

INTERDEPENDENCE BETWEEN INDIAN FINANCIAL STRESS INDEX AND GLOBAL COMMODITY PRICES: A WAVELET BASED APPROACH AND ANOMALY DETECTION

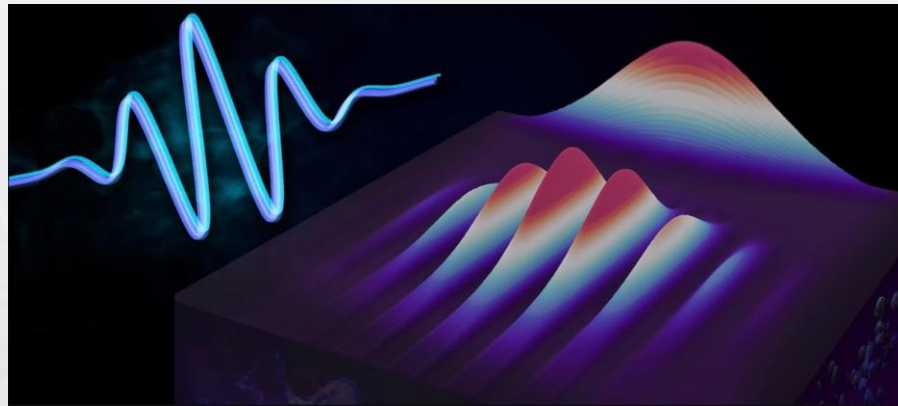


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ABSTRACT

This research examines the relationship between the **Indian Financial Stress Index (IFSI)** and **key global commodities (gold, silver, copper, crude oil, natural gas)** using a wavelet-based approach. Wavelet analysis effectively captures dynamic, multi-scale interactions in volatile markets. The study uses **Daubechies Discrete Wavelet Transform (DWT)** to convert monthly data into weekly frequency, with interpolation for enhanced insights.

This study uses the **Continuous Wavelet Transform (CWT) with the Morlet wavelet** to analyze the time-frequency characteristics of the Indian Financial Stress Index (IFSI) and global commodity prices. The **Cross Wavelet Transform (XWT)** identifies co-movement and lead-lag relationships, focusing on events like **2008 Global Financial Crisis and the 2020 COVID-19 pandemic**. Wavelet Coherence (WTC) assesses the strength of these relationships, while **Monte Carlo simulations** validate the robustness of the results.

Wavelet-based anomaly detection was used to identify unusual fluctuations in commodity prices relative to changes in the Indian Financial Stress Index (IFSI). Using **Daubechies (DWT)**, commodity price series were decomposed into **approximation** (long-term trends) and **detail** (short-term movements) coefficients. Anomalies were flagged by defining a threshold on the detail coefficients and compared with periods of financial stress.

INTRODUCTION

- The **Indian Financial Stress Index (IFSI)** is a key indicator used to track instability in the financial system.
- **Commodity markets**, are often considered **sensitive to financial stress**.
- Traditional time-domain methods often **fail to capture evolving patterns** over time and across different frequencies.
- Therefore, this study adopts a **wavelet-based framework** to explore **time-frequency relationships** between IFSI and major commodity prices.
- This research can be used in the real world for improved **forecasting of commodity prices**, enhanced **investor decision-making**, **Improved Anomaly Detection**, and providing **sector-specific insights for commodity markets**.

OBJECTIVES

- **Wavelet Upsampling**: Evaluate the use of wavelet decomposition to convert monthly financial data into weekly frequency for **more detailed time-series insights**.
- **Wavelet Coherence Analysis**: Analyze the **co-movements and lead-lag relationships** between global commodity prices (gold, silver, copper, crude oil, natural gas) and the Indian Financial Stress Index (IFSI) using wavelets also validate our results using **Monte Carlo simulations**
- **Anomaly Detection**: Identify abnormal trends, patterns, or shocks in financial time series by analyzing **wavelet detail coefficients** and comparing them with **periods of financial stress**.

LITERATURE REVIEW

Wavelet Applications in Finance and Commodities:

- Armah et al. (2022), Ferrer et al. (2018), Aguiar-Contraria & Soares (2011), and Karamati & Belhassine (2022) explore the use of wavelet analysis in examining financial and commodity market dynamics.

Financial Stress Transmission and Economic Impacts:

- Aboura & Van Roye (2017), Doornik & Van Roye (2014), and Hubrich & Tetlow (2015) investigate the transmission of financial stress and its macroeconomic consequences.

Financialization, Commodity Markets, and Volatility:

