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Quantile Return Connectedness between Crude Oil, Forex, and Indian Sectoral Equities: A Comparative QVAR Analysis of Forex-Exposed and Crude-Exposed Blocks

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Abstract: This paper studies how shocks travel between crude oil, the US dollar–Indian rupee exchange rate, and six Indian sectoral equity indices. We estimate a quantile vector autoregression (QVAR) connectedness model on daily log returns from January 2022 to June 2026 at five quantiles ($\tau = 0.05$, 0.25, 0.50, 0.75, 0.95), which stand for panic, bear, normal, bull, and boom market states. The six sectors are grouped by their dominant exposure into a forex-exposed block (Nifty IT, Pharma, and Metal) and a crude-exposed block (Nifty Oil & Gas, Commercial & Transport Services, and Chemicals). We test five hypotheses with transparent non-parametric tools: the Friedman omnibus test, the paired Wilcoxon signed-rank test with Holm correction, sign tests, and bootstrap confidence intervals. Return connectedness is U-shaped: the corrected total connectedness index reaches 93.07 percent in a crash and 92.43 percent in a boom but only 52.26 percent in normal times. Both crude oil and the rupee act as net receivers of shocks at every quantile, so macro dominance in crashes is insulation-driven rather than transmission-driven, and the crude-exposed block absorbs significantly more shock than the forex-exposed block. The results inform portfolio hedging, currency intervention, and quantile-based stress testing for India.

Keywords: Quantile vector autoregression; Return connectedness; Crude oil; USD/INR exchange rate; Indian sectoral equities; non-parametric hypothesis testing.

JEL Classification: G11; G15; F31

Research Paper

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1. INTRODUCTION

The way oil prices, exchange rates, and stock prices move together has become one of the most heavily studied questions in finance, because an oil price shock raises production costs, feeds inflation, and changes the discount rate on future cash flows all at the same time, with effects that differ across sectors and market states (Park & Ratti, 2008). For an oil-importing emerging economy such as India the question is even more pointed. (Kumar, 2019) shows that a positive oil price shock of one percent depreciates the rupee by about 1.31 percent and lowers Indian stock returns in the long run, whereas negative shocks matter far less, so the oil–rupee–stock link in India is asymmetric and nonlinear, echoing importer–exporter asymmetries found across countries (Mokni, 2020; Ramos & Veiga, 2013).

The question becomes still more serious when markets are under stress. (Mazur *et al.,* 2021) document that the Dow Jones Industrial Average fell about 26 percent in four trading days in March 2020 while crude petroleum lost roughly 77 percent of its value, and the winning and losing sectors differed sharply from normal times. A growing body of quantile-based work confirms that oil–equity links strengthen dramatically in the tails of the return distribution: total connectedness is U-shaped, spiking in bearish and bullish states and staying low in calm periods (Ando *et al.,* 2022; Chatziantoniou *et al.,* 2021; Hanif *et al.,* 2024; Yaya *et al.,* 2024). India experienced exactly such a stress-rich sample between January 2022 and June 2026, covering the post-Ukraine inflationary shock, the fastest monetary tightening in a generation, and the subsequent stabilization, which makes it an ideal laboratory for studying how crude oil and currency shocks travel through sectoral equities.

We therefore attempt to uncover the dynamics of the relationships between crude oil, the USD/INR exchange rate, and six Nifty sectoral indices using a quantile vector autoregression (QVAR) connectedness framework estimated on daily returns. Crude oil futures from the Multi Commodity Exchange of India (MCX) and the USD/INR rate from the National Stock Exchange of India (NSE) sit alongside two economically motivated groups of sectors: a forex-exposed block (Nifty IT, Nifty Pharma, and Nifty Metal) whose dollar revenues rise when the rupee weakens, and a crude-exposed block (Nifty Oil & Gas, Nifty Commercial & Transport Services, and Nifty Chemicals) whose costs rise when crude oil becomes expensive. We estimate the network at five quantiles, compare crude oil and the rupee head-to-head as competing macro transmitters, measure which block absorbs more shock in a crash, rank all eight assets from the largest net giver to the largest net taker, and ask whether macro dominance in a crash comes from sending out more shock or from shutting itself off from incoming shock. In place of heavy bootstrapping we test five simply stated hypotheses with a transparent non-parametric toolkit that any researcher can replicate with basic software. The paper proceeds from the literature (Section 2) through the research gap and hypotheses (Section 3) and the methodology (Section 4) to the results and discussion (Section 5), the implications (Section 6), the limitations (Section 7), and the conclusion (Section 8).

2. LITERATURE REVIEW

Early empirical work measured the oil–stock relationship with average, linear tools and established that oil shocks do move stock markets, although the estimated strength differs across countries. (Park & Ratti, 2008) study the United States and thirteen European countries and find that oil price shocks have a statistically significant impact on real stock returns in a majority of them, with oil shocks explaining a median of about six percent of the volatility of real stock returns over a two-year horizon and as much as about ten percent in Sweden. (Malik & Hammoudeh, 2007) show that Gulf equity markets receive significant volatility from the oil market. (Ramos & Veiga, 2013) add an important asymmetry: oil price increases depress the stock returns of importing countries and raise those of exporting countries, while oil price declines have little effect on importers because they raise oil volatility, whose negative effect cancels the benefit of cheaper oil. (Mokni, 2020) confirms with a time-varying parameter model that stock return reactions to structural oil shocks change through time and differ between importers and exporters. This strand of literature suggests that the oil–equity link is real but conditional on the country, the direction of the shock, and the period.

A second strand focuses on emerging economies and on India in particular. (Kumar, 2019) examines oil prices, the real effective exchange rate, and the BSE Sensex and finds strong nonlinear bidirectional causality between oil and the rupee and between oil and stocks, with positive oil shocks producing a long-run rupee depreciation of about 1.31 percent per one percent oil increase and a fall in stock returns, effects far stronger than those of negative shocks. (Bagchi, 2017) applies an asymmetric power ARCH model to BRIC countries and documents volatility transmission between crude oil and national stock. (Mensi *et al.,* 2021) study oil, natural gas, and BRICS stock markets in the time-frequency domain and report that oil–stock co-movements are strongest at long horizons during crisis periods. (Naeem *et al.,* 2022) use a cross-quantilogram on decomposed oil shocks and BRIC equities and find that oil demand shocks and stock returns display positive and highly persistent tail dependence, booming and busting together, while the dependence is negligible in normal conditions. These studies make clear that the Indian and emerging-market evidence cannot simply be read off the developed-market literature.

