International Journal of Accounting and Economics Studies, 12 (8) (2025) 513-529

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/w3dx2d59
Research paper

Time-Frequency Dynamics and Cross-Market Integration among Metal, Energy, Carbon, and AI Sectors

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Received: November 24, 2025, Accepted: December 4, 2025, Published: December 17, 2025

Abstract

This study examines the dynamic co-movement and interconnectedness of the Metal, Energy, Carbon, and Artificial Intelligence (AI) markets to understand their evolving interactions in the context of technological progress and sustainability transitions. The study employs wavelet coherence analysis to investigate the interactions between these markets across various time scales, encompassing both short-term variations and long-term trends. The results demonstrate substantial long-term coherence, especially between Energy and Carbon, as well as between Carbon and AI, signifying robust and enduring interdependencies. Medium-term correlations demonstrate modest variability, likely influenced by market restrictions and innovation cycles, whereas short-term linkages seem more unstable, reflecting acute shocks and developing technologies. This paper presents new empirical evidence about the increasing integration of financial and resource-based markets, highlighting the impact of AI advancements and environmental issues on conventional sectors. The study enhances comprehension of cross-market behavior, providing significant insights for investors, policymakers, and researchers investigating market predictability, risk management, and sustainable economic planning.

Keywords: *Co-Movement; Wavelet Coherence; Metal Market; Energy Market; Carbon Market; Artificial Intelligence; Financial Integration; Sustainability.*

1. Introduction

The increasing relationships and reliance among global markets for finance and commodities like metals, energy, carbon, and artificial intelligence have led to more people studying and investigating how these sectors are connected. (Gubareva, Shafiullah and Teplova, 2025). The changes towards renewable energy and digitization make the relationships between these markets stronger, thanks to technological advancements, new regulations, and changes in what investors look for (Hossain et al., 2024). In ordinary times, commodities trade in grouped markets, yet during major crises or policy revamps, these sectors join forces to a remarkable degree. Research studies indicate that how metals and energy markets affect each other and move in synchrony can change markedly over the years, especially during global turmoil or when there are big advances in technology or fast policy changes. (Balcilar, Usman and Agan, 2024). New carbon markets, driven by efforts to fight climate change and support sustainability, have added more ways for risks to be spread and for prices to be determined. (Wang et al., 2022). Artificial intelligence is becoming more and more well-known for changing all these fields. These advanced technologies are not only improving how metals and energy businesses function, but are also playing a key part in addressing carbon conversion, controlling emissions, and improving market processes. (Xu, Shao and Tanasescu, 2024). AI technology is bridging new ties between commodity and carbon markets as it influences trading, forecasting, and risk control activities. (Balcilar et al., 2025).
The expansion of renewable energy heavily relies on the availability of critical metals (such as lithium, cobalt, and rare earths). Consequently, there is an increasing link between metal and energy markets, supported by carbon markets that also serve a regulatory and financial purpose. (Ghorbani et al., 2024) AI is now being used to enhance resource use, improve things that use energy, and boost the growth of circular strategies for metals and carbon-based materials. Recognizing the way these markets interact and move together is very important for several reasons. (Onyeaka et al., 2023). First, it lets investors protect their portfolios by diversifying in a market with higher uncertainty. Second, it helps guide policymakers as they shape interventions to stabilize markets and back the energy transformation. (Xiang et al., 2024). In addition, it gives industry stakeholders tips for making use of AI and other innovative technologies both for strengthening their business and for sustainability. Academic investigations recently used advanced methods to estimate market linkages, discovering that they vary and react to shocks, inventions, and changes in policies. (Siddik et al., 2025).
At the same time, Artificial Intelligence (AI) has progressed from being just a specialized area to having a major effect on the economy, encouraging progress and development in several industries, including healthcare, finance, manufacturing, and defense. The great strides these companies have made in AI are responsible for a major increase in their share prices (Li, Wang, and Wang, 2024). As a result of financial AI—including the rise of AI ETFs, indices, and thematic products—AI is now deeply integrated into world markets. Metals, energy, carbon, and AI had different histories, but now they all link up in today's integrated economy. Producing AI hardware is largely based on technical metals, including lithium, cobalt, and rare earth elements. At the same time, when we look at the energy and carbon

used by data centres, servers, and GPUs in AI, we see that the sector is very much tied to the energy and carbon markets. Both the energy industry and carbon markets are using AI to help achieve greater energy efficiency and more accurate carbon forecasts, forming a strong feedback system. Besides, disturbances in world politics, such as the blocking of energy supplies or limits on top technologies, usually lead to increased unpredictability in all four fields. Because countries are so connected, it is clear that a full investigation of how their actions and markets are linked and influenced by one another is necessary (Li, Wang, and Wang, 2024).

The study aims to understand the interactions and changes occurring between the Metals, Energy, Carbon, and AI-driven markets. When these markets mingle, it becomes more important to discuss issues related to systemic risk, spillovers between different markets, protective hedging practices, and the connectedness of industries. Given events like today's energy shocks, carbon credit changes, and explosive rise in AI-based industries, it is more important than ever to grasp how these markets affect one another over the years. By modeling relationships with time-varying data, the study looks at how shocks from one market reach others and uncovers what happens next. It also examines if AI contributes to market volatility, looks at its impact on diverse investment plans, and determines what role it might play in policy planning. This study has important benefits in many fields of study. In academics, it joins the study of Artificial Intelligence markets with usual commodity markets, using new approaches to better explain the complicated links between industries. The research informs regulators about the links between emerging carbon markets, AI, energy, and metals, which helps them create effective energy and technology regulations. By showing how assets in different markets are linked, the study provides practical insights for financial experts, helping them protect their portfolios, arrange better hedging, and detect markets that either increase or help dissipate volatility. The findings help industry players understand how AI and new sustainability rules can affect costs and their overall risks, and they also back up approaches to climate-friendly investment needed for the global move to net-zero emissions. One of the principal goals of this research is to investigate the co-movement of Metal, Energy, Carbon, and Artificial Intelligence (AI) markets. Through an investigation into how such markets move relative to each other across various time horizons and economic conditions, this research seeks to identify underlying trends of synchronization or divergence. Recognition of such co-movements facilitates the identification of systemic connections and interdependencies that are important for investors and policy-makers wishing to forecast market behavior, improve diversification, and better manage portfolio risks in more highly integrated financial systems.

1.1. Significance of the study

The study makes an important academic contribution by bridging the gap between AI and traditional commodity market research, using dynamic modeling techniques to enhance the understanding of market interlinkages in a novel multi-sectoral context. From a policy perspective, it provides timely insights into how emerging carbon markets and AI innovation interact with energy and metals, supporting evidence-based decisions for regulators in energy, environment, and technology governance. For investors and financial analysts, the study offers actionable insights into cross-market risk transmission and co-movement patterns, helping them identify opportunities for diversification, hedging, and detecting market segments that act as volatility transmitters or absorbers. Strategically, the findings will benefit industry stakeholders by clarifying how shifts in AI technology and sustainability regulations impact resource costs and operational risks, while also supporting climate-aligned investment strategies as the world transitions toward net-zero goals.

2. Literature Review

The integration of commodity, energy, carbon, and AI markets represents an emerging research frontier at the intersection of financial economics, sustainability science, and technological innovation. This literature review synthesizes existing knowledge across three thematic areas: (1) cross-market connectedness and spillovers, (2) time-frequency dynamics in commodity markets, and (3) the emerging role of AI in market integration. By organizing the literature thematically rather than chronologically, we identify key patterns, contradictions, and the specific gap this study addresses.

Research on market interconnections has evolved from static correlation analysis to dynamic modelling of spillover effects. Studies consistently show that connectedness varies across time horizons and intensifies during crisis periods. Luo et al. (2025) demonstrate that carbon, energy, and metal markets exhibit heterogeneous spillover effects along frequency bands, with robust medium- and long-run co-movements observed particularly during 2022–2024. This finding aligns with Jiang et al. (2022b), who reveal that total connectedness increased considerably during periods of global uncertainty, with short-term spillovers being the main drivers. However, the literature reveals important distinctions in directional spillovers. Jiang and Chen (2022b) identify copper and silver as key transmitters, with copper exerting strong explanatory power over carbon price fluctuations, while Adewuyi et al. (2024) find natural gas to be the most influential transmitter in energy-metal linkages. These contrasting findings suggest that spillover directions are context-dependent and vary across commodity types and time periods.

