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FINANCIAL STRESS AND COMMODITY DYNAMIC: A WAVELET-BASED ANOMALY DETECTION APPROACH

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Abstract

This study investigates the dynamic interdependence between the Indian Financial Stress Index (IFSI) and major global commodity prices—gold, silver, copper, crude oil, and natural gas—using a wavelet-based analytical framework. Given the inherent volatility and non-stationarity of financial and commodity markets, wavelet analysis provides an effective approach to capture their evolving, multi-scale interactions. The research employs the Daubechies wavelet Discrete Wavelet Transform (DWT) to upscale monthly data into weekly series through interpolation, thereby enhancing the granularity of insights. Continuous Wavelet Transform (CWT) and Wavelet Coherence (WTC) with the Morlet wavelet are applied for time–frequency decomposition and phase difference analysis, enabling detection of bi-directional lead–lag relationships between IFSI and commodity prices. Results highlight that financial stress indicators alternately lead or lag commodity price movements, particularly during high-volatility episodes such as the Global Financial Crisis (2008–09) and the COVID-19 pandemic (2020). Monte Carlo simulations confirm the statistical significance of these dynamics. Furthermore, wavelet-based anomaly detection successfully identifies abnormal fluctuations in commodity prices aligned with stress-induced market shifts, providing potential early-warning signals of distress. The findings offer valuable implications for risk management, investment strategies, and policy interventions in emerging economies like India.

Keywords: Financial stress, Commodity dynamics, Wavelet coherence, Discrete Wavelet Transform, Anomaly detection, Indian economy.

1 Literature Review

The study of financial stress and commodity markets has gained momentum following recurrent global disruptions such as the Global Financial Crisis (GFC), the COVID-19 pandemic, and various policy shocks. These crises have heightened the need for advanced methods to capture volatility, dynamic correlations, and systemic risks. Traditional econometric tools often fall short in addressing the non-stationary, multi-scale nature of financial and commodity time series, prompting a shift toward wavelet-based methodologies.

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Financial Stress and Economic Dynamics

Financial stress indexes (FSIs) have been widely used to capture systemic fragility in national and international contexts. Cardarelli et al. [7] show that episodes of heightened financial stress are strongly linked with economic contractions, while Aboura and Van Roye [2] examine France and find that stress shocks significantly influence business cycles. Hubrich and Tetlow [15] extend this understanding by exploring how crises propagate through economies, while Dovern and Van Roye [11] highlight the international transmission of financial stress across borders. More recently, Soltani and Boujelbène Abbes [19] examine GCC markets, showing asymmetric spillover effects of stress and investor sentiment across different market regimes.

Commodities and Financial Stress

Commodity markets, particularly oil and metals, are deeply entwined with global financial stability. Cheng and Xiong [9] discuss the financialization of commodities, whereby speculative activities increase their sensitivity to systemic stress. Empirical evidence suggests heterogeneous responses: gold typically exhibits safe-haven behaviour, while industrial commodities react negatively during stress episodes. Das et al. [10] confirm that gold and crude oil co-move with financial stress, but with varying intensity depending on quantiles of volatility. Kocaarslan et al. [17] further highlight how financial stress interacts with gold and oil in BRIC markets, revealing contagion pathways. Similarly, Chen et al. [8] demonstrate that oil shocks interact with underlying financial shocks to influence macroeconomic outcomes.

Wavelet Analysis in Financial Research

Wavelet analysis has emerged as a particularly powerful tool for capturing non-stationary, multi-scale relationships in finance. Unlike Fourier methods, wavelets provide simultaneous time–frequency localisation, enabling the study of evolving dependencies. Gençay et al. [13] laid the foundation for wavelet applications in finance, while Aguiar-Conraria and Soares [3] used wavelets to explore oil–macro linkages. Ferrer et al. [12] applied wavelet coherence to U.S. data, identifying time-varying interactions between financial stress and economic activity. More recently, Karamti and Belhassine [16] used wavelet coherence to examine COVID-19's effects on global markets, while Umar et al. [20] highlighted the impact of pandemic-driven panic levels on commodity price volatility. Guo et al. [14] provide a comprehensive review of wavelet applications, underscoring both opportunities and challenges.

Lead–Lag Dynamics and Information Flow

Wavelet methods also enable the analysis of lead–lag effects between financial stress and commodities. Armah et al. [1] apply time–frequency analysis to uncover interactions between global financial stress and commodities, offering insights into cyclical co-movements. Bouri et al. [6] adopt a copula approach, complementing wavelet results, to explore causal dynamics between Bitcoin and financial stress. Agyei et al. [5] extend the literature by examining information flows between food commodities and equity markets, reinforcing the relevance of nonlinear, multi-scale tools. Such studies provide methodological parallels for examining IFSI–commodity linkages in the Indian context.

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Anomaly Detection and Policy Relevance

Commodity anomalies—sharp deviations caused by shocks—have significant implications for risk management. Studies show that global crises, geopolitical tensions, and policy interventions trigger extreme volatility. Roesch et al. [18] developed computational tools for wavelet-based anomaly detection, while Umar et al. [21] identify return and volatility transmission between oil and agricultural commodities. Detecting anomalies is essential for early-warning systems, guiding policymakers and investors in mitigating financial instability. In India, where commodities like gold and crude oil directly affect inflation, trade balances, and household savings, such tools are particularly valuable.

1. Methodology:

Data Preparation

The monthly Indian Financial Stress Index (IFSI) dataset, obtained from the Asian Regional Integration Center (ARIC), spans the period from January 2006 to August 2023. An attempt was initially made to convert the monthly IFSI into a weekly frequency using the Discrete Wavelet Transform (DWT), specifically with the Daubechies wavelet. However, the transformed series did not align consistently with the original monthly values. To maintain accuracy and avoid the introduction of synthetic data into a sensitive financial indicator, the analysis was ultimately conducted at the original monthly frequency.

Daily spot price data for commodities—gold, silver, copper, crude oil, and natural gas—were collected from the official Multi Commodity Exchange (MCX) of India website, covering January 1, 2006, to August 31, 2023, with non-trading days excluded. To ensure comparability with the IFSI, the daily commodity prices were consolidated into monthly series using the median method, which helps to reduce the influence of outliers. The same approach was applied when preparing monthly data for anomaly detection, ensuring methodological consistency across all analyses.

Wavelet analysis is a powerful tool for examining the interdependence between the Indian Financial Stress Index (IFSI) and commodity prices. It allows researchers to analyse relationships across different time scales, capturing both short-term fluctuations and long-term trends.The wavelet transform is a powerful tool for time-frequency analysis, particularly suitable for non-stationary time series such as financial and commodity markets data. Unlike traditional Fourier transforms that assume stationarity and provide only frequency information, wavelet transforms allow decomposition of a time series into both time and frequency domains simultaneously. This dual localization enables the detection of transient relationships, making it ideal for examining the evolving dynamics between financial stress indicators and commodity prices. Wavelet Analysis Helps in Understanding Interdependence as:

Upsampling the data: From Monthly to Weekly Time Series Using DWT

To explore the underlying dynamics of financial stress with greater precision, we initially adopted a decomposition-based frequency expansion approach, moving from monthly to higher-frequency representations using Discrete Wavelet Transform (DWT). This wavelet-based methodology allowed us to dissect the composite signal into its constituent frequency

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components, offering insights into both high-frequency fluctuations and underlying low-frequency trends.

The implementation was carried out in Python, leveraging powerful scientific libraries to manage computations and visualizations effectively. NumPy facilitated efficient numerical operations and array management, while Matplotlib was employed for graphical representation and signal plotting. PyWavelets (pywt) served as the core library for performing the wavelet transforms and reconstructions.