A third strand reacts to the growing recognition that the oil–stock interaction is nonlinear and state-dependent by moving the analysis to the tails of the distribution. (Sim & Zhou, 2015) develop a quantile-on-quantile approach and show that although the average relationship between oil shocks and US stock returns is negligible, large negative oil shocks boost US equities when the stock market itself is at its low quantiles, a pattern no linear model can capture. (Das *et al.,* 2018) apply causality-in-quantiles tests and find that financial stress causes gold, oil, and stock returns only in bearish and bullish ranges and not at the median. (Das & Kannadhasan, 2020) decompose oil price changes into demand, supply, and risk shocks for emerging-market sectoral indices and show that sectoral vulnerability is concentrated in bearish states, with positive shocks exerting more pressure than negative ones. (Balcilar *et al.,* 2019) document that oil risk exposures across emerging and frontier markets are highly heterogeneous and quantile-specific, and (Audi *et al.,* 2025) reach a similar conclusion for European equities. At the sectoral level, (Bakić, 2024) reports quantile-specific oil-to-sector spillovers in the United States, and (Zhou *et al.,* 2019) show with a cross-quantilogram that international oil volatility predicts BRICS stock returns mainly in the tails. Extreme risk studies point the same way: (Du & He,

2015) find Granger causality in extreme risk between oil and stock markets that strengthens around the 2008 crisis, while (Shahzad *et al.,* 2018) and (Hadhri, 2021) document strong lower-tail dependence between oil and Islamic equity markets with bidirectional downside spillovers. (Hanif *et al.,* 2024) provide the closest quantile-connectedness evidence for large oil producers and consumers including India: the total connectedness index reaches 79.07 percent in bearish states against 37.40 percent in normal states, and India behaves as a net receiver of oil shocks.

A fourth strand supplies the measurement machinery that all connectedness work now uses. (Koop *et al.,* 1996) introduce the generalized impulse response function, which is independent of the ordering of the variables, and (Pesaran & Shin, 1998) extend the idea to the generalized forecast error variance decomposition (GFEVD) in linear vector autoregressions. (Diebold & Yilmaz, 2012) turn the GFEVD into a directional spillover index and show for a four-asset US system that total connectedness averaged only 12.6 percent in calm times but surged above 30 percent during the 2008 crisis. (Diebold & Yılmaz, 2014) generalize the framework to full network topology, with connectedness among US financial firms peaking at 89.2 percent on the day of the Lehman bankruptcy. (Baruník & Křehlík, 2018) add a frequency dimension and show that crises are driven mainly by the long-term component of connectedness, and (Antonakakis *et al.,* 2020) replace the rolling-window VAR with a time-varying parameter VAR whose refined measures adjust instantly to structural breaks. Each of these refinements, however, keeps the conditional mean as the object of interest, so none of them can describe what happens in the extreme market states that matter most for risk management.

The quantile connectedness approach closes this gap by moving the whole variance-decomposition apparatus to a chosen conditional quantile. (Ando *et al.,* 2022) combine a quantile factor VAR with GFEVD and find that connectedness among sovereigns and financial sectors is U-shaped: the spillover index reaches 76.57 percent at the first quantile and 83.32 percent at the ninety-ninth quantile while remaining below nine percent across the central part of the distribution. (Chatziantoniou *et al.,* 2021) formalize the QVAR version of this idea, apply it to interest rate swap markets, and show that connectedness is very strong both for highly negative changes (below the twenty percent quantile) and highly positive changes (above the eighty percent quantile), with the dollar acting as a steady net transmitter and the yen as a persistent net receiver. Applications have since spread quickly: (Mensi *et al.,* 2022) show that negative returns connect European subsectors more tightly than positive ones (89.00 against 85.70 percent); (Yaya *et al.,* 2024) find connectedness for African markets jumping from 16.33 percent at the median to 56.22 and 80.10 percent in the bearish and bullish states; (Balci & Dogan, 2026) report a U-shaped 76 to 97 percent range for Russia in which the ruble and the volatility index act as shock absorbers; (Kayral *et al.,* 2025) document regime-dependent resilience in emerging indices; (Stenfors *et al.,* 2022) extend the framework to European yield curves; (Chatziantoniou *et al.,* 2022) show that green-market connectedness is asymmetric across tails and horizons; and (Gabauer & Stenfors, 2024) push the idea to quantile-on-quantile connectedness for the US Treasury curve.

Crisis studies complete the picture: (Mazur *et al.,* 2021) show the sectoral dispersion of the March 2020 crash, (Liao *et al.,* 2021) find Brent oil to be the major volatility transmitter during the COVID-19 health emergency, (Lin *et al.,* 2021) document regime-switching oil–stock spillovers, (Siwar & Mellouli, 2023) frequency-dependent oil–stock linkages, (Cui *et al.,* 2021) strong long-horizon oil–stock dependence, (Tiwari *et al.,* 2022) pandemic-era spillovers among green assets, (He *et al.,* 2025) climate-policy-uncertainty transmission, and (Liu *et al.,* 2021) tail risk in the oil–stock nexus through a novel quantile spillover measure. (Gökgöz *et al.,* 2025) connect BRICS markets with volatility indices, and (Cui *et al.,* 2025) study crude oil, the dollar index, and the S&P 500 jointly and find that crude oil consistently acts as a net transmitter of realized-volatility risk (+21.78 percent) while the dollar index is a large net receiver (−18.56 percent). Despite this rich and rapidly growing literature, no study has yet placed crude oil, the rupee, and Indian sectoral equities in a single quantile connectedness network, and none has confronted the transmission-versus-insulation nature of macro dominance in a crash. The present study is designed to fill these gaps.

3. Research Gap and Hypotheses of the Study

3.1 Research gap

The review above shows a fast-growing literature, but three simple things are still missing. First, most quantile studies depend on heavy computer bootstrapping to put confidence intervals around their connectedness estimates, and this bootstrapping often fails to converge at the extreme quantiles, where it is needed most (Ando *et al.,* 2022; Chatziantoniou *et al.,* 2021), and its results change with the random draws. This study drops the bootstrapping machinery altogether and tests its hypotheses with plain statistical tests—the Friedman test, the Wilcoxon signed-rank test, and the sign test—applied to the daily time series of connectedness. These tests are transparent, easy to repeat, and well suited to the fat-tailed return data that motivate the quantile approach.

Second, earlier studies usually look at oil and equities, or currencies and equities, one pair at a time, and they treat the equity market as one block (Hanif *et al.,* 2024; Kumar, 2019). They therefore cannot say whether crude oil or the exchange rate is the bigger shock giver when the market crashes, and they cannot say which group of sectors suffers more. This study puts crude oil and the USD/INR rate in the same eight-variable network as six sectoral indices, and it groups the sectors into a forex-exposed block (IT, Pharma, Metal) and a crude-exposed block (Oil & Gas, Commercial & Transport Services, Chemicals), so that both questions can be answered inside one model.

Third, some recent studies add a volatility proxy on top of returns to compare price shocks with uncertainty shocks (Cui *et al.,* 2025). This makes the model richer, but it also makes it harder to rank crude oil against the currency, because the volatility proxy reacts to forces of its own and blurs the comparison. This study deliberately uses returns only, so the ranking of the two macro drivers and of the two sector blocks stays clean.

Within this design, the study pursues five objectives: (i) to estimate total, directional (TO/FROM), and net return connectedness among crude oil, USD/INR, and six Indian sectoral indices at five quantiles standing for panic, bear, normal, bull, and boom states; (ii) to compare crude oil and USD/INR as competing macro transmitters in the crash state and across the full quantile grid; (iii) to compare how much shock the forex-exposed block and the crude-exposed block receive from the two macro variables in the crash state; (iv) to rank all eight assets from the largest net transmitter to the largest net receiver within each quantile and test whether the ranking is statistically meaningful; and (v) to find out whether macro dominance in a crash is transmission-driven (sends more) or insulation-driven (receives less).