The application of wavelet coherence and time-frequency methods has proven particularly valuable for capturing non-stationary relationships in financial data. Marín-Rodríguez et al. (2022) provide a comprehensive scientometric review spanning four decades, mapping key methodologies including co-movement, copula, wavelet, and volatility analyses. Their work identifies a conspicuous gap in the application of newer methods such as machine learning and AI, particularly in emerging markets. Adewuyi et al. (2024) advance this literature by applying time-varying quantile and frequency connectedness approaches, demonstrating how shocks permeate differently across short-, medium-, and long-term horizons. They distinguish between horizontal integration (within energy markets) and vertical linkages (between energy and metals), enhancing understanding of market structure. Interestingly, they identify zinc as an isolated market—a finding that challenges assumptions of universal commodity market integration. The rapid growth of artificial intelligence as both a technology sector and market force creates novel interdependencies with traditional commodity markets. AI's dual role—as a consumer of metals and energy, and as a transformative force in market operations—remains understudied. Raggad and Bouri (2025) provide a nuanced analysis of return and volatility connectedness between AI stock ETFs and energy market segments, highlighting stronger linkages between clean energy and AI stocks, with connectedness intensifying during the COVID-19 period. Yang (2024) establishes the positive correlation between commodity futures and stock market dynamics in China's framework, emphasizing the role of urbanization and industrial development. However, the study lacks investigation of causal relationships and global comparative considerations, pointing to areas requiring further exploration. Market relationships are dynamic, intensifying during crises and structural transitions (Jiang and Chen, 2022a; Luo et al., 2025). Short-term and long-term dynamics differ substantially, requiring multi-horizon analysis (Adewuyi et al., 2024; Jiang et al., 2022). AI markets show increasing integration with traditional sectors, particularly energy and carbon markets (Raggad and Bouri, 2025)

While prior research has explored selected bilateral or tri-lateral market interactions, comprehensive analysis integrating all four major markets—metals, energy, carbon, and artificial intelligence (AI)—remains scarce. Existing studies typically focus on pairwise linkages or three-market dynamics, leaving a gap in understanding the full complexity of this interconnected system. Moreover, conventional correlation-based approaches often overlook relationships that emerge only at specific time horizons, particularly during periods of structural breaks or regime shifts. Time–frequency analytical methods, such as wavelet-based techniques, are well-suited to capture these hidden and scale-dependent interactions. Although earlier studies have examined AI–energy or AI–financial market relationships, no existing work systematically evaluates the influence of AI integration on the broader commodity–energy–carbon nexus across multiple time scales. This study addresses these gaps by employing wavelet coherence analysis to investigate co-movements among all six pairwise relationships within the four-market framework: Energy–Carbon, Metals–AI, Metals–Energy, Metals–Carbon, Carbon–AI, and Energy–AI. By mapping these dynamics across multiple time–frequency domains, the study provides the first comprehensive characterization of the emerging four-market ecosystem.

3. Objective of The Study

1) To study the co-movement among Metal, Energy, Carbon, and Artificial Intelligence markets.

4. Methodology

The process starts with the gathering of raw time series data, which is then log-transformed and first differenced to stabilize variance and eliminate non-stationarity. This is followed by stationarity tests like the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to ensure that the data transformed is stationary. After ensuring stationarity, the differenced series is standardized to place all variables on a similar scale. The standardized information is further processed in a Time-Varying Parameter Vector Autoregression (TVP-VAR) framework using Generalized Forecast Error Variance Decomposition (GFEVD) to know the dynamic connectedness and spillover relationships between variables. Meanwhile, Wavelet Coherence Analysis is conducted to follow time-frequency domain relationships and examine how the relationships evolve across different frequencies. Both the results of wavelet analysis and TVP-VAR are then filtered using DCC-GARCH modeling that captures dynamic conditional correlations and helps in constructing a Minimum Connectedness Portfolio, which is the objective of reducing systemic risk. The procedure culminates in the consolidation of all the findings, providing an integrated explanation of market linkedness, risk management procedures, and portfolio optimization.

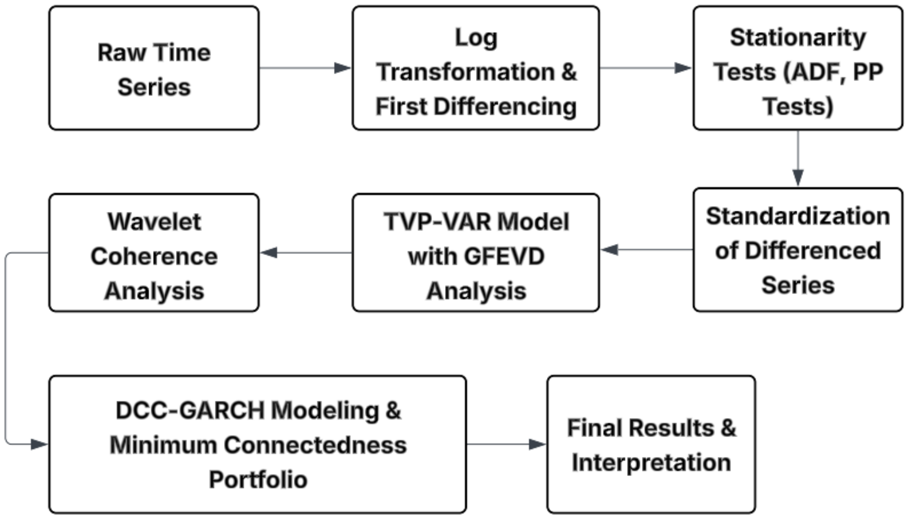

Fig. 1: Methodological Framework of the Study. Figure Created by the Authors.

A comprehensive and robust multivariate econometric framework is utilized in this study to analyze the dynamic linkages among four major markets in finance: metals, energy, carbon, and artificial intelligence. Considered to be the copula for a modern industrial and technological economy, these markets are affected by crashes and shocks emanating from economic, political, or environmental sources. To understand the nature and strength of their price interdependencies, co-movements, and hedging opportunities, we use an arsenal of advanced time-series techniques, each adapted to unearth a specific feature of these financial dynamics. The data employed in the empirical analysis is taken daily from January 2015 to December 2023, with reliable sources such as Bloomberg and Refinitiv used to obtain the data. The indices considered for this study are the S&P GSCI Industrial Metals Index for metals, Brent Crude Oil Futures for energy, the EUA for carbon, and a composite index of leading AI-sector stocks for artificial intelligence.

4.1. Data preprocessing

Before proceeding with the empirical analysis, first, there needs to be thorough data cleaning to safeguard the robustness and validity of the econometric models. The very first step taken is logging the raw time series data to stabilize variance and make the series more homoscedastic. The transformation is given by:

$$Y_t = \log(P_t)$$

Where P_t Is the price or index level at time t, and Y_t Is the log-transformed series. Following this, the log-transformed series are differenced to achieve stationarity, a prerequisite for most time-series models. The first differencing operation is defined as:

$$\Delta Y_t = Y_t - Y_{t-1}$$

Stationarity is tested with ADF and PP unit root tests. The null hypothesis of the presence of a unit root gets rejected at conventional significance levels, confirming that the differenced series is stationary. To enable comparability and avoid scaling effects, the standardized version of each differenced series is computed:

$$Z_t = \frac{\Delta Y_t - \mu}{\sigma}$$

Where μ and σ Represent the mean and standard deviation of the differenced series, respectively. This standardization is critical for multivariate analyses that rely on the assumption of normalized data.

4.2. Wavelet coherence analysis

To analyze the raw time-frequency co-movement patterns between the financial markets, wavelet coherence analysis is employed. Wavelet coherence is especially well-equipped to deal with non-stationary time series and to identify phase relationships at different time scales. Let $x(t)$ and $y(t)$ Be a two-time series. Their continuous wavelet transforms are $W_x(s,\tau)$ and $W_y(s,\tau)$, where s denotes scale and τ Denotes time. The wavelet coherence is then defined as:

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

Where $W_{xy}(s,\tau) = W_x(s,\tau)W_y^*(s,\tau)$ is the cross-wavelet transform, and $S\{\cdot\}$ It is a smoothing operator in both time and scale.
Squared wavelet coherence values lie between 0 and 1 and represent the strength of co-movement. High coherence at certain frequencies and times implies a robust synchronization, whereas phase difference is defined as:

$$\phi_{xy}(s,\tau) = \tan^{-1}\left(\frac{\operatorname{Im}(W_{xy}(s,\tau))}{\operatorname{Re}(W_{xy}(s,\tau))}\right)$$

Measures the lead-lag relationship between markets, helping distinguish short-term speculative co-movements from long-term structural alignments.

