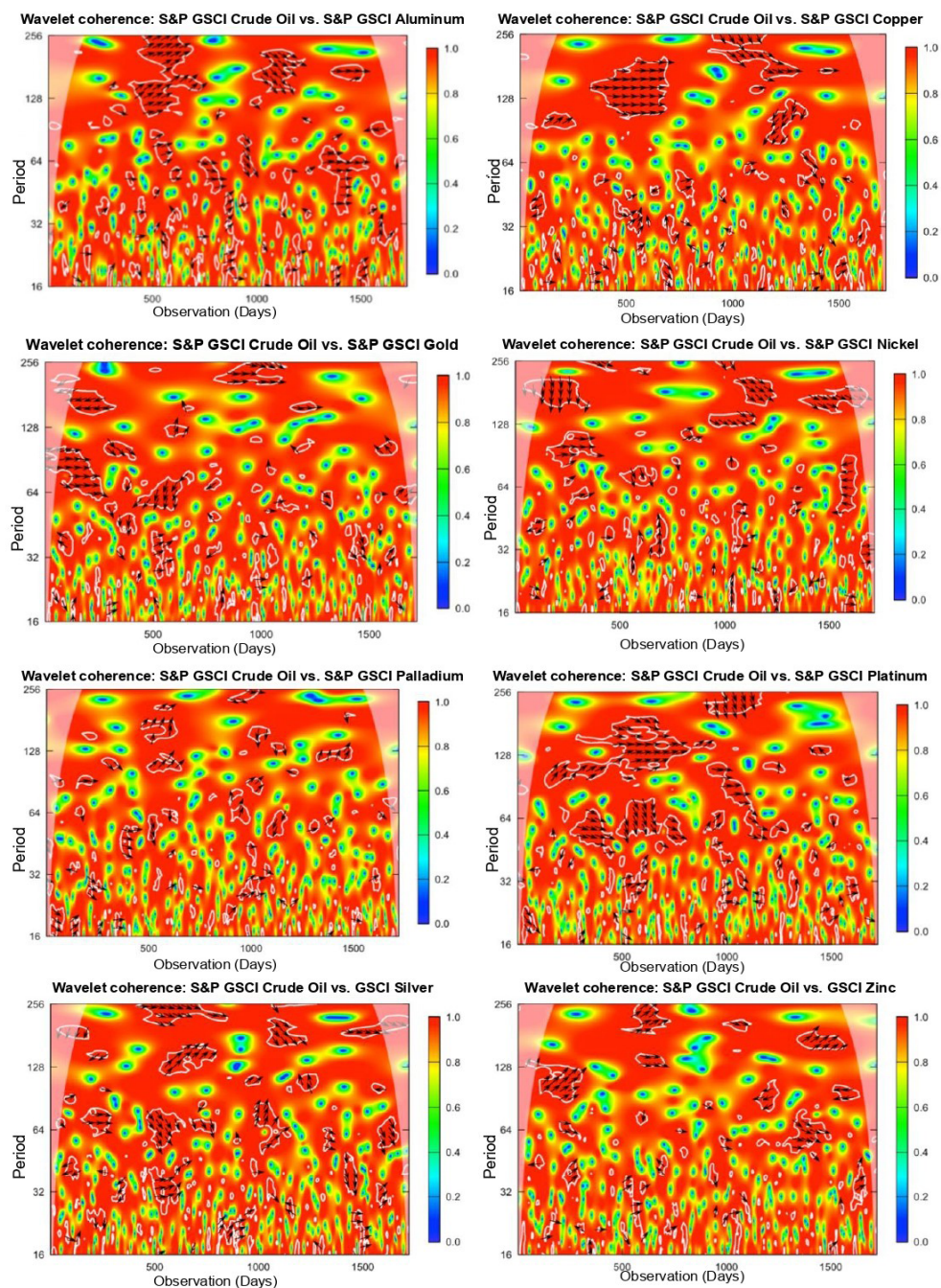


Figure 1. Wavelet coherence of Standard & Poor's (S&P) Goldman Sachs Commodity Index (GSCI) Crude Oil to other commodities

- Iran–Israel Tensions (2,261–2,608): During this event, coal was strongly linked to S&P GSCI Palladium in the short- and medium-term and exhibited a long-term coherence with S&P GSCI Nickel.

Figure 5 highlights how the carbon market, tied to industrial emissions, co-moved with key commodities:

- Oil Crisis 2018: Carbon futures showed short-term coherence with S&P GSCI Aluminum and S&P GSCI Zinc, reflecting the immediate link between industrial activity and emissions pricing.
- COVID-19 (505–757): A strong and sustained relationship was established with S&P GSCI Palladium, which exhibited both medium- and long-

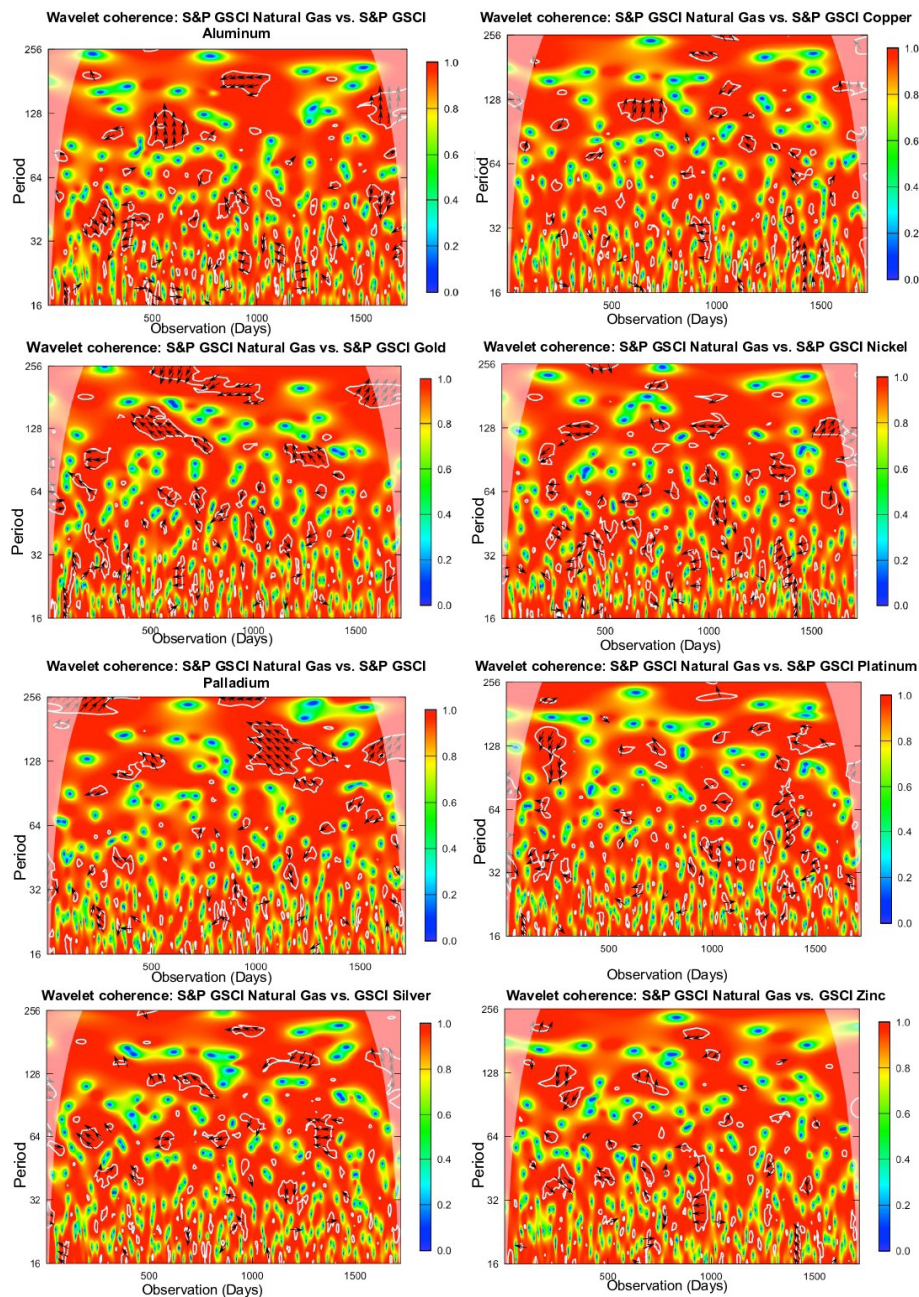


Figure 2. Wavelet coherence of Standard & Poor's (S&P) Goldman Sachs Commodity Index (GSCI) Natural Gas to other commodities

term coherence with the carbon index.