3.2 Research hypotheses

The five hypotheses are tied to simple test applied to the daily time series of connectedness measures extracted from the QVAR model at the five quantiles:

H1: (systemic risk rises in extreme market states). The system as a whole is more connected at the crash quantile ($\tau = 0.05$) and the boom quantile ($\tau = 0.95$) than at the median ($\tau = 0.50$), so the pattern of total connectedness across the five quantiles is U-shaped. Test: the Friedman omnibus test across the five quantile TCI series, followed by paired Wilcoxon tests of the tails against the median.

H2: (crude oil and the rupee as competing shock givers). Both crude oil and USD/INR send out more shock than they receive across the quantile grid, and at the crash quantile one of the two gives out significantly more than the other. Tests: sign tests on the net connectedness of each macro variable, and a paired Wilcoxon test between the two net series at $\tau = 0.05$.

H3: (which sector block suffers more in a crash). During a crash ($\tau = 0.05$) the forex-exposed block and the crude-exposed block receive different average shock from the two macro variables. Test: a paired Wilcoxon signed-rank test on the two block-average net connectedness series.

H4: (a meaningful ranking of assets). Within each quantile the eight assets can be ranked from the biggest net giver to the biggest net taker, and the ranking is not the result of chance. Test: the Friedman omnibus test across the eight assets for every quantile, with Holm-corrected pairwise Wilcoxon tests afterwards.

H5: (insulation or transmission). When a macro variable dominates the network in a crash, we test whether it dominates because it sends out more shock (transmission) or because it shuts itself off from incoming shock (insulation). Test: paired Wilcoxon tests of the TO series against the FROM series for each macro variable at $\tau = 0.05$ and $\tau = 0.50$, with the TO–FROM gap compared across the two states.

4. RESEARCH METHODOLOGY

4.1 Data and sample

The dataset comprises daily closing prices for an eight-variable network spanning January 1, 2022 to June 18, 2026, capturing the inflationary pressures and aggressive monetary tightening of 2022–23, the Russia–Ukraine conflict, US-Iran Conflict and the subsequent stabilization. The macro block consists of crude oil futures from the Multi Commodity Exchange of India (MCX) and the USD/INR exchange rate from the National Stock Exchange of India (NSE). The forex-exposed block comprises Nifty IT, Nifty Pharma, and Nifty Metal, whose revenues are predominantly earned in, or linked to, US dollars, while the crude-exposed block comprises Nifty Oil & Gas, Nifty Commercial & Transport Services, and Nifty Chemicals, whose costs are directly driven by energy prices. Log-returns, computed as first differences of natural logarithms of closing prices, are the sole input of the model, and the descriptive statistics in Section 5.1 confirm the non-normality, fat tails, and volatility clustering that motivate a quantile-based framework (Das *et al.,* 2018; Naeem *et al.,* 2022).

4.2 The quantile connectedness approach

We employ the quantile connectedness approach proposed by (Ando *et al.,* 2022) and formalized by (Chatziantoniou *et al.,* 2021) to examine the quantile propagation mechanism of returns. To calculate all connectedness metrics, we first estimate a quantile vector autoregression, QVAR(p), which can be outlined as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau)\, y_{t-j} + u_t(\tau) \tag{1}$$

where y_t and y_{t-j} are k × 1 dimensional endogenous variable vectors consisting of the first-differenced return series of the eight assets, τ is between [0, 1] and represents the quantile of interest, p stands for the lag length of the QVAR model, μ(τ) is a k × 1 dimensional conditional mean vector, $\Phi_j(\tau)$ is a k × k dimensional QVAR coefficient matrix, and $u_t(\tau)$ demonstrates the k × 1 dimensional error vector which has a k × k dimensional variance–covariance matrix, Σ(τ) (Chatziantoniou *et al.,* 2021). To transform the QVAR(p) to its QVMA(∞) representation, we use Wold's theorem:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) u_{t-i} \quad (2)$$

Afterwards, the H-step-ahead Generalised Forecast Error Variance Decomposition (GFEVD) of (Koop *et al.,* 1996; Pesaran & Shin, 1998) is calculated, which illustrates the impact a shock in variable j has on variable i:

$$\psi_{ij}^{g}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_h(\tau) \Sigma(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_h(\tau) \Sigma(\tau) \Psi_h(\tau)' e_i\right)}$$

$$\tilde{\psi}_{ij}^{g}(H) = \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{k} \psi_{ij}^{g}(H)} \quad (3)$$

where e_i represents a zero vector with unity on the ith position. This normalization leads to the two equalities that the rows of the normalized decomposition sum to one and that all elements sum to k. To obtain the information on the overall impact variable i has on all other variables j, the total directional connectedness TO others is computed (Chatziantoniou *et al.,* 2021):

$$C_{i\to j}^{g}(H) = \sum_{j=1,\ i\neq j}^{k} \tilde{\psi}_{ji}^{g}(H) \quad (4)$$

Subsequently, the impact of shocking all other variables j on variable i is evaluated by the total directional connectedness FROM others:

$$C_{i\leftarrow j}^{g}(H) = \sum_{j=1,\ i\neq j}^{k} \tilde{\psi}_{ij}^{g}(H) \quad (5)$$

The difference between the total directional connectedness TO others and the total directional connectedness FROM others results in the net total directional connectedness, which can be regarded as the net influence variable i has on the analysed network:

$$C_i^{g}(H) = C_{i\to j}^{g}(H) - C_{i\leftarrow j}^{g}(H) \quad (6)$$

The last connectedness metric is the adjusted total connectedness index (TCI) of (Chatziantoniou *et al.,* 2021), which ranges between [0, 1] and is often used as a proxy for market risk, because the higher the TCI is, the higher is the degree of network interconnectedness:

$$TCI(H) = \frac{\sum_{i,j=1,\ i\neq j}^{k} \tilde{\psi}_{ij}^{g}(H)}{k-1} \quad (7)$$

Following the reference implementation of the approach (Chatziantoniou *et al.,* 2021), each quantile model is estimated with a 200-day rolling window, the lag length selected by the Bayesian information criterion, and an H = 20-step-ahead forecast variance decomposition, repeated for τ = 0.05, 0.25, 0.50, 0.75, and 0.95, which we label panic, bear, normal, bull, and boom states. Because the GFEVD is order-invariant (Koop *et al.,* 1996; Pesaran & Shin, 1998), no causal ordering needs to be imposed among crude oil, the exchange rate, and the sectoral indices, and the common quantile grid allows direct comparison with the tail evidence for other markets (Ando *et al.,* 2022; Yaya *et al.,* 2024).

4.3 Hypothesis testing framework

The study deploys a non-parametric testing toolkit applied directly to the daily time series of connectedness measures. The Friedman omnibus test establishes whether multiple quantiles (H1) or multiple assets (H4) are jointly distinct; where the null is rejected, post-hoc comparisons use the paired Wilcoxon signed-rank test with Holm correction. Sign tests evaluate whether each macro variable is a net transmitter in a majority of rolling windows (H2), and paired Wilcoxon tests compare the two macro variables with each other (H2, H5) and the two sector blocks with each other (H3). Bootstrap confidence intervals complement the tail-versus-median comparisons in H1, and effect sizes are reported as percentage-point differences so that statistical and economic significance can be judged together.

5. RESULTS AND DISCUSSION

This section presents the empirical results of the QVAR connectedness analysis estimated on the return series across the five-quantile grid, using a 200-day rolling window, an information-criterion lag, and the GFEVD of (Pesaran & Shin, 1998). The results are reported in four steps: descriptive and stationarity diagnostics, the regime-dependent level of total connectedness, the full pairwise spillover matrices at all five quantiles, and the hypothesis-wise test outcomes, followed by a discussion in the context of the reviewed literature.