Wavelet Decomposition

The Daubechies wavelet of order 4 ('db4') was used for its optimal balance between time and frequency localization. The Financial Stress Index (FSI) data, initially available at a monthly frequency, was decomposed at level 4 using DWT. This process involved recursive filtering and downsampling of the signal, systematically revealing hierarchical structures across multiple scales. Through this decomposition, we extracted two critical sets of coefficients:

- Approximation coefficients, which captured the overall trend of the signal.
- Detail coefficients, which represented transient, high-frequency variations

Daubechies Wavelet:

Proposed by Ingrid Daubechies, the Daubechies wavelets are a family of orthogonal wavelets defined by their maximal number of vanishing moments. They are particularly well-suited for capturing sharp discontinuities and changes in data, making them excellent for analyzing abrupt market shocks.

The scaling function $\phi(t)$ and the wavelet function $\Psi(t)$ satisfy the following recursive relations:

$$\phi(t) = \sum_k h_k \, \phi(2t - k)$$

$$(t) = \sum_k g_k \, \Psi(2t - k)$$

where:

- h_k are the low-pass filter coefficients,
- g_k are the high-pass filter coefficients.

Key characteristics are Compact support (finite domain), Orthogonal basis functions, Good for detecting abrupt transitions and non-stationary behaviours, Number of vanishing moments determines the ability to capture polynomial trends: Daubechies N has N/2 vanishing moments.

To interpret the decomposition effectively, comprehensive visualizations were generated. These included the original composite signal for baseline reference, separate plots for approximation and detail coefficients at each level, and a final comparison of the reconstructed signal alongside the original. Using the inverse DWT (IDWT), the signal was reconstructed

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from its coefficients to validate the accuracy of our process, confirming the transformation's integrity and losslessness.

However, despite the robustness of the wavelet technique, the results were constrained by the monthly granularity of the original FSI data. The analysis did not uncover the desired level of detail or nuanced insights due to the limited temporal resolution. Recognizing this limitation, we explored data refinement through interpolation to enrich the dataset's granularity

Cubic Spline Interpolation for FSI

To address the resolution gap, cubic spline interpolation was employed to resample the monthly FSI data into a weekly time series. The objective was to construct a higher-resolution dataset capable of capturing more subtle fluctuations in financial stress, thereby enhancing the effectiveness of advanced analyses. The interpolation process involved a structured sequence of steps to convert monthly data into a consistent weekly frequency. First, each monthly data point was assigned a sequential numerical index to simplify the interpolation calculations. Next, a continuous weekly timeline was generated to ensure complete temporal coverage across the dataset. To capture smooth transitions between data points, the **Cubic Spline** function from SciPy was applied to fit a curve through the monthly FSI values. Finally, this fitted spline was evaluated at the newly created weekly indices, allowing for the estimation of corresponding FSI values at a weekly resolution.

Data Frame Construction: A new Data Frame was created, integrating weekly dates with their interpolated FSI values. This refined, high-resolution time series allowed for a deeper exploration of financial stress dynamics, supporting advanced analytical techniques such as time-frequency transformations, anomaly detection, and predictive modelling. By increasing the data’s granularity, we were better equipped to reveal subtle patterns and enhance the robustness of our analysis.

Nevertheless, while the interpolation yielded promising insights and smoother data trends, we ultimately chose to retain the original monthly frequency for our core financial analysis. This strategic decision was made to avoid reliance on synthetic data, ensuring that our conclusions remained firmly grounded in actual observed values. By doing so, we maintained alignment with real-world financial events and preserved the authenticity and credibility of our results.

Lead/Lag Relationship Analysis between IFSI and Commodity Prices

This study employs an advanced wavelet-based methodological framework to examine the dynamic lead-lag interactions between the Indian Financial Stress Index (IFSI) and selected commodity prices. By leveraging the Continuous Wavelet Transform (CWT), Cross Wavelet Transform (XWT), and Wavelet Coherence (WTC), the analysis captures the intricate time-frequency co-movements and directional causality that traditional time-domain methods may overlook.

The analysis begins with data acquisition and pre-processing. Monthly time-series data for the IFSI and multiple commodity prices were sourced and imported into R using the read.csv() function. Subsequently, the datasets were converted into zoo or xts objects to ensure accurate

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$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

time indexing and facilitate seamless manipulation for time-series analysis. To stabilize the variance and focus on proportional changes, log returns of both IFSI and commodity prices were calculated using the formula:

where P_t represents the price or index value at time t. This transformation rendered the series stationary, which is essential for robust wavelet analysis.

The core analytical technique utilised is the Continuous Wavelet Transform (CWT), operationalized through the bi-wavelet package in R. The CWT decomposes each time series into time-frequency space, enabling the exploration of how the interplay between financial stress and commodity prices evolves over different time horizons. The mathematical formulation of CWT is given by:

$$W_x(a,b) = \int_{-\infty}^{\infty} x(t)\, \Psi^*\left(\frac{t-b}{a}\right)\, dt$$

where $W_x(a,b)$ represents the wavelet transform at scale a and position b,

$x(t)$ is the time series, and Ψ is the mother wavelet.

For this study, the Morlet wavelet was selected due to its excellent balance between time and frequency localization. The Morlet wavelet, defined as:

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

where ω_0 is the non-dimensional frequency (commonly set at 6 to satisfy the admissibility condition), enables high-resolution analysis of cyclical patterns embedded in the data.

To uncover joint dynamics, the Cross Wavelet Transform (XWT) was applied, which highlights regions of common power between IFSI and commodity prices. The XWT is mathematically represented as:

$$W_{xy}(a,b) = W_x(a,b)W_y^*\,(a,b)$$

where , W_x and W_y are the wavelet transforms of the two time series, and * denotes the complex conjugate. The magnitude $\left|W_{xy}(a,b)\right|$ illustrates the common power, while the argument provides information on the phase difference, which is critical for identifying lead-lag relationships.

To quantify the strength and significance of co-movement, Wavelet Coherence (WTC) analysis was performed. WTC functions as a localized correlation coefficient in the time-frequency domain and is expressed as:

$$R^2(a,b) = \frac{\left|S\left(a^{-1}\, W_{xy}(a,b)\right)\right|^2}{S(a^{-1}|W_x(a,b)|^2).S\left(a^{-1}\left|W_y(a,b)\right|^2\right)}$$

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where S denotes a smoothing operator in both time and scale. Values of R^2 close to 1 indicate strong coherence, whereas values near 0 suggest weak or no co-movement.

The phase difference, derived from the XWT, was interpreted using directional arrows in the wavelet coherence plots. Arrows pointing to the right indicate in-phase movement, while arrows pointing to the left denote anti-phase behaviour. Vertically oriented arrows (upward or downward) suggest leading or lagging dynamics, where upward arrows imply that the IFSI leads commodity prices, and downward arrows indicate the opposite.

To ensure the robustness of the findings, significance testing was performed using Monte Carlo simulations at the 5% significance level. These simulations helped identify statistically significant coherence regions, minimizing the risk of spurious correlations driven by noise.

Finally, the results were visualized using comprehensive plots generated via the plot( ) functions from the biwavelet and WaveletComp packages. The cross-wavelet power spectrum and wavelet coherence graphs vividly illustrated power intensity and directional phase relationships across different time scales. These visual outputs enabled a nuanced interpretation of the dynamic interactions between IFSI and commodity prices, shedding light on periods where financial stress predominantly influenced commodity price movements and vice versa.

The findings from this methodological framework are extensively analysed in the results section, contextualized with global economic events to provide a comprehensive understanding of the interconnectedness between financial stress and commodity markets.

Anomaly Detection in Commodity Prices to IFSI

The anomaly detection framework employed in this research is designed to uncover irregular patterns or deviations in commodity price movements, specifically in relation to the Indian Financial Stress Index (IFSI). This approach harnesses the power of time series decomposition, statistical thresholding, and signal reconstruction, implemented entirely within Python's scientific computing ecosystem, ensuring both methodological rigour and reproducibility.