- Russia–Ukraine War (1,031–1,260): The conflict triggered a broad short-term market reaction, linking carbon futures with S&P GSCI Gold, Platinum, Aluminum, and Zinc. The long-term coherence with S&P GSCI Palladium also persisted through this period.
- Iran–Israel Tensions (2,261–2,608): Short-term

co-movements were identified between carbon futures and S&P GSCI Platinum and S&P GSCI Copper.

Figure 6 explores the relationship between the clean energy technology sector (SMOG) and the commodities vital for its growth:

- Oil Crisis 2018: The SMOG index showed significant coherence with several metals. It was linked to S&P

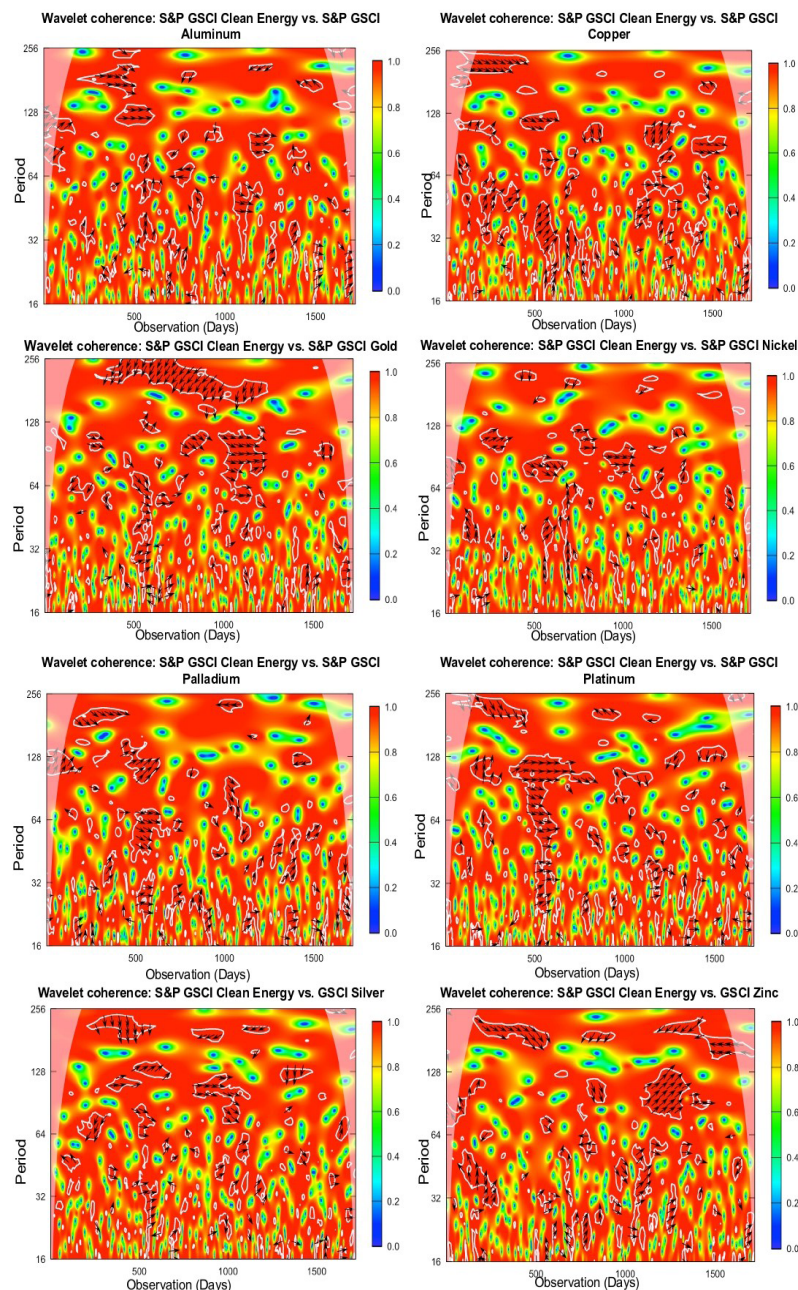


Figure 3. Wavelet coherence of Standard & Poor's (S&P) Goldman Sachs Commodity Index (GSCI) Clean Energy to other commodities

- GSCI Aluminum and S&P GSCI Zinc across both short- and medium-term horizons. Additionally, a medium-term link to S&P GSCI Platinum and a short-term link to S&P GSCI Palladium were observed.
- COVID-19 (505–757): During the pandemic, the SMOG index developed a durable medium- and long-term coherence with S&P GSCI Palladium. A short-term link was also noted with S&P GSCI Copper.
 - Russia–Ukraine War (1,031–1,260): No significant coherence was identified between the SMOG index and the listed commodities during this event.
 - Iran–Israel Tensions (2,261–2,608): A short-term co-movement emerged between the SMOG index and S&P GSCI Gold, suggesting a brief period in which both were treated as assets sensitive to geopolitical risk.

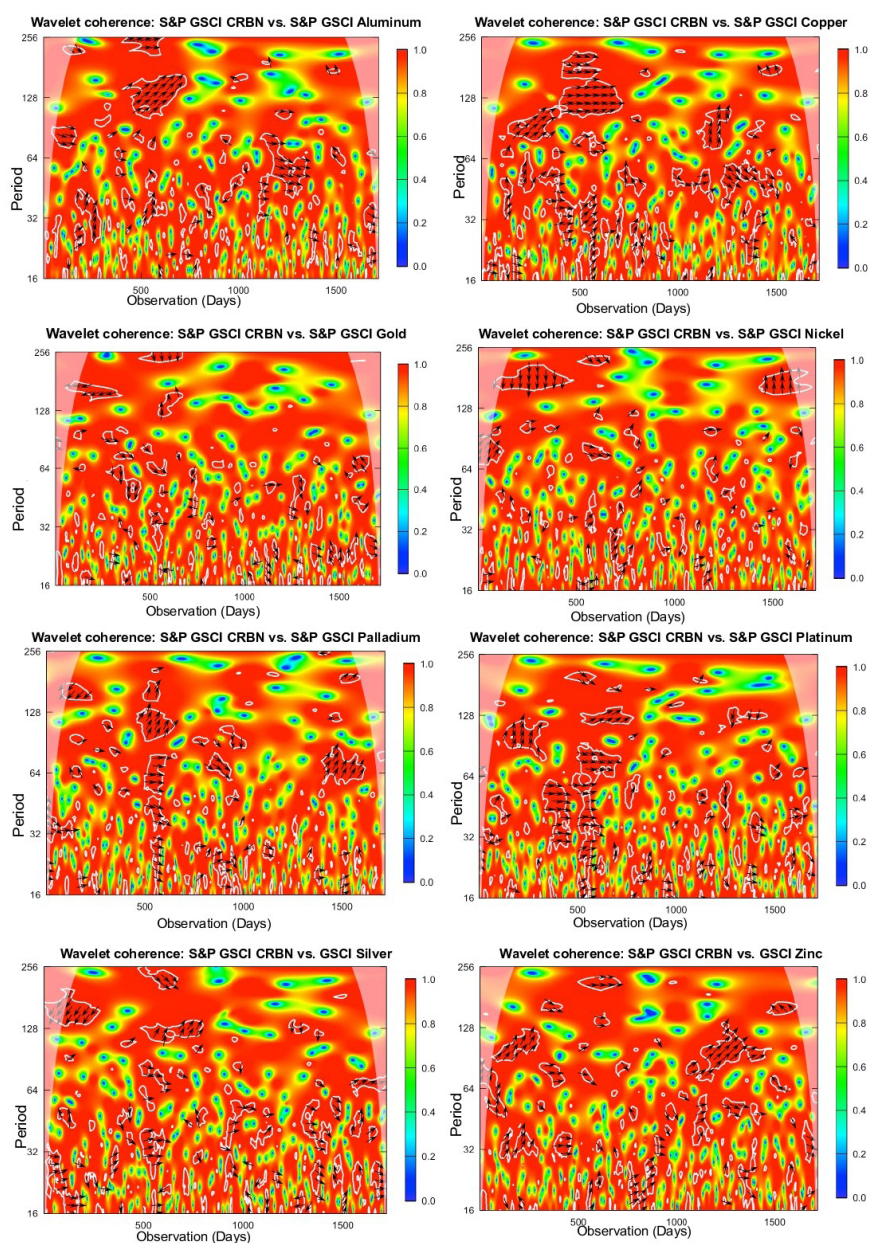


Figure 4. Wavelet coherence of Standard & Poor's (S&P) Global Carbon Efficient Index (CRBN) to other commodities

4.2. Analysis of partial wavelet coherence

The PWC plots for CRBN reveal strong, persistent, and frequency-dependent relationships with other key market sectors. The most striking finding is the exceptionally strong, broad, and persistent coherence between CRBN and artificial intelligence (AI). This relationship was statistically significant across almost all time scales and for the majority of the sample period, indicating a deeply integrated and fundamental linkage. A similarly powerful coherence was found between CRBN and Clean Energy,

concentrated in the short-to-medium term (16-64 day scale), suggesting a strong and consistent alignment in their cyclical movements and responses to market news. These results position CRBN not just as an environmental metric but as a core component of the modern technology and green energy investment landscape.

