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Carbon Commodity Linkages in Emerging and Mature Markets: Comparative Evidence from Indonesia and the EU ETS

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ABSTRACT

This study investigates the relationship between carbon prices and major food, energy, and mineral commodities in Indonesia and Europe using a multi method framework that includes correlation analysis, hierarchical clustering, random matrix theory (RMT), rolling window eigenvalue diagnostics, and vector autoregression (VAR). The Indonesian dataset (2024-2025) reflects the early stage of the IDX Carbon market, while the European dataset (2015-2025) represents the mature structure of the EU Emissions Trading System. The combination of RMT filtering and VAR modelling allows for the identification of systemic comovement and dynamic transmission channels. The results show a clear contrast between the two markets. In Indonesia, correlation measures, clustering patterns, and RMT indicators suggest that commodity price movements are mostly noise driven, with no stable link between carbon prices and food, energy, or mineral commodities. In Europe, the eigenvalue spectrum, the systemic risk index, and rolling RMT patterns reveal strong and time varying comovement across energy and metal commodities, with VAR results identifying natural gas as the main driver of carbon price dynamics. Overall, the findings highlight how market maturity and energy system structure shape carbon commodity interactions and offer guidance for carbon market design in emerging economies.

Keyword: Carbon market, Commodity Prices, Random Matrix Theory, Vector Autoregression, Market Integration, EU ETS, IDX Carbon, Indonesia
JEL Classifications: Q40, Q54, C32, G15

1. INTRODUCTION

Climate change continues to reshape environmental and economic systems worldwide and remains one of the most pressing global challenges of the twenty first century, as emphasized by the IPCC (2021) and Stern (2007). Market based mitigation instruments, particularly emissions trading schemes, have therefore become central to climate policy. The World Bank (2022) notes that carbon pricing mechanisms can accelerate the transition toward cleaner energy systems by shaping investment decisions, production costs, and expectations of future emissions. The European Union Emissions Trading System is the most established carbon market and plays a major role in influencing industrial behavior and carbon price formation in Europe, as discussed by Ellerman et al. (2016). Evidence from other jurisdictions, including New Zealand, shows that carbon markets can become integrated with energy and financial systems (Tao et al., 2024), while recent work reports linkages between carbon prices and energy inflation across EU member states (Olasehinde-Williams et al., 2025).

Carbon prices also influence energy costs, industrial production, while climate-related policy shifts and energy costs continue to pressure global food systems (FAO et al., 2022). Studies in China find that carbon trading can reduce emissions while supporting industrial output (Zhang et al., 2020) and can stimulate renewable energy development (Huang et al., 2023). Other research reports volatility spillovers between carbon and fossil energy markets (Wang et al., 2024), as well as strong energy food interactions driven by causality, volatility transmission, and biofuel related channels (Kirikkaleli and Darbaz, 2021; Nazlioglu et al., 2013;

Serra and Zilberman, 2013; Taghizadeh-Hesary et al., 2018). These findings collectively show that carbon pricing operates within multi commodity systems characterized by cross market dependencies.

In Indonesia, the integration of food security, resource governance, and energy transition has emerged as a cornerstone of the country's sustainable development strategy (Asian Development Bank, 2021). Domestic food prices remain a key driver of inflation (Bank Indonesia, 2024), while supply shocks in major staples generate price volatility that pressures household purchasing power (National Food Agency, 2025). The energy system remains highly dependent on coal and resource-intensive minerals such as nickel, cobalt, and aluminium (Ministry of Energy and Mineral Resources, 2023). These structural conditions suggest that carbon price changes may transmit across food, energy, and mineral markets, yet such linkages remain empirically unexplored. The launch of IDX Carbon in September 2023 marked Indonesia's first formal carbon market, although trading activity remains limited (Financial Services Authority, 2023; Indonesia Stock Exchange, 2023).

By contrast, the EU ETS has operated for almost two decades and serves as a global benchmark. Matrix completion estimates suggest that the system reduced emissions by about 15% between 2005 and 2020 (Biancalani et al., 2024), and policy expansions such as ETS2 are expected to raise future carbon prices (Gunther et al., 2024). Previous research documents strong linkages between EU carbon prices and energy commodities (Aatola et al., 2013; Hammoudeh et al., 2014), as well as spillovers into financial markets through carbon premia and risk transmission channels (Oestreich and Tsiakas, 2015; Zhou et al., 2025). Although carbon energy and carbon financial interactions are well studied (Zhao et al., 2023; Reboredo, 2018; Lyu et al., 2025), research integrating carbon prices with both food and mineral commodities remains limited.

To the best of our knowledge, no study compares Indonesia's emerging carbon market with the mature EU ETS within a unified multivariate and high dimensional framework. Commodity markets typically display strong correlation structures, and random matrix theory (RMT) provides a robust method for distinguishing information from noise (Mantegna, 1999; Marchenko–Pastur, 1967). Rolling RMT further enables the detection of time varying systemic patterns that conventional models may not capture.

This study fills these gaps by examining the relationships between carbon prices and major food, energy, and mineral commodities in Indonesia, and by comparing them with patterns observed in Europe. We apply correlation based techniques, shrinkage estimation, hierarchical clustering, random matrix theory (RMT), rolling RMT, and vector autoregression (VAR) to uncover both static and dynamic interdependencies. The contributions of this paper are threefold. First, it provides the first empirical assessment of Indonesia's carbon market and its relationship with strategic commodity groups. Second, it offers a comparative analysis between an emerging market and a mature market using systemic risk tools. Third, it extends the application of rolling RMT to carbon commodity systems, allowing the identification of time varying structures not captured by standard econometric models.

2. DATA AND VARIABLES

This study uses monthly price data for carbon, food, energy, fertilizer, and mineral commodities from Indonesia and the European Union. The Indonesian sample spans January 2024-August 2025, corresponding to the period after the launch of the domestic carbon market. Although relatively short, the Indonesian dataset reflects the structural characteristics of an emerging market with limited trading activity. The European sample covers January 2015-August 2025, capturing the mature dynamics of the EU Emissions Trading System across multiple regulatory phases. All series are transformed into continuously compounded returns to ensure comparability and to satisfy the stationarity requirements of correlation based and VAR based models.

2.1. Data Sources

Indonesian data are obtained from official administrative sources: Carbon prices from IDX Carbon, food commodities from the National Food Agency, and energy and mineral prices from the Ministry of Energy and Mineral Resources. These series represent benchmark prices used primarily for policy monitoring and market surveillance (IDX Carbon, 2025; National Food Agency, 2025; Ministry of Energy and Mineral Resources, 2025). The European dataset consolidates daily or monthly benchmarks into monthly frequency. EU ETS prices are proxied by EUA futures from Investing.com (2025), while other commodity prices are sourced from the World Bank Pink Sheet (2025). Table 1 summarizes the variables used.

2.2. Variable Construction

Monthly returns are computed as

$$r_t = l\,n(P_t) - l\,n(P_{t-1})$$

Table 1: Summary of variables included in the analysis

Region	Category	Variables
Indonesia	Carbon	Harga Karbon (Carbon Price)
	Food	GKP Petani (Farmer-level Harvested Dry Paddy), GKG Penggilingan (Miller-level Milled Dry Paddy), Beras Medium (Medium-grade Rice), Beras Premium (Premium-grade Rice), Jagung Pipilan Kering (Dry Shelled Corn), Kedelai Lokal (Local Soybeans), Bawang Merah (Shallots), Cabai Merah Keriting (Curly Red Chili), Cabai Rawit Merah (Bird's Eye Chili), Daging Sapi (Beef), Ayam Ras Pedaging (Broiler Chicken), Telur Ayam Ras (Chicken Eggs).
	Energy	Minyak (Crude Oil) dan Batubara (Coal)
	Minerals	Nikel (Nickel), Kobalt (Cobalt), Tembaga (Copper), dan Aluminium (Aluminium)
Europe	Carbon	Carbon Price
	Energy	Crude Oil, Natural Gas, Coal
	Food	Soybeans, Maize, Rice, Wheat, Beef, Chicken
	Fertilizers	DAP, Urea
	Metals	Aluminum, Iron Ore, Copper, Nickel, Zinc

Indonesian variable names follow the original terminology used by the National Food Agency, the Ministry of Energy and Mineral Resources, and IDX Carbon where P_t denotes the closing price of each series. The return transformation is required for RMT, shrinkage correlation estimation, and VAR, all of which rely on stationary inputs. Correlation matrices are estimated using Pearson and Spearman correlations, as well as the Ledoit and Wolf shrinkage estimator to reduce sampling noise in high dimensional settings.