The process commenced with the meticulous preparation of the time series data. The commodity price datasets were cleaned and meticulously aligned with the IFSI data to guarantee temporal consistency. To facilitate mathematical manipulation and wavelet processing, all datasets were converted into numerical formats using pandas Data Frames and NumPy arrays. A preliminary visual inspection of the cleaned data was undertaken to comprehend the inherent volatility and behavioural trends, ensuring the data's suitability for subsequent advanced transformations.

Central to the methodology is the application of the Haar wavelet transform for signal denoising and decomposition. The Haar wavelet, known for its orthogonality and piecewise constant basis functions, is exceptionally adept at detecting sharp discontinuities and sudden changes within time series data—characteristics often indicative of anomalies in financial datasets. Mathematically, the Haar wavelet transform decomposes a discrete signal f(t) into approximation and detail coefficients by convolving the signal with scaling and wavelet functions. Specifically, the approximation coefficients cA capture the low-frequency, general

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trend component of the data, while the detail coefficients cD isolate the high-frequency components, which encompass noise and abrupt deviations.

This transformation was executed using the pywt.dwt function from the PyWavelets library, producing the decomposition:

$$Signal(t) = cA(t) + cD(t)$$

where $cA(t)$ represents the approximation (trend), and $cD(t)$ represents the detail (noise and potential anomalies).

Following decomposition, the focus shifted to the thresholding of the detail coefficients cD. This crucial step aimed to distinguish genuine anomalies from normal price fluctuations. Employing a universal thresholding technique, the threshold value was computed using the expression:

$$thresold = \sigma\, X\, \sqrt{2}\ logn$$

Here, σ denotes the standard deviation of the detail coefficients cD, and n is the length of the time series. This formulation, grounded in Donoho and Johnstone's universal thresholding principle, ensures that coefficients representing normal variability are effectively suppressed, while those exceeding the threshold are retained as potential indicators of anomalous activity. All coefficients below this calculated threshold were nullified, under the assumption that they reflected routine market behaviour.

The denoised signal was then reconstructed using the inverse discrete wavelet transform (pywt.idwt function), which reassembled the time series from the thresholded coefficients. This reconstruction isolated the abnormal component of the commodity price series, offering a clear delineation of periods marked by unusual pricing behaviour, distinct from the overarching market trends. By juxtaposing the reconstructed signal with the original series, points of deviation were systematically identified and validated.

To augment interpretability, the detected anomalies were visually mapped using Matplotlib. The original commodity price series was rendered, and the anomalies were overlaid as distinct, contrasting markers—typically in red—to highlight their divergence from typical market movements. This visual representation not only substantiated the numerical results but also provided temporal insights, revealing clustering patterns of anomalies around periods marked by significant financial stress.

Further analytical depth was achieved by cross-referencing the identified anomalies with the temporal dynamics of the IFSI. This comparative analysis evaluated the co-occurrence and temporal alignment between commodity price anomalies and peaks or troughs in the IFSI series. Through this examination, the research probed the hypothesis that elevated financial stress within the economy correlates with abnormal commodity market behaviour, potentially offering predictive insights.

Throughout this process, careful documentation of intermediary computations, thresholds, and visual outputs was maintained to ensure the transparency and reproducibility of the findings. Python scripts were modularized and systematically saved, enabling the reuse of the anomaly

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detection framework on alternative datasets or for longitudinal studies involving updates to the commodity price series.

This integrated methodology, leveraging the robustness of Haar wavelet theory alongside precise statistical thresholding and signal reconstruction, provides a sophisticated mechanism for isolating true anomalies in commodity prices. The combination of mathematical rigour and practical implementation not only enhances the credibility of the results but also delivers a scalable, adaptable tool for ongoing surveillance of financial stress impacts on commodity markets.

3 Results:

Wavelet Upsampling:

The graph illustrates the comparison between the original monthly Financial Stability Index (FSI) data and the upsampled weekly FSI series generated using wavelet-based methods. The blue curve represents the original monthly FSI values, while the red curve shows the upsampled weekly FSI obtained through wavelet transformation. Notably, the wavelet approach successfully captures the overall trend and volatility patterns from the monthly data, preserving the peaks and troughs across the timeline. However, the graph also reveals some discrepancies: the upsampled weekly series displays irregular fluctuations, and certain abrupt spikes do not align naturally with the original monthly progression. Additionally, the noise amplification is visible, particularly during periods of high volatility, which suggests that while wavelets are powerful in handling non-stationary data, they may not always produce smooth or expected transitions for time-series upsampling. Consequently, since the results obtained from the wavelet method did not fully meet our desired accuracy and smoothness for upsampling, we decided to move forward with cubic interpolation to enhance the continuity and reliability of the upsampled data.

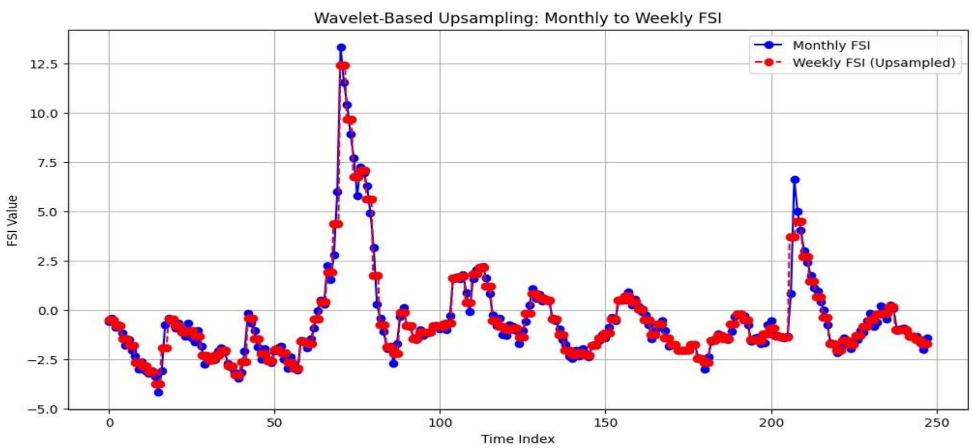

Fig. 1 *Upsampling FSI with wavelets*

Cubic Spline Interpolation:

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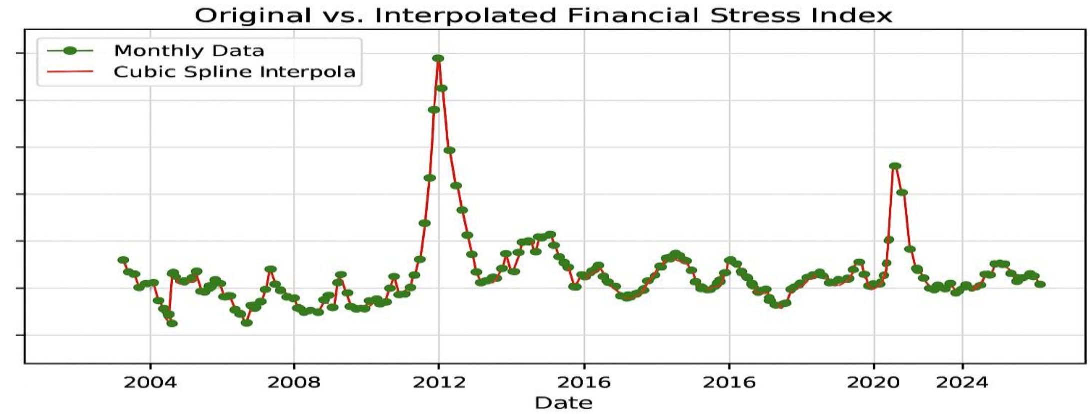

Fig. 2 *Upsampling FSI with cubic interpolation*

The interpolated plot revealed several key findings that highlight significant periods of financial stress. A sharp spike was observed in 2008, corresponding to the peak of the global financial crisis, while another notable surge appeared in early 2020, aligning with the market disruptions triggered by the COVID-19 pandemic. In addition to these major events, the time series also displayed multiple smaller oscillations, which reflect periods of moderate systemic stress dispersed across the timeline.