The CRBN exhibited strong, statistically significant coherence with S&P GSCI Crude Oil, but this relationship was almost exclusively confined to the long-term (64-256 day) scale. This indicates that while the two assets may

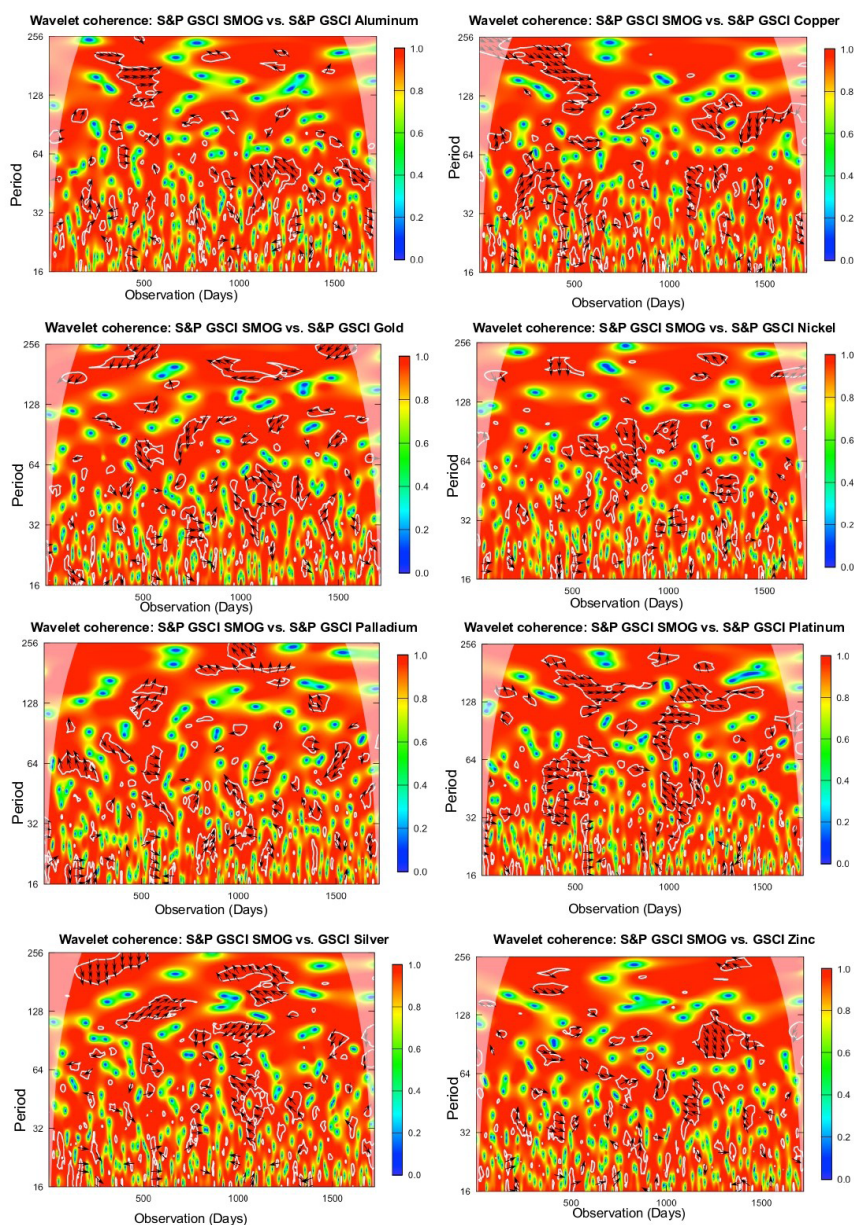


Figure 5. Wavelet coherence of Standard & Poor's (S&P) Kensho Smart Grids Index (SMOG; clean energy technology) to other commodities

diverge in the short run, their long-term fundamental trends are highly synchronized, likely driven by their shared exposure to the global business cycle. In contrast, the coherence with Coal and Natural Gas was markedly weaker and more sporadic, appearing only in small, isolated islands. This suggests CRBN's linkage is primarily with the main driver of the global economy (Oil), not with all fossil fuels equally.

A strong long-term coherence, similar to that with oil, was observed between CRBN and S&P GSCI Copper,

reinforcing the interpretation of CRBN as a proxy for long-run industrial and economic activity. The relationships with other industrial and precious metals (e.g., Aluminum, Zinc, Gold, Silver) were significantly weaker, intermittent, and typically confined to the short-to-medium term, suggesting that CRBN's fundamental connection is to core industrial inputs rather than the broader commodity complex.

The PWC plots for SMOG, while sharing some similarities with CRBN, reveal distinct economic drivers

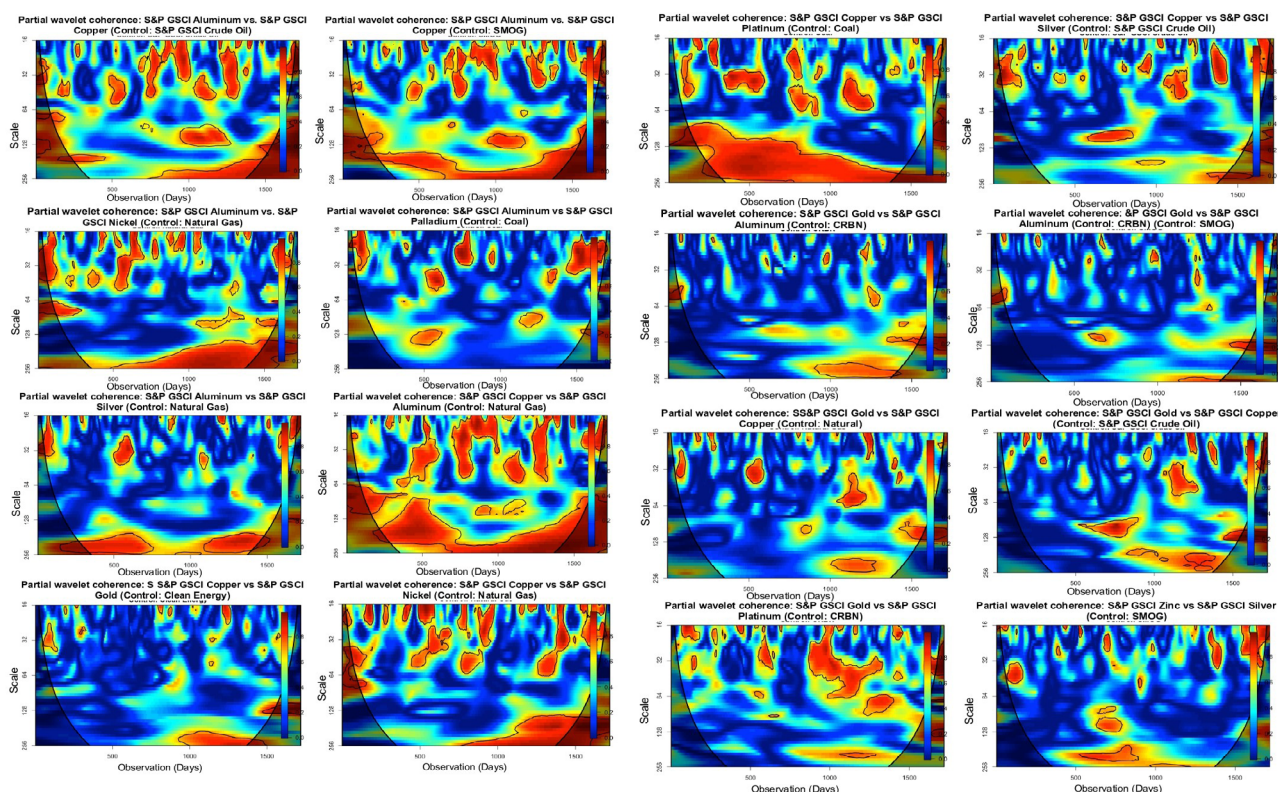


Figure 6. Partial wavelet coherence (PWC) between two assets (A and B), controlling for the Chicago Board Options Exchange Volatility Index, West Texas Intermediate front-month futures (CL1), and the US 10-year Treasury yield. Color intensity indicates the strength of PWC (0–1). Arrows indicate phase and lead-lag: → in-phase; ← anti-phase; ↗ (A leads B, in-phase); ↘ (B leads A, in-phase). The cone of influence (COI) is indicated by a dashed line; regions outside the COI should be interpreted with caution. Frequency bands are annotated on the Y-axis: 1–4 days (short), 4–16 days (short-medium), 16–64 days (medium), 64–256 days (long).