2.3. Descriptive Characteristics

Indonesian commodity prices exhibit substantial heterogeneity. Food commodities show short term volatility driven by seasonal supply conditions, weather disruptions, and distributional bottlenecks. Energy and mineral price movements are relatively muted, reflecting Indonesia's regulated coal market, domestic stabilization policies, and the early stage of the carbon market where trading activity remains thin. These characteristics result in low cross market variation, which motivates the use of RMT to distinguish structural dependencies from noise.

In contrast, the European dataset displays stronger and more persistent price dynamics shaped by energy market shocks, regulatory reforms, geopolitical developments, and active futures trading. The EU ETS in particular exhibits market driven fluctuations, making the European system suitable for analyzing systemic structure and dynamic linkages using rolling RMT and VAR.

3. METHODOLOGY

This study integrates correlation-based techniques, hierarchical clustering, and Random Matrix Theory (RMT) to characterize carbon-commodity interactions in Indonesia and Europe. To capture time-varying dynamics and causal channels, rolling-window RMT and Vector Autoregression (VAR) are applied exclusively to the EU ETS dataset. These methods provide three complementary perspectives: (i) Contemporaneous dependence via correlation matrices, (ii) systemic structure through eigenvalue filtering and clustering (Mantegna, 1999), and (iii) dynamic transmission through impulse responses and variance decomposition (Pesaran and Shin, 1998; Lütkepohl, 2005).

The analysis begins by constructing return series and estimating correlation matrices, including the Ledoit and Wolf (2004) shrinkage estimator to handle cases where the time dimension is small relative to the number of variables. Subsequently, hierarchical clustering identifies latent commodity groupings, while static RMT distinguishes informative eigenvalues from noise using the Marchenko–Pastur (1967) distribution. For the EU ETS dataset, temporal variations in systemic dependence are examined via rolling-window RMT, leveraging its longer sample length for reliable windowed estimation.

The Indonesian dataset contains only 20 observations, making rolling analysis statistically unreliable; therefore, the domestic results focus on static correlation, clustering, and RMT structure.

Similarly, the VAR framework is estimated only for the EU ETS data to evaluate dynamic linkages between carbon prices and commodity groups. Impulse responses and forecast error variance decomposition are used to assess transmission channels and the relative importance of shocks. The Indonesian sample is too short for stable multivariate estimation.

The following subsections describe each methodological component.

3.1. Return Construction and Correlation Estimation

Let P_t denote the monthly closing price of a commodity at time t. Continuously compounded returns are computed as

$$r_t = l\,n(P_t) - l\,n(P_{t-1})$$

A standard transformation in financial econometrics to promote stationarity.

The Indonesian dataset contains N = 19 commodities and T = 20 monthly observations (January 2024-August 2025), yielding a dimension ratio:

$$Q = \frac{T}{N} \approx 1.05$$

Which implies that the sample correlation matrix is highly sensitive to noise. To provide a more stable characterization of dependence, three estimators are used: Pearson correlation for linear relationships, Spearman correlation for monotonic dependence, and the Ledoit and Wolf shrinkage estimator for improved conditioning in low sample settings (Ledoit and Wolf, 2004).

These estimators serve as inputs for subsequent clustering, RMT filtering, and for selecting representative variables in the VAR model.

3.2. Hierarchical Clustering for Market Structure

Hierarchical clustering is used to examine the latent structure of commodity markets. Following the approach introduced by Mantegna (1999), pairwise distances are computed from the correlation matrix as

$$d_{ij} = \sqrt{2\left(1-\rho_{ij}\right)}$$

where ρ_{ij} is the correlation between commodities i and j. This metric satisfies ultrametric properties and has been widely applied to identify sectoral organization in multi asset systems.

Agglomerative clustering with the average linkage criterion is used to construct the dendrogram. This method balances sensitivity to local structure with robustness to outliers, making it suitable for commodity systems that include food, energy, and metal markets. The resulting hierarchical tree provides an intuitive representation of how closely carbon prices relate to different commodity groups and complements the eigenvalue based systemic analysis obtained from RMT.

3.3. Random Matrix Theory (RMT)

RMT provides a formal framework for distinguishing meaningful structure from noise in empirical correlation matrices. This is particularly relevant for the Indonesian dataset, where the number of variables ($N = 19$) is nearly equal to the number of observations ($T = 20$), making the sample correlation matrix highly susceptible to sampling noise.

The Marchenko–Pastur (1967) distribution characterizes the eigenvalue density of correlation matrices generated from uncorrelated random variables. Let $Q = T/N$. The theoretical bounds of the Marchenko–Pastur distribution are

$$\lambda_{\min} = (1-\sqrt{1/Q})^2, \lambda_{\max} = (1+\sqrt{1/Q})^2$$

Eigenvalues within this interval are attributed to noise, while those outside it contain information about genuine market structure.

The empirical correlation matrix is decomposed into eigenvalues and eigenvectors. Eigenvalues that exceed the upper bound typically represent collective market behavior, often referred to as the market mode, while subsequent informative eigenvalues capture sector specific interactions. A filtered correlation matrix is reconstructed by retaining only informative eigenvalues, which reduces noise and improves the reliability of clustering results and subsequent systemic analysis.

3.4. Rolling Random Matrix Theory (Rolling RMT)

Rolling RMT is used to capture temporal variation in systemic dependence across commodities. For each window of length W, a correlation matrix is computed, decomposed into eigenvalues, and compared with the theoretical bounds of the Marchenko–Pastur (1967) distribution. This produces a sequence of eigenvalue sets

$$\lambda_{1,t}, \lambda_{2,t}, \ldots, \lambda_{N,t}, t = W, W+1, \ldots, T$$

Rolling analysis is implemented only for the EU ETS dataset, whose longer sample length ($T = 129$) allows statistically meaningful windowed estimation. The Indonesian dataset contains only 20 observations, which is insufficient for reliable rolling construction, so the domestic analysis relies solely on static RMT.

Changes in the magnitude and number of eigenvalues that exceed the Marchenko Pastur upper bound indicate evolving systemic coupling. Increases in the dominant eigenvalue typically signal periods of strong market integration or stress, while declines point to weaker common forces. Rolling RMT thus provides a dynamic perspective on market coherence and reveals structural shifts in carbon commodity linkages in the EU ETS.

3.5. Vector Autoregression (VAR)

Dynamic interactions between carbon prices and key commodity groups are examined using a Vector Autoregression model. A VAR(p) takes the general form

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$$

where y_t is a k-dimensional vector of returns, A_i are coefficient matrices, and u_t is a vector of white noise disturbances (Lütkepohl, 2005).

Lag order p is selected using the Akaike Information Criterion and the Bayesian Information Criterion. All series are tested for covariance stationarity, and model stability is evaluated using the eigenvalues of the companion matrix.

Because the Indonesian dataset contains only 20 observations, estimating a multivariate VAR would lead to severe overparameterization and unreliable inference. Therefore, VAR analysis is applied exclusively to the EU ETS dataset, which provides a sufficiently long time series to support robust dynamic modelling.

3.6. Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD)

Impulse Response Functions trace the reaction of each commodity to a one unit shock in carbon prices. Since orthogonalized IRFs are sensitive to variable ordering, the generalized IRF proposed by Pesaran and Shin (1998) is used to obtain order invariant responses.

Forecast Error Variance Decomposition complements the IRF results by quantifying the proportion of each commodity's forecast variance attributable to carbon price shocks. FEVD is derived from the moving average representation of the VAR model, following the approach outlined by Lütkepohl (2005), and highlights the relative importance of carbon innovations across different horizons.