Cubic spline interpolation proves more effective than wavelet-based decomposition for converting monthly Financial Stress Index (FSI) data to weekly frequency. While wavelet methods are powerful for smoothing and trend extraction, they often suppress sharp variations critical in financial datasets. In contrast, cubic splines preserve localized spikes and transitions—essential for capturing periods of economic turbulence—while maintaining temporal accuracy and interpretability. This makes them better suited for high-resolution interpolation where fidelity to original data patterns is key.

LEAD/LAG Relationships:

The wavelet coherence analysis of the Indian Financial Stress Index (IFSI) and each commodity price is represented with time on the X-axis, spanning from 2006 to 2024, and the period on the Y-axis, expressed in months to capture both short-term fluctuations and long-term trends. The strength of the relationship is depicted through a color spectrum, where blue indicates low coherence, suggesting little to no significant relationship, while red and orange denote high coherence, reflecting strong co-movements or inverse relationships between the variables. Additionally, arrows within the plots provide directional insights: arrows pointing right (→) indicate an in-phase relationship where the variables move together, arrows pointing left (←) represent an anti-phase relationship where they move in opposite directions, and diagonal arrows (↗ or ↘) highlight lead–lag dynamics, showing when one variable leads or lags behind the other.

The wavelet coherence analysis between the Indian Financial Stress Index (IFSI) and Gold reveals distinct patterns across major economic and financial events. During the Global Financial Crisis (2008–2010), a strong red patch at the 32–64 month period with right-pointing arrows indicates high coherence, showing that financial stress and Gold moved together as

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investors sought the metal as a safe haven. In 2013, during the Taper Tantrum, moderate coherence (yellow to light red) was observed at the 16–32 month scale, with upward-tilting arrows suggesting that Gold slightly led financial stress, reflecting capital outflows and a weakened Rupee that spurred Gold demand. In contrast, the 2016 demonetization period showed low coherence (green/blue), implying that the disruption was largely internal, with only a temporary spike in Gold demand and no strong link with broader financial stress. A sharp increase in coherence re-emerged during the COVID-19 pandemic (2020–2021), where red/orange patches and rightward arrows at the 16–32 month period highlighted synchronous movements between stress and Gold prices, as both surged in response to global uncertainty. More recently, in 2022–2023, scattered orange/red patches indicated moderate coherence during the Adani crisis and post-COVID jitters, though the relationship was weaker compared to earlier global shocks. Overall, the findings demonstrate that Gold maintains a strong and positive relationship with financial stress during global crises, underscoring its role as a safe haven, whereas localized shocks such as demonetization or the Adani episode yield weaker coherence. The directional arrows consistently reinforce the in-phase movement of Gold with financial stress, while the post-2022 decline in coherence suggests either financial stabilization or greater portfolio diversification by investors.

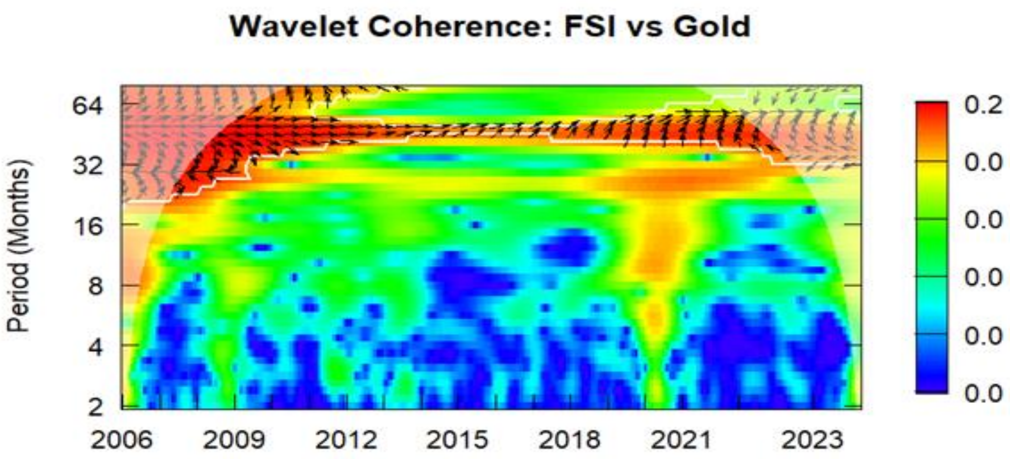

Fig. 3 *Wavelet Coherence : FSI vs Gold*

The wavelet coherence analysis between the Indian Financial Stress Index (IFSI) and Silver reveals distinct phases of interaction shaped by both global crises and commodity-specific dynamics. From 2006 to 2008, the predominance of blue and green regions indicated low coherence, reflecting a period of relative market stability where silver prices and financial stress moved largely independently. This changed dramatically during the Global Financial Crisis (2008–2011), when a thick red zone at the 32–64 month periods with right-pointing arrows signalled strong in-phase movement, as financial turmoil drove investors toward safe-haven assets, fuelling a sharp rally in Silver alongside Gold. However, between 2011 and 2013, coherence weakened as Silver decoupled from stress levels, with the metal suffering a steep crash after its speculative bubble peaked near $50/oz, despite financial stress remaining moderately high. The years 2013–2018 were characterized by calm, with mostly blue and green

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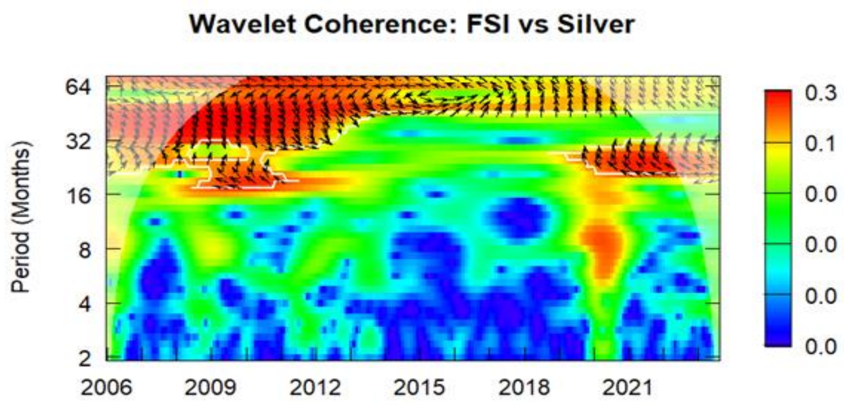
areas indicating low coherence, as Silver's price behavior was shaped more by industrial demand and global commodity trends than by financial stress, even during events like the Taper Tantrum. A mild uptick in coherence emerged between 2018 and 2020, visible in yellow-green patches, reflecting moderate market tensions such as the US-China trade war, though these did not trigger significant safe-haven demand. Coherence surged again during the COVID-19 pandemic (2020–2022), with large red patches at the 32–64 month scales and rightward arrows showing strong co-movement, as heightened financial stress and global uncertainty drove a powerful rally in Silver. In the subsequent period (2022–2024), coherence remained moderate, with yellow and red patches indicating links between Silver and financial stress driven by inflationary pressures and aggressive rate hikes, though Silver's response was less pronounced compared to Gold. Overall, the analysis demonstrates that Silver aligns strongly with financial stress during prolonged global crises, particularly at long-term scales, while decoupling during calmer periods when industrial demand and broader commodity cycles dominate. Compared to Gold, Silver often reacts more slowly to stress spikes, highlighting its dual role as both an industrial metal and a crisis hedge.