5.1 Descriptive statistics

Table 1 reports the summary statistics. All eight series have a mean indistinguishable from zero, consistent with the martingale property of efficient returns, and the variance is uniformly low, with crude oil marginally higher. Seven series display significantly negative skewness—Nifty Oil & Gas (−1.046), Nifty Commercial & Transport (−1.132), and Nifty Metal (−0.779) are the most pronounced—while USD/INR is the only positively skewed series (0.161), reflecting episodic steep depreciations. Every series shows excess kurtosis between 1.1 and 10.2 and rejects the Jarque–Bera null at the one percent level, and the significant Ljung–Box statistics on squared returns indicate volatility clustering throughout the network (Das & Kannadhasan, 2020; Sim & Zhou, 2015).

Table 1: Summary statistics of the daily log-return series

Series	Mean	Variance	Skewness	Ex.Kurtosis	JB	Q(20)	Q2(20)
Pharma	0.000* (0.087)	0.000	-0.057 (0.442)	1.114*** (0.000)	57.162*** (0.000)	9.897 (0.516)	88.224*** (0.000)
Oil & Gas	0.000 (0.319)	0.000	-1.046*** (0.000)	10.238*** (0.000)	4981.540*** (0.000)	9.686 (0.539)	67.271*** (0.000)
Metal	0.001 (0.122)	0.000	-0.779*** (0.000)	4.276*** (0.000)	944.840*** (0.000)	5.520 (0.931)	84.277*** (0.000)
IT	0.000 (0.488)	0.000	-0.235*** (0.002)	2.431*** (0.000)	279.743*** (0.000)	6.874 (0.835)	15.773* (0.092)
Comm.	0.001 (0.211)	0.000	-1.132*** (0.000)	7.933*** (0.000)	3105.351*** (0.000)	12.844 (0.243)	77.192*** (0.000)
Chem	0.000 (0.509)	0.000	-0.358*** (0.000)	1.857*** (0.000)	180.768*** (0.000)	15.782* (0.092)	166.089*** (0.000)
Crude	0.000 (0.799)	0.001	-0.602*** (0.000)	5.942*** (0.000)	1677.041*** (0.000)	24.180*** (0.003)	370.839*** (0.000)
USD	0.000** (0.024)	0.000	0.161** (0.029)	8.661*** (0.000)	3427.349*** (0.000)	53.734*** (0.000)	147.916*** (0.000)

Note. *, **, *** denote significance at the 10%, 5%, and 1% levels; p-values in parentheses. JB = Jarque–Bera; Q(20) and $Q^2(20)$ = Ljung–Box statistics at 20 lags on returns and squared returns. Comm. = Nifty Commercial & Transport Services, Chem = Nifty Chemicals, Crude =Crude Oil, USD = USDINR

5.2 Unit root and stationarity tests

Table 2 reports the ADF, PP, and ERS tests. The raw price series are non-stationary for seven of the eight variables, crude oil being the exception over this sample. The log-return series are stationary at the one percent level for all eight variables under all three tests: ADF statistics range from −22.65 to −25.47, PP from −31.79 to −40.05, and ERS from −5.86 to −12.87. Stationarity of the returns is a precondition for the QVAR specification, because the quantile propagation mechanism is defined on first-differenced inputs (Chatziantoniou *et al.,* 2021).

Table 2: Unit root test results for the log-return series

Series	ADF Stat.	ADF Verdict	PP Stat.	PP Verdict	ERS Stat.	ERS Verdict
Pharma	−23.13***	Stationary	−33.03***	Stationary	−6.38***	Stationary
Oil & Gas	−22.65***	Stationary	−32.56***	Stationary	−5.86***	Stationary
Metal	−23.21***	Stationary	−33.68***	Stationary	−12.87***	Stationary
IT	−22.66***	Stationary	−31.79***	Stationary	−10.21***	Stationary
Comm	−23.79***	Stationary	−34.18***	Stationary	−11.07***	Stationary
Chem	−22.85***	Stationary	−32.21***	Stationary	−6.17***	Stationary
Crude	−24.95***	Stationary	−32.89***	Stationary	−9.41***	Stationary
USD	−25.47***	Stationary	−40.05***	Stationary	−8.82***	Stationary

Note. *** denotes rejection of the unit-root null at the 1% level. ADF 5% critical value: −2.86; PP: −2.8646; ERS: −1.94. Comm. = Nifty Commercial & Transport Services, Chem = Nifty Chemicals, Crude =Crude Oil, USD = USDINR

Table 3: Total Connectedness Index across the five quantiles (time-averaged rolling window)

Quantile (τ)	Regime	cTCI (%)	TCI (%)	Interpretation
0.05	Panic (lower tail)	93.07	81.44	Peak systemic connectedness
0.25	Bearish	65.37	57.20	Moderate connectedness
0.50	Normal (median)	52.26	45.73	Minimum connectedness
0.75	Bullish	67.34	58.92	Moderate connectedness

0.95	Boom (upper tail)	92.43	80.88	Peak systemic connectedness

Note. cTCI = corrected Total Connectedness Index; TCI = uncorrected index. Both are time-averaged over the rolling windows at each quantile.

5.3 Total connectedness across market states

Table 3 reports the time-averaged Total Connectedness Index. The corrected TCI traces a pronounced U-shape: 93.07 percent at the crash quantile ($\tau = 0.05$), declining to 65.37 percent at $\tau = 0.25$ and to a minimum of 52.26 percent at the median ($\tau = 0.50$), then rising to 67.34 percent at $\tau = 0.75$ and back to 92.43 percent at the boom quantile ($\tau = 0.95$).

The tail amplification is symmetric: the crash quantile exceeds the median by 40.81 percentage points and the boom quantile by 40.17 percentage points, so on average more than nine of every ten units of forecast-error variance in a crash is transmitted across the network. This mirrors the tail behaviour documented for CDS networks by (Ando *et al.,* 2022), for interest rate swaps by (Chatziantoniou *et al.,* 2021), for African markets by (Yaya *et al.,* 2024), and for the Russian market by (Balci & Dogan, 2026), and it confirms for India the strong bearish-state connectedness of 79.07 percent reported by (Hanif *et al.,* 2024), with the Indian sectoral network pushing the tail value even higher. Figure 1 displays the distribution of the time-varying TCI: the crash and boom distributions are visibly shifted upward, with wider interquartile ranges and far more tail-risk outliers, while the median quantile exhibits the tightest distribution.