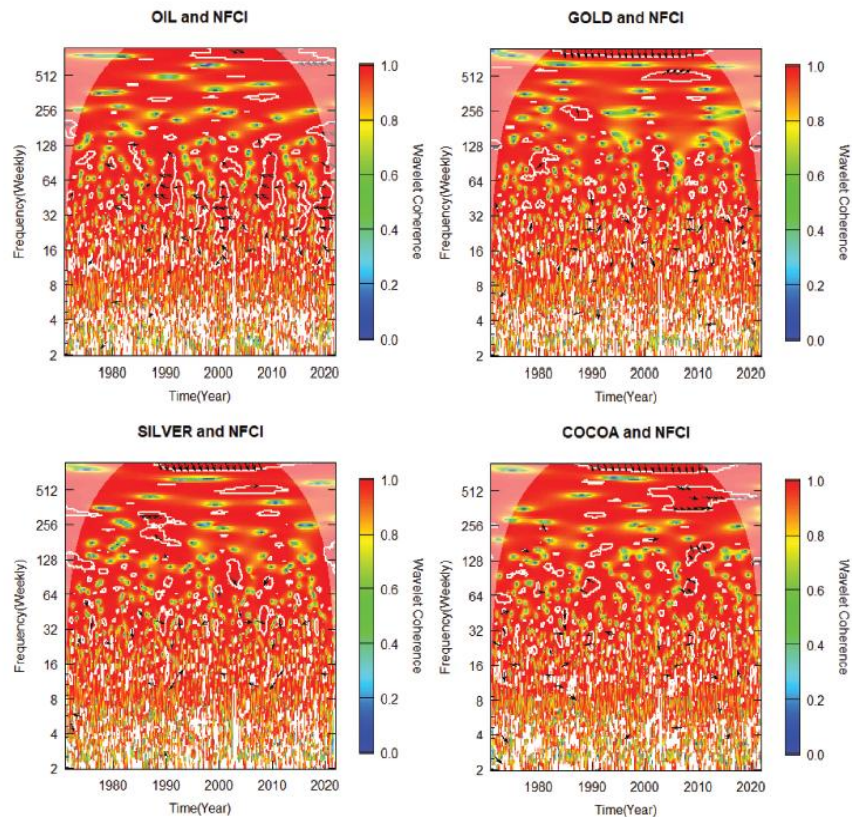
- Cheng & Xiong (2014), Das et al. (2018), and Umar et al. (2021) focus on the role of financialization in commodity markets, with particular attention to volatility patterns.

Methodological and Technical Contributions:

- Agrapart & Batailly(2020), Gençay et al. (2001), and Roesch et al. (2014) provide key methodological advancements and technical foundations for the use of wavelet analysis in economics and finance.

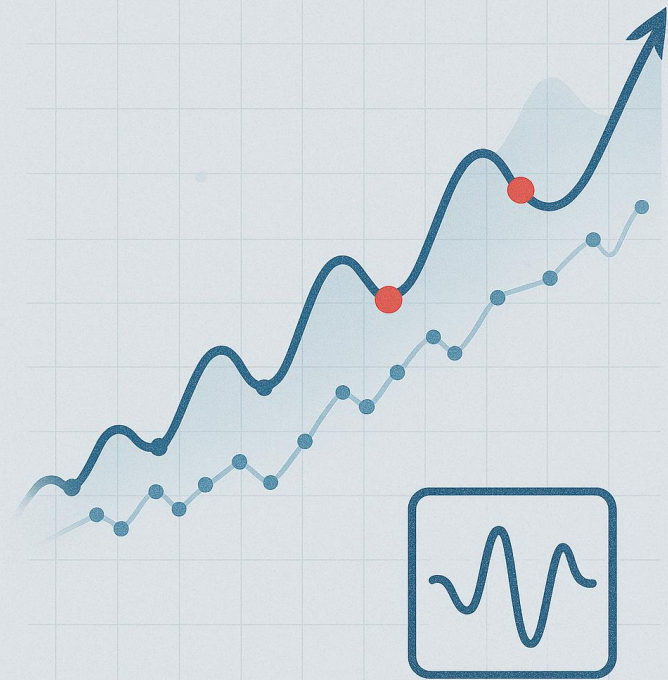
LITERATURE REVIEW

Figure 2. Wavelet coherence of NFCI and global commodities prices.



DATA-PREPARATION

- **IFSI Data:** Monthly IFSI data (Jan 2006–Aug 2023) sourced from Asian Regional Integration Center (ARIC)
- **Frequency Conversion Attempt:** Tried converting IFSI to weekly using DWT (Daubechies), but results misaligned, retained monthly frequency to preserve data integrity.
- **Commodity Data:** Daily spot prices for gold, silver, copper, crude oil, and natural gas from Multi Commodity Exchange (MCX) (Jan 2006–Aug 2023), excluding non-trading days.
- **Data Aggregation:** Daily MCX prices converted to monthly values using the **median method** to align with IFSI data.
- **Anomaly Detection:** Used **monthly median-aggregated data** for identifying price anomalies in commodities.



UPSAMPLING

FROM MONTHLY
TO WEEKLY



01

UPSAMPLING

UPSAMPLING ANALYSIS

01

Wavelet based upsampling

Discrete Wavelet Transform (DWT) was used to convert monthly data into higher-frequency components.

02

Cubic Spline Interpolation

Cubic spline interpolation is used to generate smooth, realistic curves from coarse or sparse data ideal for weekly upsampling from monthly time series.

DAUBECHIES WAVELET

Daubechies Wavelet

A family of orthogonal wavelets characterized by maximum vanishing moments for a given support length which is ideal for analyzing non-stationary signals with sharp changes or discontinuities.

Why Daubechies?

- Captures both **long-term trends** (approximation) and **short-term fluctuations** (detail).
- Powerful for **denoising, compression, and multi-resolution analysis**.
- Suitable for **economic and financial signals** with abrupt shifts (e.g., financial stress indicators).

