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Clustering and Volatility Spillovers in Steel-Related Commodity Markets: Evidence from US Producer Prices and Global Metal Indices

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Abstract

This research examines the clustering structure and volatility spillover among steel-related products in monthly data from July 2004 to September 2025. Using various clustering methods, K-means, hierarchical techniques and market network analysis with correlations, four distinct marketing clusters have been identified: (1) US (United States) steel products, (2) global cyclical raw materials, (3) US iron ore market, and (4) global base metals. The overall volatility spillover index stands at 15.39%, exhibiting significant dynamics that vary over time, driven by major economic events, including the 2008 global financial crisis, the 2015 Chinese currency devaluation, the COVID-19 outbreak, the 2022 Ukrainian conflict, and the 2025 Trump trade tariffs. The primary driver of volatility in global trade is US carbon steel wire prices, while the largest net recipient of volatility shocks is the global copper price. These findings have key implications for understanding the global interconnectedness of steel markets in the current context.

Keywords: steel markets; clustering analysis; volatility spillovers; commodity prices; network analysis; market connectedness; trade policy

1. Introduction

One of the world's core industries is the global steel industry, which plays a vital role by providing the backbone for the construction, automotive, infrastructure, and manufacturing sectors. Investors, policymakers, and industry stakeholders need to understand the structural and transmission mechanisms of volatility in steel-related commodity markets, given that the actual operation and/or integration of interests across different markets has made the issue of interconnectedness important in a world of global supply chains and increasing economic uncertainty [1,2].

Over the last two decades, the steel market has experienced considerable structural changes. China's rapid industrialization transformed the global landscape of steel, positioning the country as the world's largest producer and consumer of steel products [3], as evolving market dynamics, including environmental regulations, trade policies, and technological innovations, have progressively altered the interactions among steel-related commodities [4]. Most recently, protectionist trade policies, of which the comprehensive

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tariff measures taken by the Trump administration in 2025 are the apex, have brought in new uncertainties and may potentially split the market [5].

The literature has generally focused on how market linkage and spillovers could take place across an array of commodities. The approach developed by [6,7] is the most influential one in the literature. This is a very widely used system in risk-bearing pattern evaluation in commodity markets [8,9]. There has been limited research interest in the steel-related markets in comparison to their economic importance. Therefore, clustering techniques have focused on these market fields, identifying market segments and their distinctive behavioral characteristics [10,11].

This paper adds to the existing literature by offering an integrated examination of steel-related commodity markets, where clustering methods are combined with a volatility spillover framework to uncover underlying market dynamics. We analyzed market segmentation clusters using K-means, hierarchical clusters, and correlation measures. Moreover, a volatility spillover analysis is performed by employing the rolling-window technique to capture the time-varying interaction of variables. Our dataset encompasses data of nine variables taken from the Producer Price Indices (PPI) of US and global commodity prices from July 2004 to September 2025.

Taken together, the results expand upon existing research in three key ways. First, to our knowledge, this is the first study to integrate cluster analysis (K-means, hierarchical, and network-based) with volatility connectivity analysis specifically for steel-related commodity markets. This combined framework reveals structural features, such as the four-cluster solution and the isolated position of US Iron Ore, that would not emerge from either method applied separately. Second, while the literature on spillover effects has extensively covered energy, precious metals, and agricultural commodities, steel-related markets have received comparatively little attention despite their economic importance. Our analysis provides a systematic mapping of volatility co-movement channels along the value chain of US domestic steel and global metal benchmark indices. Third, the inclusion of the 2025 tariff episode provides early evidence of how recent protectionist measures have affected market interconnectedness, which is directly relevant to current policy debates. We note that the volatility interconnectedness measure employed in this study is based on squared returns correlations, which capture joint movement rather than causal contagions in the Vector Autoregression (VAR) sense; implementation of the full Diebold–Yilmaz forecast error variance decomposition framework is identified as a priority for future research.

Moving forward, the paper is organized as follows: Section 2 reviews earlier work on the integration of commodity markets and clustering methodologies; Section 3 presents the data and methodology used in this study; Section 4 involves the aggregation and discussion of the empirical results; and, finally, Section 5 concludes with policy implications and directions for future research.

2. Literature Review

2.1. Commodity Market Integration and Spillovers

Many studies have been done in commodities market integration in financial economics. The early studies have focused mostly on the concepts of the law of one price and market efficiency across different geographic areas [12]. Recently, studies shifted attention to ongoing administration and management of individual commodity markets, specifically focusing on the volatility transmission, as well as contagious behaviors among different commodity markets [13,14].

Since its introduction by [6], the spillover index methodology has become a benchmark for analyzing market interconnectedness. Built on forecast error variance decomposition, it provides a systematic way to identify and measure overall spillovers, as well as determine

the direction in which shocks propagate across markets. An extension of this methodology to foster various stages registered the adjustment in the associated time-varying estimation techniques for various market dynamics [7].

Spillovers in the commodities market between different precious metals have been thoroughly examined in several studies. For example, ref. [15] examined volatility spillovers among precious metals and documented a bidirectional relationship between gold and silver markets. Further, ref. [16] pursued analysis to encompass industrial metals and concluded the endeavor with this evidence uncovered: copper prices often act as a leading indicator for the other base metals.

Since its original formulation, the framework presented in [7] has been extended in several important directions, introducing the generalized forecast error variance decomposition, which eliminates the sensitivity to variable ordering that characterized the earlier Cholesky-based approach. More recently, ref. [17] proposed a Time-Varying Parameter Vector Autoregression (TVP-VAR)-based connectedness approach that avoids the need for rolling windows by allowing parameters to vary continuously over time. In this sense, ref. [18] decomposed connectedness measures into different frequency bands, enabling researchers to distinguish between short- and long-run spillover channels. These extensions have been applied widely to energy and precious metal markets but remain largely unexplored in the context of steel-related commodities.

2.2. Clustering Approaches in Steel Market

Presently, methods of clustering have increasingly been employed in the analysis of financial markets in a way that identifies the homogenous groups of assets or markets. K-means clustering, hierarchical clustering, and density-based methods all offer several unique advantages when applied with different research questions [19,20]. These methods allow for the discovery of the structures in the market that are not normally apparent through simple correlation analysis.

More recent contributions have explored dynamic clustering approaches that allow group membership to evolve over time. For example, ref. [21] deals with time-varying clustering to equity markets, demonstrating that cluster stability varies across market regimes. Likewise, ref. [22] compared alternative distance metrics for clustering financial time series, finding that measures based on dynamic time warping and wavelet features can outperform standard Euclidean distance when series exhibit lead–lag relationships. In commodity markets, ref. [23] employed network-based clustering to identify communities within energy and metal price systems, revealing structural changes in market groupings around major economic events.