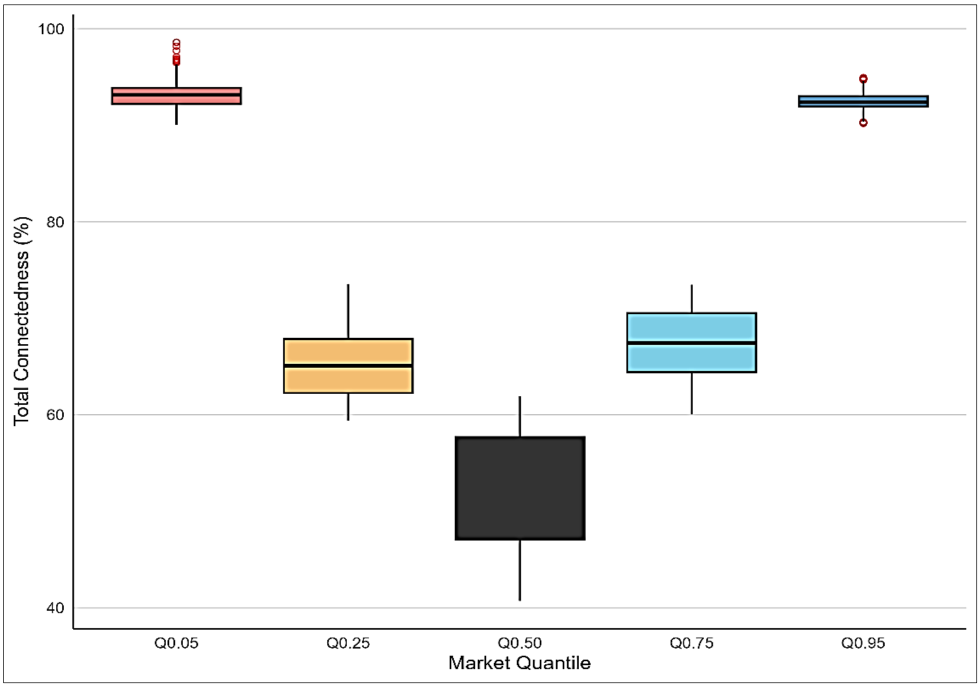

Figure 1: Distribution of the Total Connectedness Index (TCI) across quantiles: box plot showing median, interquartile range, and tail-risk outliers

Note. Time-varying TCI across the five quantiles ($\tau = 0.05, 0.25, 0.50, 0.75, 0.95$) from the 200-day rolling-window QVAR.

5.4 Pairwise spillover matrices across the five quantiles

Tables 4–8 report the complete pairwise spillover matrices at all five quantiles, in which each cell measures how much of the row variable's forecast-error variance is explained by the column variable. At the crash quantile (Table 4, $\tau = 0.05$) the off-diagonal cells are strikingly uniform: every sectoral index transmits more than 78 percent of its variance to the network, with Nifty Metal (TO = 90.43 percent) and Nifty Commercial & Transport (89.95 percent) the largest transmitters, and every cell among the sectoral indices lies between 11 and 14.3 percent, a picture of nearly homogeneous contagion. In sharp contrast, crude oil and USD/INR transmit only 70.33 percent and 60.21 percent of their own variance while receiving 79.16 percent and 77.68 percent, so both macro variables are net recipients of shocks precisely when the sectoral network is in panic, and the rupee records the largest negative net position in the system (−17.47 percent).

Table 4: Pairwise return spillover matrix at τ = 0.05 (panic)

Variable	PHARMA	OIL	METAL	IT	COMM.	CHEMICALS	CRUDEOIL	USDINR	FROM
PHARMA	17.79	12.36	12.74	11.79	12.95	13.29	10.31	8.77	82.21
OIL	11.97	17.49	13.98	11.14	14.22	13.21	9.55	8.44	82.51
METAL	12.12	13.93	16.66	11.08	14.21	13.29	10.39	8.33	83.34
IT	12.40	12.04	12.40	19.43	12.26	12.25	10.70	8.52	80.57
COMM.	12.31	14.10	14.23	11.25	16.95	13.69	9.18	8.29	83.05
CHEMICALS	12.87	13.47	13.82	11.43	14.03	17.00	9.50	7.87	83.00
CRUDEOIL	11.94	11.23	11.90	11.61	11.11	11.38	20.84	9.99	79.16
USDINR	11.05	12.18	11.36	10.31	11.17	10.91	10.70	22.32	77.68
TO	84.65	89.31	90.43	78.62	89.95	88.01	70.33	60.21	651.52
Inc.Own	102.45	106.81	107.09	98.05	106.90	105.01	91.17	82.53	cTCI/TCI
NET	2.45	6.81	7.09	−1.95	6.90	5.01	−8.83	−17.47	93.07/81.44
NPT	3	5	7	2	6	4	1	0	

Note. Each cell reports the share of the row variable's H-step-ahead forecast error variance attributable to the column variable at quantile τ = 0.05 (panic). FROM = row total received from all other variables; TO = column total transmitted to all other variables; Inc.Own = total including own-variance share; NET = TO − FROM; NPT = number of variables to which the row asset is a net pairwise transmitter; cTCI/TCI = corrected/uncorrected Total Connectedness Index. OIL = Nifty Oil & Gas; COMM. = Nifty Commercial & Transport Services; time-averaged rolling-window estimates.

At the bear quantile (Table 5, τ = 0.25) the structure loosens: sectoral own-variance shares rise to between 29.7 and 43.8 percent, Nifty Commercial & Transport becomes the largest net transmitter (NET = +10.84 percent), and the two macro variables turn into outright shock sinks, receiving 31.97 and 25.95 percent while transmitting 21.94 and 11.22 percent.

Table 5: Pairwise return spillover matrix at τ = 0.25 (bearish)

Variable	PHARMA	OIL	METAL	IT	COMM.	CHEMICALS	CRUDEOIL	USDINR	FROM
PHARMA	36.69	10.64	11.68	9.41	11.51	13.77	4.50	1.80	63.31
OIL	9.23	30.71	17.32	6.89	18.14	13.90	2.51	1.30	69.29
METAL	9.66	16.83	30.00	7.02	17.61	15.08	2.76	1.03	70.00
IT	10.60	9.68	9.97	43.81	9.66	11.45	3.84	0.98	56.19
COMM.	9.55	17.35	17.39	6.85	29.74	16.58	1.31	1.23	70.26
CHEMICALS	11.71	14.24	15.57	8.46	17.15	29.41	2.52	0.94	70.59
CRUDEOIL	6.16	4.18	4.93	5.73	2.63	4.40	68.03	3.94	31.97
USDINR	3.66	4.79	3.67	1.79	4.39	3.15	4.49	74.05	25.95
TO	60.58	77.71	80.53	46.15	81.10	78.33	21.94	11.22	457.56
Inc.Own	97.27	108.43	110.53	89.96	110.84	107.74	89.97	85.27	cTCI/TCI
NET	−2.73	8.43	10.53	−10.04	10.84	7.74	−10.03	−14.73	65.37/57.20
NPT	3	5	6	2	7	4	1	0	

Note. See Table 4 for definitions. Time-averaged rolling-window estimates at quantile τ = 0.25 (bearish).

At the median quantile (Table 6, τ = 0.50) the network is at its most fragmented. Own-variance shares of the sectoral indices climb to 35.2–62.4 percent, Nifty Commercial & Transport remains the leading net transmitter (NET = +15.16 percent), and the macro variables become almost disconnected from the equities: crude oil receives 9.66 percent and transmits 7.18 percent, and USD/INR receives 17.53 percent and transmits 5.64 percent, so in calm markets the rupee and crude barely participate in sectoral price discovery. The bullish quantile (Table 7, τ = 0.75) restores an intermediate structure close to the bear one, with connectedness at 67.34 percent, Nifty Commercial & Transport again the top net transmitter (+14.00 percent), and USD/INR posting its deepest net-receiving position of the whole grid (−18.64 percent). Finally, at the boom quantile (Table 8, τ = 0.95) the panic-like contagion pattern returns almost symmetrically at 92.43 percent, and the leading net transmitter rotates to Nifty Chemicals (+7.33 percent). Across all five matrices the macro variables are net receivers without exception, and the top sectoral transmitter rotates with the market state: Nifty Metal in panic, Nifty Commercial & Transport in bearish, normal, and bullish states, and Nifty Chemicals in boom.