5. Results and Discussion

This section outlines the compelling evidence of the dynamic and evolving interconnections among the metal, energy, carbon, and AI markets. Using wavelet coherence analysis, we uncover the degree and timing of co-movements across six critical market pairs: Energy vs Carbon, Metals vs AI, Metals vs Energy, Metals vs Carbon, Carbon vs AI, and Carbon vs Energy. The results demonstrate that these relationships are not static but vary across time and frequency, reflecting the influence of technological innovation, environmental regulation, and economic activity.
Wavelet Coherence Analysis of Co-Movements Among Metal, Energy, Carbon, and Artificial Intelligence Markets

5.1. Metals vs energy

Table 1 shows how close the wavelet coherences are between Metals and Energy. Every number in the table shows the level of connection between the two markets now and in that specific market range. Markets are extremely correlated at a certain time and frequency when their values are close to 1. The early years and small scales are visible in the first group of values to show how the characteristics changed over time.

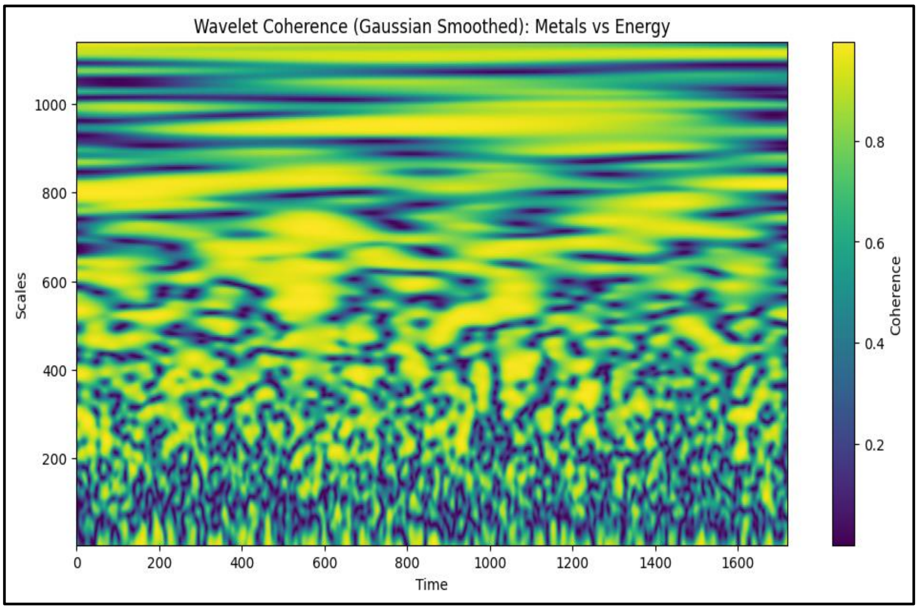

Fig. 2: Wavelet Coherence (Gaussian Smoothed) between Metal and Energy Markets. Figure created by the authors.

In Figure 2, the wavelet coherence plot (Gaussian smoothed) between Metals and Energy spans a time range of 0 to 1700 units on the X-axis and scales from 0 to 1100 on the Y-axis. At high scales (900–1100), coherence remains strong, frequently above 0.8, indicating a stable long-term correlation between Metals and Energy trends. These yellow regions suggest shared macroeconomic influences such as industrial demand or energy-intensive metal production. In the mid-scale range (400–800), coherence varies between 0.5 and 0.8, reflecting a moderate correlation that may be tied to commodity cycles or market shocks. At lower scales (0–300), coherence drops below 0.4, with several areas dipping below 0.2, pointing to weak short-term alignment. The plot highlights that the relationship is strongest at long-term frequencies, especially between times 200 and 1400, where coherence exceeds 0.7, underlining a persistent structural linkage between energy consumption and metal demand across time.

5.2. Metals vs carbon

Table 2 demonstrates how much the Metals and Carbon markets are related, using wavelet coherence. Every value in the table means how much these two markets change together at both the short and long terms (rows) and during different data periods (columns). If the value is at 1, it means that at the given time and frequency, the Co-movement between Metals and Carbon is very high. The first plots below highlight how the model responds to the initial conditions and the smallest details.

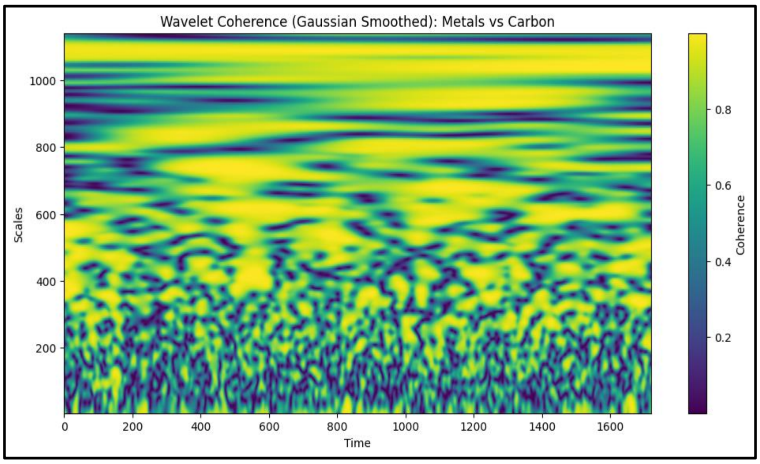

Fig. 3: Wavelet Coherence (Gaussian Smoothed): Metals vs Carbon. Figure Created by the Authors.

Figure 3: The wavelet coherence plot (Gaussian smoothed) between Metals and Carbon illustrates the time-frequency relationship across a period of 0 to 1700 units and scales ranging from 0 to 1100. High coherence values, particularly above 0.8, are observed at larger scales (900–1100), denoted by dominant yellow bands. These bands persist through most of the time domain, suggesting a strong and stable long-term correlation between metals and carbon markets—likely reflecting structural economic factors such as industrial output and environmental policy impacts. At the mid-scale range (400–800), coherence remains moderate, generally between 0.5 and 0.7, with intermittent bursts of higher coherence exceeding 0.75, especially noticeable around times 500 to 1000. This indicates that medium-term interactions between metal and carbon prices are somewhat periodic, possibly linked to regulatory cycles or commodity supply adjustments.
In contrast, low scales (0–300) display weak coherence, frequently falling below 0.3, with occasional short-lived peaks around 0.5. This suggests limited short-term synchronicity in price dynamics, likely due to noise or uncorrelated market movements. The plot highlights that Metals and Carbon share a more pronounced relationship over longer-term trends, with persistent coherence beyond scale 800 and throughout much of the time interval examined.

5.3. Metals vs AI

Table 3 is based on Wavelet coherence, shows the main metrics for this comparison. Every number reflects how strongly the correlation is between these two markets at a given moment (in a column) and scale (in a row). Higher numbers show a firmer link between the variables at that particular interval. As an example, the value of coherence is shown for the first few rows and columns.

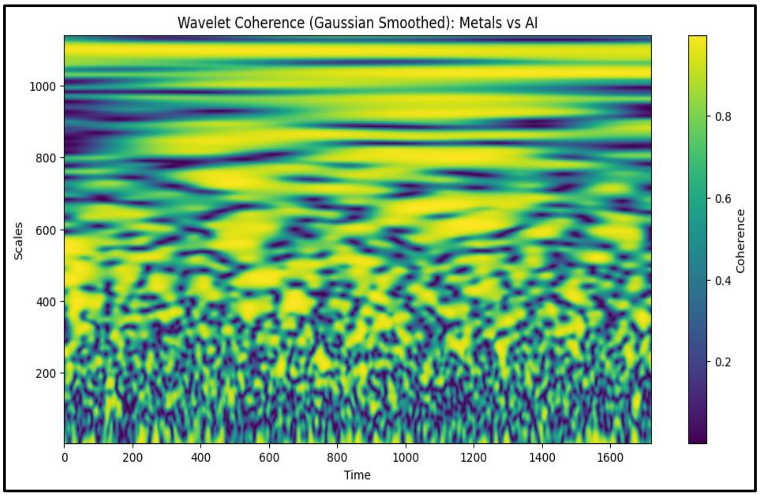

Fig. 4: Wavelet Coherence (Gaussian Smoothed) – Metals vs AI. Figure Created by the Authors.

Figure 4 shows the wavelet coherence plot (Gaussian smoothed) between Metals and AI, illustrating their dynamic relationship across both time and frequency domains. The X-axis denotes time ranging from 0 to approximately 1700 units, while the Y-axis represents scales from 0 to 1100, where higher scales correspond to lower frequencies (long-term patterns) and lower scales correspond to higher frequencies (short-term variations). The coherence color bar ranges from 0.0 (dark purple) to 1.0 (bright yellow), indicating the strength of correlation. At high scales between 900 and 1100, the coherence remains predominantly above 0.8, showing strong and persistent long-term coherence between Metals and AI throughout most of the time series. This suggests that the broader trends in the metals market and AI-related developments are closely aligned over long durations, possibly driven by shared macroeconomic or industrial factors.