Use:

- Apply **Discrete Wavelet Transform** on **monthly FSI** to:
 - Decompose signal into **approximation & detail coefficients**
 - **Denoise** and **enhance resolution** for interpolation
- Enable **multi-scale analysis** of financial stress
- Support further **reconstruction** via **inverse DWT (IDWT)** for refined time series

METHODOLOGY

Wavelet Based Upsampling

Discrete Wavelet Transform (DWT) was used to convert monthly data into higher-frequency components.

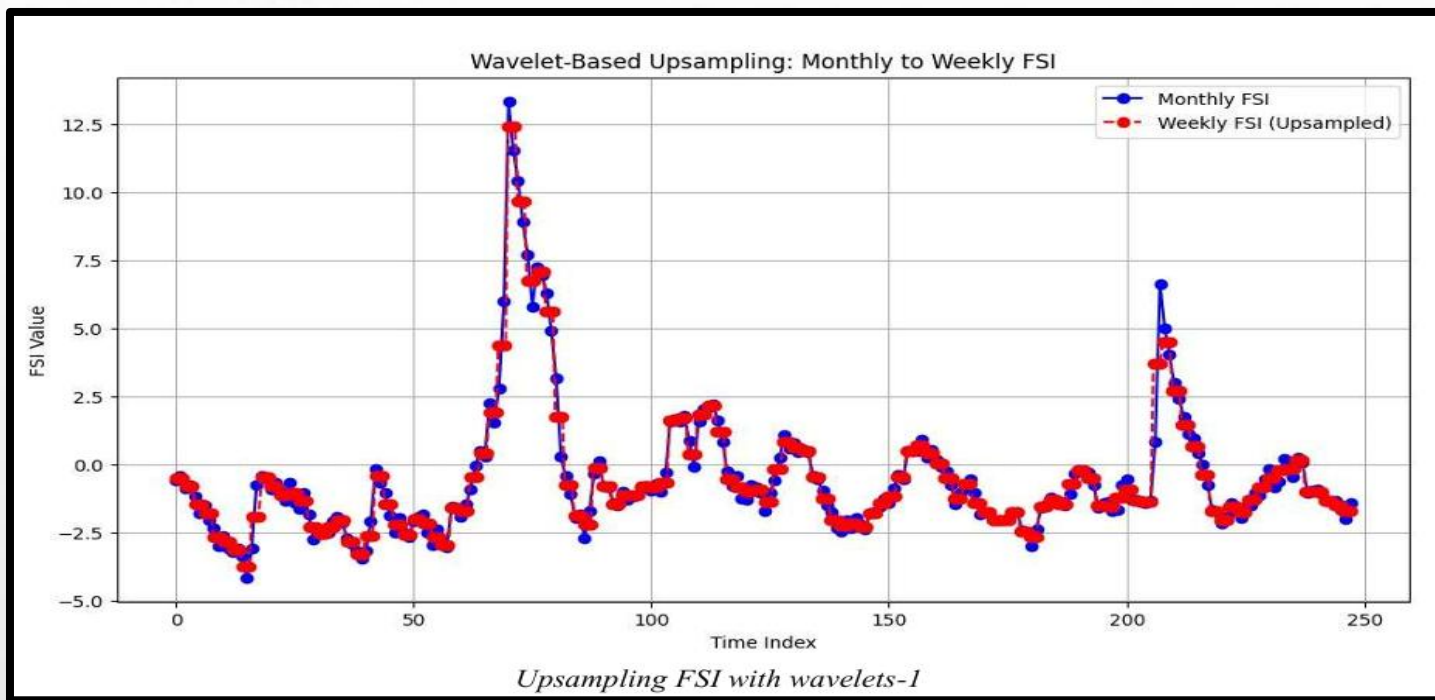
This approach enabled the separation of the signal into:

- **High-frequency components** – capturing short-term fluctuations.
- **Low-frequency components** – revealing long-term trends.

The implementation was conducted in **Python** using scientific computing libraries:

- **NumPy** for efficient numerical operations and array handling.
- **Matplotlib** for visualization and signal plotting.
- **PyWavelets (pywt)** as the core tool for wavelet transformation and reconstruction.