An early application of clustering methods in commodity markets is found in [24], where these techniques were used to identify cointegration patterns in agricultural commodities, and ref. [25] employed similar methods for analyzing energy markets. Still, clustering in steel market applications seldom surfaces.

2.3. Steel Market Dynamics, Trade Policy, and Volatility Transmission

The global steel market has had great changes, particularly due to trade policy interventions. The US rolled out its Section 232 tariffs in 2018, which marked the turning point in its steel trade policy [26]. Since the establishment of the Trump administration in 2025, the tariff measures have added more market uncertainties, potentially disrupting global supply chains and prices [5,27]. Whether such policy shocks affect the arrangement of the markets and the transmission process is critical for market players.

Recent empirical work has begun to examine steel market dynamics more directly. For instance, in [28] the authors analyzed the volatility transmission in Chinese steel futures

markets, finding significant spillovers between rebar, hot-rolled coil, and iron ore futures. Likewise, ref. [29] studied the effects of the 2018 Section 232 tariffs on US steel prices and documented significant structural breaks in the domestic price formation process, while ref. [30] examined the role of iron ore in global steel supply chains, highlighting how concentration in iron ore production has amplified price transmission to downstream steel products. Despite these contributions, a comprehensive clustering and connectedness analysis of steel-related markets that spans both domestic and international dimensions remains absent from the literature, which is the gap this study aims to address.

3. Data and Methodology

3.1. Data Description

The focus was on examining data from US steel market reports and global commodity price reports monthly for the given period, which goes from July 2004 through to September 2025, and afterward recorded 255 monthly observations. For a study like this, the nine variables chosen were not only nine variables connected to US domestic steel markets, but also global commodity price indicators. Explanations for each variable in the study are described in Table 1:

Table 1. Description of variables.

Series	Category	Commodity/Segment	Official Description	Typical Unit
PIORECRUSDM	Global commodity price	Iron ore	Global iron ore price (international benchmark)	USD per metric ton
PCOPPUSDM	Global commodity price	Copper	Global copper price	USD per metric ton
PZINCUSDM	Global commodity price	Zinc	Global zinc price	USD per metric ton
PCOALAUUSDM	Global commodity price	Coal	Australian coal price (global reference series)	USD per metric ton
WPU101	U.S. Producer Price Index (PPI)	Iron and steel (aggregate)	PPI: Iron and Steel (aggregate index)	Index (base = 100)
WPU1011	U.S. PPI	Iron ores	PPI: Iron Ores	Index (base = 100)
WPU101704	U.S. PPI	Flat steel (hot-rolled)	PPI: Hot-rolled steel products	Index (base = 100)
WPU101707	U.S. PPI	Flat steel (cold-rolled)	PPI: Cold-rolled steel products	Index (base = 100)
WPU10170501	U.S. PPI	Steel manufacturing	PPI: Carbon steel wire	Index (base = 100)

The PPI series capture domestic steel market dynamics through the aggregate Iron and Steel index (WPU101), the PPI for iron ores (WPU1011), hot-rolled steel products (WPU101704), cold-rolled steel products (WPU101707), and carbon steel wire (WPU10170501). The global commodity price series cover iron ore (PIORECRUSDM), copper (PCOPPUSDM), zinc (PZINCUSDM), and Australian coal (PCOALAUUSDM), and are sourced from the International Monetary Fund via FRED.

All price series are transformed into logarithmic returns to ensure stationarity. The return for variable i at time t is calculated as:

$$r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}) \quad (1)$$

where $P_{i,t}$ denotes the price level of variable i at time t. Table 2 presents descriptive statistics for the return series.

Table 2. Descriptive statistics and Stationarity Tests for Steel-Related Market Returns.

Variable	Mean (% Annual)	Std (% Annual)	Min (%)	Max (%)	Skewness	Kurtosis	JB Stat	JB *p*-Value	ADF Stat	ADF *p*-Value
US Iron and Steel PPI	3.06	11.08	−14.93	11.48	−0.20	3.29	110.41	0.00	−7.17	0.00
US Iron Ore PPI	3.49	12.30	−33.24	11.61	−3.08	32.28	10,983.79	0.00	−10.18	0.00
US Hot-Rolled Steel	3.15	8.96	−12.26	9.80	−0.03	3.79	144.02	0.00	−8.15	0.00
US Cold-Rolled Steel	4.01	18.60	−19.78	32.33	1.04	8.16	718.25	0.00	−5.40	0.00
US Carbon Steel Wire	2.72	6.77	−5.99	8.77	0.88	4.53	238.70	0.00	−5.84	0.00
Global Iron Ore	8.36	33.91	−35.44	53.95	0.81	6.09	402.01	0.00	−9.16	0.00
Global Copper	5.91	22.21	−35.42	22.98	−0.82	5.83	370.94	0.00	−4.76	0.00
Global Zinc	4.67	23.76	−29.18	23.42	−0.42	1.20	21.60	0.00	−12.08	0.00
Global Coal (AU)	2.21	32.67	−50.47	36.51	−0.40	4.73	231.79	0.00	−4.70	0.00

3.2. Clustering Methodology

We apply a combination of clustering techniques to uncover groups of steel-related markets with similar characteristics. The core methodology relies on K-means clustering, while hierarchical clustering using Ward's linkage method is employed as a robustness check. Prior to clustering, all return series were standardized (z-scored) to ensure that variables with different volatility scales do not disproportionately influence the cluster assignments. The K-means procedure assigns observations to a predefined number of clusters by seeking to minimize the dispersion within each group, measured through the within-cluster sum of squares (WCSS):

$$\text{WCSS} = \sum_{j=1}^{k} \sum_{x_i \in C_j} |x_i - \mu_j|^2 \tag{2}$$

where C_j represents cluster j, μ_j is the centroid of cluster j, and x_i is the observations assigned to that cluster.

To identify the optimal number of clusters, we rely on a set of complementary evaluation criteria. First, the elbow method is used to detect the point at which further increases in the number of clusters lead to progressively smaller reductions in the within-cluster sum of squares. Another way is to get a silhouette score. Such a score can show how good the internal cohesion of clusters and the distance between clusters are in an extractive feature representation:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{3}$$

In the above equation, the term $a(i)$ refers to the mean distance between observation i and the remaining observations in the cluster to which it is assigned. By contrast, $b(i)$ is defined as the lowest mean distance between observation i and the observations that belong to any other cluster, which reflects how close i is to its nearest competing group. We also report the Calinski–Harabasz index (*CHI*), since it summarizes the trade-off between separation across clusters and cohesion within clusters, and therefore serves as an additional benchmark for assessing clustering quality:

$$CHI = \frac{\text{tr}(B_k)}{\text{tr}(W_k)} \times \frac{n-k}{k-1} \tag{4}$$

Under the *CHI* criterion, B_k refers to the dispersion computed across cluster centroids, whereas W_k captures the dispersion of observations around their corresponding cluster

centers. Here, n is the total sample size and k is the number of clusters under evaluation. In addition, we report the Davies-Bouldin index (DBI) as a complementary diagnostic. This measure summarizes how similar clusters are on average by relating their internal spread to the separation between their centroids.

$$DBI = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\left(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)}\right) \tag{5}$$

Here, σ_i captures the typical spread of observations within cluster i, computed as their average distance to the cluster centroid. The term $d(c_i, c_j)$ represents the distance between the centroids of clusters i and j, and therefore reflects how far apart the two groups are in the feature space. Smaller values of the index indicate tighter clusters with greater separation from one another. Figure 1 consolidates the evidence from these optimization metrics.