Fig. 4 *Wavelet Coherence : FSI vs Silver*



The wavelet coherence analysis between copper prices and the Financial Stress Index (FSI) highlights copper's role as an economically sensitive commodity closely tied to global growth conditions. From 2006 to 2008, coherence remained low, with predominantly blue zones showing that copper prices and financial stress moved independently during a period of global stability. This changed drastically during the Global Financial Crisis (2008–2011), when intense red zones at the 32–64 month scale with leftward or downward-right arrows indicated a strong negative correlation, as soaring financial stress coincided with a sharp collapse in copper prices. In the recovery phase (2011–2014), coherence weakened, with fading red zones turning green, reflecting that copper prices were increasingly driven by supply-demand fundamentals and the support of emerging markets rather than financial stress. Between 2014 and 2018, coherence remained low, dominated by blue zones, as copper's movements were shaped by commodity oversupply and industrial demand fluctuations rather than systemic stress. Trade tensions between 2018 and 2020 brought yellow patches that suggested weak coherence, with copper displaying mild sensitivity to the U.S.–China trade war but remaining largely influenced by industrial and trade dynamics. The COVID-19 pandemic (2020–2022) reintroduced strong coherence, with red zones at the 16–32 month period reflecting a pronounced negative correlation: financial stress surged while copper prices initially plunged, though global stimulus efforts later moderated the impact. From 2022 to 2024, coherence was moderate, with yellow to orange zones indicating that inflationary pressures and aggressive monetary tightening created recessionary fears that weighed on copper, though less dramatically than in earlier crises. Overall, copper demonstrates a cyclical and crisis-sensitive relationship with financial stress, showing strong negative coherence during deep global shocks but decoupling during stable or recovery phases. Unlike safe-haven metals, copper's price movements primarily reflect broader economic and industrial conditions, making it a key barometer of global growth while exhibiting heightened sensitivity only in prolonged crises.

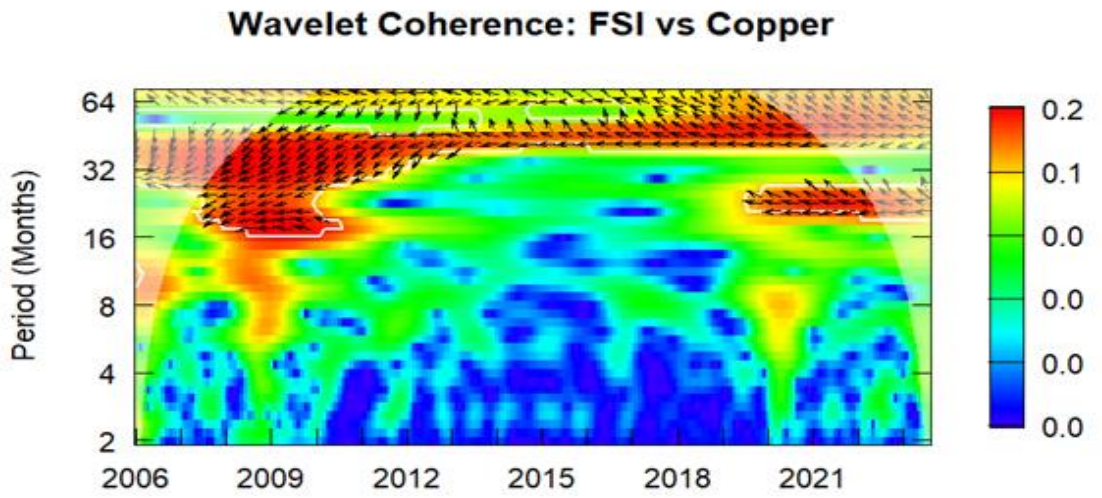


Fig. 5 *Wavelet Coherence: FSI vs Copper*

Copper Prices and Financial Stress Index (FSI) Coherence

The wavelet coherence analysis between the Financial Stress Index (FSI) and crude oil prices highlights crude oil's vulnerability to global financial turmoil and its cyclical nature. During the Global Financial Crisis (2008–2011), a prominent red zone at longer periods (32–64 months) with left-pointing arrows indicated a strong negative correlation, as soaring financial stress coincided with a sharp collapse in oil prices. This reflected the steep decline in demand across sectors such as travel, shipping, and industry during the global recession. In the post-crisis years (2012–2019), coherence was mostly weak to moderate, shown by green and light yellow zones, with inconsistent arrow directions suggesting no stable link between crude oil and financial stress. Instead, oil prices during this phase were primarily influenced by supply-side dynamics, geopolitical events, and OPEC's production decisions. The COVID-19 pandemic (2020–2022) brought back strong coherence, marked by red patches and leftward arrows, again signalling a pronounced inverse relationship. As financial stress surged with global lockdowns and market panic, crude oil prices crashed dramatically, even turning

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negative in 2020 due to unprecedented demand destruction and storage shortages. Importantly, these patterns fall within the Cone of Influence (COI), making them reliable, while results near 2022–2023 are less dependable due to edge effects. Overall, crude oil exhibits a strong negative correlation with financial stress during periods of severe global crises, whereas in stable times, its pricing dynamics are driven more by industry-specific factors such as production, technology, and geopolitical tensions. This dual behavior underscores crude oil's sensitivity to both financial shocks and structural energy market fundamentals.

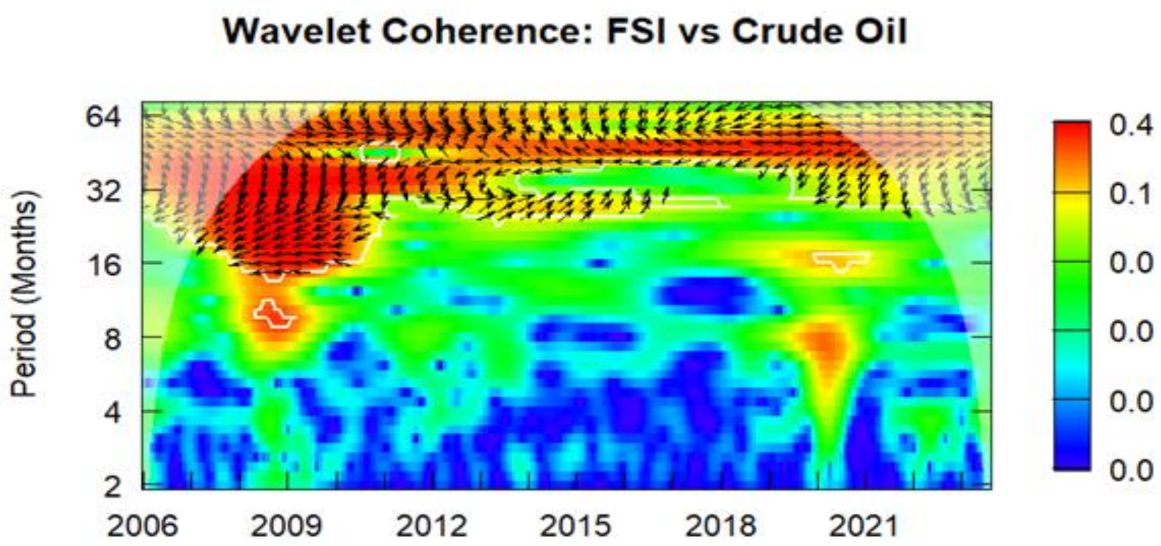

Fig. 6 *Wavelet Coherence : FSI vs Crude Oil*

The wavelet coherence analysis between the Financial Stress Index (FSI) and natural gas prices highlights a cyclical but weaker connection compared to other energy commodities like crude oil. During the Global Financial Crisis (2008–2011), a bright red zone at the 32–64 month scale with left-pointing arrows revealed a strong negative correlation, showing that surging financial stress coincided with falling natural gas prices. However, this red zone appeared thinner than that of crude oil, suggesting that natural gas was affected by the crisis but with less intensity across time scales. From 2012 to 2019, coherence diminished sharply, dominated by blue and green zones that indicated very low coherence and scattered arrow directions, reflecting the absence of a stable relationship. This decoupling aligned with structural changes in the energy sector, particularly the shale gas revolution, which boosted supply and drove down prices largely independent of financial stress. During the COVID-19 pandemic (2020–2022), red patches reappeared at longer periods, again pointing to a negative correlation, with leftward arrows showing that heightened financial stress coincided with an initial decline in natural gas prices. However, unlike crude oil, the fall was less severe, likely cushioned by regional demand patterns and storage capacity. Overall, natural gas demonstrates an inverse relationship with financial stress during global crises but with lower intensity and less persistence compared to crude oil. In stable periods, it largely decouples from financial stress, responding instead to unique supply-demand dynamics, technological shifts, and domestic energy policies. When