RESULT



METHODOLOGY

Cubic Spline Interpolation for FSI

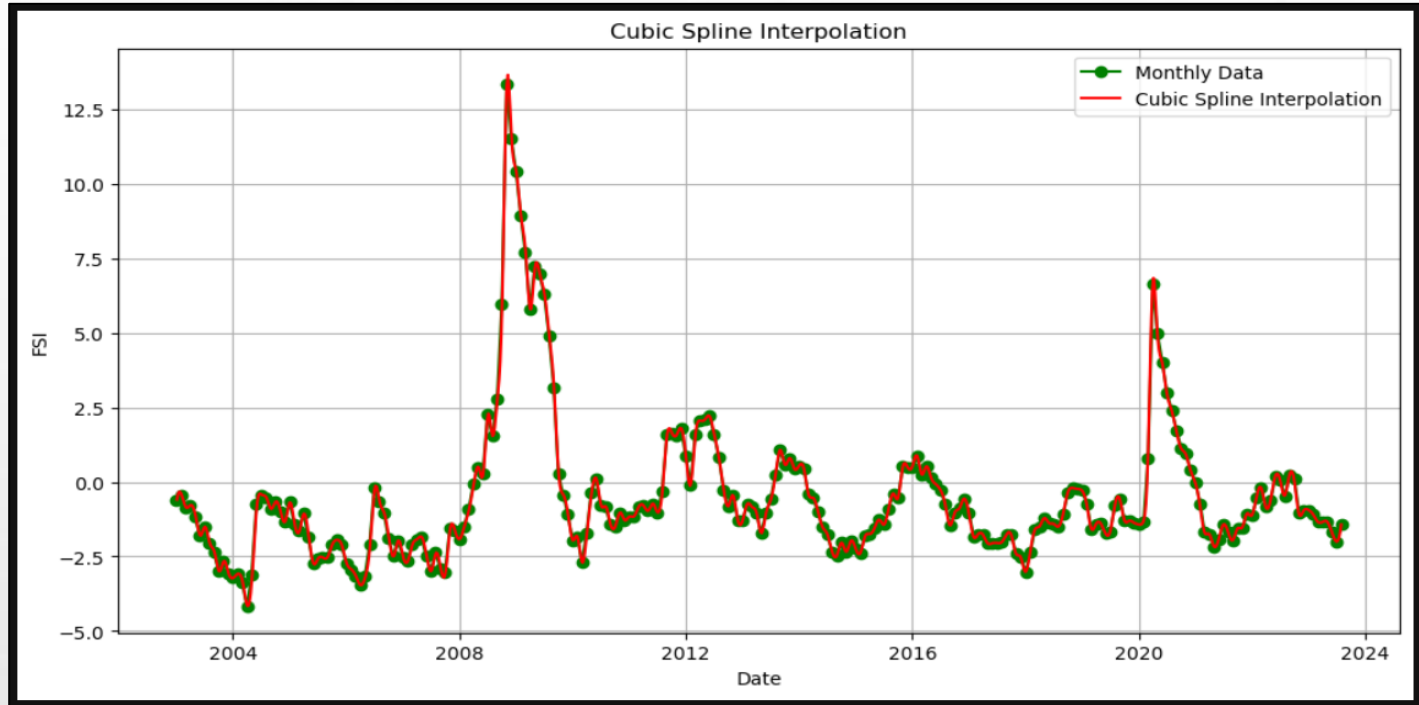
1.Interpolation Workflow:

- **Indexing Time:** Assigned numeric indices to monthly FSI points for smooth computation
- **Timeline Creation:** Generated a continuous **weekly date range**
- **Spline Fitting:** Applied **CubicSpline** from SciPy to fit a smooth curve across the monthly values
- **Weekly Estimation:** Evaluated spline at weekly intervals to estimate FSI values
- **DataFrame Construction:** Created a new DataFrame with weekly dates and interpolated FSI values

2.Limitation & Strategic Choice:

- Despite smoother trends and improved granularity, the interpolated data was **synthetic**
- Core analysis was performed on **original monthly data** to:
- Ensure reliability
- Preserve authenticity
- Maintain alignment with real-world financial events

RESULT





02

LEAD/LAG RELATIONSHIP

MORLET WAVELET

Morlet Wavelet:

- A complex wavelet combining a sinusoidal wave with a Gaussian envelope

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

ω_0 : Central frequency

$e^{i\omega_0 t}$: Complex sine wave

$e^{-t^2/2}$: Gaussian window for time localisation

why morlet?

- Balances time and frequency localisation.
- Captures both short-term shocks and long-term trends.
- Perfect for analysing financial stress (FSI) with commodity prices.

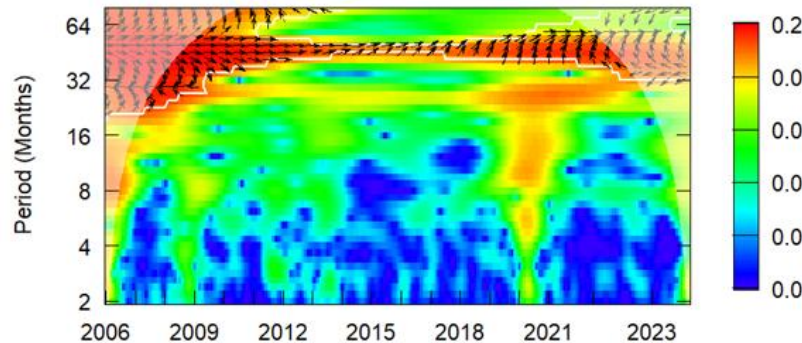
Use:

- Transform time series (FSI & Prices) into time-frequency domain.
- Compute wavelet coherence to detect:
 - Strength of relationship (coherence)
 - Direction of relationship (phase angle)

LEAD/LAG RELATIONSHIP ANALYSIS

01	Continuous Wavelet Transform (CWT) using Morlet Wavelet	Used biwavelet package in R to decompose IFSI & Commodity prices
02	Cross-Wavelet Transform (XWT) and Cross-Wavelet Power Spectrum	To understand the periods of co-movements between both the time series
03	Wavelet Coherence (WTC) Analysis	To find the coherence i.e value of R (0 to 1)
04	Phase Difference Calculation and Interpretation of Lead-Lag Dynamics	To interpret directional causality, using phase arrows
05	Monte Carlo Significance Testing and Visualisation	To validate the robustness of detected patterns(Los=5%), and visualized findings using cross-wavelet power spectrum

Wavelet Coherence: FSI vs Gold



● = Low coherence

● = Moderate coherence

● = High coherence

○ → : In phase (move together).

○ ← : Anti-phase (move opposite).