and sensitivities. The relationship between technology and clean energy, including CRBN and SMOG, showed a powerful and persistent coherence with AI and clean energy factors. However, the coherence with the clean energy technology theme was predominantly a long-term phenomenon (64–256 day scale), suggesting a shared narrative around long-run technological adoption and infrastructure development rather than a broad-spectrum co-movement. The coherence with clean energy was, as expected, extremely strong across a wide band of frequencies. The key distinction from CRBN is that the coherence between SMOG and the S&P GSCI Crude Oil index was not a persistent long-term phenomenon. Instead, it manifested as a highly significant and concentrated “island of coherence” in the medium term (32–64 day scale) during the middle of the sample period (1,000–1,300 days). This indicates that SMOG was not fundamentally tied to the long-run oil price trend but was acutely sensitive to specific, crisis-driven oil market shocks that occur over a cyclical, medium-term horizon.

Its connections to coal and natural gas were negligible. The coherence between SMOG and most commodities was generally weak and sporadic, appearing in small, isolated islands without a clear, persistent pattern. A notable exception was the relationship with S&P GSCI Gold, which showed significant coherence in both the medium and long term toward the end of the sample period, suggesting an emerging role for clean technology as a factor in long-term macroeconomic assessments that also influence gold.

Figure 7 provides a granular view of the relationship between the clean energy index and a selection of key S&P GSCI commodities across time scales from short-term (leftmost axis) to long-term (rightmost axis). The plots consistently reveal that the nature of co-movement between the clean energy sector and these raw materials depends fundamentally on the investment horizon.

Across all the examined commodity pairs—including industrial metals, such as aluminum, copper, nickel, and zinc, and precious metals, such as gold, silver, platinum,

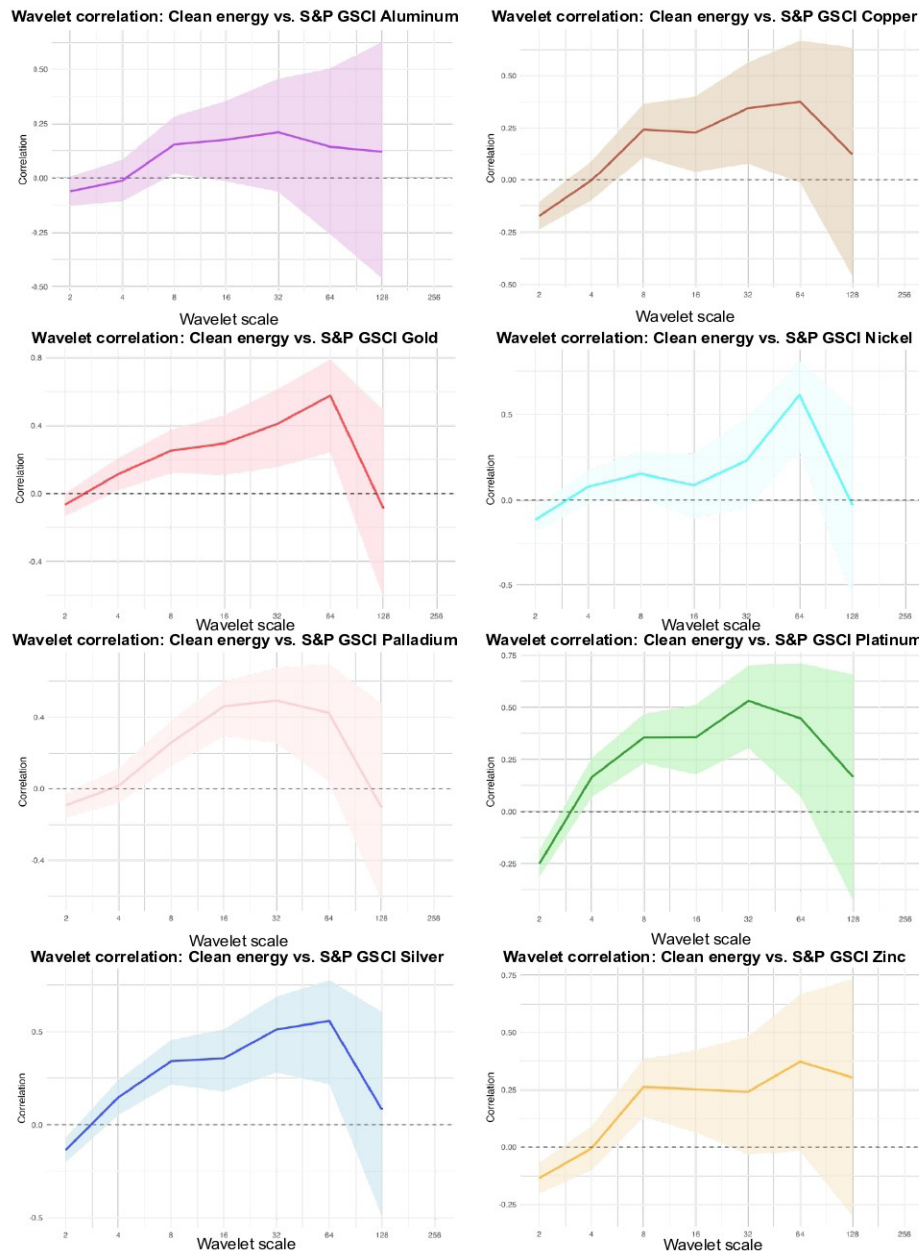


Figure 7. S&P SMOG (clean energy technology) to other commodities
Abbreviations: GSCI: Goldman Sachs Commodity Index; S&P: Standard & Poor's; SMOG: Kensho Smart Grids Index.

and palladium—a distinct and uniform pattern emerged. In the short term, the correlation was consistently weak and statistically insignificant. The correlation coefficient hovered near zero, and the confidence bands clearly straddled the zero line. This indicates that on a high-frequency basis (e.g., daily or weekly), the price movements of the clean energy index and these commodities are decoupled. Their short-term performance is likely driven

by asset-specific factors, market noise, and distinct liquidity profiles rather than a shared underlying driver.

As the time horizon extended into the medium term, a clear and significant strengthening of the relationship became evident. For nearly every commodity, WC trended sharply upward, entering a moderately positive, statistically significant range. For key metals such as copper, silver,

and platinum, the correlation strengthens substantially, indicating that, over weeks to months, their performance becomes more closely aligned with the clean energy sector's trajectory. This suggests that as the investment horizon lengthens, idiosyncratic short-term noise subsides, and shared medium-term cyclical and economic factors begin to dominate the co-movement.

The most pronounced relationship was observed in the long term. For the vast majority of commodities, the correlation became strongly positive, often peaking at these longer scales. This signifies a powerful, long-run equilibrium relationship where the fundamental, long-term trends of these commodities are highly synchronized with the growth of the clean energy sector. This is particularly true for metals that are critical inputs for green technologies, such as silver (solar panels), platinum (hydrogen fuel cells), and nickel (batteries). However, it is also in this long-term band that uncertainty, as indicated by the progressively widening confidence intervals, increases. This reflects the inherent difficulty and greater statistical uncertainty in estimating very long-run relationships from finite time series data.

In conclusion, the WC analysis revealed that the relationship between the clean energy index and key GSCI commodities was unequivocally frequency-dependent. While short-term linkages were negligible, offering potential for short-run portfolio diversification, the co-movement became progressively stronger and more significant as the time horizon extended. This confirms that, in the long run, the clean energy sector and the raw materials essential to its infrastructure are driven by a shared fundamental economic narrative, moving in strong, positive tandem.

Figure 8 offers a granular, scale-by-scale examination of the relationship between coal and a diverse set of S&P GSCI commodities. The findings reveal a complex, heterogeneous relationship that is highly time-dependent, presenting a stark contrast to the more uniform patterns observed in other energy sectors.

In the short term, the correlation between coal and most of the analyzed commodities was weak and insignificant. For key industrial metals such as aluminum, copper, nickel, palladium, and platinum, the correlation coefficient hovered near zero, with the confidence intervals consistently encompassing the zero line. This indicates a general decoupling at high frequencies, where the daily and weekly price movements of coal and these metals are driven by distinct, asset-specific factors, market noise, and differing speculative activity. Silver was a notable exception, displaying a statistically significant positive correlation even at the shortest scales, suggesting a more

immediate and persistent link to the energy complex.