Together, the IRF and FEVD provide a structural interpretation of carbon commodity interactions within the EU ETS, allowing an assessment of both short run and medium run transmission channels. Since no VAR model is estimated for Indonesia, IRF and FEVD analysis is performed only for the European dataset.

4. RESULTS

This section presents the empirical results for Indonesia and the European Union. The analysis is organized to reflect the distinct characteristics of the two markets: A newly established carbon market with limited trading activity in Indonesia, and a mature and highly integrated system in the EU ETS. For each market, the results begin with descriptive properties, followed by correlation patterns, clustering outcomes, and RMT diagnostics. For the EU ETS, the analysis is extended to include rolling RMT and VAR to capture dynamic interactions and transmission channels. The findings collectively reveal the extent to which carbon prices are connected to food, energy, and mineral commodities in each region.

4.1. Domestic Market Results (Indonesia)

The domestic results summarize the behavior of Indonesia's carbon market and its relationship with major food, energy, and mineral commodities. Given the short sample length and the structural features of the Indonesian economy, the analysis focuses on descriptive patterns, volatility characteristics, correlation structure, clustering behavior, and static RMT diagnostics. These tools reveal whether meaningful co-movement exists between carbon prices and domestic commodity groups, or whether observed variation is largely noise driven. The subsections below present the empirical findings in a stepwise manner, beginning with descriptive statistics and followed by correlation- and RMT-based assessments.

4.1.1. Descriptive statistics

The descriptive statistics in Table 2 show that carbon prices exhibit relatively high volatility, consistent with the early stage development and low liquidity of the IDX Carbon market. Staple food commodities (GKP, GKG, and rice categories) display low standard deviations due to strong price regulation, while horticultural commodities such as chili and shallots exhibit substantial volatility driven by seasonal supply shocks. Energy and mineral commodities show moderate variability in line with partial exposure to global markets.

Overall, the heterogeneous volatility structure provides no indication of systematic co movement between carbon and other commodities, motivating the use of correlation and RMT based techniques in the subsequent sections.

4.1.2. Correlation analysis

Figure 1 show Pearson correlations between carbon prices and major commodities are uniformly weak, indicating that short-term price movements in the domestic carbon market are largely independent from food, energy, and mineral price dynamics. Staple food commodities exhibit near-zero correlations due to regulated pricing and government intervention, while slightly higher but still modest associations appear in the energy and mineral groups. Overall, the correlation structure suggests that Indonesia's carbon market has not yet developed meaningful linkages with broader commodity systems.

Figure 2 show that Spearman correlations confirm that even monotonic relationships with carbon are negligible. This consistency across correlation measures indicates that the weak co movement is structural rather than driven by outliers or nonlinear effects.

Figure 1: Pearson correlation matrix of domestic commodity log-returns

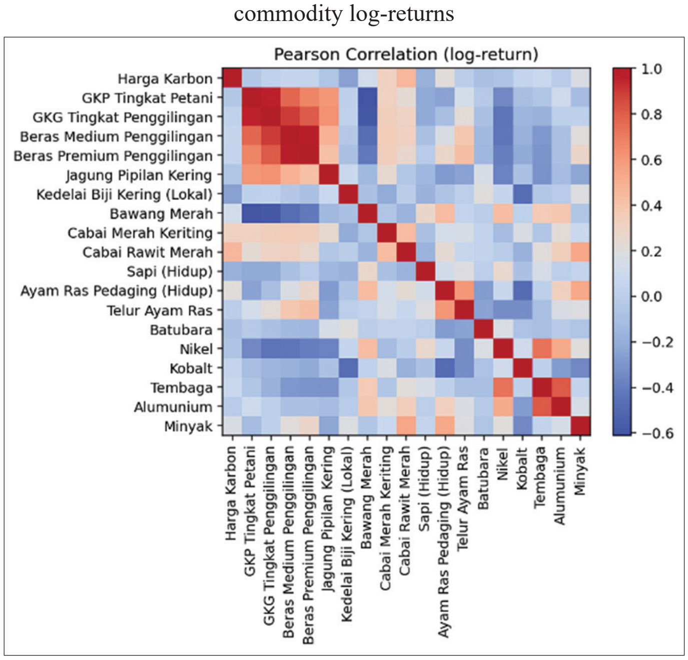


Figure 3 show that Shrinkage estimation compresses noisy correlations toward zero, revealing that several weak associations observed in the Pearson and Spearman matrices were primarily sampling artifacts. This provides strong confirmation that the domestic carbon market is not yet integrated into broader commodity price dynamics and that the observed independence is structural rather than measurement-driven.

4.1.3. Hierarchical clustering

The dendrogram in Figure 4 shows a highly fragmented clustering structure with large linkage distances, indicating that carbon prices do not form meaningful clusters with food, energy, or mineral commodities. This reflects the absence of shared underlying factors driving co-movement.