○ ↗ or ↘ : Lead-lag relationships

● **X-axis** = Time (years:2006-2024)

● **Y-axis** = Period (in months)

*Gold – Lead/Lag Relationship with FSI
Wavelet Coherence Analysis (2006-2024)*

Global Financial Crisis

- High Coherence(→)
- Gold as Safe Haven

2008-2010

Demonetization

- Low Coherence
- Domestic event, Minimal Global impact

2016

Adani Crisis & Post Covid

- Moderate Coherence
- Market Instability

2022-2023

2013

Taper Tantrum

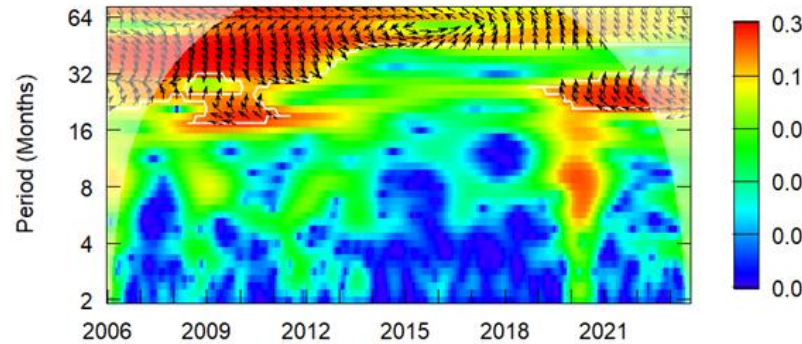
- Moderate coherence(↗)
- US Fed Tapering, Rupee Depreciation

2020-2021

Covid-19

- Strong Coherence
- Panic drove Buying Gold and FSI upwards

Wavelet Coherence: FSI vs Silver



*Silver— Lead/Lag Relationship with IFSI
Wavelet Coherence Analysis (2006-2024)*

Global Financial Crisis

- High Coherence
- Silver leads FSI

2008

2011

Trade Tensions

- Weak to moderate Coherence
- Mild Stress

2018-2020

Inflation & Rate Hikes

- Moderate Coherence
- Rising Rates Influenced prices

2022-2024

Silver Price Crash

- Moderate coherence
- Post bubble decoupling

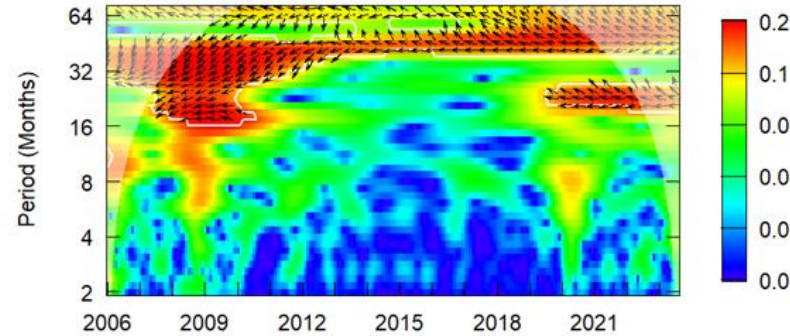
2011-2013

Covid-19 Pandemic

- High Coherence
- Panic & Stress drove alignment

2020-2022

Wavelet Coherence: FSI vs Copper



Copper — Lead/Lag Relationship with FSI
Wavelet Coherence Analysis (2006-2024)

Global Financial Crisis

- High Coherence
- Copper Collapsed, Stress Spiked

2008-2011

Demonetization

- Low Coherence
- Weak Link

2014-2018

Adani Crisis & Post Covid

- Moderate Coherence
- Scattered Patches

2022-2024

2011-2014

Recovery Phase

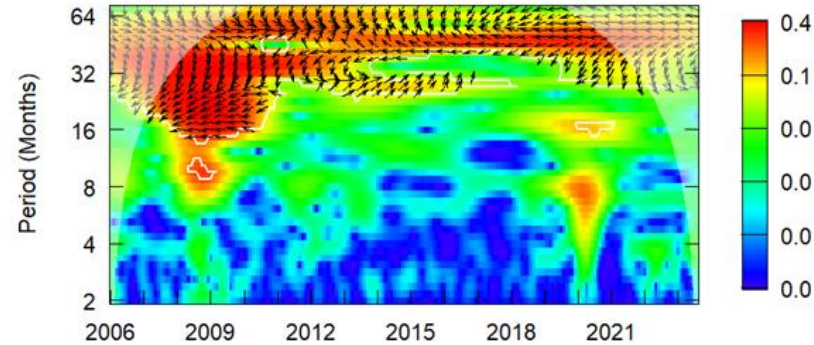
- Moderate coherence
- Gold led FSI

2020-2022

Covid-19

- Strong Coherence
- Arrows Anti phase

Wavelet Coherence: FSI vs Crude Oil



*Crude Oil – Lead/Lag Relationship with IFSI
Wavelet Coherence Analysis (2006–2024)*