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viewed alongside other commodities, these results underline clear patterns: crude oil and natural gas react negatively to stress, copper reflects economic sensitivity through demand-driven declines, while gold consistently aligns positively with stress as a safe-haven, and silver shows mixed behavior due to its dual industrial and monetary nature. Together, these findings highlight the differentiated responses of commodities to financial turmoil, offering valuable insights for market analysis, risk management, and portfolio diversification.

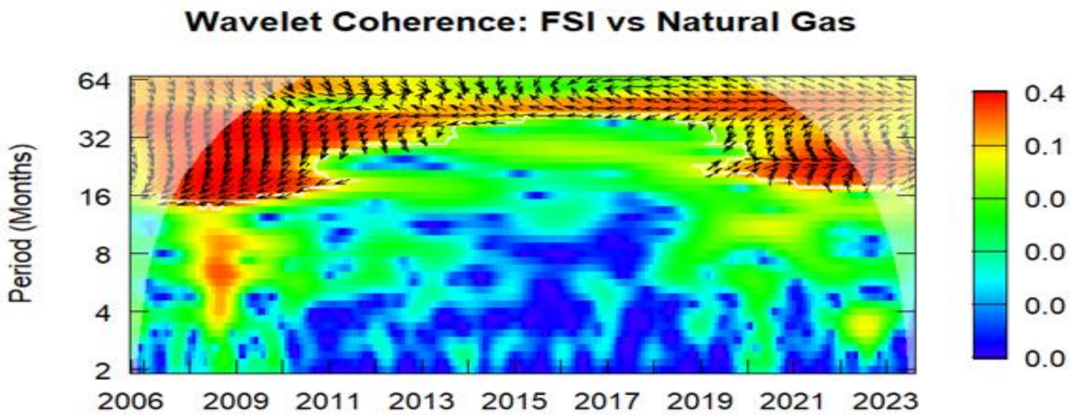

Fig. 7 *Wavelet Coherence: FSI vs Natural Gas*

ANOMALY :

The anomaly detection analysis for silver spot prices between 2006 and 2024 is presented using a wavelet-based framework. On the plot, the **X-axis** represents the timeline, while the **Y-axis** reflects the price of silver in INR per kilogram. The **blue line** traces the actual movement of silver spot prices over time, capturing both long-term trends and short-term fluctuations. The **red dots** mark the anomalies—instances where price behavior diverged significantly from the expected trend, often coinciding with major economic shocks, geopolitical disruptions, or market-specific events. These irregularities were detected using the **Daubechies (db4) wavelet transform**, which decomposed the original price series into approximation and detail coefficients. The detail coefficients, sensitive to sudden changes, were subjected to statistical thresholding to identify anomalies. This approach allows sharp price movements, whether upward spikes or downward drops, to be effectively flagged on the price curve. By integrating wavelet decomposition with anomaly detection, the method provides a powerful tool for identifying structural breaks and stress points in commodity markets. While this section focuses on silver, the same methodology has been consistently applied across all five commodities considered in the study—**Gold, Silver, Copper, Crude Oil, and Natural Gas**—to systematically capture deviations from normal market behavior and provide insights into the timing and impact of financial or external shocks.

Between 2008 and 2023, several anomalies in gold prices can be directly linked to major financial crises and geopolitical events. The **2008 Global Financial Crisis** triggered a collapse in global markets, prompting investors to rush toward gold as a safe-haven, which caused a sharp price surge. In **2011**, the **European Debt Crisis coupled with high inflation in India** created uncertainty in both global and domestic markets, driving higher gold demand as a hedge

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against risk. The **2013 Rupee Crisis** marked another key anomaly, as a steep depreciation of the rupee led to panic buying, forcing the RBI to impose import restrictions that significantly influenced gold pricing. During **2015–2016**, the **China market crash and global economic slowdown** renewed fears of instability, leading to heightened volatility and strengthening safe-haven demand for gold. The **COVID-19 outbreak in early 2020** brought massive sell-offs across global markets, but gold surged sharply as investors sought safety amid unprecedented uncertainty. This was followed in **2021** by post-COVID inflation concerns, where recovery-driven fears of currency devaluation led to another rise in gold prices. In **early 2022**, the **Russia-Ukraine war** heightened geopolitical risk and disrupted supply chains, once again pushing investors toward gold, driving up prices. Finally, in **late 2023**, fears of a global recession, coupled with significant **central bank accumulation of gold**, supported further increases, confirming gold's position as a reliable safe-haven asset during times of crisis.

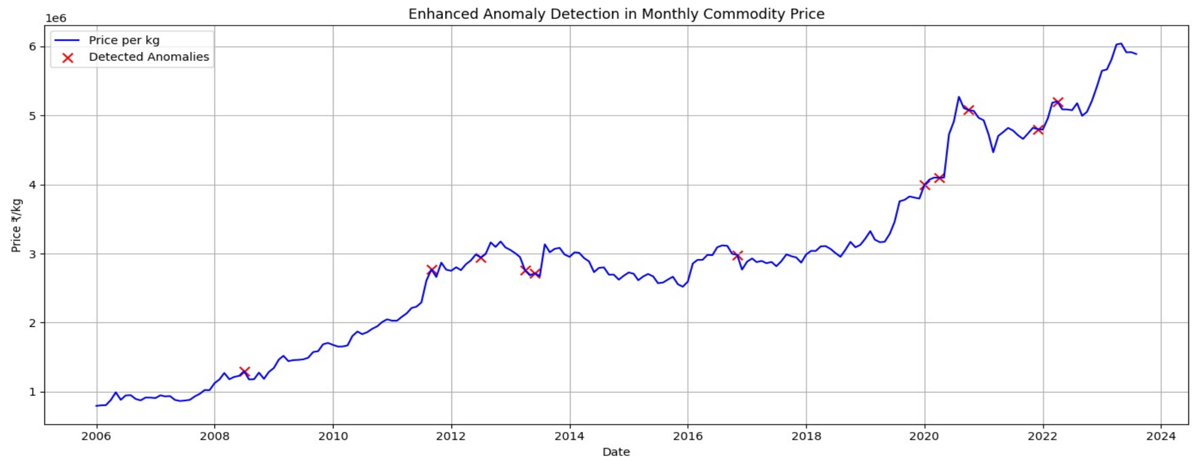

Fig. 8 *Anomaly detection in Gold Price*

Anomaly detection in silver prices between 2006 and 2024 highlights several sharp deviations from normal market behavior, often tied to global crises, domestic policy changes, and shifts in industrial demand. The **2008 Global Financial Crisis** marked the first major anomaly, as investors fled to precious metals, causing a sharp spike in silver prices due to its safe-haven appeal. Another pronounced irregularity appeared in **2010–2011**, during the Eurozone debt crisis and the implementation of quantitative easing (QE) in the US, when silver gained huge investor interest as a hedge against inflation and currency devaluation. In **2013**, India's rupee depreciation combined with strict gold import curbs led investors to silver as an alternative, significantly boosting demand and creating another anomaly. The **2015–2016 period** brought a contrasting anomaly, with silver prices dropping under the weight of global deflationary pressures and weakening industrial demand amidst an economic slowdown. A sharp disruption occurred again in **2020**, during the COVID-19 pandemic, when industrial shutdowns caused initial price volatility, followed by a strong surge as investors turned to silver in search of safety. By **2021**, silver's anomalies were linked to the recovery phase, with strong industrial demand from electronics and solar sectors pushing prices higher. In **2022**, the Russia–Ukraine war added another shock, as geopolitical uncertainty and inflation fears drove investors toward silver as a hedging asset. The most recent anomaly appeared in **late 2023**, when recession fears and a weakening dollar fuelled speculative activity and currency-driven volatility, once again

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disrupting silver's price trajectory. Overall, these anomalies illustrate silver's dual nature as both a safe-haven and an industrial commodity, making its price highly sensitive to both financial crises and shifts in real economic activity.