Figure 2: Spearman rank correlation matrix of domestic log-returns

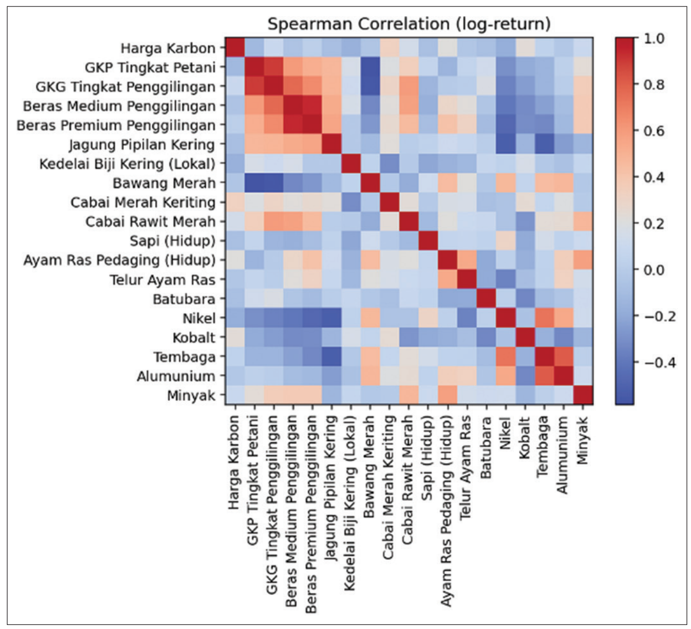


Figure 3: Ledoit–Wolf shrinkage correlation matrix

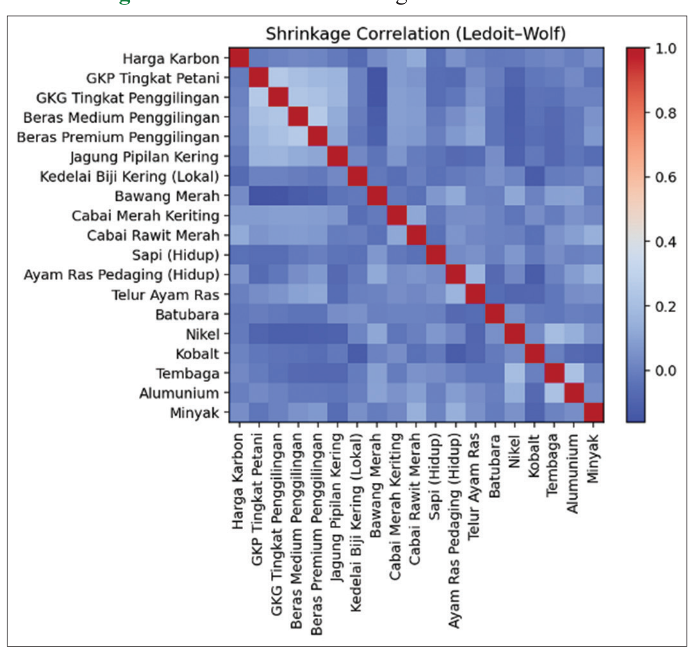


Figure 4: Hierarchical clustering of domestic commodity log-returns

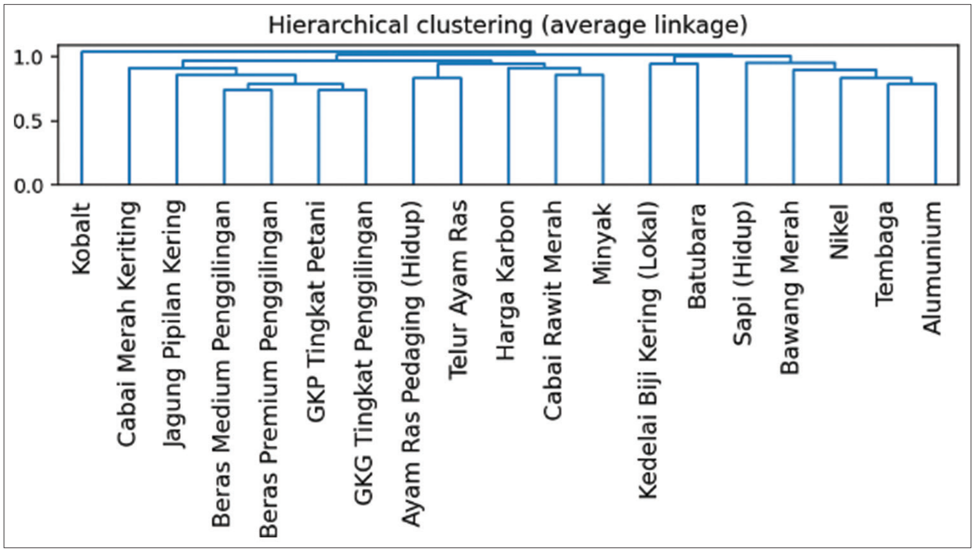


Figure 5: Clustered shrinkage heatmap

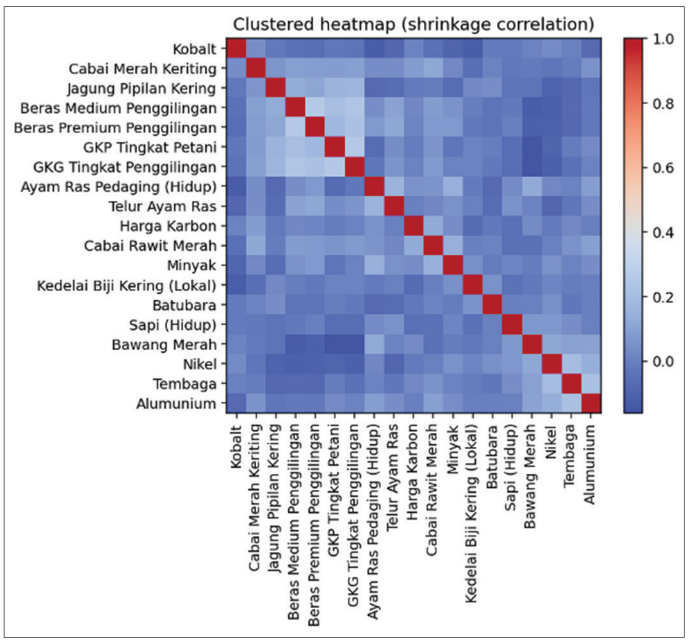


Figure 6: Eigenvalue distribution with Marchenko–Pastur bounds

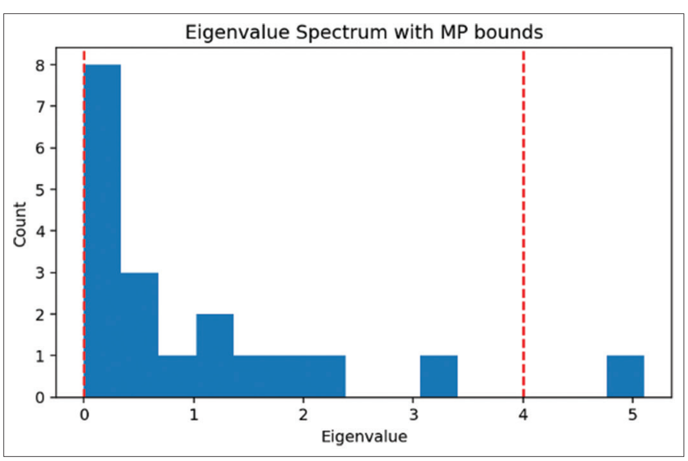
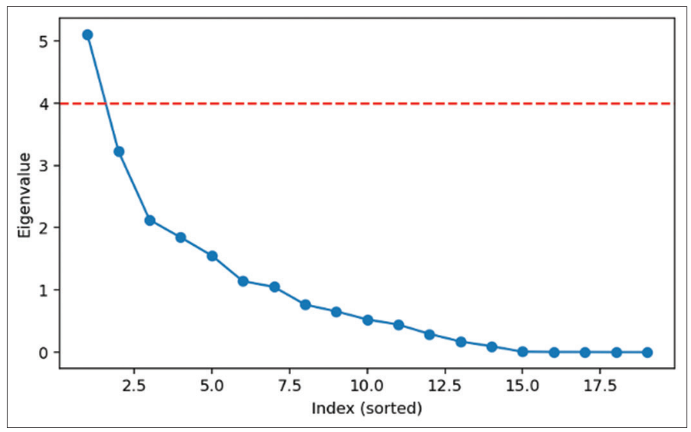


Figure 7: Scree plot of domestic eigenvalues



The clustered heatmap in Figure 5 further confirms that no block structure emerges around the carbon price after reordering, reinforcing the conclusion that the domestic market lacks systemic integration across commodity groups.

4.1.4. Random matrix theory (RMT)

Figure 6 shows that nearly all eigenvalues lie within the theoretical Marchenko–Pastur bounds, indicating that the domestic correlation matrix is largely dominated by noise. The first eigenvalue exceeds the upper bound only marginally and therefore does not capture a meaningful market-wide factor.

The scree plot similarly shows a weak leading eigenmode followed by a smooth decay, suggesting that commodity price fluctuations are primarily idiosyncratic rather than driven by common underlying forces.

Figure 8 show noise filtering reveals only mild and localized clustering among a few food commodities, while the carbon price remains independent from all major commodity groups.

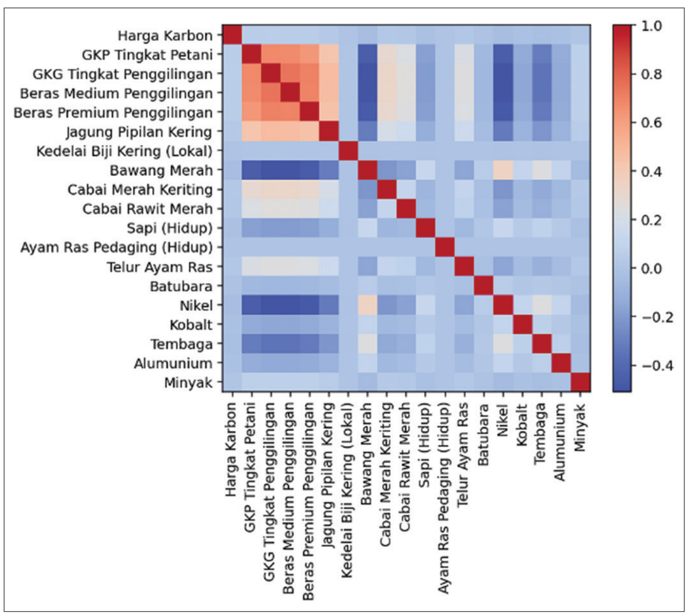
Across all analytical methods, including correlation measures, shrinkage estimation, hierarchical clustering, and RMT, the

Indonesian carbon price shows no meaningful co movement with food, energy, or mineral commodities. This pattern reflects the highly regulated nature of the food sector, the partially insulated structure of domestic energy markets, and the limited depth and liquidity of the newly established IDX Carbon system.

4.2. International Market Results

The international analysis focuses on the European Union Emissions Trading System, a mature and highly liquid carbon market that interacts closely with global energy and commodity dynamics. Unlike the fragmented and noise dominated structure observed in Indonesia, the EU ETS exhibits stronger co movement patterns and clearer systemic relationships due to deeper market integration, established price discovery mechanisms, and more diversified exposure to global shocks. This section presents the empirical results for Europe, beginning with descriptive characteristics and followed by correlation patterns, clustering structures, RMT diagnostics, and dynamic interactions captured through rolling RMT and VAR. Together, these results provide a comprehensive view of how carbon prices transmit through energy, food, and mineral markets in an advanced trading environment.