Global Financial Crisis

- High Coherence
- Demand Collapsed, Stress Spiked

2008-2011

Supply demand Factors

- Low to moderate Coherence
- Geopolitics & OPEC influenced prices

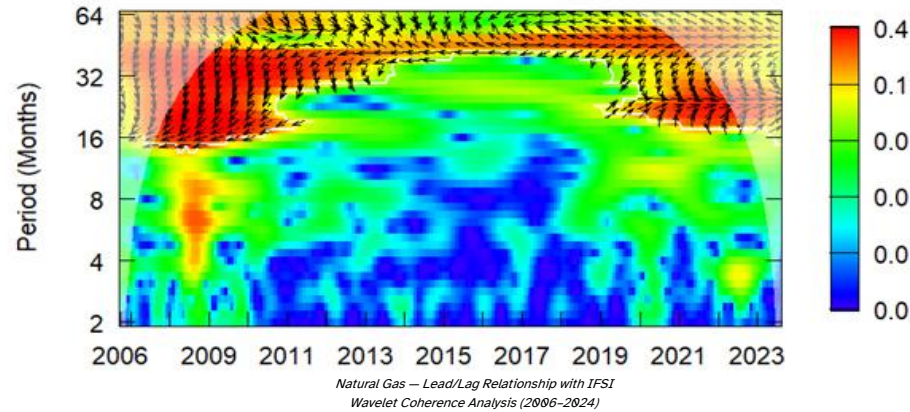
2020-2022

2012-2019

Covid-19 Crash & Recovery

- Negative Coherence
- Pandemic Panic led to oil prices collapse

Wavelet Coherence: FSI vs Natural Gas



Global Financial Crises

- High negative Coherence
- Gas prices decline as stress spiked

2008-2011

Covid-19 Pandemic

- Moderate Coherence
- Initial drop, regional resilience sustained demand

2020-2022

2012-2019

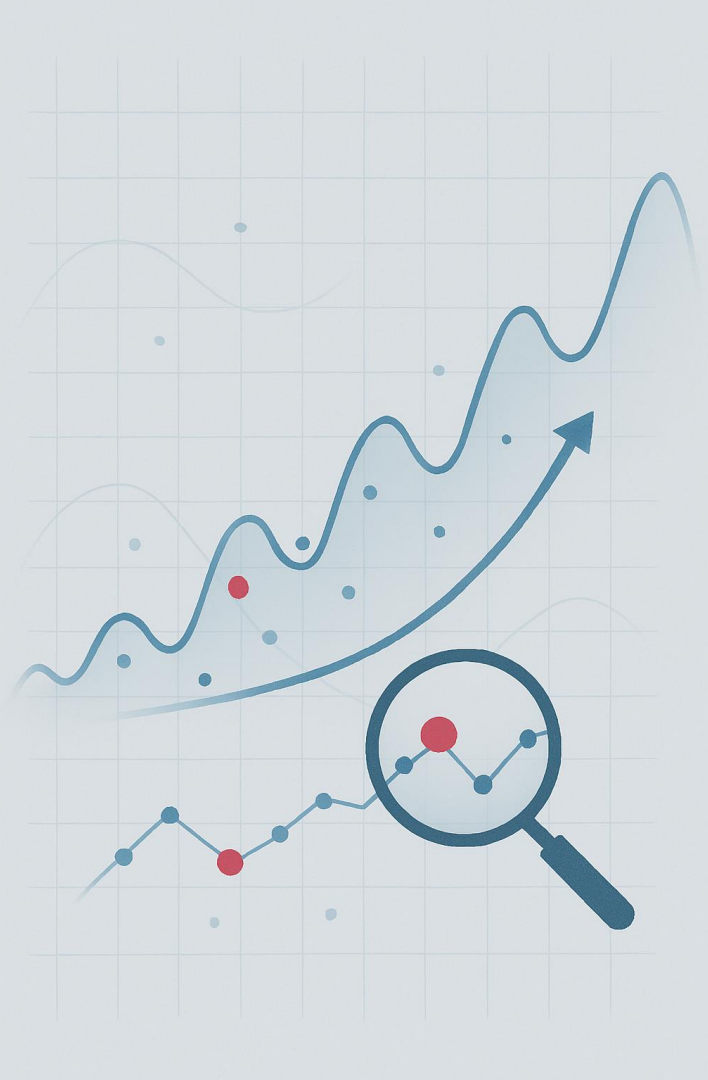
Shale Revolution

- Low Coherence
- Supply abundance, regional drivers

2022-2024

Inflation & Energy Security

- Moderate coherence
- Global energy concerns mildly impact gas prices

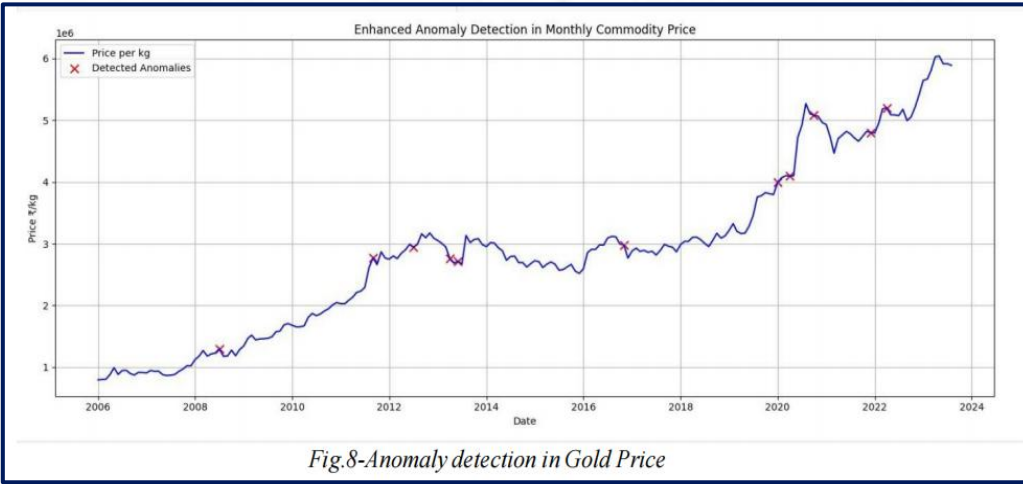


03

ANOMALY DETECTION

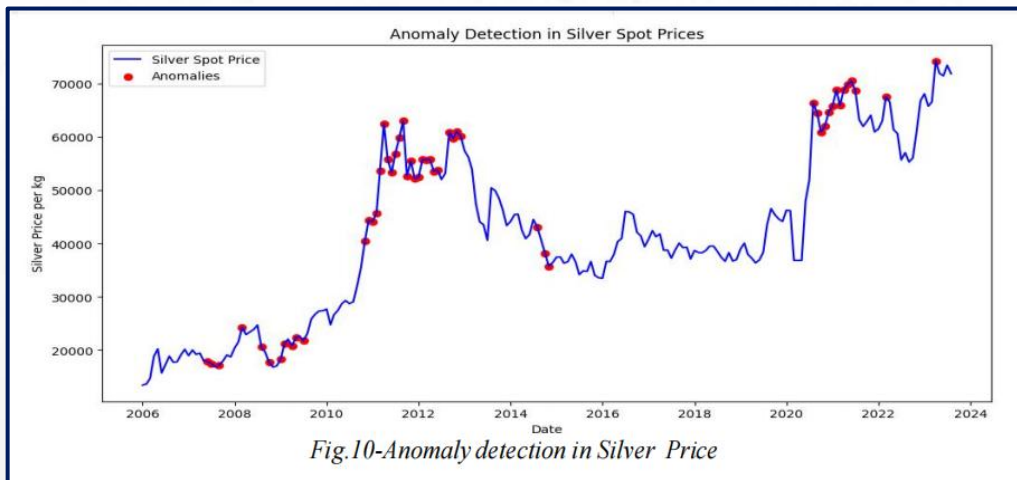