5.5 Block-level vulnerability and macro transmission

Averaging the directional measures across each block at the crash quantile shows that the crude-exposed block transmits 89.09 percent and receives 82.85 percent of variance (average NET +6.24 percent), whereas the forex-exposed block transmits 84.57 percent and receives 82.04 percent (average NET +2.53 percent). The paired Wilcoxon signed-rank test on the block-average net series confirms that the crude-exposed block receives significantly more shock from the macro block than the forex-exposed block does (Δ = −3.71 percentage points, V = 69,097, p < 0.0001). Figure 2 visualizes this block asymmetry: energy-intensive sectors are the weak link of the Indian network in a crash because a rising oil price simultaneously compresses their margins and signals global risk-off, while dollar-earning sectors enjoy a natural hedge, since a weaker rupee inflates the rupee value of their foreign revenues (Kumar, 2019; Ramos & Veiga, 2013). Figure 3 compares the two macro drivers across the whole quantile grid: crude oil's average net position is negative at every quantile and USD/INR is always more negative, so the rupee is consistently the larger shock absorber of the two.

Table 6: Pairwise return spillover matrix at τ = 0.50 (normal)

Variable	PHARMA	OIL	METAL	IT	COMM.	CHEMICALS	CRUDEOIL	USDINR	FROM
PHARMA	50.33	8.51	9.66	6.04	10.26	12.63	1.96	0.61	49.67
OIL	6.53	38.26	17.62	4.00	19.36	13.06	0.52	0.65	61.74
METAL	7.51	17.07	37.24	4.24	18.33	14.21	0.84	0.57	62.76
IT	6.80	6.16	6.91	62.39	7.31	8.32	0.95	1.17	37.61
COMM.	7.24	17.84	17.63	4.15	35.20	16.33	0.72	0.88	64.80
CHEMICALS	9.67	13.23	14.81	5.29	17.74	37.93	0.60	0.73	62.07
CRUDEOIL	2.67	0.79	0.99	1.23	2.06	0.87	90.34	1.04	9.66
USDINR	1.01	3.07	3.07	1.52	4.90	2.37	1.60	82.47	17.53
TO	41.44	66.67	70.70	26.47	79.96	67.78	7.18	5.64	365.85
Inc.Own	91.78	104.93	107.94	88.86	115.16	105.70	97.53	88.11	cTCI/TCI
NET	−8.22	4.93	7.94	−11.14	15.16	5.70	−2.47	−11.89	52.26/45.73
NPT	3	5	6	2	7	4	1	0	

Note. See Table 4 for definitions. Time-averaged rolling-window estimates at quantile τ = 0.50 (normal).

Table 7: Pairwise return spillover matrix at τ = 0.75 (bullish)

Variable	PHARMA	OIL	METAL	IT	COMM.	CHEMICALS	CRUDEOIL	USDINR	FROM
PHARMA	34.78	11.18	12.01	8.61	12.58	14.67	4.55	1.63	65.22
OIL	9.56	29.79	16.94	6.94	18.39	14.46	2.67	1.25	70.21
METAL	10.26	16.74	29.27	7.04	17.62	15.10	3.00	0.97	70.73
IT	10.39	9.77	10.15	42.25	10.49	11.60	4.52	0.83	57.75
COMM.	10.11	17.63	17.13	6.98	28.29	16.74	2.09	1.03	71.71
CHEMICALS	12.12	14.34	15.19	8.06	17.27	29.32	2.68	1.01	70.68
CRUDEOIL	6.97	4.57	5.54	5.75	3.84	5.29	64.16	3.89	35.84
USDINR	3.97	4.77	4.43	1.94	5.52	3.97	4.65	70.75	29.25
TO	63.37	79.01	81.38	45.32	85.71	81.82	24.17	10.62	471.38
Inc.Own	98.15	108.80	110.65	87.57	114.00	111.14	88.32	81.36	cTCI/TCI
NET	−1.85	8.80	10.65	−12.43	14.00	11.14	−11.68	−18.64	67.34/58.92
NPT	3	4	6	2	7	5	1	0	

Note. See Table 4 for definitions. Time-averaged rolling-window estimates at quantile τ = 0.75 (bullish).

Table 8: Pairwise return spillover matrix at τ = 0.95 (boom)

Variable	PHARMA	OIL	METAL	IT	COMM.	CHEMICALS	CRUDEOIL	USDINR	FROM
PHARMA	18.45	12.22	12.61	11.89	12.35	13.31	9.87	9.31	81.55
OIL	11.76	17.49	13.91	11.61	14.05	13.44	9.07	8.67	82.51
METAL	11.81	13.90	17.71	11.27	14.07	13.49	9.31	8.42	82.29
IT	11.95	12.14	12.29	19.18	11.91	12.66	10.93	8.94	80.82
COMM.	11.82	14.48	14.33	11.14	17.73	14.39	8.17	7.94	82.27
CHEMICALS	12.21	13.30	13.47	11.93	13.93	18.09	8.95	8.11	81.91
CRUDEOIL	11.39	10.95	11.31	11.75	10.06	11.07	22.33	11.13	77.67
USDINR	11.04	11.21	11.34	11.20	10.55	10.89	11.78	21.99	78.01
TO	81.98	88.21	89.25	80.79	86.93	89.24	68.10	62.53	647.03
Inc.Own	100.43	105.69	106.97	99.97	104.66	107.33	90.43	84.52	cTCI/TCI
NET	0.43	5.69	6.97	−0.03	4.66	7.33	−9.57	−15.48	92.43/80.88
NPT	3	5	6	2	4	7	1	0	

Note. See Table 4 for definitions. Time-averaged rolling-window estimates at quantile τ = 0.95 (boom).