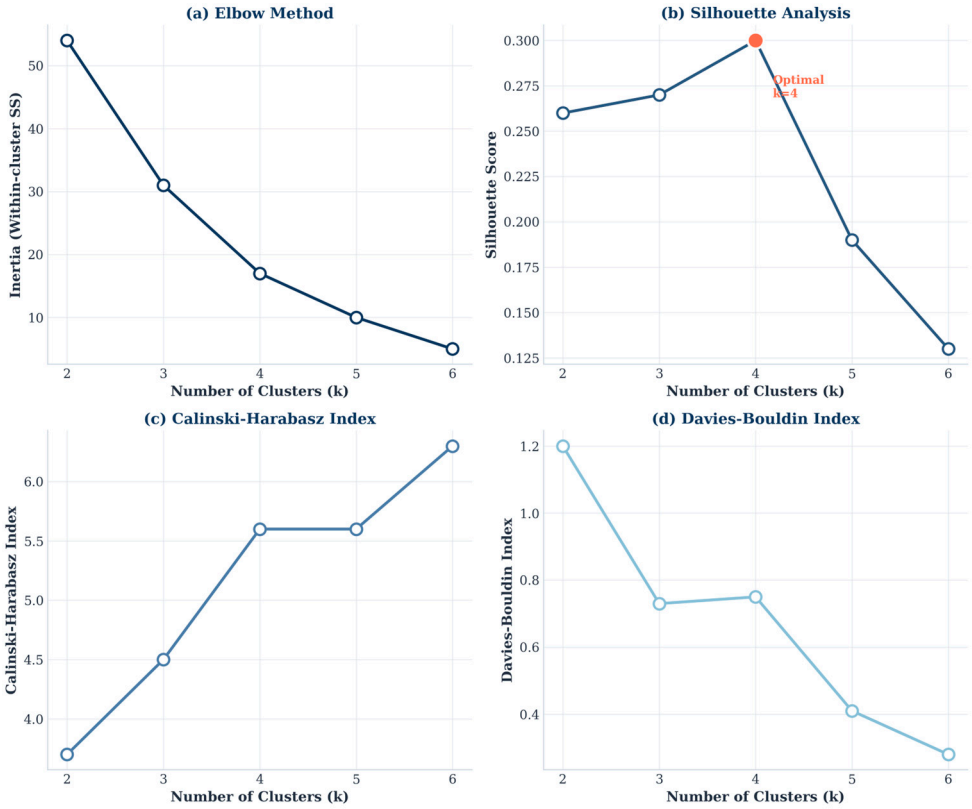


Figure 1. Cluster selection diagnostics including: (**a**) the elbow method, (**b**) the silhouette score, (**c**) the Calinski–Harabasz index, and (**d**) the Davies–Bouldin index. The preferred solution corresponds to k = 4, as indicated by the peak value of the silhouette score.

3.3. Volatility Spillover and Network Analysis

Drawing on the conceptual framework of connectedness analysis developed in [6,7], we construct a volatility co-movement index to evaluate the intensity of associations across markets. It should be noted that our measure is based on correlations of squared returns rather than on the forecast error variance decomposition within a VAR model that characterizes the full Diebold–Yilmaz approach. As such, the index captures contemporaneous volatility co-movement rather than predictive, directional spillovers in the Granger-causal sense. We adopt this simplified approach for transparency and tractability, given the relatively small cross-section of nine variables, while acknowledging that a VAR-based

implementation would provide richer directional information. The total co-movement index (*TSI*) is obtained from the correlation matrix of squared returns as:

$$TSI = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\theta_{ij} - \sum_{i=1}^{N}\theta_{ii}}{N(N-1)} \times 100 \quad (6)$$

where θ_{ij} denotes the pairwise correlation between the squared returns of variables i and j, and N is the total number of variables in the system. To determine which markets act primarily as sources or destinations of volatility shocks, we also compute directional spillovers. The spillover transmitted by variable i into all other variables is defined as:

$$S_{i\rightarrow} = \frac{\sum_{j=1,j\neq i}^{N}\theta_{ij}}{N-1} \times 100 \quad (7)$$

whereas the spillover received by variable i from all remaining variables is given by:

$$S_{\rightarrow i} = \frac{\sum_{j=1,j\neq i}^{N}\theta_{ji}}{N-1} \times 100 \quad (8)$$

The net spillover associated with variable i is then calculated as the difference between transmitted and received components:

$$S_i^{net} = S_{i\rightarrow} - S_{\rightarrow i} \quad (9)$$

A positive net value indicates that variable i is, on balance, a transmitter of volatility shocks, while a negative value implies that it is a net receiver. Finally, to allow for changes in connectedness over time, we implement a rolling-window procedure using a 24-month window and re-estimate the measures at three-month intervals. The 24-month window length reflects a trade-off between responsiveness and estimation stability: shorter windows (e.g., 12 months) produce noisier estimates at monthly frequency, while longer windows (e.g., 36 months) may mask short-lived episodes of heightened connectedness. Results were qualitatively robust to alternative window lengths of 18 and 30 months. The rolling-window approach also serves as implicit accommodation of structural instability, as it allows the connectedness estimates to evolve over time without imposing a fixed parametric structure across the entire sample period.

To assess the presence of structural breaks in the volatility connectedness series, we apply the Pelt (Pruned exact linear time) algorithm [31] with a BIC-type (Bayesian Information Criterion) penalty, which is a computationally efficient method for detecting an unknown number of change points in the mean of a time series. This approach shares the objective of the [32,33] multiple break-point procedure, identifying endogenously determined regime changes, while offering computational advantages for moderate sample sizes. As a robustness check, we also apply Binary Segmentation with the same penalty function. Additionally, we conduct a CUSUM (Cumulative Sum) test for parameter stability, which evaluates whether the cumulative sum of residuals from the series mean remains within the critical bounds of a Brownian bridge process at the 5% significance level.

In addition to the clustering and spillover results, we incorporate a network approach to describe the structure of market linkages. We construct a correlation network in which each node corresponds to an individual market, and two markets are connected when their correlation coefficient is above 0.4, as in [34].