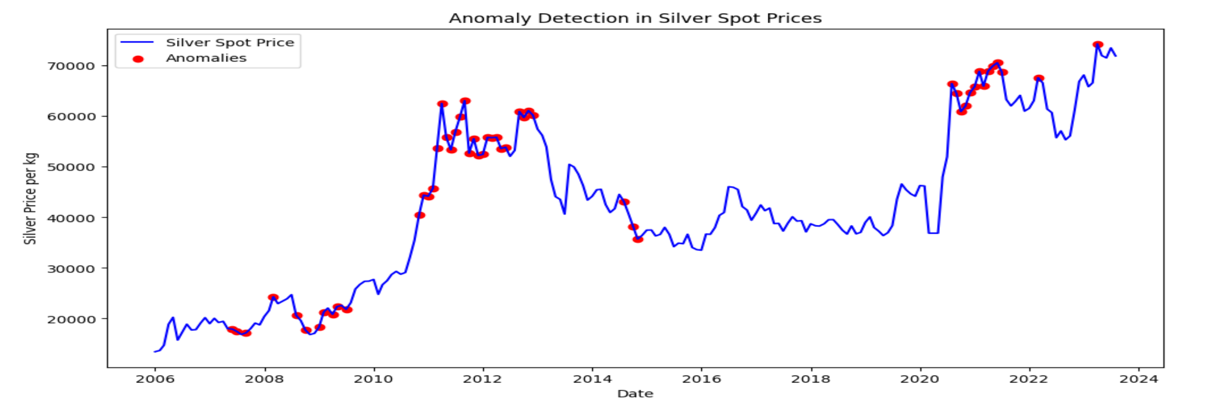

Fig. 9 *Anomaly detection in Silver Price*

Anomaly detection in copper prices between 2006 and 2024 reveals several significant deviations, closely tied to global economic shifts and industrial demand cycles. The **2008–2009 Global Financial Crisis** marked a sharp anomaly, with copper prices plunging as demand collapsed during the worldwide recession, reflecting copper's sensitivity as an industrial metal. A rebound appeared in **2010**, driven by Eurozone market uncertainty but also fueled by global stimulus measures and optimism around economic recovery, leading to a sharp upward movement in prices. In **2015–2016**, copper experienced another major anomaly when China, the largest consumer of industrial metals, slowed its economic growth, sparking a commodity bear market and pulling prices down. The **2020 COVID-19 pandemic** brought yet another disruption, with copper prices initially falling due to global lockdowns and halted industrial activity, before sharply recovering on the back of China's infrastructure-led demand and stimulus-driven growth. This recovery momentum continued into **2021–2022**, where post-COVID industrial resurgence, coupled with severe supply chain disruptions and mining bottlenecks, drove copper prices upward. The **2022 Russia–Ukraine war and ensuing energy crisis** introduced another price spike, as rising energy costs affected production while geopolitical tensions raised expectations of higher demand for metals. Finally, in **2023**, recession fears and dollar strength fluctuations produced volatile price swings, as uncertainty about global demand and interest rate policies weighed heavily on market sentiment. Overall, copper's anomalies strongly mirror global growth conditions, consistently reflecting its role as a barometer of industrial activity and economic health.

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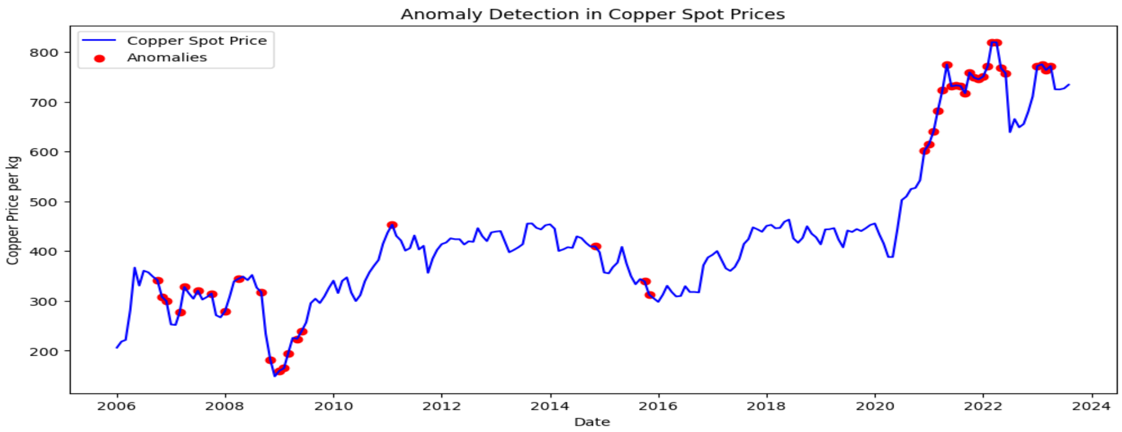

Fig. 10 *Anomaly detection in Copper Price*

Anomaly detection in crude oil prices between 2006 and 2024 highlights sharp disruptions closely linked to global economic shocks, geopolitical events, and supply-demand imbalances. During the **2008–2009 Global Financial Crisis**, crude oil prices crashed dramatically as global demand collapsed under financial panic and recessionary pressures. This was followed by a sharp **2010 recovery**, where stimulus-driven optimism and economic rebound fueled rising demand, pushing prices back up. A major anomaly occurred in **2014**, when OPEC decided not to cut production despite a supply glut, triggering a steep collapse in oil prices. This downturn extended into the **2015–2016 commodity bear cycle**, where persistently low demand and oversupply kept oil prices depressed. The **2020 COVID-19 pandemic** marked an unprecedented anomaly, with oil prices experiencing a massive drop due to lockdowns, travel restrictions, and halted industrial activity—global benchmarks even briefly turned negative, reflecting extreme supply-demand imbalances and storage shortages. As economies reopened, **2021 saw a strong rebound**, with surging demand driving prices upward once again. Finally, in **2022**, the Russia–Ukraine war and ensuing global energy crisis caused severe supply shocks and geopolitical uncertainty, resulting in a sharp spike in crude oil prices worldwide. These anomalies underscore crude oil's vulnerability to both macroeconomic turmoil and geopolitical disruptions, making it one of the most volatile commodities in global markets.