ANOMALY ANALYSIS

01	Anomaly Detection	To identify sudden fluctuations, unusual trading, and disruptions,,
02	Wavelet Transform	To isolate irregular movements from the overall trend.
03	Daubechies 4 (db4)	To highlight high-frequency variations (sudden price jumps/drops).
04	Rolling Mean Deviation	To calculate a 52-week rolling average and absolute deviation between actual prices and the rolling mean.
05	Threshold	Flagged anomalies where $ z\text{-score} > 2$ Flagged anomalies where deviation exceeded 2 times the mean deviation ,



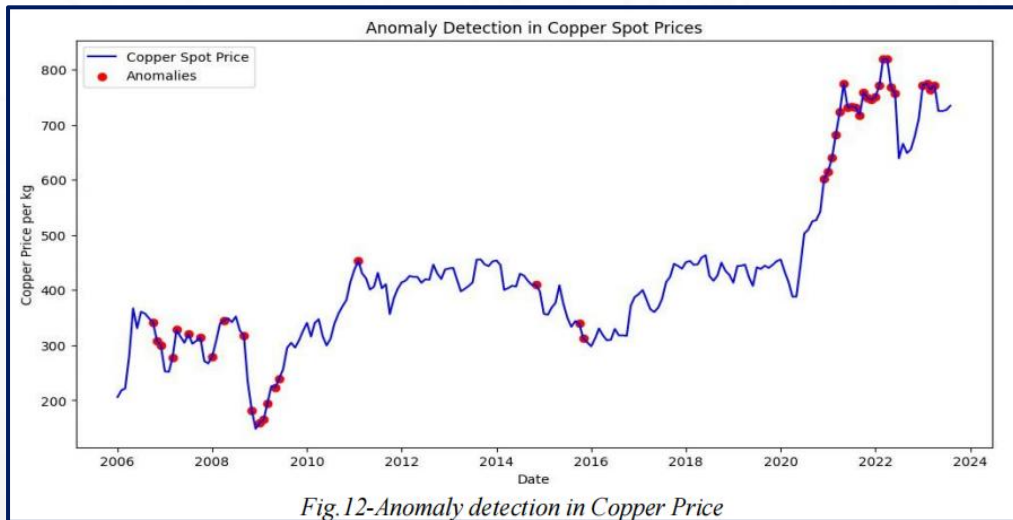
GOLD





SILVER

2008	Global Financial Crisis
2010-2011	Eurozone Debt Crisis + QE in US
2013	Rupee Crisis & Gold Import Restrictions
2015-2016	China Market Crash & Global Economic Slowdown
2020 (Early)	COVID-19 Pandemic Outbreak
2021	Recovery & Industrial Demand Surge
2022 (Early)	Russia-Ukraine War
2023 (Late)	Recession Fears & Weakening Dollar