In the mid-scale range of 400 to 800, coherence values typically vary between 0.5 and 0.8, with several patches exceeding 0.7, indicating moderate coherence and partial synchronization of medium-term fluctuations. These may reflect joint influences of technological cycles or investment patterns affecting both sectors. In contrast, at lower scales (0–300), coherence values drop significantly, often falling below 0.3, especially in the early and central segments of the time series. This implies that short-term movements in Metals and AI data are largely uncorrelated, possibly due to sector-specific volatility or noise. The plot highlights that the relationship between Metals and AI is strongest at long-term scales (above 900), with coherence frequently exceeding 0.9, while their short-term interactions are weak. These findings emphasize a structural linkage in long-run behavior, potentially tied to innovation cycles, resource demands, or investment flows shared by both domains.

5.4. Energy vs carbon

Table 4 shows the wavelet coherence for Energy and Carbon markets. Every cell shows the link between the markets at the specific time marked by the column and the range marked by the row. When the value is close to 1, it indicates that two variables respond similarly to shocks at the given time and frequency. In the shown part of the matrix, it can be seen how well the models match at the earliest stages and on the smallest scales.

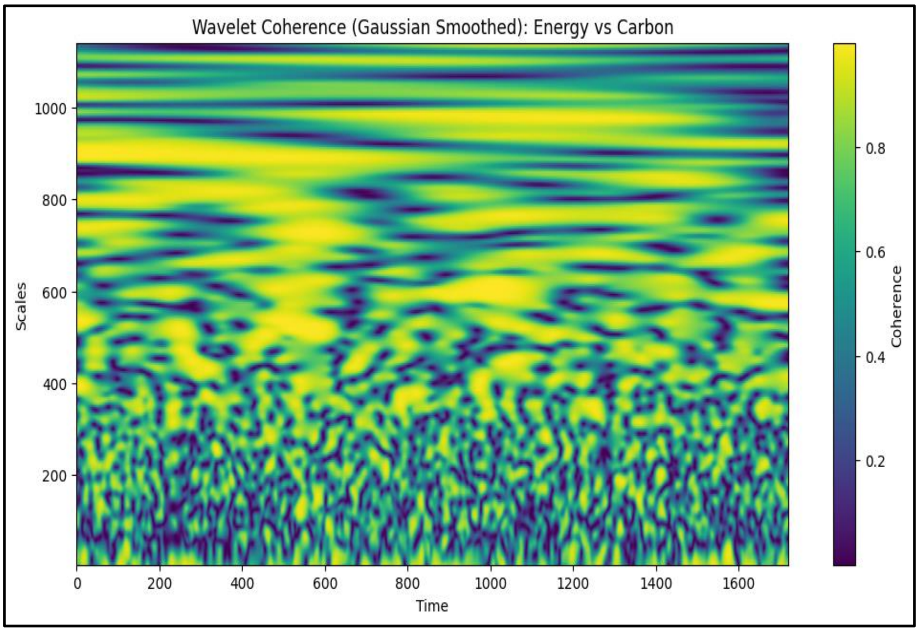

Fig. 5: Wavelet Coherence (Gaussian Smoothed) – Energy vs Carbon. Figure Created by the Authors.

Figure 5 shows the wavelet coherence plot (Gaussian smoothed) between Energy and Carbon presents a detailed time-frequency analysis of their relationship over time. The X-axis represents time from 0 to approximately 1700 units, and the Y-axis shows scales from 0 to 1100, which correspond inversely to frequency (i.e., high scales represent low-frequency or long-term patterns, and low scales correspond to high-frequency or short-term patterns). The color bar on the right quantifies coherence, where values near 1.0 (bright yellow) indicate strong coherence and values close to 0.0 (dark purple) represent weak or no coherence. At higher scales (800–1100), the plot reveals consistently strong coherence (≥ 0.8) across nearly the entire time frame, indicating a stable and significant long-term relationship between Energy consumption and Carbon emissions. This suggests that large-scale trends in energy use and carbon output are tightly connected, possibly due to structural economic or policy-linked factors.

In the mid-scale region (400–700), coherence values mostly range between 0.5 and 0.8, with frequent yellow-green patches. This implies moderate and intermittent correlation at these time scales, potentially driven by cyclical changes in energy production or seasonal carbon output variations.

Conversely, in the low-scale range (0–300), coherence values remain below 0.4, often dipping to 0.1 or less, particularly in the early and mid-portions of the time series. This indicates that short-term variations in energy and carbon data are largely uncorrelated, possibly due to noise, irregular fluctuations, or sector-specific disruptions.

The plot demonstrates that the Energy–Carbon relationship is strongest in long-term dynamics, particularly at scales above 800, with coherence often exceeding 0.9. While mid-term patterns show occasional alignment, short-term signals are weakly linked, highlighting the structural nature of their long-term interdependence.

5.5. Energy vs AI

Table 5 at the top, the coherence values for Energy vs AI are from the wavelet analysis. Every entry shows how tightly these two markets are tied together at a certain time and look (row and column). The higher the value, the stronger there is connection or relationship between the two at that certain moment and frequency. The coherence values are shown starting with the very first rows and columns.

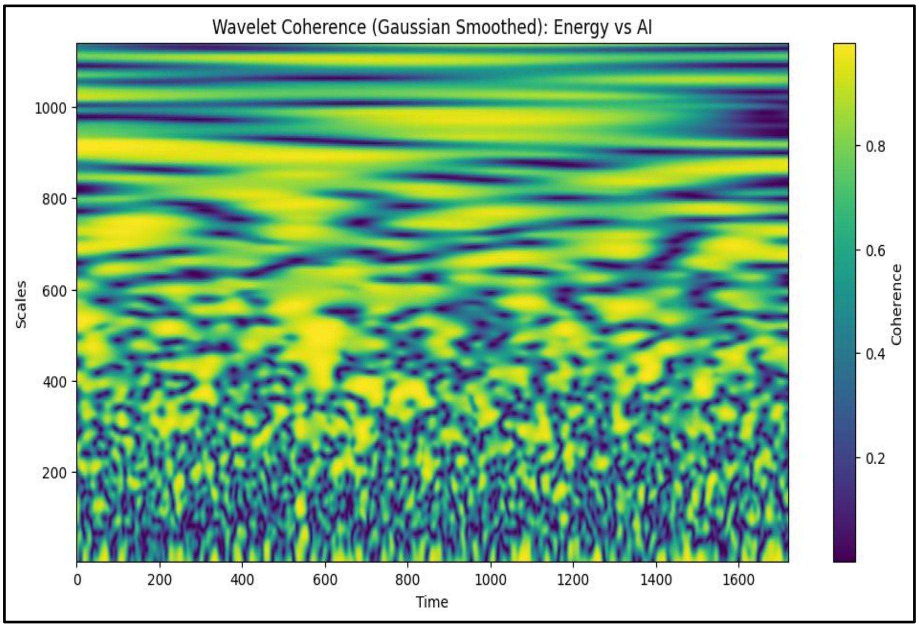

Fig. 6: Wavelet Coherence (Gaussian Smoothed) – Energy vs Aluminum. Figure Created by the Authors.

Figure 6: The wavelet coherence plot (Gaussian smoothed) between Energy and AI reveals important insights into their time-frequency relationship. The X-axis represents time ranging from 0 to approximately 1700 units, while the Y-axis represents scales from 0 to 1100, corresponding to different frequency components (with higher scales indicating lower frequencies or long-term patterns). The colour scale on the right indicates the degree of coherence, where values close to 1.0 (yellow) represent strong correlation, and values near 0.0 (dark purple) indicate weak or no correlation.

The analysis shows consistently high coherence (≥ 0.8) at larger scales between 800 and 1100, throughout most of the time domain. This indicates a strong long-term association between Energy and AI signals, implying that their broader trends are closely aligned. In the medium scale range of 400 to 700, there are several localized patches of elevated coherence values between 0.6 and 0.8, suggesting intermittent correlation at intermediate time scales. However, in the lower scale range of 0 to 300, the coherence drops significantly, often falling below 0.2, indicating little to no short-term correlation between the two signals.

Overall, the plot demonstrates that the relationship between Energy and AI is more pronounced in the long-term trends (scales > 800), while short-term interactions show minimal coherence. The temporal fluctuations in coherence also point to periods of alignment and divergence, suggesting the relationship is non-stationary and possibly influenced by external or structural changes over time.