Transitioning to the medium term (8–64-day scales), a significant positive correlation emerged for a specific subset of commodities. The co-movement with key industrial metals, copper and zinc, as well as precious metals, gold and silver, strengthened considerably, becoming statistically significant. This pattern points to a shared sensitivity to the business cycle. As a primary energy source for industrial production and power generation, coal's demand and price are intrinsically linked to economic activity over these cyclical horizons, creating a strong positive co-movement with the metals most indicative of industrial health.

The most striking and informative result was observed in the long term. For the commodities for which a significant positive relationship was established in the medium term—namely, gold, silver, copper, and zinc—the correlation sharply deteriorated at longer time scales. The relationship weakened dramatically, becoming statistically insignificant and, in the case of gold, even turning negative. This long-run decoupling suggests that while these commodities share medium-term cyclical drivers with coal, their fundamental long-term trajectories are diverging. This divergence is likely attributable to major structural shifts, such as the global energy transition away from fossil fuels, which puts the long-term outlook for coal on a different path from that of metals seen as safe-haven assets (gold) or critical inputs for new energy technologies (copper, silver).

The WC analysis demonstrated that the relationship between coal and other major commodities was not monotonic. The co-movement was generally weak in the short run, strengthened significantly in the medium term due to shared economic-cycle sensitivities, and then decoupled in the long run. This complex, frequency-dependent relationship highlights the shifting role of coal in the global commodity landscape, where its medium-term cyclical importance is clear, but its long-term fundamental narrative is increasingly distinct from other key assets.

Figure 9 offers a scale-by-scale examination of the co-movement between CRBN (a proxy for carbon emission prices) and a broad suite of S&P GSCI commodities. The results reveal that the nature of this relationship is highly dependent on the investment horizon and varies significantly between industrial metals and safe-haven assets.

A consistent and powerful pattern emerged for the majority of industrial metals, including aluminum, copper, platinum, silver, and zinc. For these commodities, the relationship with CRBN showed a statistically significant positive correlation across all time scales, from the short

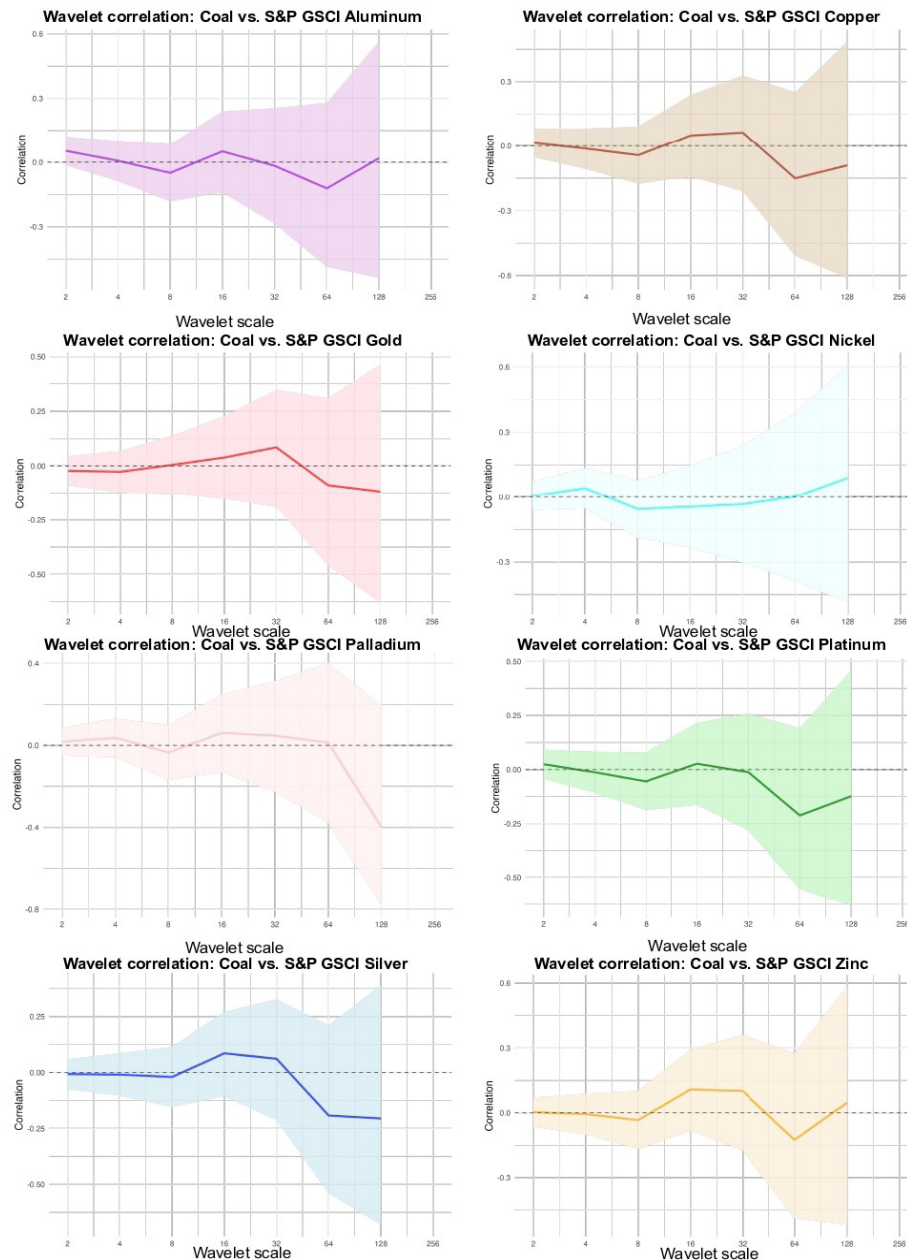


Figure 8. S&P coal to other commodities
Abbreviations: GSCI: Goldman Sachs Commodity Index; S&P: Standard & Poor's.

term to the long term. More importantly, this positive correlation exhibited a clear monotonic strengthening as the investment horizon lengthened. The correlation coefficient increased consistently as the scale increased, indicating a progressively stronger linkage over longer periods.

This pattern points to a shared, fundamental economic

driver: the global business cycle. In the short term, the positive link is present but moderate, as high-frequency noise and asset-specific factors can cause temporary deviations. However, over the medium and long term, the connection becomes exceptionally strong. This is economically intuitive, as sustained periods of economic growth and industrial expansion simultaneously increase demand for key industrial metals (the inputs of production)