4. Empirical Results and Discussion

The results of the cluster selection shown in Figure 1 suggest that the four-cluster solution provides the most relevant partitioning of the steel-affected markets. For instance, in the silhouette score, $k = 4$ is also observed to show the highest value, whereas the Davies–Bouldin index is noticed to decrease, which is indicative of well-separated and relatively tight clusters.

Additional evidence for the four-cluster solution comes from the hierarchical clustering dendrogram shown in Figure 2. The tree structure makes the grouping process easy to see, since markets that behave more similarly merge earlier, while more distinct markets join only at higher levels. The main split suggested by the dendrogram aligns with the partition implied by the optimization results, reinforcing the choice of four clusters.

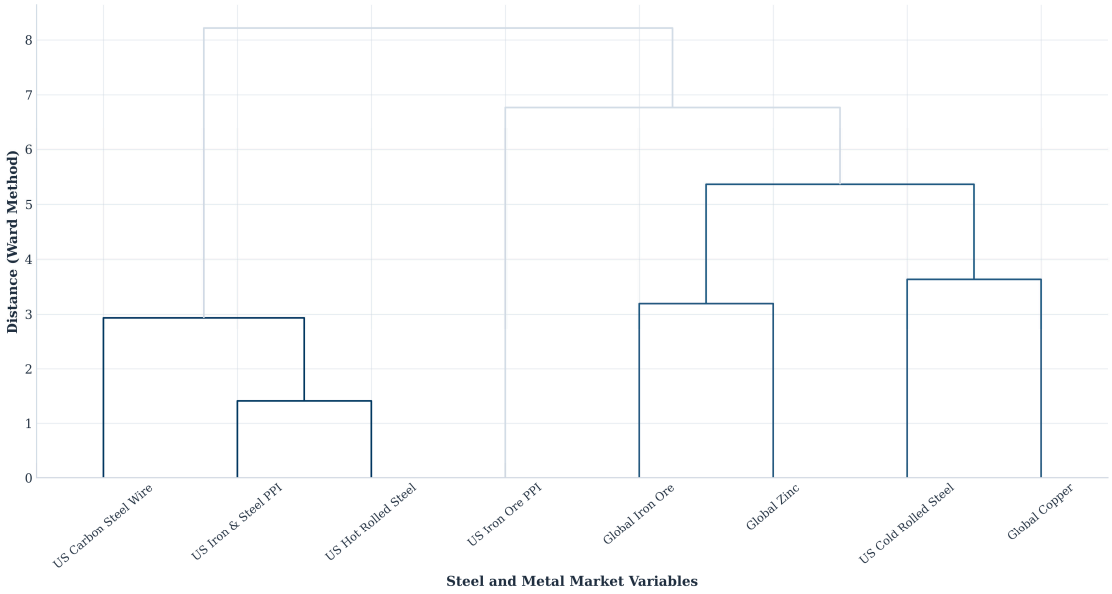


Figure 2. Hierarchical clustering dendrogram for the steel-related markets based on Ward's linkage. Different colors are used to distinguish the cluster groups.

Of important notice is the assumption which has virtually been made about the full-sample clustering to implicitly assume structural stability over the entire 2004–2025 period. Given the documented regime shifts, the 2008 financial crisis, the COVID-19 pandemic, and the 2018 and 2025 tariff episodes, a possible variation in cluster composition could occur across different sub-periods. However, with nine variables only and a monthly frequency, further splitting of the sample would only leave too few observations compared to the required number for ensuring robust clustering. Thus, scope for robust analysis for sub-periods has been left untapped for future research.

Table 3 is a snapshot of the main characteristics of the cluster memberships. The first cluster mainly consists of the domestic Iron and Steel category of the PPI, Hot-Rolled Steel, Cold-Rolled Steel, and Carbon Steel Wire. These four factors display a volatility in the middle quartile, and they tend to follow each other very closely. Again, this confirms the fact that they belong to an established production chain and the closely linked pricing chain within the US steel market.

The second cluster includes Global Copper and Australian coal, both widely traded commodities whose price movements tend to align with broader global demand cycles. The third category consists of the US Iron Ore PPI, which exhibits unique behavior and does not always align with other domestic steel indicators, and which shows almost no co-movement with the Global Iron Ore benchmark. Finally, the fourth category includes

Global Iron Ore and Global Zinc, which catch a type of base metal, all globally priced similar to co-movement patterns.

Table 3. Cluster Membership and Average Risk Return Profiles in Steel-Related Markets.

Cluster	N	Members	Avg Return (%)	Avg Volatility (%)	Avg Sharpe	Avg Correlation
1	4	US Iron and Steel PPI, US Hot-Rolled Steel, US Cold-Rolled Steel, US Carbon Steel Wire	3.23	11.36	0.3112	0.37
2	2	Global Copper, Global Coal (AU)	4.06	27.44	0.1669	0.30
3	1	US Iron Ore PPI	3.49	12.30	0.2837	0.15
4	2	Global Iron Ore, Global Zinc	6.51	28.83	0.2215	0.23

The configuration of clusters is shown in Figure 3 after projecting data onto a two-dimensional space by Principal Component Analysis (PCA). The first two principal components contribute to explaining 71.8% of the variance, indicating that it consists of features that will be retained in this lower-dimensional representation, which are good enough to differentiate broad grouping patterns within the markets.

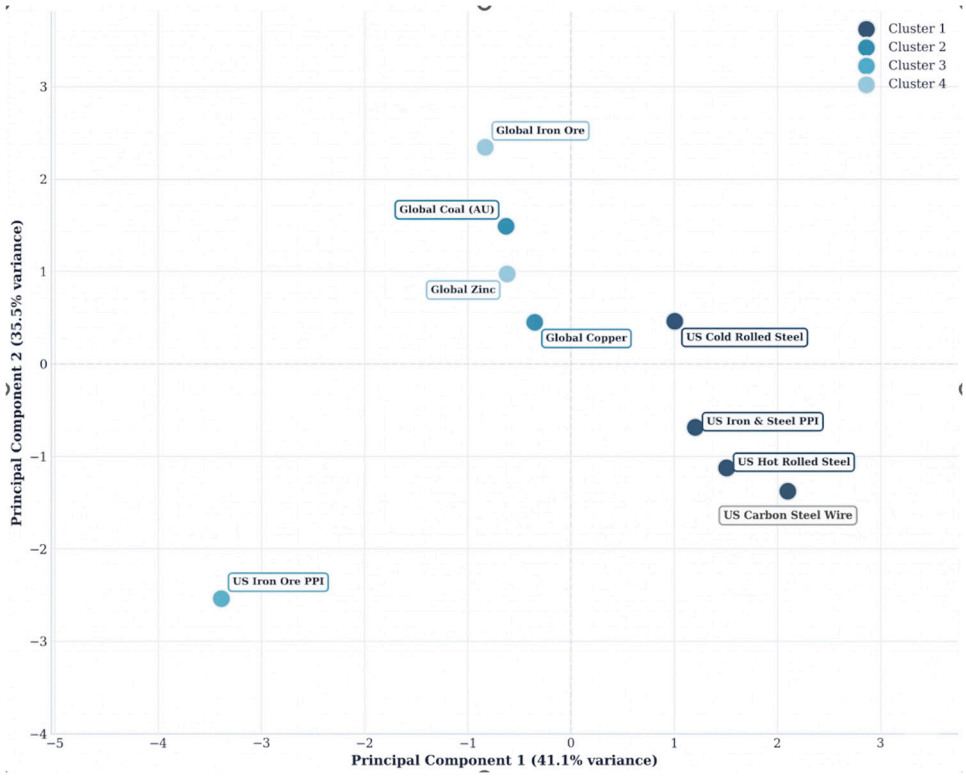


Figure 3. Principal Component Analysis (PCA) projection of steel-related markets. The first two principal components explain 71.8% of total variance. Colors indicate cluster membership based on the four-cluster K-means solution.