Figure 8: RMT-denoised correlation matrix



4.2.1. Rolling maximum eigenvalue

To examine the time varying structure of global commodity co movements, Figure 9 plots the rolling maximum eigenvalue λ_{max} (t) together with the theoretical Marchenko–Pastur upper bound. The empirical series frequently exceeds this threshold, indicating the persistent presence of a dominant global market factor.

A pronounced increase in λ_{max} (t) occurs during 2021-2023, coinciding with the European natural gas crisis and the Russia–Ukraine conflict. This period is characterized by strong market wide synchronization across energy, metal, and agricultural commodities. After mid 2023, the maximum eigenvalue declines but remains above the theoretical limit, suggesting a continued, although weaker, degree of systemic co movement. In contrast with Indonesia, the international market exhibits a robust and dynamically evolving dominant factor that reflects deeper integration and greater exposure to global shocks.

4.2.2. Systemic risk index (SRI)

The systemic risk index in Figure 10 measures the number of eigenvalues in each rolling window that exceed the theoretical Marchenko–Pastur upper bound. Eigenvalues above this threshold capture informative components that reflect genuine market structure rather than random noise.

The SRI indicates three distinct regimes. The period 2018-2019 reflects moderate market integration, followed by a temporary collapse in co movement during the early stages of the COVID 19 shock. A sharp rise in systemic risk emerges during 2021-2023, driven by energy shortages and heightened geopolitical tensions. Although the index declines after 2023, values remain consistently above one, indicating a persistent multi factor structure. In contrast with Indonesia, where informative eigenvalues are largely absent, the global market displays strong and sustained systemic linkages.

4.2.3. Evolution of the eigenvalue spectrum

Figure 11 displays the rolling eigenvalue spectrum normalized by the theoretical Marchenko–Pastur upper bound. Values >1 indicate the presence of informative eigencomponents that reflect genuine market structure.

The heatmap reveals a consistently informative dominant eigenvalue, accompanied by a noticeable strengthening of secondary eigenvalues during 2021-2023. Several mid ranking eigenvalues

Figure 9: Rolling maximum eigenvalue compared with the MP upper bound

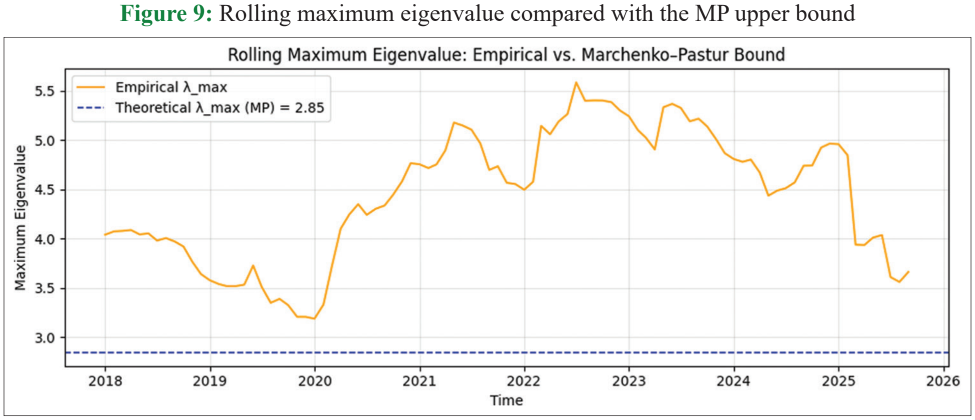


Figure 10: Systemic risk index for the global commodity system

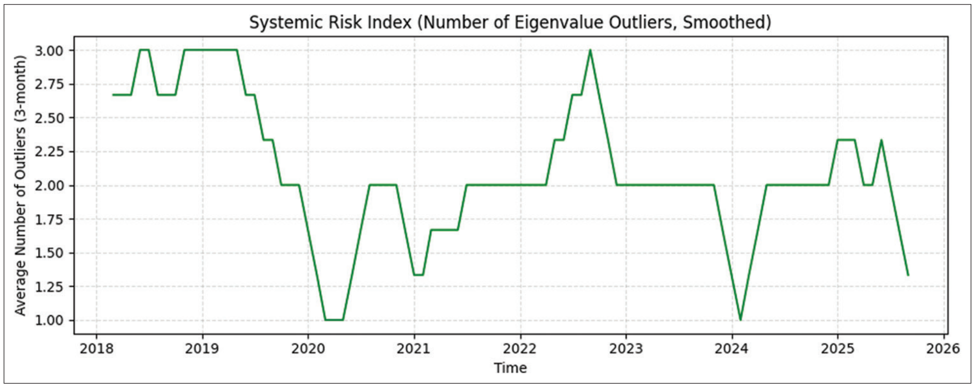
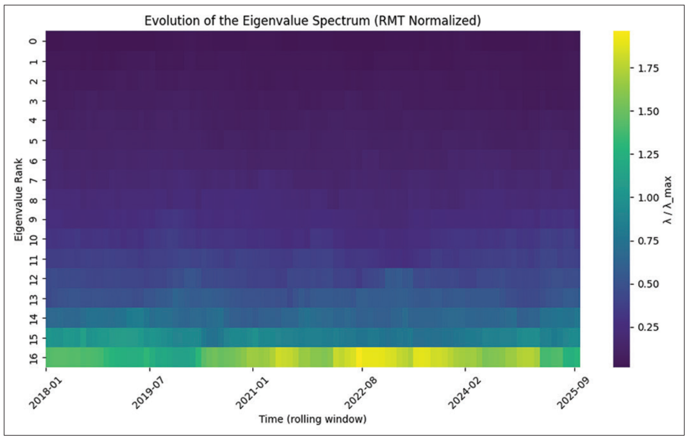


Figure 11: Evolution of the normalized eigenvalue spectrum



(approximately ranks 2-6) rise above the threshold during this period, indicating the activation of multiple systemic forces across energy, metal, and agricultural markets. After 2023, the spectrum gradually weakens as energy market pressures ease, although several components remain informative. In contrast with the shallow and noise dominated spectrum observed in Indonesia, the global market exhibits a multi layered and dynamically evolving structure characteristic of a mature and highly integrated commodity system.

4.2.4. VAR analysis

A VAR model is estimated to quantify dynamic linkages between carbon prices and major global commodities. The model is applied only to the international dataset because the Indonesian series is too short for reliable multivariate estimation.

4.2.4.1. Variable selection

The system includes carbon prices (EU ETS), crude oil, natural gas, wheat, and copper. These commodities represent key economic channels affecting carbon price formation, including energy input costs, fuel switching behavior, agricultural supply conditions, and industrial activity (Ellerman et al., 2016; Hintermann, 2010; Reboredo, 2015; Nazlioglu and Soytas, 2011).

4.2.4.2. Stationarity tests

All variables are converted into log returns. Augmented Dickey–Fuller (ADF) tests in Table 3 indicate that all series are stationary at the 0.01 significance level.

4.2.4.3. Lag length determination

The lag order selection results are reported in Table 4. Information criteria select a one period lag as the optimal specification. Both the Akaike Information Criterion (AIC) and the Final Prediction Error favor (FPE) VAR(1).

4.2.4.4. Diagnostic checks

Table 5 reports the diagnostic checks for the VAR(1) model. The VAR(1) model is stable, with all eigenvalues inside the unit circle. Residual diagnostics indicate no serial correlation (Durbin–Watson (DW) statistics near 2). Non normality is expected for commodity returns and does not reduce the validity of linear propagation analysis.

4.2.5. Impulse response functions (IRF)

Figure 12 shows that impulse responses provide insight into how carbon price innovations propagate across major global commodities. A positive carbon shock generates the strongest reaction in natural gas prices, reflecting the central role of gas in the fuel switching mechanism within the EU ETS. Crude oil and wheat display mild and short lived responses, while copper exhibits an almost negligible reaction. The weak responses outside the energy sector indicate that carbon price dynamics are transmitted primarily through energy costs rather than agricultural or industrial channels.