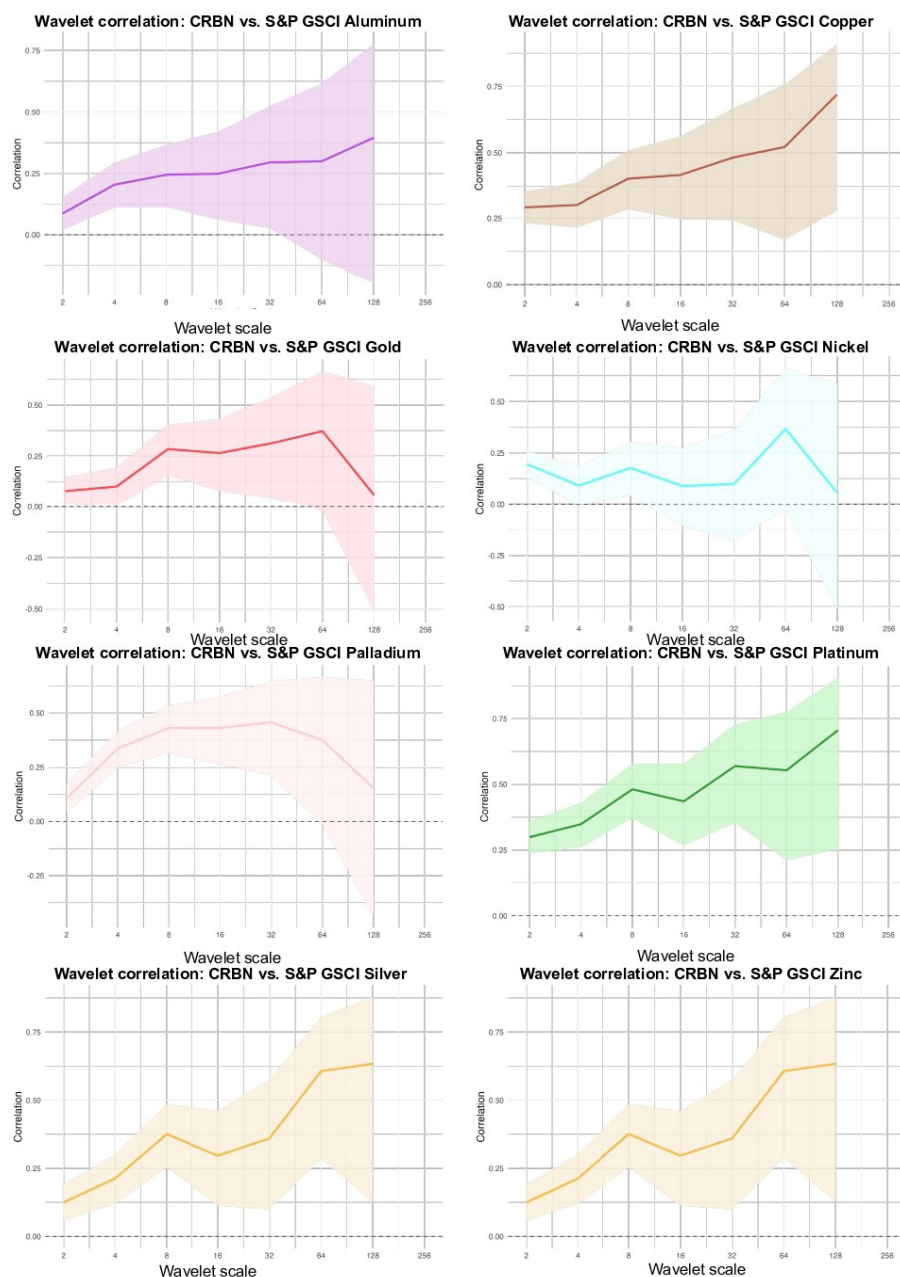


Figure 9. Wavelet correlation of CRBN to other commodities

Abbreviations: CRBN: Global Carbon Efficient Index; GSCI: Goldman Sachs Commodity Index; S&P: Standard & Poor's.

and increase carbon emissions (the byproducts of production), leading to a powerful positive co-movement in their respective prices.

In stark contrast, the relationship between CRBN and Gold followed a fundamentally different trajectory. The correlation was initially statistically insignificant in the short term, suggesting a decoupling at high frequency. It

then became moderately positive and significant in the medium term, likely reflecting a shared sensitivity to cyclical factors like inflation expectations or broad market risk over the business cycle. However, the most critical finding was the long-term deterioration of this relationship, with the correlation plummeting and becoming insignificant. This long-run decoupling highlights the distinct nature of gold as a safe-haven asset, whose long-term value is

driven by monetary policy, geopolitical risk, and store-of-value considerations rather than the industrial activity that underpins both carbon and base metal prices.

The patterns for nickel and palladium were more complex than those of other commodities. While both showed a significant positive correlation in the medium term, the relationship did not exhibit the same clear, monotonic strengthening into the long run. The correlation for palladium peaked in the medium-to-long term before weakening, while nickel's relationship was more volatile and less consistent across scales. This suggests that while they share cyclical drivers with CRBN, their prices are also heavily influenced by specialized, industry-specific factors (e.g., battery production for nickel, automotive catalysts for palladium) that complicate a straightforward long-run linkage.

In summary, the WC analysis confirmed that CRBN's relationship with commodities is highly frequency-dependent. It acts as a strong, long-run complement to industrial metals, reflecting their shared exposure to the fundamental economic cycle. Conversely, its long-run decoupling from gold underscores the clear distinction between assets tied to industrial production and traditional safe-haven assets, offering important insights for long-term asset allocation and risk.

Figure 10 provides a scale-dependent examination of the relationship between natural gas and a broad basket of S&P GSCI commodities. The results reveal a clear and consistent pattern of long-term decoupling, where the nature of the co-movement fundamentally inverts as the investment horizon lengthens. This highlights the unique market drivers of natural gas compared to other major commodities.

Across almost all the examined commodities—including industrial metals such as aluminum, copper, nickel, and zinc, and precious metals such as gold, silver, platinum, and palladium—a distinct, uniform pattern emerged. In the short term, the correlation was generally positive or neutral. For several commodities, including zinc and copper, this initial relationship was statistically significant, suggesting a degree of positive co-movement at high frequency. This short-run linkage can be attributed to a shared sensitivity to broad, high-frequency macroeconomic news, inflation data, and fluctuations in the US dollar, which can cause commodity classes to move in tandem over brief periods.

However, as the time horizon extended into the medium and long term, a powerful and consistent trend emerged: the correlation progressively weakened and became strongly negative. For a wide array of assets, including

gold, silver, copper, aluminum, and nickel, the correlation coefficient trended sharply downwards, eventually becoming statistically significant on the negative side at the longest scales. This signifies a fundamental divergence in the long-run drivers of natural gas from those of the broader commodity complex.

The economic intuition behind this long-term decoupling is clear. The long-term price of natural gas is predominantly influenced by a unique set of factors, including regional supply and demand dynamics, storage levels, seasonal weather patterns (which dictate heating and cooling demand), and the structural shift toward renewable energy sources. These drivers are fundamentally different from those that determine the long-term value of other commodities. Industrial metals are primarily driven by the global manufacturing and construction cycles, while precious metals are influenced by monetary policy, geopolitical risk, and their role as safe-haven assets.

In conclusion, the WC analysis unequivocally demonstrated that the relationship between natural gas and other major commodities is strongly frequency-dependent. While a weak positive link may exist in the short run due to shared macro-sensitivities, natural gas acts as a powerful long-term diversifier. Its fundamental drivers are sufficiently distinct that, over longer investment horizons, it exhibits a significant negative correlation with a wide range of industrial and precious metals. This finding has critical implications for strategic asset allocation, highlighting the potential of natural gas to hedge long-term risks in a diversified commodity portfolio.

Figure 11 provides a scale-dependent decomposition of the relationship between S&P GSCI Crude Oil and a broad selection of S&P GSCI commodities. The results consistently reveal a powerful pattern of long-term convergence, where the co-movement between crude oil and other key commodities strengthens significantly as the investment horizon lengthens.

For the vast majority of the analyzed commodities—encompassing both industrial metals, such as aluminum, copper, nickel, and zinc, and precious metals, such as platinum and silver—a clear, uniform pattern emerged. In the short term, the correlation was positive but generally moderate in strength. While statistically significant for most pairs, the relationship at these high frequencies is susceptible to considerable noise, reflecting asset-specific supply/demand news, inventory reports, and speculative trading that can cause temporary divergences.

As the time horizon extends into the medium and long term, a distinct, statistically robust trend was observed: the positive correlation consistently strengthened. For nearly

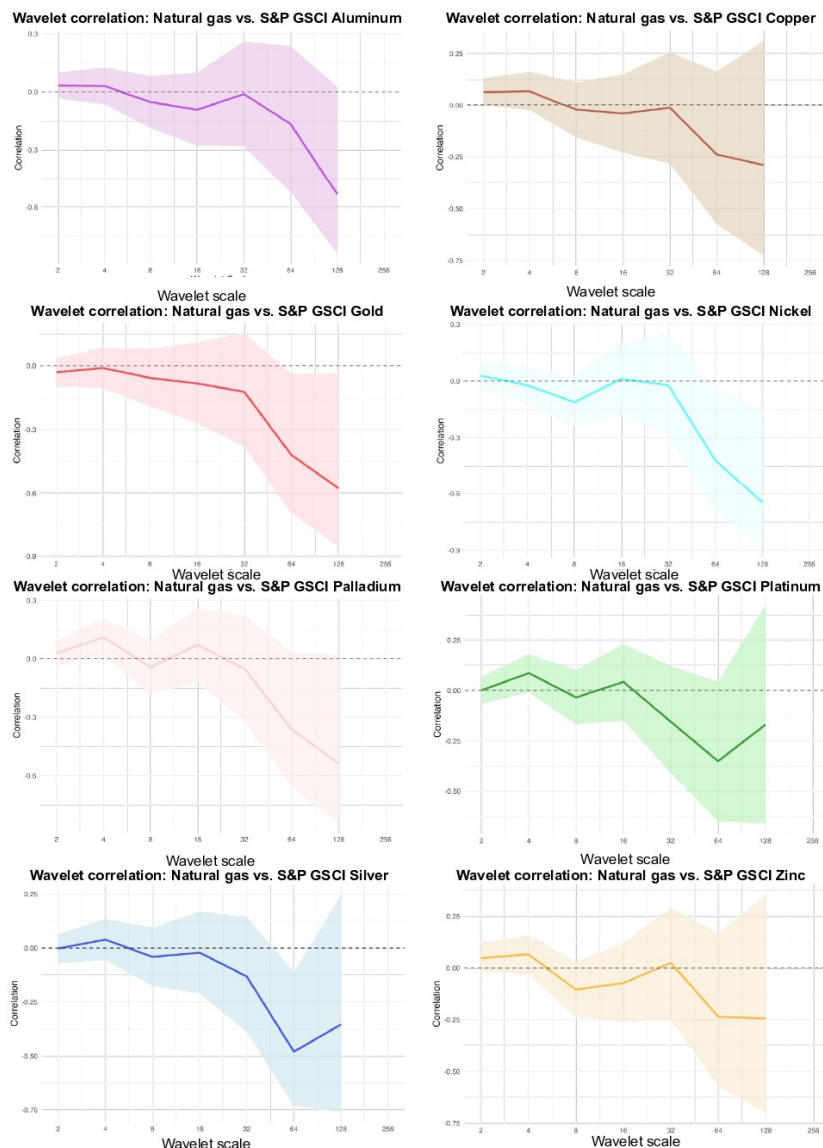


Figure 10. Wavelet correlation plots for natural gas vs. commodities
Abbreviations: GSCI: Goldman Sachs Commodity Index; S&P: Standard & Poor's.