In Figure 4 the returns correlation matrix appears, variables arranged in conformity with their cluster assignments. Rendering very high co-movement are the US domestic steel series in Cluster 1, the correlations of which go from 0.42 up to 0.74. The highest correlation is established between the Iron and Steel PPI and Hot-Rolled Steel's return at 0.74, thereby indicating an extremely strong relationship between the two measures.

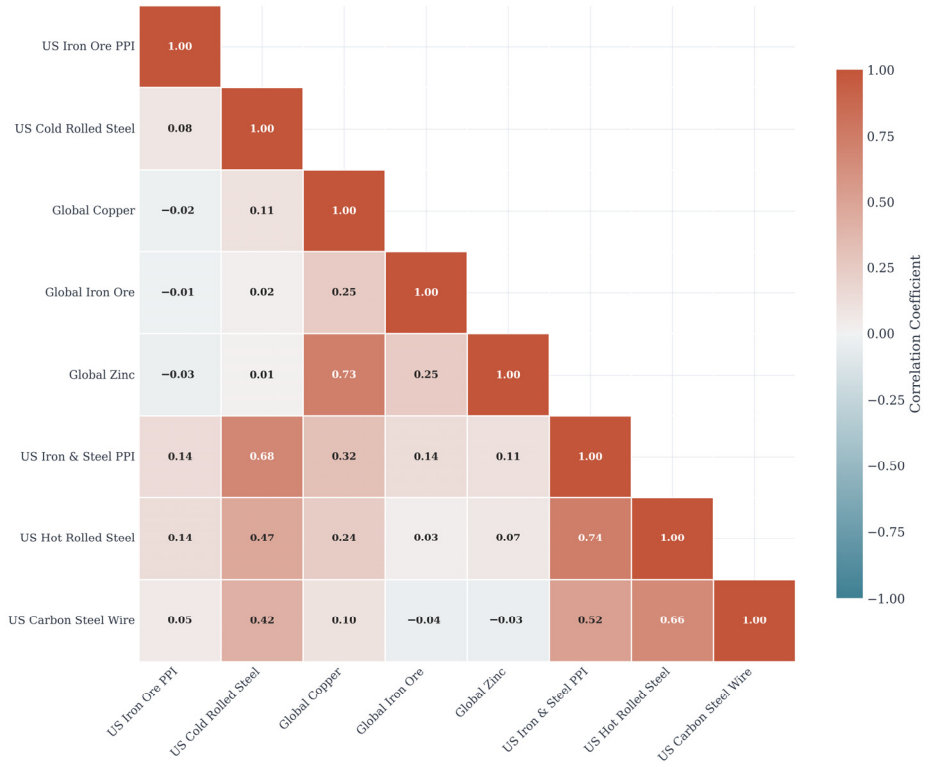


Figure 4. Return correlation matrix with variables arranged according to their cluster assignments. The redder shading denotes stronger positive correlations.

A key result is the lack of co-movement between the Global Iron Ore benchmark and the US Iron Ore PPI. The estimated correlation is essentially zero ($\rho = -0.01$), which implies that changes in US domestic iron ore prices do not systematically track shifts in the international reference series. In other words, the domestic measure appears to be shaped by factors that are largely specific to the US market rather than by global price swings. This difference in the time series may be, in part, due to differences in the measurement system. The US Producer Price Index is a domestic price index with a fixed base period, while the international benchmark is denominated in USD per metric ton and reflects the conditions on the spot market. Also, the natures of the arrangements are different as ore sales within the United States are based on long-term supply agreements with local mining operations. As a result, the full impact of international signals, if any, is limited. While the explanation that has been provided is cogent, a test of statistical independence, for example, cointegration analysis or rolling correlations set up with confidence intervals, would make this finding all the stronger and is recommended for future direction in research.

The network representation in Figure 5 points to the same conclusion from a different angle. The links in the graph form visually distinct groups that mirror the cluster assignments. In particular, the US domestic steel variables sit close to one another and are connected by multiple strong edges, indicating a compact and highly interconnected block within the broader system.

Over the full sample period, the total co-movement index computed from the unconditional (full-sample) correlation matrix of squared returns stands at 15.39%, suggesting a moderate level of volatility association among steel-related markets. This static estimate differs from the arithmetic mean of the rolling-window estimates (8.1%), which is reported in Figure 6. The difference arises because the rolling procedure uses smaller sub-samples (24 months each) that capture local correlation structures, which tend to be lower on average than the unconditional full-sample correlations.

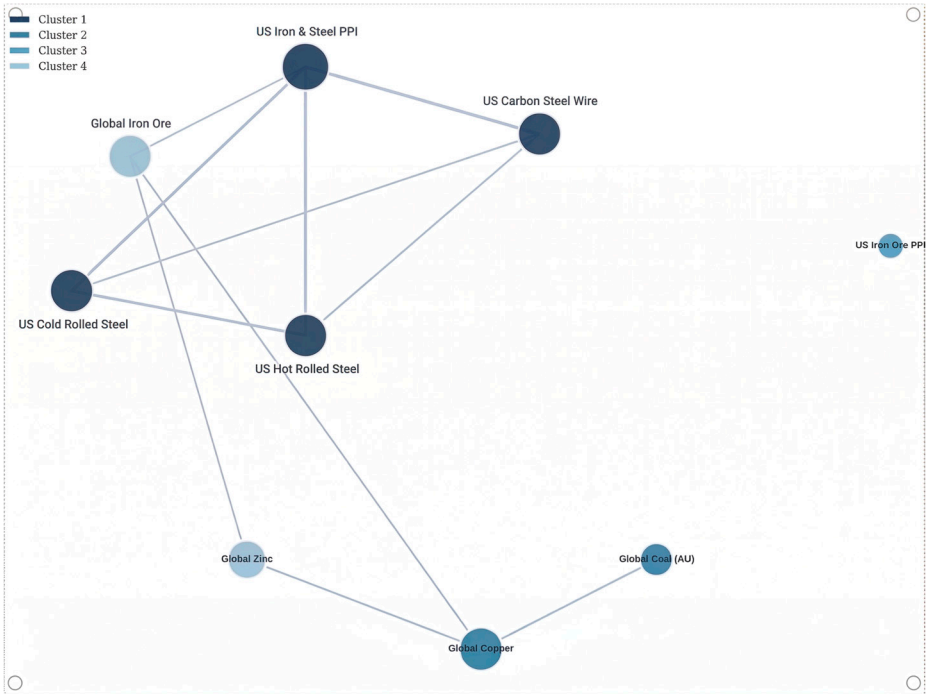


Figure 5. Correlation-based network of steel-related markets (threshold ≥ 0.4). Node size reflects degree centrality; colors indicate cluster membership.