5.6. Carbon vs AI

Wavelet coherence is presented in Table 6, Carbon vs AI. Every number shows the strength of the link between these markets at the chosen time and level of data. When the values come close to 1, it means the two assets were moving together strongly at that time and at that frequency. In the shown image, the comb connects well at the start and for very small wavelengths.

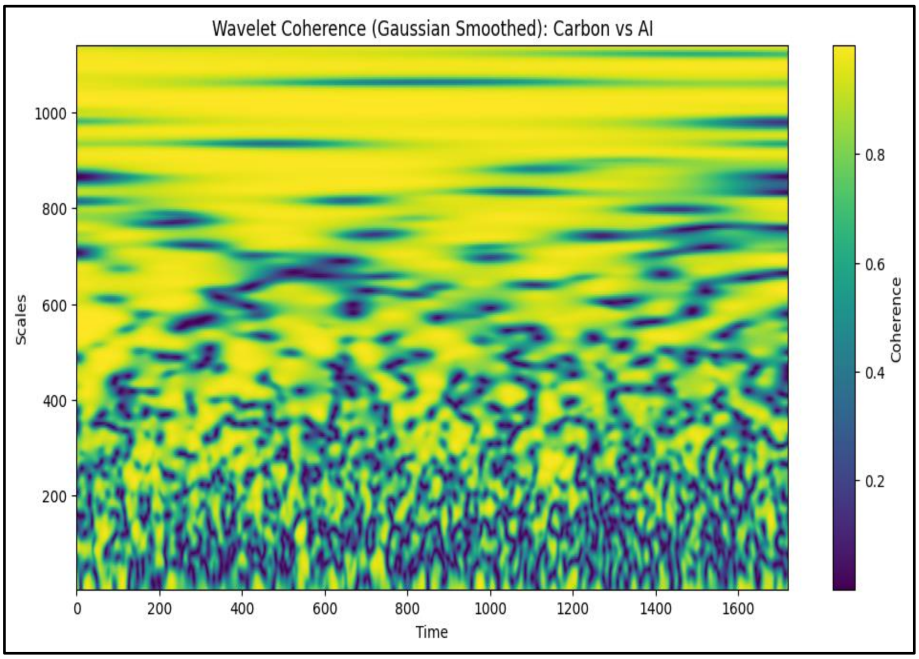

Fig. 7: Wavelet Coherence (Gaussian Smoothed) – Carbon vs AI. Figure Created by the Authors.

Figure 7 shows the wavelet coherence (Gaussian smoothed) plot between Carbon and Artificial Intelligence (AI) spans a time range from 0 to 1700 units and scale levels from 0 to 1100. The most prominent feature of the plot is the consistently high coherence levels (above 0.8) in the larger scale range (900–1100) across nearly the entire time axis, indicating a strong and sustained long-term relationship between carbon metrics and AI trends. This suggests that AI developments may be increasingly influenced by—or influencing—carbon-related factors, potentially due to rising concerns over AI energy consumption and carbon footprints. In the medium-scale range (600–800), the coherence remains relatively strong, ranging between 0.6 and 0.75, especially during the time intervals from 400 to 1200, pointing to a moderate mid-term alignment. These periods may reflect coordinated trends such as policy shifts linking AI adoption to sustainability frameworks. Lower-scale coherence (0–300), which reflects short-term interactions, is more fragmented and weaker, mostly between 0.2 and 0.5, with occasional bursts up to 0.6 around time points 200, 900, and 1500. These brief alignments could correspond to immediate events such as announcements about green AI initiatives or carbon-efficient computing innovations.

6. Conclusion and Future Work

This study provides novel empirical evidence of dynamic, frequency-dependent integration across metal, energy, carbon, and AI markets. By applying wavelet coherence analysis to all six pairwise relationships, we document three principal findings. First, market co-movements are strongest at long-term horizons (scales > 800), with coherence consistently exceeding 0.8 across all pairs and reaching 0.95+ for Energy-Carbon and Carbon-AI relationships. This indicates robust structural interdependencies driven by physical production requirements, energy consumption patterns, and regulatory frameworks. Second, medium-term dynamics (scales 400-800) show moderate coherence (0.5-0.7) with considerable time variation, reflecting adjustment periods following policy changes, technological innovations, and commodity cycles. These patterns support the theoretical prediction that markets exhibit transitional dynamics as economies adapt to sustainability transitions. Third, short-term relationships (scales 0-300) display weak coherence (< 0.4), suggesting that daily to weekly price movements are dominated by sector-specific factors—inventory adjustments, speculative trading, localized supply disruptions—rather than common underlying trends.

The emergence of AI as a market force fundamentally reshapes commodity market dynamics. The exceptionally high Carbon-AI coherence (> 0.95) at long horizons indicates that AI expansion is increasingly constrained by environmental considerations, while moderate AI-Metals coherence (0.6-0.7) reflects growing hardware dependencies. These patterns suggest AI is becoming deeply integrated into physical resource markets, contradicting earlier characterizations of AI as a purely digital economy phenomenon. For theory, these findings extend resource dependence frameworks to emerging technologies, demonstrating how AI-driven demand creates novel linkages between knowledge-intensive and commodity-intensive sectors. The frequency-dependent nature of relationships supports multi-horizon portfolio theory and highlights the importance of time-scale considerations in understanding market integration.

Investors should recognize that diversification benefits vary dramatically across time horizons, with strategic portfolios requiring broader asset class diversification given strong long-term coherence. Policymakers must account for cross-market spillovers when designing carbon regulations or technology policies, as interventions in one market increasingly propagate to others. Industry stakeholders, particularly in AI and renewable energy sectors, face growing resource constraints requiring integrated supply chain strategies.

Limitations and future research: While wavelet coherence reveals co-movement patterns, it does not establish causality. Future research should employ time-varying Granger causality or directed coherence methods to identify specific transmission channels. Additionally, expanding the analysis to include regional market variations (e.g., China vs. US vs. EU) would illuminate how different regulatory and industrial structures shape market integration. Finally, integrating textual analysis of policy announcements with quantitative co-movement patterns could better explain the mechanisms driving observed relationships.

Ethical Compliance Statement

This research was conducted in full compliance with ethical guidelines. The study does not involve human subjects, and no data collection from individuals was conducted. All methodologies used in this research adhere to ethical standards and principles.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest, whether financial or non-financial, that could influence the outcomes of this research.

Funding Disclosure

The authors declare that no funding was received for this research study.

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Appendix

Table 1: Wavelet Coherence Between Metal and Energy Markets Across Multiple Time Scales