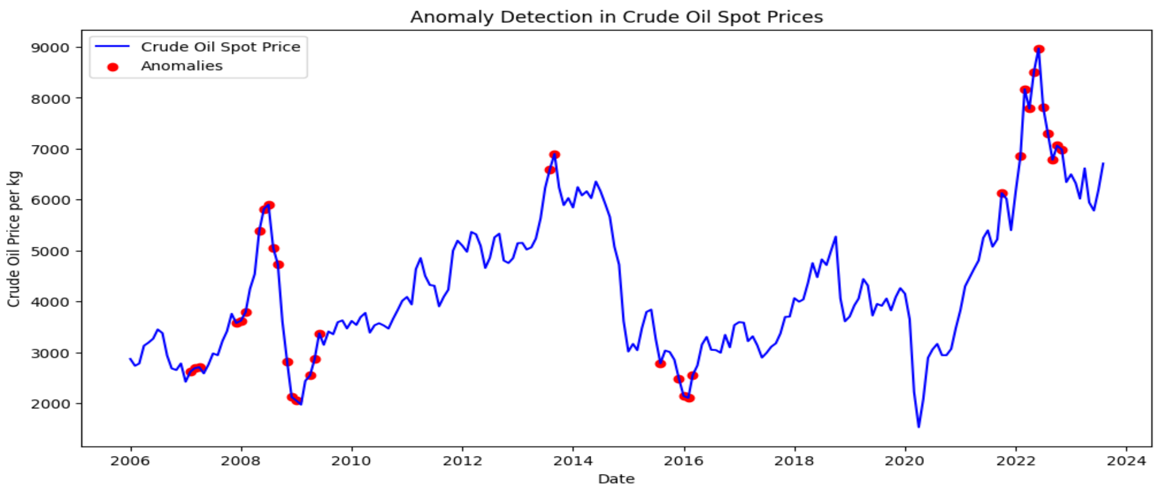

Fig. 11 *Anomaly detection in Crude Oil Price*

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Anomaly detection in natural gas prices between 2006 and 2024 reveals several key deviations influenced by economic crises, supply-demand dynamics, and geopolitical events. During the **2008–2009 Global Financial Crisis**, natural gas experienced an initial price spike followed by a steep decline as reduced industrial activity and lower energy demand depressed markets. In **2010–2011**, prices remained volatile during post-crisis recovery, with oversupply contributing to fluctuations despite gradual stabilization. Weather-related events caused anomalies in **2013–2014**, when unusually cold winters and increased heating demand, such as during the Polar Vortex, drove temporary price spikes. The **post-pandemic recovery in 2021** generated another anomaly, as rising industrial and residential demand coupled with supply chain disruptions led to surging natural gas prices. In **2022**, the Russia–Ukraine war and the ensuing European gas crisis created a severe global supply shock, causing natural gas prices to soar as Europe sought alternatives to Russian supplies. Finally, in **2023**, price corrections emerged as supply chains adjusted and demand moderated, partially stabilizing the market. Overall, natural gas demonstrates sensitivity to both macroeconomic downturns and short-term shocks, with prices responding strongly to crises affecting supply or demand, while displaying moderated volatility during periods of market adjustment.

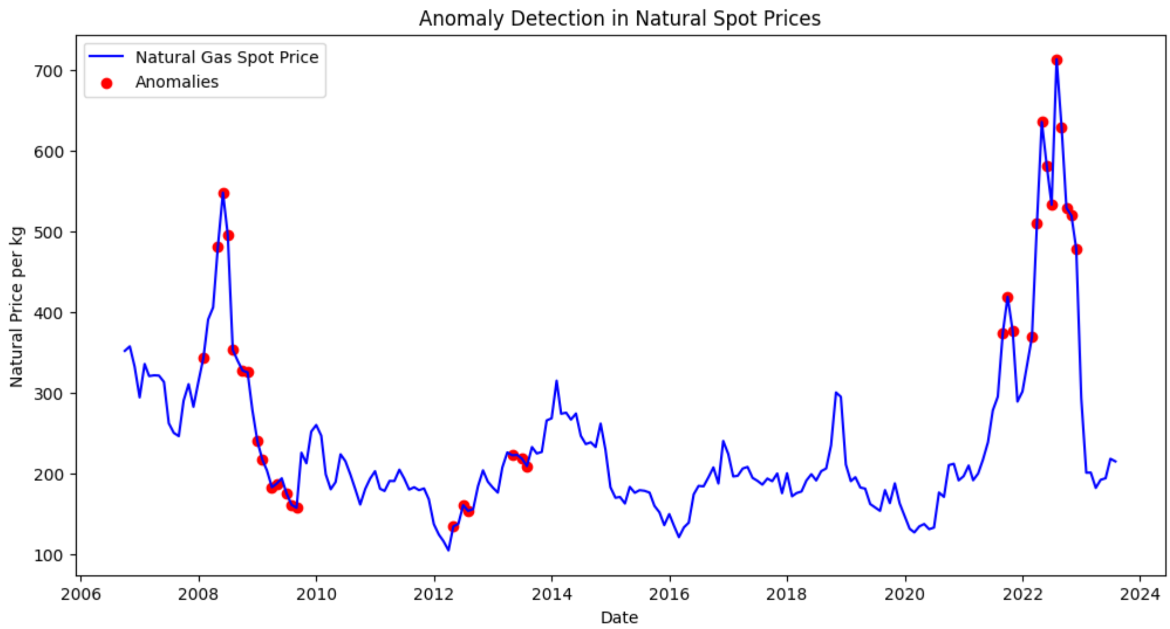

Fig. 12 *Anomaly detection in Natural Gas Price*

Analysis of commodity price responses to domestic liquidity shocks, such as India's demonetisation, reveals clear patterns across different asset classes. **Gold**, being globally priced, remained largely insulated from short-term domestic cash shortages; while local demand dipped temporarily, global market trends dictated overall price movements. Similarly, **silver**, due to its dual role as an industrial and investment metal with global pricing, was not significantly affected by a domestic cash crunch. **Copper**, closely linked to global industrial cycles, showed minimal sensitivity to India-specific events unless these coincided with broader international trends. **Crude oil** prices are primarily driven by global supply-demand dynamics, meaning India's cash-driven consumption fluctuations had negligible influence on worldwide benchmarks. **Natural gas**, largely centrally managed in India and less price-sensitive, also remained unaffected by domestic liquidity shocks. Across these observations, **safe-haven assets like gold and silver** exhibited strong responses to major global financial panics, including the GFC, COVID-19 crisis, and geopolitical conflicts, whereas **industrial metals like copper** reacted primarily to global manufacturing and trade conditions rather than domestic events. **Energy commodities, such as crude oil and natural gas**, were influenced mainly by worldwide supply-demand imbalances and geopolitical tensions, with little impact from localized monetary policies. Notably, the absence of discernible effects from demonetisation across all commodities underscores that localized monetary policy shocks in India exert limited influence on globally traded commodities unless linked to broader demand shifts or import policy changes.

4 Conclusion:

In conclusion, the study compared spline interpolation and wavelet decomposition for expanding the Financial Stress Index (FSI) from monthly to weekly frequency, coherence analysis between FSI and commodities, and anomaly detection using wavelets. Spline interpolation produced a smoother and more consistent weekly series that aligned well with known market events, while wavelet decomposition, though less effective with the limited dataset, remains valuable for larger or more volatile time series due to its ability to capture multi-scale variations. The coherence analysis revealed that gold and silver, as safe-haven assets, showed strong positive coherence with the FSI during periods of heightened stress, whereas copper, crude oil, and natural gas exhibited weaker coherence, reflecting their sensitivity to broader macroeconomic and geopolitical factors. Morlet wavelet coherence proved effective in uncovering these dynamic relationships, although extreme market shifts posed challenges to its accuracy. Furthermore, wavelet-based anomaly detection demonstrated strong effectiveness in identifying irregularities in commodity prices, successfully capturing disruptions linked to major events such as the 2008 Global Financial Crisis, the 2016 demonetisation, and the 2020 COVID-19 pandemic. By localizing anomalies in both time and frequency domains, wavelets provided nuanced insights into structural shifts and abrupt shocks, underscoring their potential as a robust tool for forecasting, risk management, and policy analysis in financial markets.

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