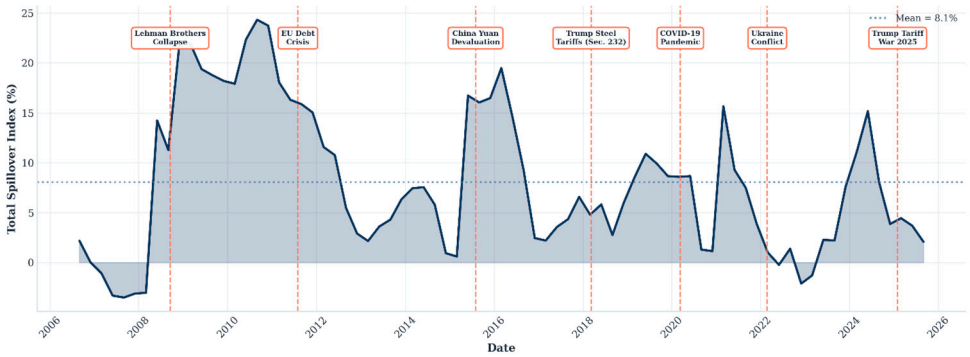


Figure 6. Dynamic volatility co-movement index estimated with a 24-month rolling window. Vertical dashed lines mark major economic and policy events, while the horizontal dotted line shows the arithmetic mean of the rolling-window estimates (8.1%), which differs from the full-sample (static) index of 15.39% because the rolling procedure captures local correlation structures over shorter sub-samples.

Figure 6 confirms that instead of being merely constant, the time-varying spillover measure exhibits a sharp increase during times of stress or major external policy and macro shocks. There are several obvious spikes here; the first is from the financial crisis from 2008 to 2009, during which the index hits around 22%. A second episode of highs became most prominent at the time of the 2011 European Debt Crisis, with spillovers approaching 18%. Another jump emerged around 2015 to 2016, with the event of the China yuan devaluation, a bigger commodity-price downturn, and connectedness getting close to 20% once more. A smaller increase was observed around the implementation of the 2018 Section 232 steel tariffs.

Spillovers are sure to increase with the onset of the COVID-19 pandemic in early 2020, whereas another peak is exhibited at the 2022 Ukraine conflict. In conclusion, the series witnessed a new rise in 2025 during the episode of the Trump tariff wars, signifying the return of uncertainty and stronger cross market transmission.

To formally assess whether the volatility connectedness series exhibits structural instability, we apply change-point detection methods to the rolling spillover estimates. The Pelt algorithm with BIC penalty identifies two structural breaks: February 2009 and November 2012. The first break coincides with the aftermath of the global financial crisis, marking the transition from the high-connectedness regime of 2008–2009 to a period of declining spillovers. The second break, in late 2012, separates the post-crisis adjustment period from the subsequent regime characterized by episodic spikes around specific policy and macroeconomic events. Binary Segmentation confirms both break dates, providing robustness to the finding. The CUSUM test for parameter stability rejects the null hypothesis of constant parameters at the 5% significance level, confirming that the connectedness structure is not stationary over the sample period. These results are presented in Figures 7 and 8.

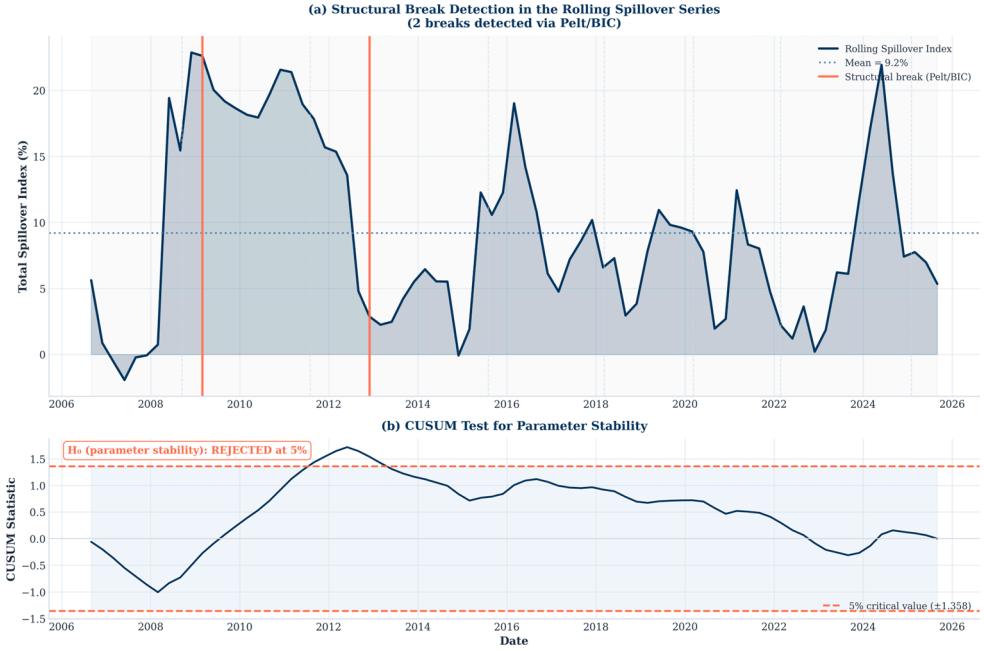


Figure 7. Structural break analysis of the rolling spillover series. Panel (**a**) shows the Pelt/BIC change-point detection with two identified breaks (February 2009 and November 2012). Panel (**b**) presents the CUSUM test for parameter stability, which rejects the null hypothesis at the 5% significance level.