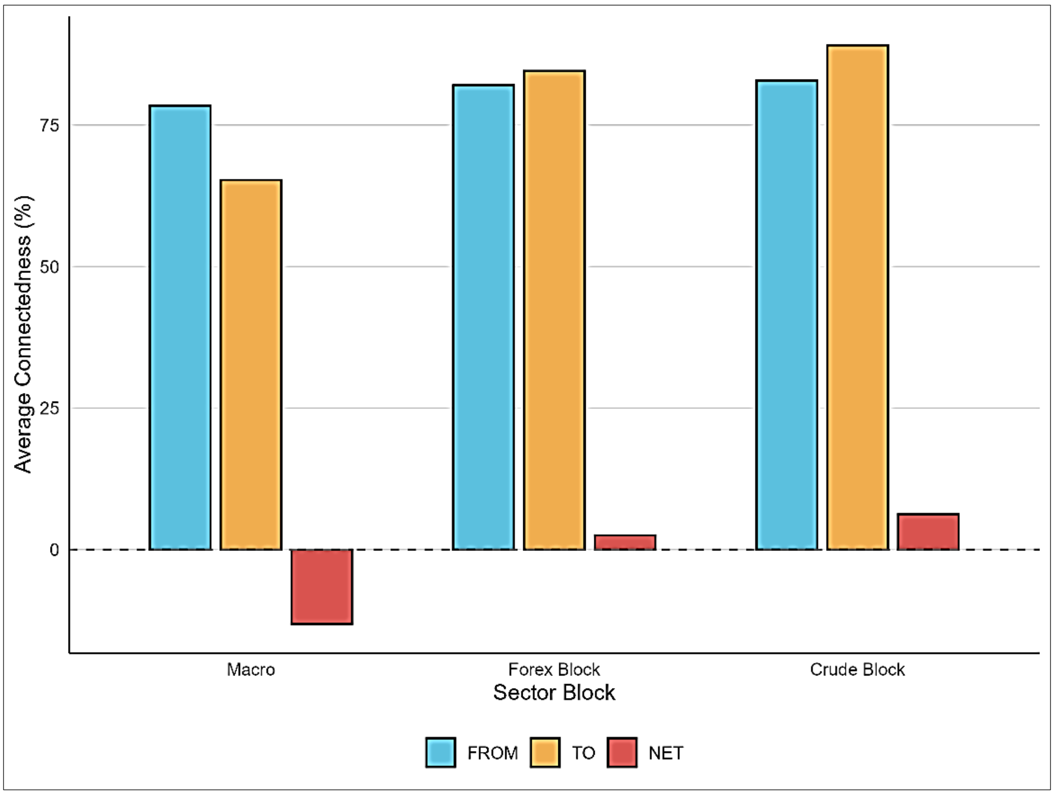

Figure 2: Block vulnerability and transmission: average directional spillovers across the macro, forex-exposed, and crude-exposed blocks

Note. Average FROM, TO, and NET connectedness of the macro block, the forex-exposed block (IT, Pharma, Metal), and the crude-exposed block (Oil & Gas, Commercial & Transport, Chemicals) at τ = 0.05.

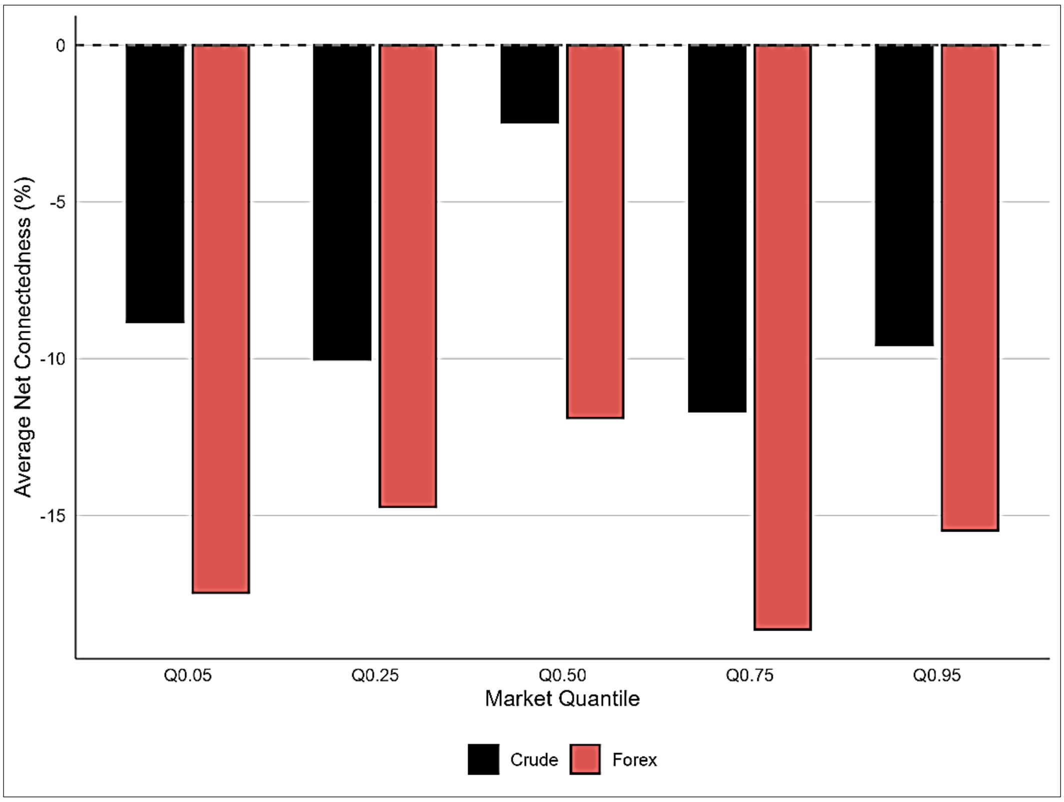

Figure 3: Competing macro transmitters: average net connectedness of crude oil versus USD/INR across market quantiles

Note. Average net connectedness (NET = TO − FROM) of crude oil and USD/INR at each quantile; negative values indicate net receivers of shocks.

5.6 Hypothesis-wise test outcomes

Table 9 summarizes the outcomes of the five hypotheses with their test statistics and p-values.

Table 9: Summary of hypothesis test outcomes

Hypothesis	Test	Statistic	p-value	Verdict
H1: State-dependent TCI	Friedman omnibus	$\chi^2 = 3360.23$, df = 4	<0.0001	Supported
H1: TCI (0.05 vs 0.50)	Wilcoxon + bootstrap	V = 402,753; Δ = 40.81 [40.47, 41.15]	<0.0001	Supported
H1: TCI (0.95 vs 0.50)	Wilcoxon + bootstrap	V = 402,753; Δ = 40.17 [39.81, 40.52]	<0.0001	Supported
H2: Persistent net transmitters	Sign test	Pct. positive 0.0–14.5%	1.000	Rejected
H2: Forex > Crude at τ = 0.05	Paired Wilcoxon	USD/INR more negative	<0.0001	Part (direction only)
H3: Forex > Crude block vulnerability	Paired Wilcoxon	V = 69,097; Δ = −3.71	<0.0001	Rejected (crude > forex)
H4: Cross-sectional hierarchy	Friedman + pairwise	$\chi^2 = 3911–5248$, df = 7	<0.0001	Supported
H5: Transmission-driven dominance	Paired Wilcoxon (TO vs FROM)	FROM > TO at both quantiles	<0.0001	Rejected (insulation)

Note. Δ = percentage-point difference; V = Wilcoxon signed-rank statistic; square brackets enclose the 95% bootstrap confidence interval of Δ.

H1 (systemic risk rises in extreme states) is supported. The Friedman test rejects the equality of the five quantile TCI series ($\chi^2 = 3360.23$, df = 4, $p < 0.0001$), and the Wilcoxon tests with bootstrap confidence intervals place the crash-versus-median differential at 40.81 percentage points [40.47, 41.15] and the boom-versus-median differential at 40.17 percentage points [39.81, 40.52]. The U-shape is a persistent feature of the Indian return network, matching the tail behaviour found across sovereign CDS (Ando *et al.,* 2022), swap markets (Chatziantoniou *et al.,* 2021), and African equities (Yaya *et al.,* 2024).

H2 (crude oil and the rupee as shock givers) is rejected in its main form. Sign tests show that the percentage of rolling windows in which the macro variables are net transmitters ranges from 0.0 to 14.5 percent for crude oil and from 0.0 to 9.8 percent for USD/INR, so neither comes close to being a persistent net transmitter (every sign test returns p = 1.000). The paired Wilcoxon test at the crash quantile does confirm a significant difference between the two ($p < 0.0001$), but in the opposite direction to the transmission narrative: USD/INR is significantly more net-receiving than crude oil, so of the two competing macro drivers the rupee is the bigger shock sponge, not the bigger shock source.