4.2.6. Forecast error variance decomposition (FEVD)

Forecast error variance decomposition quantifies the contribution of each commodity to carbon price uncertainty at different horizons. In the very short run, carbon price fluctuations are entirely self driven, indicating that immediate variation in carbon returns is dominated by market-specific factors. At horizon 2, crude oil becomes the primary external contributor, reflecting short-term energy market spillovers. At horizon 3, natural gas dominates the variance decomposition, consistent with its central role in the fuel switching mechanism of the EU ETS. Wheat emerges as the main contributor at horizon 4, which may reflect geopolitical influences on global agricultural markets. At horizon 5, copper becomes the leading driver, capturing longer-run industrial and macroeconomic dynamics.

Figure 12: IRFs of crude oil, natural gas, wheat, and copper to a carbon price shock

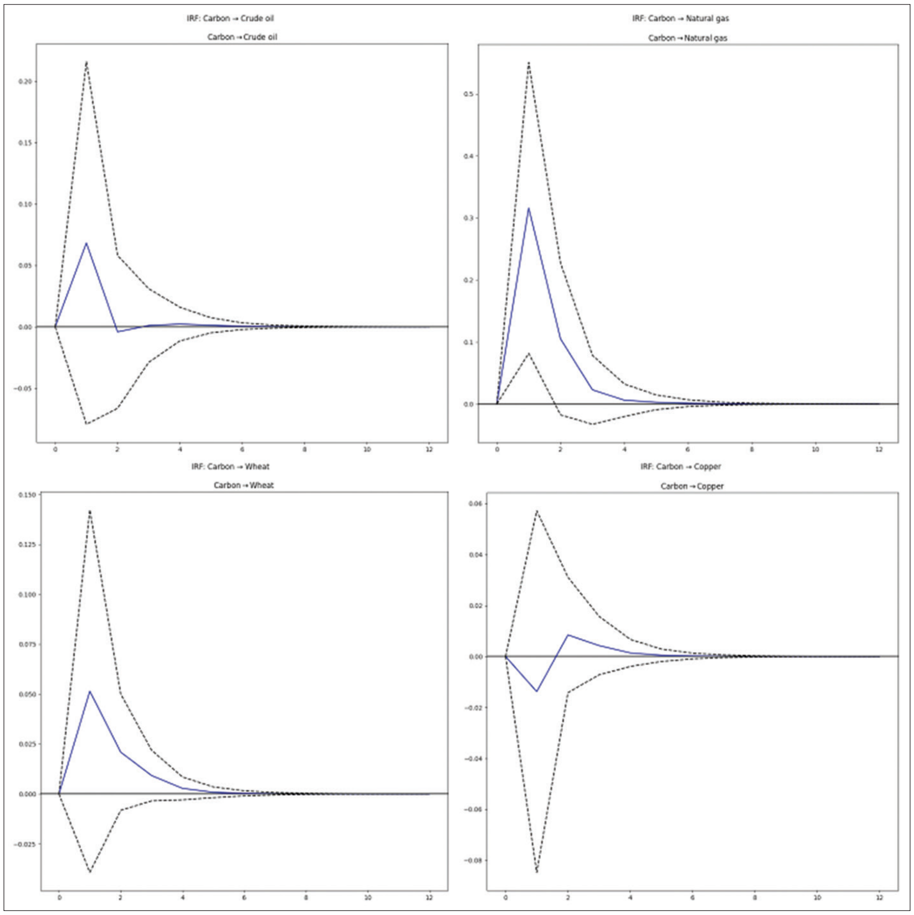


Table 2: Descriptive statistics of domestic commodity prices

Variable	Mean	Std Dev	Min	Max
Harga Karbon	62590.0000	14710.3792	46000.000	112050.000
GKP Tingkat Petani	6504.9000	302.3590	5878.000	7104.000
GKG Tingkat Penggilingan	7588.4500	332.3696	6978.000	8208.000
Beras Medium Penggilingan	12488.0000	438.8613	11872.000	13280.000
Beras Premium Penggilingan	13899.6000	333.8984	13426.000	14554.000
Jagung Pipilan Kering	4871.2000	655.5696	4073.000	6762.000
Kedelai Biji Kering (Lokal)	9799.8000	709.2760	8987.000	11243.000
Bawang Merah	23666.1000	5140.1839	15119.000	33485.000
Cabai Merah Keriting	30277.1500	8881.8255	16045.000	46992.000
Cabai Rawit Merah	38335.5000	11106.2176	25397.000	64895.000
Sapi (Hidup)	52306.7000	359.9269	51566.000	52972.000
Ayam Ras Pedaging (Hidup)	21677.1000	1112.0318	19840.000	23594.000
Telur Ayam Ras	24668.8000	786.6624	23415.000	26635.000
Batubara	118.5135	9.1974	99.790	131.170
Nikel	16284.5048	1159.4932	14934.335	18962.110
Kobalt	28055.3390	3643.6130	22158.000	33267.695
Tembaga	9218.8100	537.4743	8313.830	9978.750
Alumunium	2443.2198	163.5367	2154.070	2666.070
Minyak	74.5975	6.5373	62.750	87.610

Indonesian variable names follow the original terminology used by the National Food Agency, the Ministry of Energy and Mineral Resources, and IDX Carbon

Table 3: ADF test on log returns

Variable	ADF statistic	P-value
Carbon	−11.814	(8.72×10^{-22})
Crude oil	−8.683	(4.23×10^{-14})
Natural gas	−8.073	(1.54×10^{-12})
Wheat	−10.110	(1.01×10^{-17})
Copper	−3.674	(4.49×10^{-3})

4.2.7. Summary of global VAR results

Overall, the global VAR analysis demonstrates that carbon price dynamics are shaped by a combination of short-run energy shocks and medium-run industrial forces. Crude oil accounts for most of the short-horizon variation in carbon returns, reflecting the sensitivity of carbon prices to immediate movements in global energy costs. At intermediate horizons, natural gas emerges as the dominant driver, consistent with the central role of gas in the fuel switching mechanism embedded in the EU ETS. At longer horizons, copper becomes increasingly influential, indicating that carbon prices also incorporate broader industrial and macroeconomic conditions associated with metal-intensive production and investment cycles. The impulse response functions reinforce these patterns: carbon shocks transmit strongly to natural gas, with comparatively modest spillovers to agricultural commodities and non-ferrous metals.

Table 4: VAR lag order selection

Lag	AIC	BIC	FPE	HQIC
0	−24.51	−24.40	(2.262×10^{-11})	−24.47
1	−24.64	−23.95	(1.992×10^{-11})	−24.36

Table 5: Diagnostic checks for VAR (1) model

Variable	DW	JB	P-value
Carbon	2.03	4.39	0.111
Crude oil	1.83	125.16	0.000
Natural gas	2.16	19.76	0.000
Wheat	2.05	23.44	0.000
Copper	1.93	20.97	0.000

Table 6: FEVD of carbon price forecast error variance

Horizon	Carbon	Crude oil	Natural gas	Wheat	Copper
1	1.000	0.000	0.000	0.000	0.000
2	0.055	0.945	0.000	0.000	0.000
3	0.001	0.008	0.992	0.000	0.000
4	0.002	0.001	0.000	0.996	0.000
5	0.011	0.115	0.002	0.023	0.848

Taken together, the FEVD and IRF results depict a carbon market that is highly intertwined with global energy dynamics and, to a lesser extent, with industrial activity. These findings align closely with the RMT-based evidence. The international commodity system exhibits a multi-layered eigenvalue structure, persistent systemic risk, and strong cross-market integration, reflecting its maturity, liquidity, and exposure to global shocks. In contrast, the Indonesian domestic system remains weakly connected, dominated by noise, and characterized by minimal inter-commodity linkages. This divergence highlights the structural differences between an established carbon trading scheme such as the EU ETS and an emerging platform like IDX Carbon, where limited liquidity, regulatory insulation, and shallow market depth restrict the formation of systemic price relationships.