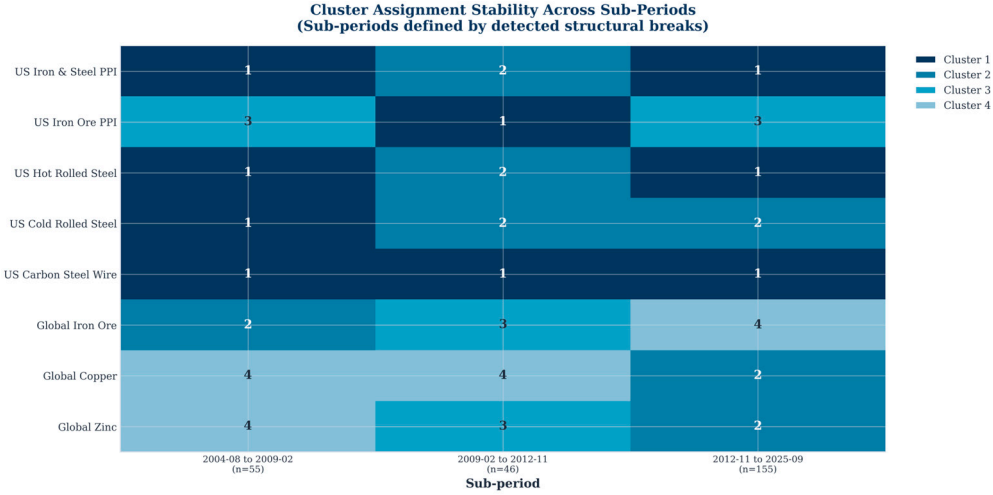


Figure 8. Cluster assignment stability across the three sub-periods defined by the detected structural breaks. Numbers indicate cluster membership. The core US domestic steel group remains stable, while global commodity variables show greater sensitivity to regime changes.

The detected break points define three sub-periods: August 2004 to February 2009 (55 observations), February 2009 to November 2012 (46 observations), and November 2012 to September 2025 (155 observations). Re-estimating the K-means clustering within each sub-period reveals that the broad structure is partially preserved but not entirely stable (Figure 8). The core US domestic steel group (Iron and Steel PPI, Hot-Rolled Steel, and Carbon Steel Wire) remains together across all three sub-periods, confirming the robustness of this cluster. However, some variables migrate between clusters: US Iron Ore PPI moves from Cluster 3 in the first period to Cluster 1 in the crisis period and back to Cluster 3 in the post-2012 period, while Global Iron Ore shifts from Cluster 2 to Cluster 3 and then to Cluster 4 across the three regimes. Global Copper and Global Zinc, which form a stable pair in the full-sample analysis, also exhibit some reassignment during the crisis sub-period. These findings suggest that the four-cluster solution captures the dominant structure of the market but that the global commodity variables are more sensitive to regime changes than the domestic steel series.

Figure 9 summarizes the evolution of prices across all markets over the sample period, allowing a direct comparison of their trajectories and major turning points.

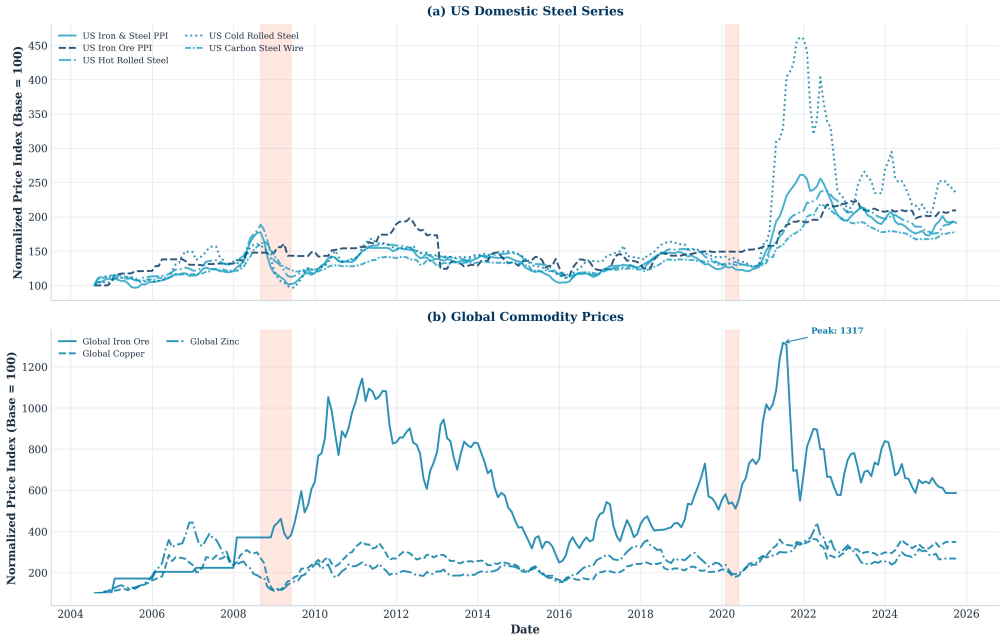


Figure 9. Normalized price paths for the steel-related markets, indexed to 100 in July 2004. Panel (**a**) shows US domestic steel series and panel (**b**) shows global commodity prices. Red-shaded bands highlight periods of crisis.

Directional spill-over results in Figure 10 point to US Carbon Steel Wire as the most predominant net transmitter of volatility shocks. This corresponds well with the contention that with a good deal of flexibility, scrap prices tend to visibly lead all steel production chain variables in response to demand and supply scenario shifts. In stark contrast stands Global Copper as the principal net receiver, and it appears that copper absorbs the volatility coming in the opposite direction more than it contributes towards transferring the shocks outward.

The central role of US Carbon Steel Wire as the primary net transmitter of volatility can be attributed to three factors. First, carbon steel wire is a downstream product that sits at the intersection of multiple supply chain segments, including construction (rebar, wire mesh), automotive (springs, fasteners), and general manufacturing. This broad demand base means that the wire price index responds quickly to shifts in overall industrial activity, effectively functioning as an early signal of changing market conditions. Second, wire production is particularly sensitive to scrap steel prices, which are among the most volatile

inputs in the steel value chain. Scrap markets adjust rapidly to demand fluctuations, and these price movements are transmitted directly into wire product pricing. Third, carbon steel wire products tend to be traded in shorter-term contracts compared to flat-rolled products, which often involve longer-term supply agreements. This contractual flexibility allows wire prices to adjust more rapidly to market shocks, making the series a leading indicator for the broader domestic steel market.