every commodity, the WC coefficient showed a clear upward trend as scale increased. This indicates that over investment horizons spanning from weeks to months and beyond, the performance of these commodities becomes increasingly synchronized with the price of crude oil.

The economic rationale for this long-term convergence is multifaceted and powerful. Firstly, crude oil is a universal input cost for the production, processing, and transportation of virtually all other physical commodities. Energy costs are a fundamental component of mining,

smelting, and logistics, creating a direct causal link: higher oil prices translate into higher production costs and, consequently, higher prices for other commodities. Secondly, both crude oil and the broader commodity complex are highly sensitive to the same fundamental driver: the global economic cycle. Sustained periods of global economic growth simultaneously boost demand for energy (oil) and the raw materials needed for manufacturing and construction (industrial metals). This shared pro-cyclicality ensures that their long-term price trends are tightly interwoven.

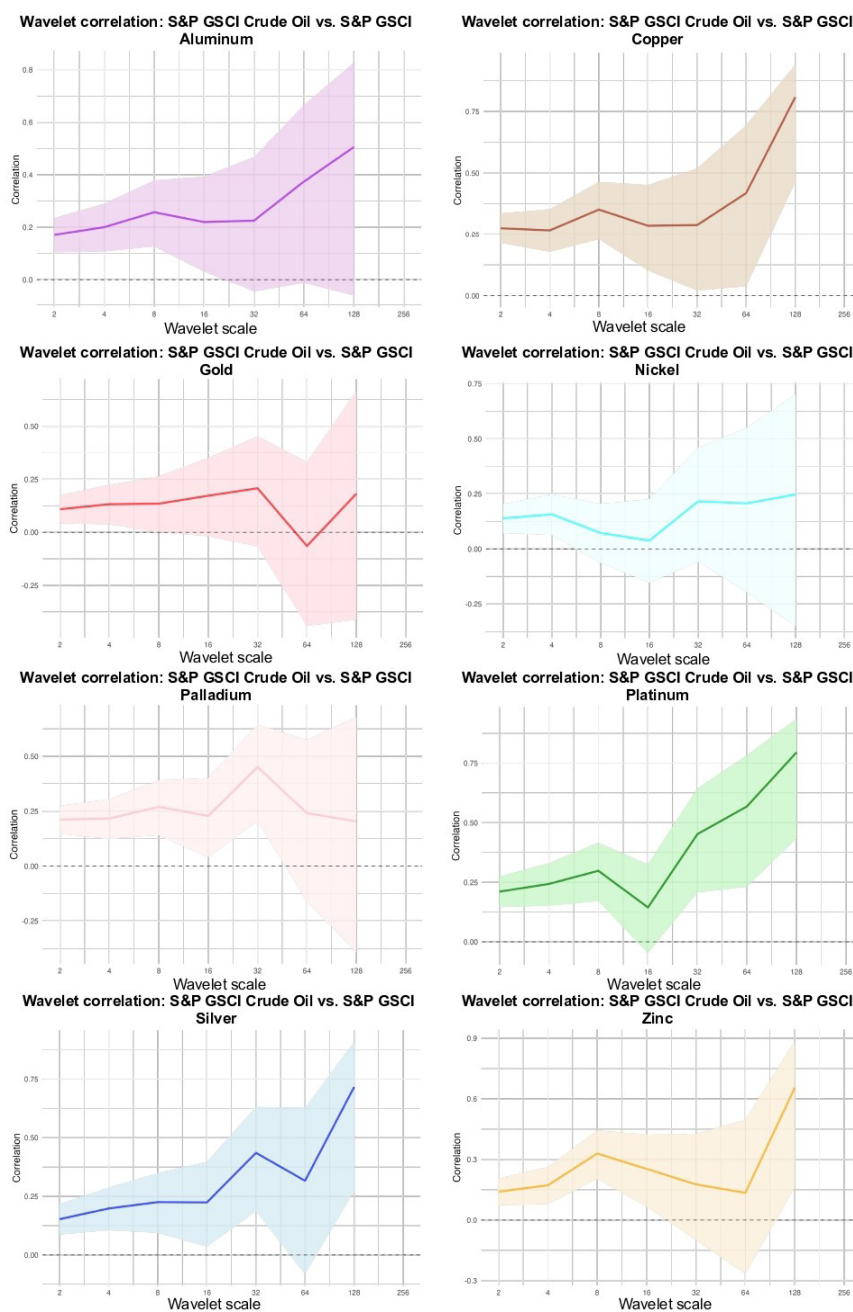


Figure 11. Wavelet correlation plots for S&P GSCI Crude Oil to other commodities
Abbreviations: GSCI: Goldman Sachs Commodity Index; S&P: Standard & Poor's.

The relationships with gold and palladium showed a similar pattern of strengthening positive correlation from the short to the medium term. However, the linkage became more volatile and less consistently positive at the longest scales, with wider confidence intervals reflecting greater uncertainty. This suggests that while they share medium-term cyclical drivers with oil, their unique roles—

gold as a safe-haven asset and palladium in the specialized automotive industry—can lead to divergence in their long-run fundamental trajectories.

In conclusion, the WC analysis confirmed that the relationship between crude oil and the broader commodity market is strongly frequency-dependent. The co-movement, while positive in the short run, became progressively and

significantly stronger as the time horizon extended. This robust, long-term positive linkage underscores the central role of energy prices in the commodity ecosystem and the shared exposure of all commodities to the fundamental global business cycle, limiting the diversification benefits for long-term investors.

Figure 12 provides a scale-dependent examination of

the relationship between the SMOG index, representing the clean energy technology sector, and a range of S&P GSCI commodities. The findings reveal a multifaceted relationship that is highly dependent on the investment horizon, highlighting the distinction between commodities that serve as fundamental inputs for clean technologies and those that act as traditional safe-haven assets.