4.3. Comparative Analysis: Indonesia versus European Markets

Table 7 provides a comparative summary of the key differences in carbon–commodity dynamics between Indonesia and the European

Table 7: Comparative summary of indonesia and european carbon–commodity dynamics

Dimension	Indonesia (emerging market)	European union (mature market)
Systemic structure (RMT)	• Nearly all eigenvalues lie within the Marchenko–Pastur bounds. • First eigenvalue only slightly above the upper limit. • Correlation matrix dominated by noise, indicating no persistent market-wide factor.	• Rolling maximum eigenvalue frequently exceeds the theoretical bound. • Strong and time-varying dominant factor. • Multiple informative eigencomponents active (high SRI values).
Eigenvalue spectrum (Dynamic RMT)	• Shallow spectrum with no meaningful deviations. • RMT-denoised matrix shows fragmented and unstructured relationships.	• Wide high-value bands in the eigenvalue spectrum, especially during 2021-2023. • Spectrum expands during geopolitical stress (European gas crisis, Russia–Ukraine conflict).
Clustering/market connectivity	• No stable clusters around carbon. • Food staples tightly regulated, showing minimal variation. • Energy and mineral commodities weakly connected to carbon.	• Energy commodities (natural gas, crude oil, coal) display synchronized behavior. • Metals (especially copper) correlate with industrial activity. • Carbon moves within a cohesive, multi-commodity system.
Correlation behavior	• Pearson, Spearman, and shrinkage correlations mostly near zero. • Weak or absent co-movement across commodity groups.	• Stronger and persistent correlations across energy, metals, and agricultural commodities. • Clear evidence of cross-market integration.
Dynamic transmission (VAR/IRF/FEVD)	• VAR not feasible due to short sample. • No identified transmission channels.	• Carbon shocks strongly affect natural gas (fuel-switching mechanism). • Mild, short-lived effects on oil, wheat, and copper. • Reverse effects show oil has limited influence on carbon. • FEVD: crude oil (short run), natural gas (medium run), copper (long run).
Market maturity & structure	• Early-stage IDX Carbon market. • Limited liquidity and market participation. • Strong regulatory insulation (especially food prices).	• Deep, liquid EU ETS with established trading activity. • Integrated with energy and industrial systems. • Exposed to global shocks and geopolitical events.
Overall conclusion	Weakly integrated, noise-dominated system with minimal inter-commodity linkages.	Highly integrated, dynamically evolving system with strong cross-market transmission channels.

Union across systemic structure, market connectivity, and dynamic transmission mechanisms.

5. DISCUSSION

This section integrates the domestic and international results to provide broader economic interpretation, theoretical implications, and policy relevance. By contrasting an emerging carbon market (Indonesia) with a mature and highly integrated system (EU ETS), the findings highlight how institutional structures and market maturity shape carbon–commodity linkages.

5.1. Synthesis of Key Findings

Three central insights emerge from the analysis. First, the Indonesian commodity system shows almost no co-movement with domestic carbon prices across all correlation measures, clustering outputs, and RMT diagnostics. The eigenvalue spectrum remains within the Marchenko–Pastur bounds, which indicates that observed correlations are largely driven by noise. No latent market factors appear to connect carbon with food, energy, or mineral commodities.

Second, the global system represented by EU ETS carbon prices and major commodity benchmarks exhibits a clear multi-layered pattern of co-movement. Rolling RMT identifies strong systemic factors during periods of global stress such as the European energy crisis and the Russia and Ukraine conflict. The presence of multiple outlier eigenvalues confirms the existence of an integrated international market where shocks propagate across energy, agriculture, and metal commodities.

Third, the VAR analysis shows that carbon price dynamics in the EU ETS are driven mainly by energy markets. Natural gas has the strongest influence, followed by smaller and shorter-lived effects from crude oil, wheat, and copper. At longer horizons, copper gains importance through its connection with industrial and macroeconomic activity.

5.2. Economic Interpretation

The contrast between Indonesia and Europe reflects fundamental differences in price formation. In Indonesia, food prices are tightly regulated, energy prices are partially insulated from international movements, and the IDX Carbon market remains thin and strongly policy-driven. These characteristics suppress co-movement and limit the role of carbon prices as a market signal.

In the EU ETS, natural gas frequently sets the marginal cost of electricity. As a result, gas prices affect generation decisions and the demand for carbon allowances. Industrial metals influence carbon dynamics through the energy-intensive nature of manufacturing and the sensitivity of carbon prices to global business cycles. Agricultural commodities show only occasional links to carbon prices, with wheat influenced mainly by conflict-related supply disruptions rather than long-term climate or agricultural mechanisms.

5.3. Theoretical and Methodological Contributions

The findings reinforce three theoretical points. First, the strength of carbon and commodity linkages depends greatly on market maturity and institutional settings. Second, fuel switching is a central mechanism that shapes carbon price dynamics in the EU ETS. Third, RMT and rolling eigenvalue methods are effective tools for distinguishing meaningful structure from noise, especially in short or heavily regulated markets.

Methodologically, the combined use of RMT, rolling eigenvalue tracking, hierarchical clustering, and VAR provides complementary insights. RMT identifies the underlying systemic structure, rolling analysis captures its evolution, and VAR quantifies the direction and magnitude of transmission channels. Together, these methods offer a more complete characterization of carbon commodity relationships than any single technique.

5.4. Policy Implications

For Indonesia, the limited integration across commodities suggests that short-term carbon price volatility poses little risk to food or energy stability. Policymakers therefore have space to continue developing the carbon market without immediate concern about spillovers. At the same time, the absence of meaningful linkages indicates that the carbon price has not yet become an effective driver of emissions reduction. Increasing liquidity, expanding sectoral coverage, and aligning carbon pricing with broader energy planning will be necessary for stronger market-based incentives.

For the European Union, the strong dependence on natural gas highlights the vulnerability of the EU ETS to geopolitical disruptions and energy supply shocks. Ensuring carbon price stability requires closer coordination between climate policy and energy security. The rising influence of industrial metals at longer horizons implies that decarbonization strategies must also account for wider industrial and macroeconomic conditions.

5.5. Limitations and Future Research

Limitations include the short sample available for Indonesia, differences in market structures across regions, and the reduced ability to apply advanced multivariate models in the domestic context. Future work may extend the analysis as the IDX Carbon market matures, incorporate structural VAR or network-based spillover models, and compare Indonesia with other emerging carbon markets in Asia. The use of higher-frequency data could also improve the assessment of systemic risk and transmission dynamics.

6. CONCLUSION

This study examined the relationship between carbon prices and major commodity groups in Indonesia and Europe by combining correlation-based methods, hierarchical clustering, RMT, rolling-window eigenvalue analysis, and VAR. Using monthly data from 2024 to 2025 for Indonesia and from 2015 to 2025 for global markets, the analysis provides a comprehensive assessment of systemic structure, co-movement, and dynamic transmission mechanisms in both emerging and mature carbon markets.

The empirical evidence reveals a clear divergence between the two systems. In Indonesia, carbon prices show no meaningful integration with food, energy, or mineral commodities. All correlation measures remain weak, hierarchical clustering yields no stable grouping around carbon, and the eigenvalue spectrum lies almost entirely within the Marchenko–Pastur bounds. These patterns indicate that the Indonesian commodity system is characterized by idiosyncratic and noise-driven dynamics. This behavior is consistent with strong regulation in food markets, partial insulation of energy prices, and the early-stage development of the IDX Carbon market.

In contrast, the European system displays a well-organized and time-varying structure of co-movement. Rolling RMT identifies persistent systemic factors that intensify during global shocks such as the European energy crisis and the Russia and Ukraine conflict. The VAR results confirm natural gas as the dominant transmission channel influencing carbon price dynamics, with crude oil contributing to short-horizon uncertainty and copper affecting longer-run movements through industrial conditions. These findings align with the fuel-switching mechanism in the European electricity sector and reflect the deeper integration of energy and industrial markets within the EU ETS.