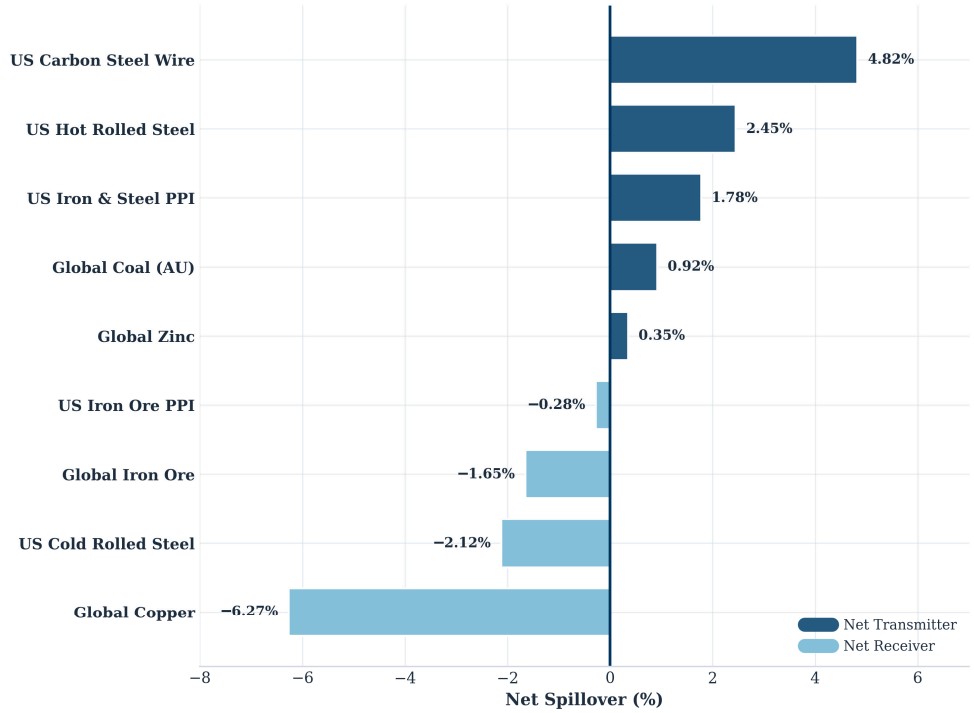


Figure 10. Net volatility spills over the market. Positive values, shown with darker blue shading, correspond to net transmitters, whereas negative values, shown with lighter blue shading, correspond to net receivers.

Our results powerfully reflect a strong segmentation within the steel-related markets into three or maybe four groups depending on the analysis, each with an economic interpretation. It is also observed in the data that US domestic steel products are distinct from a more internationally traded spectrum of commodities which is also consistent with structural differences in price formulation, contractual aspects, and underlying demand factors across the different market segments [35,36].

One notable result is that the US Iron Ore PPI emerges as a separate cluster, indicating that domestic iron ore pricing is driven by dynamics that are largely independent of both US finished steel products and international benchmark prices. One plausible explanation for such a pattern might indicate that specific institutional features of the US market—perhaps, particularly the prevalence of long-term prospective agreements with domestic field mining houses—accumulate dampened international pricing signals [37].

The evolving nature of market interconnectedness reveals clear differences across regimes, with spillover effects strengthening during episodes of economic stress or elevated policy uncertainty, as adverse expectations and higher risk premia spread across markets. Thus, one can argue that the Trump tariff measures of 2025 enlarged risk transmission across markets due to an increase in policy uncertainty while squeezing or tightening channels through which volatility transmits [38,39].

5. Conclusions

This paper examines market segmentation and volatility spillover dynamics in steel-related commodities. We find that an economic division into four markets emerges based on sample statistics for the timeline beginning from July 2004 through to September 2025: (1) US domestic steel products, (2) global commodities of cyclical trade, (3) US iron ore, and (4) global base metals. In terms of calculations, the overall level of the estimated volatility spillover index of 15.39% registered a moderate degree of interrelation, while the rolling-window results indicated that this interrelation varied greatly in response to major economic episodes and policy shocks.

These findings point to a few conclusions. Firstly, the US domestic steel series act like a single block characterized by low co-movements with global commodity benchmark prices. Secondly, the US Iron Ore series exhibits a pattern difficult to align with either of the two other markets, namely domestic steel and international iron ore. The third refers to spillovers heightened by financial stress and political uncertainties; noticeable increases were registered with the 2010 tariffs as examples at the turn of 2025 into 2026. The last remark among direct results distinguishes US steel scrap as the main volatility transmitter blockchain-wide, shedding light on its central role in shock propagation.

The implications of these findings also hold some practical value. The resulting cluster structure offers a useful basis for portfolio diversification, since assets within the same group tend to exhibit similar risk profiles. At the same time, the observed variation in spillover intensity over time indicates that portfolio allocations cannot remain static. During episodes of elevated spillover (such as the 2008–2009 global financial crisis, the COVID-19 period, and the 2025 tariff episode) the correlation structure across clusters tightens, reducing diversification benefits precisely when they are most needed. In practice, the rolling spillover index could serve as a monitoring tool when the index rises above its historical mean. In this case, investors may consider increasing hedge ratios or shifting allocations toward assets in Cluster 3 (US Iron Ore PPI), which exhibits the lowest average correlation with other markets. A formal back-testing framework to evaluate the performance of such strategies is proposed as a direction for future research.

Formal structural break analysis of the rolling spillover series identifies two change points (February 2009 and November 2012), and the CUSUM test rejects parameter stability at the 5% significance level. Re-estimating the clustering within each sub-period reveals that the core US domestic steel group remains robust across regimes, while the global commodity variables exhibit some reassignment, particularly during the 2009–2012 crisis-and-recovery period. These results confirm that the four-cluster solution reflects the dominant market structure, but that the composition of internationally traded commodity clusters is sensitive to changes in the macroeconomic regime.

From a policy standpoint, the findings highlight the importance of jointly monitoring domestic and international market conditions, especially in environments where trade policy developments generate heightened uncertainty. Given the stronger spillovers during the 2025 tariff episode, there is even more evidence that protectionism can engender great instability and disrupt the functioning of market stability beyond the intended goals.

One methodological limitation of the analysis is that the spillover index is derived from correlations of squared returns, rather than from the full VAR-based forecast error variance decomposition proposed in [6,7]. Although this approach captures the core features of volatility transmission, the absolute magnitude of the spillover index and the precision of directional measures would likely improve under the complete framework. This simplification should be borne in mind when interpreting the quantitative results.

Several directions for future research emerge from this analysis. First, implementing the full VAR-based forecast error variance decomposition framework of [6,7] would

yield more precise estimates of directional spillovers and allow for a direct comparison with the correlation-based measures used here. Second, a sub-period clustering analysis, splitting the sample at key structural break points such as the 2018 Section 232 tariffs or the 2020 COVID-19 onset, would help assess whether the four-cluster solution is robust across different market regimes. Third, clustering based on alternative features, such as volatility measures, tail-risk indicators, or dynamic conditional correlations, could provide complementary insights into market segmentation. Fourth, the near-zero correlation between the US Iron Ore PPI and the Global Iron Ore benchmark deserves formal statistical testing through cointegration analysis and rolling correlations with confidence intervals. Fifth, extending the dataset to include higher-frequency observations (weekly or daily) would capture short-run spillover mechanisms and rapid adjustments that monthly data cannot discern. Finally, broadening the geographic scope to encompass other major steel-producing regions, such as China and the European Union, would allow for a widespread assessment of global market integration.

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