COPPER



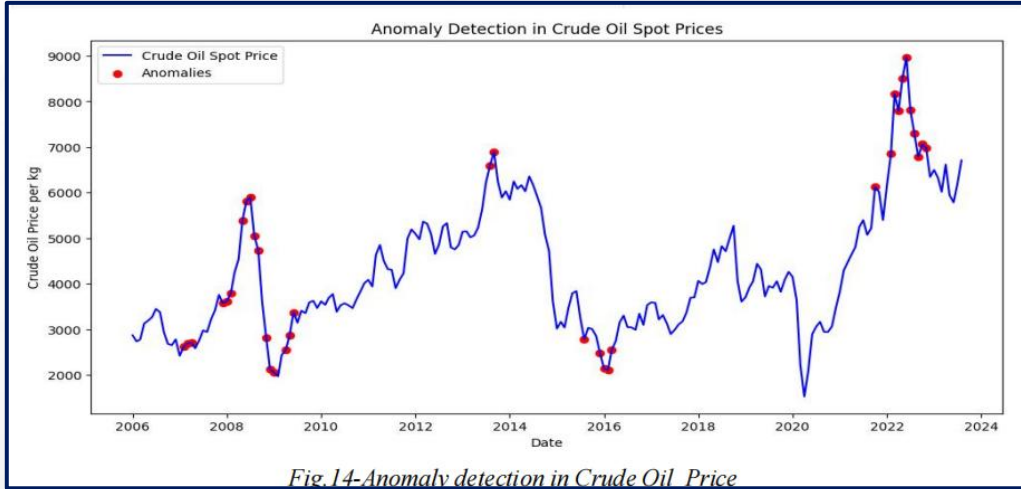
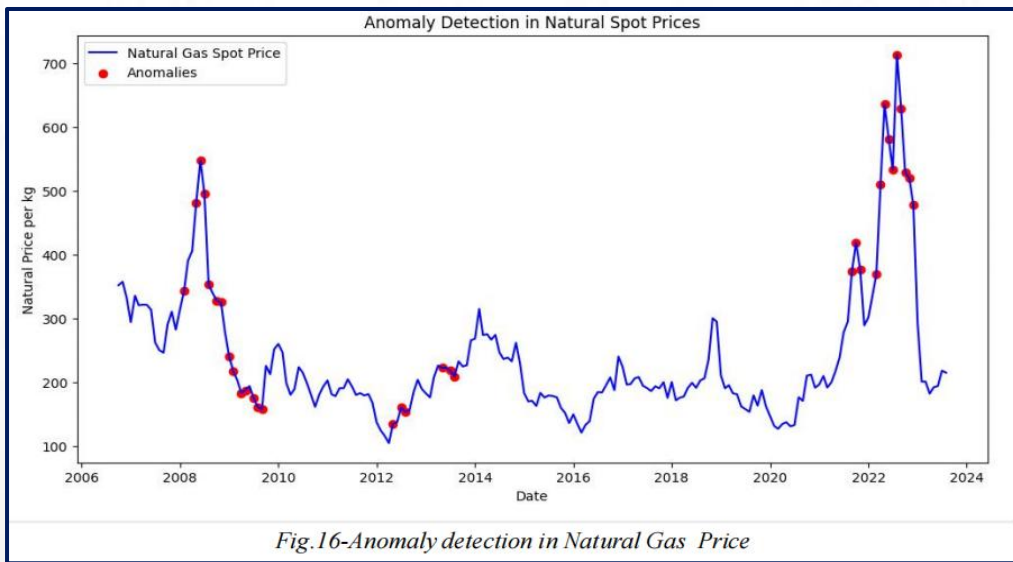


Fig.14-Anomaly detection in Crude Oil Price

CRUDE OIL





NATURAL GAS



CONCLUSIONS

01

Spline Interpolation vs. Wavelet Upsampling for FSI Expansion

Spline interpolation outperformed wavelet decomposition for upsampling monthly FSI to weekly, offering smoother trends aligned with market events.

Wavelet-based upsampling remains valuable for larger or more volatile datasets due to its ability to capture multi-scale signal variations.

02

Wavelet Coherence Analysis

During financial stress, clear patterns emerge: **crude oil and Natural Gas show Strong Negative correlations with Financial Stress**, especially during the 2008 crisis and 2020 pandemic, with oil being the most reactive. Copper also shows Negative correlations, influenced by global demand. **Gold acts as a Safe-haven**, rising with stress, while **Silver shows Mixed behavior** due to its dual industrial and monetary roles

03

Anomaly Detection

Wavelet methods successfully detected anomalies during key events (2008 GFC, 2016 Demonetization, COVID-19). **Gold and Silver rise during Financial Crises** as safe-haven assets, **Copper is driven by Manufacturing and Trade**, while **Crude Oil and Natural Gas prices are influenced by Demand-Supply dynamics and Geopolitical factors**.

LIMITATIONS

- Monthly Data Resolution: Using monthly data smooths short-term volatility but might miss quick shocks or flash crashes that occur within a month.
- Limited Commodity Scope: Only major commodities (gold, silver, copper, crude oil, natural gas) were analyzed. Other factors (like food prices, broader indexes) might also play roles during stress periods.

FUTURE SCOPE

- Extend the analysis using high-frequency (daily/intraday) data for finer insights.
- Apply alternative wavelet families or advanced time-frequency tools like Empirical Mode Decomposition (EMD).
- Develop real-time financial stress monitoring systems using wavelet-based analytics.
- Analyse policy impacts by examining shifts in wavelet coherence pre/post interventions.
- Integrate macroeconomic indicators to capture broader economic dynamics.

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