Taken together, the results show that carbon price transmission is highly dependent on institutional context and market maturity. In emerging markets such as Indonesia, carbon prices currently operate in relative isolation from broader commodity systems, which suggests that short-term fluctuations in carbon prices pose limited risks to food or energy price stability. In mature systems such as the EU ETS, strong interactions with natural gas and industrial metals indicate that carbon pricing is closely linked to energy security, market volatility, and macroeconomic forces.

Future research may extend the Indonesian analysis as the carbon market develops further and more data become available. Additional work could incorporate structural VAR, network-based spillover models, or comparisons with other emerging carbon markets in Asia. The use of higher-frequency or sector-specific data may also improve the understanding of systemic risk and transmission channels as Indonesia's market evolves.

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REFERENCES

Aatola, P., Ollikainen, M., Toppinen, A. (2013), Price determination in the EU ETS market. Energy Economics, 36, 380-395.

Asian Development Bank. (2021), Asian Development Outlook 2021: Financing a Green and Inclusive Recovery. Manila: Asian Development Bank. Available from: https://www.adb.org/publications/asian-development-outlook-2021 [Last accessed on 2025 Sept 07].

Bank Indonesia. (2024), Laporan Perekonomian Indonesia 2023. Jakarta: Bank Indonesia. Available from: https://www.bi.go.id/id/publikasi/laporan/pages/lpi-2023.aspx [Last accessed on 2025 Sep 07].

Biancalani, F., Gnecco, G., Metulini, R., Riccaboni, M. (2024), The impact of the EU ETS on carbon emissions: A matrix completion analysis. Scientific Reports, 14, 19676.

Ellerman, A.D., Marcantonini, C., Zaklan, A. (2016), The European Union emissions trading system: Ten years and counting. Review of Environmental Economics and Policy, 10(1), 89-107.

FAO, IFAD, UNICEF, WFP, WHO. (2022), The State of Food Security and Nutrition in the World 2022: Repurposing Food and Agricultural Policies to Make Healthy Diets More Affordable. Rome: FAO. Available from: https://doi.org/10.4060/cc0639en [Last accessed on 2025 Sep 03].

Financial Services Authority. (2023), Financial Services Authority Regulation Number 14 of 2023 Concerning Carbon Trading Through Carbon Exchanges. Jakarta: Otoritas Jasa Keuangan (OJK).

Gunther, C., Löschel, A., Ziegler, M. (2024), Carbon prices on the rise? Shedding light on the emerging second EU ETS. Climate Policy, 24(1), 1-15.

Hammoudeh, S., Nguyen, D., Sousa, R. (2014), Energy prices and CO_2 emission allowance prices. Energy Policy, 70, 201-206.

Hintermann, B. (2010), Allowance price drivers in the first phase of the EU ETS. Journal of Environmental Economics and Management, 59(1), 43-56.

Huang, S., Du, C., Jin, X., Zhang, D., Wen, S., Jia, Z. (2023), The impact of carbon emission trading on renewable energy: A comparative analysis based on the CGE model. Sustainability, 15(16), 12649.

IDX Carbon. (2025), IDX Carbon Trading Data. Jakarta: Indonesia Stock Exchange. Available from: https://idxcarbon.co.id [Last accessed on 2025 Sep 12].

Indonesia Stock Exchange. (2023), Bursa Karbon Indonesia (IDXCarbon) Resmi Diluncurkan. Press Release No: 086/BEI.SPR/09-2023. Jakarta: Indonesia Stock Exchange. Available from: https://www.idx.co.id [Last accessed 2025 Sep 07].

Investing.com. (2025), EU Allowance Futures Historical Data. Available from: https://www.investing.com/commodities/carbon-emissions-historical-data [Last accessed on 2025 Sep 25].

IPCC. (2021), Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press. Available from: https://www.ipcc.ch/report/ar6/wg1 [Last accessed on 2025 Sep 12].

Kirikkaleli, D., Darbaz, I. (2021), The causal linkage between energy price and food price. Energies, 14(14), 4182.

Ledoit, O., Wolf, M. (2004), A well-conditioned estimator for large-dimensional covariance matrices. Journal of Multivariate Analysis, 88(2), 365-411.

Lütkepohl, H. (2005), New Introduction to Multiple Time Series Analysis. Berlin: Springer-Verlag.

Lyu, J., Li, Z., Zhou, W., Xu, S. (2025), Risk spillover between the carbon market and financial market in China. Management System Engineering, 4, 5.

Mantegna, R.N. (1999), Hierarchical structure in financial markets. The European Physical Journal B, 11(1), 193-197.

Marchenko, V.A., Pastur, L.A. (1967), Distribution of eigenvalues for some sets of random matrices. Mathematics of the USSR-Sbornik, 1(4), 457-483.

Ministry of Energy and Mineral Resources. (2023), Handbook of Energy and Economic Statistics of Indonesia 2023. Jakarta: Ministry of

Energy and Mineral Resources. Available from: https://www.esdm.go.id [Last accessed on 2025 Sep 15].

Ministry of Energy and Mineral Resources. (2025), Energy and Mineral Commodity Price Data. Jakarta: Ministry of Energy and Mineral Resources. Available from: https://www.esdm.go.id [Last accessed on 2025 Sep 27].

National Food Agency. (2025), Food Price Panel. Jakarta: National Food Agency of the Republic of Indonesia. Available from: https://panelharga.badanpangan.go.id [Last accessed on 2025 Sep 28].

Nazlioglu, S., Erdem, C., Soytas, U. (2013), Volatility spillover between oil and agricultural commodity markets. Energy Economics, 36, 658-665.

Nazlioglu, S., Soytas, U. (2011), World oil and agricultural commodity prices: Evidence from nonlinear causality. Energy Policy, 39(5), 2935-2943.

Oestreich, A., Tsiakas, I. (2015), Carbon emissions and stock returns. Journal of Banking and Finance, 58, 294-308.

Olasehinde-Williams, G., Akadiri, S.S., Sambou, M. (2025), A quantile panel-type analysis of the relationship between carbon price and energy inflation in the EU-27. Energy Research Letters, 6, 132428.

Pesaran, M.H., Shin, Y. (1998), Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1), 17-29.

Reboredo, J.C. (2015), Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics, 48, 32-45.

Reboredo, J.C. (2018), Green bonds and financial markets: Co-movement and price spillovers effect. Energy Economics, 74, 38-50.

Serra, T., Zilberman, D. (2013), Biofuel-related price transmission literature: A review. Energy Economics, 37, 141-151.

Stern, N. (2007), The Economics of Climate Change: The Stern Review. Cambridge: Cambridge University Press.

Taghizadeh-Hesary, F., Rasoulinezhad, E., Yoshino, N. (2018), Volatility Linkages between Energy and Food Prices: Case of Selected Asian Countries. ADBI Working Paper, No. 829. Tokyo: Asian Development Bank Institute.

Tao, M., Poletti, S., Sheng, M., Wen, L. (2024), Nexus between carbon, stock, and energy markets in New Zealand: An analysis of causal domains. Energy, 299, 131409.

Wang, J., Zeng, R., Wang, L. (2024), Volatility spillover between the carbon market and traditional energy market using the DGC-t-MSV model. Mathematics, 12(23), 3789.

World Bank. (2022), State and Trends of Carbon Pricing 2022. Washington, DC: World Bank. Available from: https://openknowledge.worldbank.org/handle/10986/37455 [Last accessed on 2025 Sep 25].

World Bank. (2025), Commodity Markets: Pink Sheet Data. Washington, DC: World Bank. Available from: https://www.worldbank.org/commodities [Last accessed on 2025 Sep 25].

Zhang, Y.J., Liang, T., Jin, Y.L., Shen, B. (2020), The impact of carbon trading on economic output and carbon emissions reduction in China's industrial sectors. Applied Energy, 260, 114290.

Zhao, Z., Lau, C.K.M., Soliman, A., Farhani, S. (2023), Energy commodity and stock market interconnectedness: Evidence from carbon emission trading system. Technological Forecasting and Social Change, 194, 122669.

Zhou, P., Li, X., Shi, X., Jiang, K. (2025), Spillover of the carbon risk along the supply chain: Evidence from the U.S. Corporate bond market. Journal of Business Research, 201(C), 115742.