H3 (which block suffers more in a crash) is rejected in its expected direction: the paired Wilcoxon test on the block-average net series gives Δ = −3.71 percentage points (V = 69,097, $p < 0.0001$), showing that the crude-exposed block—Oil & Gas, Commercial & Transport, and Chemicals—receives significantly more shock during crashes than the forex-exposed block, making it the vulnerable block of the Indian network in panic states.

H4 (a meaningful ranking of assets) is supported. The Friedman test rejects equal net connectedness across the eight assets at every quantile (χ^2 from 3,910.99 at τ = 0.05 to 5,248.53 at τ = 0.75, df = 7, $p < 0.0001$), with post-hoc pairwise Wilcoxon tests confirming most pairwise differences. The top transmitter rotates across market states—Nifty Metal at τ = 0.05, Nifty Commercial & Transport at τ = 0.25, 0.50, and 0.75, and Nifty Chemicals at τ = 0.95—while USD/INR is the largest net receiver at every single quantile.

H5 (insulation or transmission) is rejected in favour of insulation. Paired Wilcoxon tests confirm that FROM significantly exceeds TO for both crude oil and USD/INR at both the crash and the median quantile ($p < 0.0001$). The TO–FROM gap for crude oil widens from −2.47 at the median to −8.83 at the crash quantile, and for USD/INR from −11.89 to −17.47 (widening significant at $p < 0.0001$). Macro dominance in the tails is therefore insulation-driven: the macro variables dominate the system's risk accounting not because they push shocks into the sectors but because they absorb the shocks coming out of them.

5.7 Discussion

Three insights emerge. First, the U-shaped and state-dependent nature of return connectedness in India, with a crash-versus-median differential of roughly 41 percentage points, is consistent with the tail amplification documented by (Ando *et al.,* 2022) and with the symmetric tail behaviour of the quantile connectedness approach itself (Chatziantoniou *et al.,* 2021; Hanif *et al.,* 2024; Yaya *et al.,* 2024). The near-uniform off-diagonal cells of the panic matrix echo the homogeneous contagion observed at the height of the Lehman crisis (Diebold & Yılmaz, 2014) and confirm that diversification across Indian sectors effectively disappears when it is needed most (Liao *et al.,* 2021; Liu *et al.,* 2021; Mazur *et al.,* 2021).

Second, the conventional narrative that crude oil and the exchange rate act as principal net transmitters to equities is not supported by the return-only evidence: both macro variables are net receivers at every quantile, and the rupee is the largest net receiver throughout. This contrasts with (Cui *et al.,* 2025), who find crude oil a persistent net transmitter of realized-volatility risk (+21.78 percent) in a system with the dollar index and the S&P 500, and it complements (Mensi *et al.,* 2022), who show that negative returns connect subsectors more tightly than positive ones. The contrast is interpretable rather than contradictory: in returns, an oil price move is quickly impounded in the prices of crude-sensitive sectors, while the currency and the commodity act as clearing houses that absorb the capital-flow pressure the sectors release. The rupee's role parallels the shock-absorbing behaviour of the Russian ruble and the VIX in (Balci & Dogan, 2026) and extends the exchange-rate asymmetries of (Kumar, 2019) from the mean to the entire conditional distribution.

Third, the block result refines how macro shocks propagate through Indian sectoral equities: the crude-exposed block, not the forex-exposed block, absorbs the larger macro shock in a crash. The logic mirrors the importer–exporter asymmetry of (Ramos & Veiga, 2013) and the Indian long-run evidence of (Kumar, 2019): a weakening rupee is revenue-positive for dollar-earning IT and Pharma firms, whereas an oil spike is cost-negative for transport, energy, and chemical users with no offsetting revenue channel. Pooled sector studies (Bakić, 2024; Das & Kannadhasan, 2020) would average these opposite channels away, underlining the value of the block design introduced here.

6. IMPLICATIONS

The findings carry four actionable implications. First, because the crude-exposed block absorbs significantly more shock during crashes ($\Delta = -3.71$ percentage points, $p < 0.0001$), portfolio managers with concentrated exposure to Nifty Oil & Gas, Commercial & Transport, and Chemicals should pair long equity positions with tail-risk hedges that activate in the lower quantile—crude-oil call options and USD/INR put options—and size them with quantile-conditional hedge ratios rather than static mean-based ratios, which under-hedge precisely when protection is worth most. Second, since USD/INR is the single largest net receiver at every quantile (NET between −11.89 and −18.64 percent), the rupee functions as a systemic shock sponge; Reserve Bank of India intervention that smooths extreme currency movements therefore eases balance-sheet pressure and absorbs part of the systemic risk that would otherwise propagate through the sectoral network. Third, the top transmitter rotates across quantiles, so macro-prudential buffers and stress tests for sectorally exposed institutions should be calibrated to the relevant quantile rather than to the unconditional mean; a framework that only knows the median would miss both the 93-percent contagion of the crash state and the rotation of the systemic role from Nifty Metal to Nifty Commercial & Transport to Nifty Chemicals. Fourth, the insulation-driven nature of macro dominance suggests that foreign institutional outflows are a main conduit from sectoral equity stress to the currency, so measures that smooth the rhythm of such flows during stress episodes can dampen the feedback loop between the macro variables and the sectoral network.

7. LIMITATIONS AND FUTURE RESEARCH

Four limitations should be kept in mind. The analysis is restricted to returns and deliberately excludes a volatility channel; a paired return-and-volatility QVAR would test whether the net-transmitter verdict for crude oil reverses in the volatility domain, as the evidence of (Cui *et al.,* 2025) suggests. The sample covers January 2022– June 2026 and therefore one broad regime of global tightening; extending it to earlier crises would show whether the block asymmetry survives outside this window. The block split follows dominant macro exposure and leaves hybrid sectors unpicked; a finer industry mapping could sharpen the vulnerability estimates. Finally, the non-parametric toolkit delivers significance but not a full sampling theory for the connectedness estimators themselves, so the confidence intervals for tail effects should be read as approximate.

8. CONCLUSION

This study examined how crude oil and foreign exchange return shocks travel through Indian sectoral equities using a quantile connectedness framework that compares two macro drivers and two exposure-based sector blocks across five market states, estimated on eight return series over January 2022 to June 2026 and tested with a transparent non-parametric toolkit. The results are fourfold. Total return connectedness is strongly state-dependent and U-shaped, peaking above 92 percent in crash and boom states against 52 percent at the median. Crude oil and the rupee do not transmit shocks to the sectoral network; they absorb them, and the rupee is the largest net receiver in every market state, so macro dominance in the tails is insulation-driven. The crude-exposed block, rather than the forex-exposed block, absorbs significantly more macro shock during crashes. And the largest sectoral transmitter rotates with the market state, from Nifty Metal in panic to Nifty Commercial & Transport in ordinary states to Nifty Chemicals in boom. For investors, the message is that hedges should be bought for the tails and pointed at energy-sensitive sectors; for policymakers, that currency stabilization is systemic-risk management; and for researchers, that exposure-based block designs reveal transmission patterns that pooled sector studies average away.

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