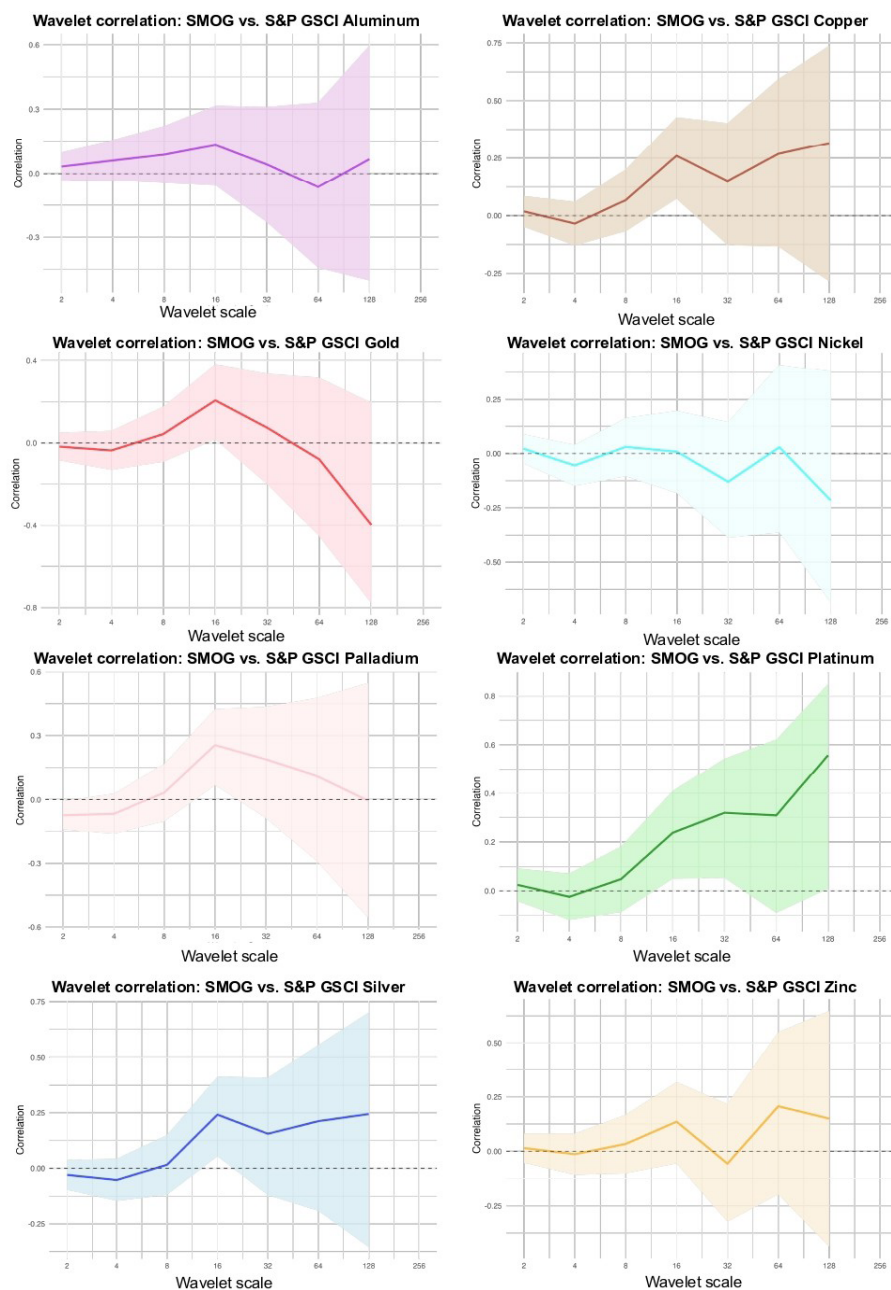


Figure 12. Wavelet correlation plots for SMOG to other commodities

Abbreviations: GSCI: Goldman Sachs Commodity Index; S&P: Standard & Poor's; SMOG: Kensho Smart Grids Index.

For a core group of industrial metals, a consistent and economically intuitive pattern emerged. The relationship between SMOG and key metals, such as platinum, silver, and zinc, showed a positive correlation that strengthened significantly as the time horizon lengthened. In the short term, the co-movement was often weak and statistically insignificant, indicating that high-frequency price movements were driven by distinct, asset-specific factors. However, as the scale extended to the medium and long term, the correlation trended firmly upwards, becoming strongly positive and statistically significant. This long-run convergence signifies a powerful fundamental linkage. The growth and innovation within the clean energy technology sector (SMOG) are primary drivers of future demand for these specific raw materials—platinum for hydrogen fuel cells, silver for photovoltaics, and zinc for galvanizing and battery applications. Consequently, their long-term price trajectories are intrinsically linked.

In stark contrast, the relationship between SMOG and gold followed a completely different path. While the correlation was insignificant in the short term, it became moderately positive and significant in the medium term, likely reflecting a shared sensitivity to broader market sentiment and the business cycle. Critically, however, this relationship was inverted in the long term, with the correlation plummeting to a strongly negative value. This long-run decoupling underscores the fundamental difference between a growth-oriented technology index and a traditional safe-haven asset. The long-term drivers for gold—monetary policy, geopolitical instability, and its role as a store of value—are fundamentally distinct from the industrial and technological trends that underpin the SMOG index.

The relationships with palladium, copper, and aluminum are more complex than those of other commodities. They exhibited a strengthening positive correlation from the short to the medium term, similar to other industrial metals. However, the linkage did not uniformly strengthen in the long run. The correlation for palladium peaked in the medium term before weakening substantially, likely reflecting its heavy reliance on the traditional automotive industry, which faces a structural transition. Copper and aluminum maintained a positive but more volatile long-term correlation, suggesting that, while they are important to the clean energy transition, their prices are also influenced by broader global industrial demand.

In summary, the WC analysis demonstrated that SMOG's relationship with commodities is highly frequency-dependent. It serves as a strong long-run complement to the specific industrial metals that are foundational to clean energy technologies. Conversely, its long-run decoupling

from safe-haven assets such as gold provides a clear basis for portfolio diversification. These scale-dependent relationships offer critical insights into the evolving role of the clean energy sector as a fundamental driver of the 21st-century commodity landscape.

5. Conclusion

This study employed a suite of advanced wavelet techniques WTC, PWC, and WC to dissect the dynamic, time- and frequency-dependent relationships between key energy and environmental assets (crude oil, natural gas, coal, clean energy, SMOG, CRBN) and a broad range of S&P GSCI commodities. The analysis provides compelling evidence that the co-movement between these asset classes is not static but evolves significantly across different time horizons and is acutely sensitive to periods of market crisis.

The WTC analysis consistently identified that periods of significant market stress, including the 2018 Oil Crisis, the COVID-19 pandemic, the Russia–Ukraine War, and the Iran–Israel geopolitical tensions of 2023–2024, acted as powerful catalysts for increased co-movement. During these episodes, strong, statistically significant “islands of coherence” emerged, indicating sharp, sudden asset coupling. This confirms that diversification benefits, particularly between energy and industrial commodities, tend to evaporate precisely when they are most needed, a phenomenon widely recognized as financial contagion.

The WC analysis revealed that the nature of the relationship between assets is fundamentally dependent on the investment horizon. A robust pattern of long-term convergence was identified between the clean energy/SMOG/CRBN indices and key industrial metals (copper, aluminum, silver, platinum). While short-term correlations were consistently weak, the co-movement became strongly positive over longer time scales. This points to a shared fundamental driver: the global economic cycle and the material demands of the energy transition. In stark contrast to long-term decoupling and diversification patterns, natural gas emerged as a strong long-term diversifier. Its correlation with the broader commodity complex, while sometimes positive in the short run, became significantly negative over longer horizons due to its unique, localized, and weather-dependent market drivers. Similarly, the relationship between coal and other commodities deteriorated in the long run, reflecting structural shifts away from fossil fuels. The PWC analysis untangled complex, multi-asset relationships to isolate direct linkages. This provides evidence that the coherence between CRBN and SMOG, once common macro-financial drivers are controlled for, reflects a direct, structural linkage rooted in their shared exposure to the green transition rather

than a spurious co-movement driven by broader market conditions.

The time–frequency heterogeneity documented in our results has direct implications for Environmental, Social, and Governance (ESG) disclosure quality and corporate reporting. Firms that exhibit high long-term coherence with CRBN (i.e., high CRBN sensitivity) are likely to be perceived as materially exposed to the industrial economy and the macro business cycle, a positioning that can reduce the cost of capital under stable conditions but elevates audit and disclosure risk during oil-driven macro shocks. Christensen *et al.* (2021) suggested that increased environmental disclosure can both lower capital costs and raise scrutiny from assurance providers; our time–frequency findings nuance this picture by showing that such benefits may be horizon-dependent. In particular, auditors and ESG rating agencies should incorporate horizon-specific stress tests (medium-term crisis bands vs. long-term business-cycle bands) into their assessment frameworks to better capture contingent risks that manifest only in particular frequency bands.

The clear scale-dependence of correlations means that asset allocation and hedging strategies must be tailored to specific investment horizons. Natural gas serves as an effective long-term hedge in a commodity portfolio, whereas industrial metals become complements to clean energy investments over the long run, not diversifiers. Furthermore, the evidence of contagion during crises suggests that static diversification strategies are inadequate and must be supplemented with dynamic risk management approaches that can adapt to changing market regimes. Understanding the time–frequency dynamics of these key economic assets is crucial for effective policymaking. The strong long-term link between carbon prices (CRBN), clean energy indices, and the industrial economy implies that policies aimed at stimulating economic growth will likely exert upward pressure on both emission costs and the raw material prices for the energy transition. The PWC results also illuminate the direct channels through which risk can be transmitted across the digital asset ecosystem, providing a clearer map for monitoring financial stability. For firms operating in the energy and materials sectors, these findings highlight the long-term strategic alignment between the growth of clean energy and the demand for specific industrial metals. This underscores the need to secure long-term supply chains for materials critical to the energy transition and to understand the cross-commodity impact of energy price volatility.

Acknowledgments

None.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Conflict of interest

The authors declare no potential conflicts.

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All authors have read and approved the final version of the manuscript.

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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