Wavelet Coherence Results for Metals vs Energy:
Scales: [3.830413 3.9142883 4. 4.087589 4.177095
4.268562 4.362031 4.457547 4.5551543 4.6548996
4.7568283 4.8609896 4.967431 5.076204 5.1873584
5.3009467 5.417022 5.53564 5.656854 5.780723
5.907305 6.036658 6.1688433 6.3039236 6.4419613
6.583022 6.7271714 6.8744774 7.0250087 7.1788363
7.3360324 7.4966707 7.660826 7.8285766 8.
8.175178 8.35419 8.537124 8.724062 8.915094
9.110309 9.309799 9.513657 9.721979 9.934862
10.152408 10.374717 10.601893 10.834044 11.07128
11.313708 11.561446 11.81461 12.073316 12.337687
12.607847 12.883923 13.166044 13.454343 13.748955
14.050017 14.357673 14.672065 14.993341 15.321652
15.657153 16. 16.350355 16.70838 17.074247
17.448124 17.830189 18.220617 18.619598 19.027313
19.443958 19.869724 20.304815 20.749434 21.203787
21.668089 22.14256 22.627417 23.122892 23.62922
24.146631 24.675373 25.215694 25.767845 26.332088
26.908686 27.49791 28.100035 28.715345 29.34413
29.986683 30.643305 31.314306 32. 32.70071
33.41676 34.148495 34.896248 35.660378 36.441235
37.239197 38.054626 38.887917 39.73945 40.60963
41.498867 42.407574 43.336178 44.28512 45.254833
46.245785 47.25844 48.293262 49.350746 50.43139
51.53569 52.664177 53.81737 54.99582 56.20007
57.43069 58.68826 59.973366 61.28661 62.628613
64. 65.40142 66.83352 68.29699 69.792496
71.320755 72.88247 74.47839 76.10925 77.77583
79.4789 81.21926 82.997734 84.81515 86.672356
88.57024 90.50967 92.49157 94.51688 96.586525
98.70149 100.86278 103.07138 105.328354 107.63474
109.99164 112.40014 114.86138 117.37652 119.94673
122.57322 125.257225 128. 130.80284 133.66704
136.59398 139.58499 142.64151 145.76494 148.95679

```
 152.2185     155.55167    158.9578     162.43852    165.99547
 169.6303     173.34471    177.14047    181.01933    184.98314
 189.03375    193.17305    197.40298    201.72556    206.14276
 210.65671    215.26949    219.98328    224.80028    229.72276
 234.75304    239.89346    245.14644    250.51445    256.
 261.60568    267.33408    273.18796    279.16998    285.28302
 291.52988    297.91357    304.437      311.10333    317.9156
 324.87704    331.99094    339.2606     346.68942    354.28094
 362.03867    369.96628    378.0675     386.3461     394.80597
 403.4511     412.28552    421.31342    430.53897    439.96655
 449.60056    459.44553    469.50607    479.78693    490.29288
 501.0289     512.         523.21136    534.66815    546.3759
 558.33997    570.56604    583.05975    595.82715    608.874
 622.20667    635.8312     649.7541     663.9819     678.5212
 693.37885    708.5619     724.07733    739.93256    756.135
 772.6922     789.61194    806.9022     824.57104    842.62683
 861.07794    879.9331     899.2011     918.89105    939.01215
 959.57385    980.58575   1002.0578    1024.        1046.4227
1069.3363    1092.7518    1116.6799    1141.1321  ]
Coherence Matrix (first 5 rows and columns):
array([[0.63792446+3.71885482e-09j, 0.60021376+4.12002719e-10j,
        0.71045952+3.39924649e-09j, 0.85581457+4.05293336e-09j,
        0.93719915+5.51259611e-10j],
       [0.75901494+2.52374159e-09j, 0.7580504 +3.12773160e-09j,
        0.82145373-2.44173009e-09j, 0.9095989 +1.15422607e-09j,
        0.97067163-4.46056332e-09j],
       [0.82261518+3.50601508e-09j, 0.82800455+3.56531310e-09j,
        0.8671527 +6.08375820e-09j, 0.92461608+1.26883843e-08j,
        0.972237  +1.27612708e-08j],
       [0.85144711-3.71484716e-10j, 0.85358425+3.37873182e-09j,
        0.8741678 +1.84286709e-09j, 0.90533594+1.85583738e-09j,
        0.9287297 +1.79634527e-09j],
       [0.85926155+4.26717691e-11j, 0.85509101-5.78044443e-10j,
        0.85867245+3.95781044e-10j, 0.86197581+3.23061241e-09j,
        0.8441908 +2.66577452e-09j]])
```

Table 2: Wavelet Coherence for Metals and Carbon

```
Wavelet Coherence Results for Metals vs Carbon:
Scales: [  3.830413    3.9142883   4.          4.087589    4.177095
   4.268562    4.362031    4.457547    4.5551543   4.6548996
   4.7568283   4.8609896   4.967431    5.076204    5.1873584
   5.3009467   5.417022    5.53564     5.656854    5.780723
   5.907305    6.036658    6.1688433   6.3039236   6.4419613
   6.583022    6.7271714   6.8744774   7.0250087   7.1788363
   7.3360324   7.4966707   7.660826    7.8285766   8.
   8.175178    8.35419     8.537124    8.724062    8.915094
   9.110309    9.309799    9.513657    9.721979    9.934862
  10.152408   10.374717   10.601893   10.834044   11.07128
  11.313708   11.561446   11.81461    12.073316   12.337687
  12.607847   12.883923   13.166044   13.454343   13.748955
  14.050017   14.357673   14.672065   14.993341   15.321652
  15.657153   16.         16.350355   16.70838    17.074247
  17.448124   17.830189   18.220617   18.619598   19.027313
  19.443958   19.869724   20.304815   20.749434   21.203787
```

```
  21.668089    22.14256     22.627417    23.122892    23.62922
  24.146631    24.675373    25.215694    25.767845    26.332088
  26.908686    27.49791     28.100035    28.715345    29.34413
  29.986683    30.643305    31.314306    32.          32.70071
  33.41676     34.148495    34.896248    35.660378    36.441235
  37.239197    38.054626    38.887917    39.73945     40.60963
  41.498867    42.407574    43.336178    44.28512     45.254833
  46.245785    47.25844     48.293262    49.350746    50.43139
  51.53569     52.664177    53.81737     54.99582     56.20007
  57.43069     58.68826     59.973366    61.28661     62.628613
  64.          65.40142     66.83352     68.29699     69.792496
  71.320755    72.88247     74.47839     76.10925     77.77583
  79.4789      81.21926     82.997734    84.81515     86.672356
  88.57024     90.50967     92.49157     94.51688     96.586525
  98.70149    100.86278    103.07138    105.328354   107.63474
 109.99164    112.40014    114.86138    117.37652    119.94673
 122.57322    125.257225   128.         130.80284    133.66704
 136.59398    139.58499    142.64151    145.76494    148.95679
 152.2185     155.55167    158.9578     162.43852    165.99547
 169.6303     173.34471    177.14047    181.01933    184.98314
 189.03375    193.17305    197.40298    201.72556    206.14276
 210.65671    215.26949    219.98328    224.80028    229.72276
 234.75304    239.89346    245.14644    250.51445    256.
 261.60568    267.33408    273.18796    279.16998    285.28302
 291.52988    297.91357    304.437      311.10333    317.9156
 324.87704    331.99094    339.2606     346.68942    354.28094
 362.03867    369.96628    378.0675     386.3461     394.80597
 403.4511     412.28552    421.31342    430.53897    439.96655
 449.60056    459.44553    469.50607    479.78693    490.29288
 501.0289     512.         523.21136    534.66815    546.3759
 558.33997    570.56604    583.05975    595.82715    608.874
 622.20667    635.8312     649.7541     663.9819     678.5212
 693.37885    708.5619     724.07733    739.93256    756.135
 772.6922     789.61194    806.9022     824.57104    842.62683
 861.07794    879.9331     899.2011     918.89105    939.01215
 959.57385    980.58575   1002.0578    1024.        1046.4227
1069.3363    1092.7518    1116.6799    1141.1321   ]
Coherence Matrix (first 5 rows and columns):
array([[0.98520246+1.97023978e-09j, 0.98393568-1.04236061e-12j,
        0.98338162+5.80385379e-10j, 0.98413714+4.25648136e-09j,
        0.98681938-4.91968418e-10j],
       [0.98362053+4.81994613e-09j, 0.98226269+6.23578397e-09j,
        0.98165105+5.77997412e-09j, 0.98242824+1.06775001e-08j,
        0.98528234+2.79987883e-09j],
       [0.98132489+4.49131338e-09j, 0.97957555+8.93469444e-09j,
        0.97839868+1.07893098e-08j, 0.97837705+1.53541238e-08j,
        0.98011878+1.71082228e-08j],
       [0.97801234+3.96598731e-10j, 0.97540208+2.07282249e-09j,
        0.97283443+1.75521448e-09j, 0.97056943-9.29134958e-10j,
        0.96861203+3.10625005e-09j],
       [0.97336244+5.76158513e-10j, 0.96921042+1.71333190e-09j,
        0.9640408 +2.76469812e-09j, 0.95730824+2.24611776e-09j,
        0.9471808 -3.43975259e-10j]])
```

Coherence Results for Metals vs Carbon:

Table 3: Wavelet Coherence Result for Metal vs AI

Wavelet Coherence Results for Metals vs AI:
Scales: [3.830413 3.9142883 4. 4.087589 4.177095
4.268562 4.362031 4.457547 4.5551543 4.6548996
4.7568283 4.8609896 4.967431 5.076204 5.1873584
5.3009467 5.417022 5.53564 5.656854 5.780723
5.907305 6.036658 6.1688433 6.3039236 6.4419613
6.583022 6.7271714 6.8744774 7.0250087 7.1788363
7.3360324 7.4966707 7.660826 7.8285766 8.
8.175178 8.35419 8.537124 8.724062 8.915094
9.110309 9.309799 9.513657 9.721979 9.934862
10.152408 10.374717 10.601893 10.834044 11.07128
11.313708 11.561446 11.81461 12.073316 12.337687
12.607847 12.883923 13.166044 13.454343 13.748955
14.050017 14.357673 14.672065 14.993341 15.321652
15.657153 16. 16.350355 16.70838 17.074247
17.448124 17.830189 18.220617 18.619598 19.027313
19.443958 19.869724 20.304815 20.749434 21.203787
21.668089 22.14256 22.627417 23.122892 23.62922
24.146631 24.675373 25.215694 25.767845 26.332088
26.908686 27.49791 28.100035 28.715345 29.34413
29.986683 30.643305 31.314306 32. 32.70071
33.41676 34.148495 34.896248 35.660378 36.441235
37.239197 38.054626 38.887917 39.73945 40.60963
41.498867 42.407574 43.336178 44.28512 45.254833
46.245785 47.25844 48.293262 49.350746 50.43139
51.53569 52.664177 53.81737 54.99582 56.20007
57.43069 58.68826 59.973366 61.28661 62.628613
64. 65.40142 66.83352 68.29699 69.792496
71.320755 72.88247 74.47839 76.10925 77.77583
79.4789 81.21926 82.997734 84.81515 86.672356
88.57024 90.50967 92.49157 94.51688 96.586525
98.70149 100.86278 103.07138 105.328354 107.63474
109.99164 112.40014 114.86138 117.37652 119.94673
122.57322 125.257225 128. 130.80284 133.66704
136.59398 139.58499 142.64151 145.76494 148.95679
152.2185 155.55167 158.9578 162.43852 165.99547
169.6303 173.34471 177.14047 181.01933 184.98314
189.03375 193.17305 197.40298 201.72556 206.14276
210.65671 215.26949 219.98328 224.80028 229.72276
234.75304 239.89346 245.14644 250.51445 256.
261.60568 267.33408 273.18796 279.16998 285.28302
291.52988 297.91357 304.437 311.10333 317.9156
324.87704 331.99094 339.2606 346.68942 354.28094
362.03867 369.96628 378.0675 386.3461 394.80597
403.4511 412.28552 421.31342 430.53897 439.96655
449.60056 459.44553 469.50607 479.78693 490.29288
501.0289 512. 523.21136 534.66815 546.3759
558.33997 570.56604 583.05975 595.82715 608.874
622.20667 635.8312 649.7541 663.9819 678.5212
693.37885 708.5619 724.07733 739.93256 756.135
772.6922 789.61194 806.9022 824.57104 842.62683

```
 861.07794    879.9331     899.2011     918.89105    939.01215
 959.57385    980.58575    1002.0578    1024.        1046.4227
1069.3363    1092.7518    1116.6799    1141.1321   ]
Coherence Matrix (first 5 rows and columns):
array([[0.98115787-1.46372081e-09j, 0.9788311 +1.32872389e-09j,
        0.97609273+3.55179410e-09j, 0.97269768+4.19958195e-09j,
        0.96820113+1.52918845e-09j],
       [0.97759371-1.75407331e-09j, 0.97482271-2.92816509e-09j,
        0.97143929-6.20369171e-09j, 0.96708424-2.41222454e-09j,
        0.96109314-7.15522759e-09j],
       [0.97310925+3.68025984e-10j, 0.96988102+1.04251374e-09j,
        0.96584995+1.87936881e-09j, 0.9605636 +7.96948340e-09j,
        0.95317317+8.54998619e-09j],
       [0.96752196-1.55656204e-09j, 0.96388229+3.08914430e-09j,
        0.95931567+3.06240287e-09j, 0.9533459 +1.23519807e-09j,
        0.9450746 +1.04630958e-08j],
       [0.96061494+6.86379021e-09j, 0.95668729+3.44649021e-09j,
        0.95184985+6.23123494e-09j, 0.94572446+4.78135570e-09j,
        0.93757539+1.84438346e-10j]])
```

Table 4: Wavelet Coherence for Energy and Carbon Markets

Wavelet Coherence Results for Energy vs Carbon:

```
Scales: [   3.830413     3.9142883    4.           4.087589     4.177095
    4.268562     4.362031     4.457547     4.5551543    4.6548996
    4.7568283    4.8609896    4.967431     5.076204     5.1873584
    5.3009467    5.417022     5.53564      5.656854     5.780723
    5.907305     6.036658     6.1688433    6.3039236    6.4419613
    6.583022     6.7271714    6.8744774    7.0250087    7.1788363
    7.3360324    7.4966707    7.660826     7.8285766    8.
    8.175178     8.35419      8.537124     8.724062     8.915094
    9.110309     9.309799     9.513657     9.721979     9.934862
   10.152408    10.374717    10.601893    10.834044    11.07128
   11.313708    11.561446    11.81461     12.073316    12.337687
   12.607847    12.883923    13.166044    13.454343    13.748955
   14.050017    14.357673    14.672065    14.993341    15.321652
   15.657153    16.          16.350355    16.70838     17.074247
   17.448124    17.830189    18.220617    18.619598    19.027313
   19.443958    19.869724    20.304815    20.749434    21.203787
   21.668089    22.14256     22.627417    23.122892    23.62922
   24.146631    24.675373    25.215694    25.767845    26.332088
   26.908686    27.49791     28.100035    28.715345    29.34413
   29.986683    30.643305    31.314306    32.          32.70071
   33.41676     34.148495    34.896248    35.660378    36.441235
   37.239197    38.054626    38.887917    39.73945     40.60963
   41.498867    42.407574    43.336178    44.28512     45.254833
   46.245785    47.25844     48.293262    49.350746    50.43139
   51.53569     52.664177    53.81737     54.99582     56.20007
   57.43069     58.68826     59.973366    61.28661     62.628613
   64.          65.40142     66.83352     68.29699     69.792496
   71.320755    72.88247     74.47839     76.10925     77.77583
   79.4789      81.21926     82.997734    84.81515     86.672356
   88.57024     90.50967     92.49157     94.51688     96.586525
   98.70149    100.86278    103.07138    105.328354   107.63474
  109.99164    112.40014    114.86138    117.37652    119.94673
```

```
122.57322    125.257225   128.        130.80284    133.66704
136.59398    139.58499    142.64151    145.76494    148.95679
152.2185     155.55167    158.9578     162.43852    165.99547
169.6303     173.34471    177.14047    181.01933    184.98314
189.03375    193.17305    197.40298    201.72556    206.14276
210.65671    215.26949    219.98328    224.80028    229.72276
234.75304    239.89346    245.14644    250.51445    256.
261.60568    267.33408    273.18796    279.16998    285.28302
291.52988    297.91357    304.437      311.10333    317.9156
324.87704    331.99094    339.2606     346.68942    354.28094
362.03867    369.96628    378.0675     386.3461     394.80597
403.4511     412.28552    421.31342    430.53897    439.96655
449.60056    459.44553    469.50607    479.78693    490.29288
501.0289     512.         523.21136    534.66815    546.3759
558.33997    570.56604    583.05975    595.82715    608.874
622.20667    635.8312     649.7541     663.9819     678.5212
693.37885    708.5619     724.07733    739.93256    756.135
772.6922     789.61194    806.9022     824.57104    842.62683
861.07794    879.9331     899.2011     918.89105    939.01215
959.57385    980.58575    1002.0578    1024.        1046.4227
1069.3363    1092.7518    1116.6799    1141.1321   ]
Coherence Matrix (first 5 rows and columns):
array([[0.74954023+6.62359393e-09j, 0.70249925+4.99151812e-10j,
        0.75632877-5.63755484e-10j, 0.84809442+4.30020109e-10j,
        0.90474815-9.95170228e-10j],
       [0.85859177+4.61689721e-09j, 0.85160562+6.11747844e-09j,
        0.88144566+4.17728651e-09j, 0.92723135+5.19926570e-09j,
        0.95846365+2.72103474e-09j],
       [0.91352986+4.58998148e-09j, 0.91610749+4.72170760e-09j,
        0.93593329+1.01112624e-08j, 0.96454725+1.23762176e-08j,
        0.98690499+8.72101395e-09j],
       [0.93998349-4.87317490e-09j, 0.94334739-1.45089873e-09j,
        0.95584318-7.88072624e-10j, 0.97332339+2.72101086e-09j,
        0.98764394-4.41358532e-09j],
       [0.95180925+3.85021406e-12j, 0.95381095+3.14437003e-09j,
        0.96021205+3.55762108e-09j, 0.96737163+1.20570656e-08j,
        0.96772879+9.29804409e-09j]])
```

Table 5: Coherence Values for Energy vs AI

```
Wavelet Coherence Results for Energy vs AI:
Scales: [  3.830413     3.9142883    4.          4.087589     4.177095
   4.268562     4.362031     4.457547     4.5551543    4.6548996
   4.7568283    4.8609896    4.967431     5.076204     5.1873584
   5.3009467    5.417022     5.53564      5.656854     5.780723
   5.907305     6.036658     6.1688433    6.3039236    6.4419613
   6.583022     6.7271714    6.8744774    7.0250087    7.1788363
   7.3360324    7.4966707    7.660826     7.8285766    8.
   8.175178     8.35419      8.537124     8.724062     8.915094
   9.110309     9.309799     9.513657     9.721979     9.934862
  10.152408    10.374717    10.601893    10.834044    11.07128
  11.313708    11.561446    11.81461     12.073316    12.337687
  12.607847    12.883923    13.166044    13.454343    13.748955
  14.050017    14.357673    14.672065    14.993341    15.321652
  15.657153    16.         16.350355    16.70838     17.074247
```

```
 17.448124    17.830189    18.220617    18.619598    19.027313
 19.443958    19.869724    20.304815    20.749434    21.203787
 21.668089    22.14256     22.627417    23.122892    23.62922
 24.146631    24.675373    25.215694    25.767845    26.332088
 26.908686    27.49791     28.100035    28.715345    29.34413
 29.986683    30.643305    31.314306    32.          32.70071
 33.41676     34.148495    34.896248    35.660378    36.441235
 37.239197    38.054626    38.887917    39.73945     40.60963
 41.498867    42.407574    43.336178    44.28512     45.254833
 46.245785    47.25844     48.293262    49.350746    50.43139
 51.53569     52.664177    53.81737     54.99582     56.20007
 57.43069     58.68826     59.973366    61.28661     62.628613
 64.          65.40142     66.83352     68.29699     69.792496
 71.320755    72.88247     74.47839     76.10925     77.77583
 79.4789      81.21926     82.997734    84.81515     86.672356
 88.57024     90.50967     92.49157     94.51688     96.586525
 98.70149    100.86278    103.07138    105.328354   107.63474
109.99164    112.40014    114.86138    117.37652    119.94673
122.57322    125.257225   128.         130.80284    133.66704
136.59398    139.58499    142.64151    145.76494    148.95679
152.2185     155.55167    158.9578     162.43852    165.99547
169.6303     173.34471    177.14047    181.01933    184.98314
189.03375    193.17305    197.40298    201.72556    206.14276
210.65671    215.26949    219.98328    224.80028    229.72276
234.75304    239.89346    245.14644    250.51445    256.
261.60568    267.33408    273.18796    279.16998    285.28302
291.52988    297.91357    304.437      311.10333    317.9156
324.87704    331.99094    339.2606     346.68942    354.28094
362.03867    369.96628    378.0675     386.3461     394.80597
403.4511     412.28552    421.31342    430.53897    439.96655
449.60056    459.44553    469.50607    479.78693    490.29288
501.0289     512.         523.21136    534.66815    546.3759
558.33997    570.56604    583.05975    595.82715    608.874
622.20667    635.8312     649.7541     663.9819     678.5212
693.37885    708.5619     724.07733    739.93256    756.135
772.6922     789.61194    806.9022     824.57104    842.62683
861.07794    879.9331     899.2011     918.89105    939.01215
959.57385    980.58575   1002.0578    1024.        1046.4227
1069.3363   1092.7518   1116.6799   1141.1321   ]
Coherence Matrix (first 5 rows and columns):
array([[0.76245922+4.07551319e-09j, 0.71626307+1.48198934e-09j,
        0.75648617+1.74234560e-09j, 0.82781216+4.13419695e-10j,
        0.8631495 +8.44167329e-10j],
       [0.87344238-1.15049346e-09j, 0.86793437-1.88230184e-09j,
        0.89172028-6.71907998e-09j, 0.9242068 -7.16768864e-09j,
        0.93434733-6.95867460e-09j],
       [0.92850507+7.66812160e-10j, 0.9325604 -2.69696407e-09j,
        0.95082101+1.63702940e-09j, 0.9737624 +5.29174442e-09j,
        0.98097158+3.44812385e-10j],
       [0.95445258-6.87076805e-09j, 0.95856645-4.39243731e-10j,
        0.97086468+5.47152396e-10j, 0.98657548+4.98076778e-09j,
        0.99090969+3.36460861e-09j],
       [0.96588633+6.33362936e-09j, 0.96718406+4.96301164e-09j,
```

```
    0.97223238+7.17863479e-09j, 0.97698326+1.48239741e-08j,
    0.96751984+9.83772700e-09j]]])
```

Table 6: Wavelet Coherence Result of Carbon vs AI

```
Wavelet Coherence Results for Carbon vs AI:
Scales: [  3.830413    3.9142883   4.          4.087589    4.177095
   4.268562    4.362031    4.457547    4.5551543   4.6548996
   4.7568283   4.8609896   4.967431    5.076204    5.1873584
   5.3009467   5.417022    5.53564     5.656854    5.780723
   5.907305    6.036658    6.1688433   6.3039236   6.4419613
   6.583022    6.7271714   6.8744774   7.0250087   7.1788363
   7.3360324   7.4966707   7.660826    7.8285766   8.
   8.175178    8.35419     8.537124    8.724062    8.915094
   9.110309    9.309799    9.513657    9.721979    9.934862
  10.152408   10.374717   10.601893   10.834044   11.07128
  11.313708   11.561446   11.81461    12.073316   12.337687
  12.607847   12.883923   13.166044   13.454343   13.748955
  14.050017   14.357673   14.672065   14.993341   15.321652
  15.657153   16.         16.350355   16.70838    17.074247
  17.448124   17.830189   18.220617   18.619598   19.027313
  19.443958   19.869724   20.304815   20.749434   21.203787
  21.668089   22.14256    22.627417   23.122892   23.62922
  24.146631   24.675373   25.215694   25.767845   26.332088
  26.908686   27.49791    28.100035   28.715345   29.34413
  29.986683   30.643305   31.314306   32.         32.70071
  33.41676    34.148495   34.896248   35.660378   36.441235
  37.239197   38.054626   38.887917   39.73945    40.60963
  41.498867   42.407574   43.336178   44.28512    45.254833
  46.245785   47.25844    48.293262   49.350746   50.43139
  51.53569    52.664177   53.81737    54.99582    56.20007
  57.43069    58.68826    59.973366   61.28661    62.628613
  64.         65.40142    66.83352    68.29699    69.792496
  71.320755   72.88247    74.47839    76.10925    77.77583
  79.4789     81.21926    82.997734   84.81515    86.672356
  88.57024    90.50967    92.49157    94.51688    96.586525
  98.70149   100.86278   103.07138   105.328354  107.63474
 109.99164   112.40014   114.86138   117.37652   119.94673
 122.57322   125.257225  128.        130.80284   133.66704
 136.59398   139.58499   142.64151   145.76494   148.95679
 152.2185    155.55167   158.9578    162.43852   165.99547
 169.6303    173.34471   177.14047   181.01933   184.98314
 189.03375   193.17305   197.40298   201.72556   206.14276
 210.65671   215.26949   219.98328   224.80028   229.72276
 234.75304   239.89346   245.14644   250.51445   256.
 261.60568   267.33408   273.18796   279.16998   285.28302
 291.52988   297.91357   304.437     311.10333   317.9156
 324.87704   331.99094   339.2606    346.68942   354.28094
 362.03867   369.96628   378.0675    386.3461    394.80597
 403.4511    412.28552   421.31342   430.53897   439.96655
 449.60056   459.44553   469.50607   479.78693   490.29288
 501.0289    512.        523.21136   534.66815   546.3759
 558.33997   570.56604   583.05975   595.82715   608.874
 622.20667   635.8312    649.7541    663.9819    678.5212
 693.37885   708.5619    724.07733   739.93256   756.135
```

```
 772.6922    789.61194   806.9022    824.57104   842.62683
 861.07794   879.9331    899.2011    918.89105   939.01215
 959.57385   980.58575   1002.0578   1024.       1046.4227
1069.3363   1092.7518   1116.6799   1141.1321  ]
Coherence Matrix (first 5 rows and columns):
array([[0.99969287+1.51497188e-09j, 0.99961558+1.38104019e-09j,
        0.99922476-1.88970614e-09j, 0.99805702+8.85685706e-11j,
        0.99487701-1.08173213e-10j],
       [0.99944406+2.57848770e-10j, 0.99930698+5.36149362e-11j,
        0.9988193 +1.32393413e-09j, 0.9974612 +1.83935424e-09j,
        0.99376295-1.05263500e-11j],
       [0.99913303+1.13961772e-09j, 0.99896671+1.92108905e-09j,
        0.99842172+5.72438425e-09j, 0.99688648+7.38186753e-09j,
        0.99251417+4.64603476e-09j],
       [0.9988209 -6.34933942e-09j, 0.99871291-2.28847259e-09j,
        0.99822528+2.59199934e-10j, 0.99661197+2.03442865e-09j,
        0.99146247+4.62833213e-09j],
       [0.99858237+7.08952416e-09j, 0.99869074+7.56524952e-09j,
        0.99845499+9.77543574e-09j, 0.99693997+1.37294400e-08j,
        0.99097672+6.58706306e-09j]])
```