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Quantile connectedness between Indian sectoral equities, gold, crude oil and the rupee: Time-varying spillovers and portfolio implications.

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Abstract

We study return connectedness among the Nifty 50 and seven sectoral indices, gold, Brent crude oil and the US dollar–Indian rupee exchange rate for 2 January 2013 to 25 June 2026 (inclusive), a sample period which covers demonetisation, COVID-19 pandemic, Russia–Ukraine war and tariff shock in year 2025. Using the framework of the time-varying parameter VAR (TVP-VAR) and its quantile extension, we show three main results. As shown, average total connectedness over the sample period is 53.2% and very much event driven: it peaks at 77.9% in response to COVID-19. In particular, equity sectors—led by automobiles, banking and energy—act as net shock transmitters while the rupee is the system's primary shock absorber and more mild net recipients are gold and crude oil. Second, connectedness of state variables is considerably stronger in the tails of the return distribution: total connectedness reaches 86.2% at the fifth percentile and 85.8% at the ninety-fifth percentile, nearly 35 pp above their medians (about {0}). Therefore mean-based spillover estimates significantly underestimate systemic linkages in the market states that matter most for risk management. Third, according to empirical estimates using the dynamic conditional correlation (DCC-GARCH) model, gold behaves as a diversifier rather than a hedge for portfolios—variance reductions of 46–71%, depending upon particular equity–gold cases—and short rupee (long US dollar) positions are the most effective direct short hedges against Indian equity exposure. The findings are robust to alternative forecasting horizons and forgetting factors, as well as the exclusion of the aggregate market index, and carry direct implications for investors, portfolio managers, and policymakers in emerging markets...

Keywords : Connectedness; Spillovers; TVP-VAR; Quantile connectedness; Hedging; Indian stock market.

JEL classification:C32; C58; G11; G15; Q02

Introduction

Emerging market financial markets have slowly but surely become more integrated with global commodity and currency markets, as the case of India illustrates well. During the last ten year span the Indian equity marke1t has grown into one of the largest by capitalisation, but is also still highly vulnerable to global risk factors which operate through two main channels: (i) Imported energy price – costlier oil not only affects inflationary pressures in India because some 75% of its crude oil requirement is met from imports; and, (ii) Rupee exchange rate—this mediates global portfolio flows as latest market movements demonstrated. Gold holds a separate, third place in this balance: India is one of the largest markets for the metal globally and gold sits relatively easily on Indian household balance sheets as a store of value or regarded haven during periods of stress. Understanding the dynamics of cross-market shocks—is important for investors building portfolios, corporates that are exposed to input-cost and currency risk, and policymakers who watch for systemic vulnerabilities.

The sample period studied in this paper, January 2013 to June 2026, is unusually rich in shocks with which to study these questions. It contains a major domestic policy shock (the November 2016 demonetisation), a global health and economic crisis (COVID-19), a major geopolitical shock with direct energy-price consequences (the Russia–Ukraine war beginning February 2022), the October 2023 escalation of conflict in the Middle East, and the trade-policy upheaval of 2025, when sweeping tariff announcements by the United States triggered sharp repricing across global equity, commodity and currency markets. Each episode potentially rewires the transmission of shocks between Indian equities, oil, gold and the rupee. A framework that allows connectedness to vary over time, and across the conditional distribution of returns, is therefore essential.

This paper provides such an analysis. We assemble a daily dataset of eleven variables—the Nifty 50, seven sectoral indices (banking, information technology, pharmaceuticals, energy, fast-moving consumer goods, automobiles and metals), gold, Brent crude oil and the USD/INR exchange rate—covering 3,295 trading days. Our empirical strategy proceeds in three layers. First, we estimate the time-varying parameter vector autoregression (TVP-VAR) connectedness framework of Antonakakis, Chatziantoniou and Gabauer (2020), which refines the seminal Diebold and Yilmaz (2012, 2014) approach by replacing arbitrary rolling windows with Kalman-filtered time-varying coefficients. Second, we estimate connectedness across the conditional distribution of returns using the quantile VAR approach of Chatziantoniou, Gabauer and Stenfors (2021) and Ando, Greenwood-Nimmo and Shin (2022), which reveals how transmission intensifies in bear and bull states relative to normal times. Third, we translate the connectedness evidence into portfolio practice by estimating dynamic conditional correlations (Engle, 2002), computing time-varying hedge ratios (Kroner and Sultan, 1993), optimal portfolio weights (Kroner and Ng, 1998) and hedging effectiveness (Ederington, 1979).

The paper makes three contributions. First, to the best of our knowledge it is the first study of the Indian sectoral equity–commodity–currency system whose sample extends through mid-2026, allowing us to characterise the connectedness consequences of the 2025 tariff shock alongside earlier crises; we show that this episode raised total connectedness to 60.4%, comparable to the Russia–Ukraine peak of 62.1% though well below the COVID-19 maximum of 77.9%. Second, we document a pronounced and remarkably stable U-shaped pattern of connectedness across quantiles: total connectedness of 86.2% and 85.8% in the lower and upper tails against 50.5% at the median. As we can see, the rolling estimates are highly asymmetric—median connectedness varies widely with crisis events (40.1–65.5%), whereas tail connectedness remains uniformly high during the length of our sample (85%-90%) and has a standard deviation of less than one percentage point. In other words, diversification across these markets is only reliable in the market states where it is least needed.. Third, we connect the distributional evidence to concrete portfolio prescriptions: gold's near-zero hedge ratios but substantial portfolio variance reduction (46–71%) identify it as a diversifier rather than a hedge in the sense of Baur and Lucey (2010), while consistently negative equity–currency hedge ratios identify long US dollar positions as the most effective direct hedge for Indian equity risk.

The remainder of the paper is organised as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data. Section 4 sets out the methodology. Section 5 presents the empirical results, Section 6 reports robustness checks, and Section 7 concludes with implications for investors and policymakers.

2. Literature review and hypotheses

2.1 Measuring connectedness

The modern spillover literature originates with Diebold and Yilmaz (2009), who proposed summarising cross-market linkages through forecast error variance decompositions (FEVD) of a vector autoregression. Diebold and Yilmaz (2012) generalised the framework using the order-invariant generalised FEVD of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), and Diebold and Yilmaz (2014) established the connection between variance decompositions and network topology, defining total, directional and net connectedness measures now standard in the literature. Two refinements are central to this paper. Antonakakis, Chatziantoniou and Gabauer (2020) replaced the rolling-window VAR with a TVP-VAR estimated by Kalman filtering with forgetting factors (Koop and Korobilis, 2014), eliminating the arbitrary window-length choice, avoiding the loss of initial observations and making the estimates less sensitive to outliers. Chatziantoniou, Gabauer and Stenfors (2021) and Ando, Greenwood-Nimmo and Shin (2022) extended connectedness estimation to conditional quantiles, showing that shock transmission in the tails of the distribution can differ dramatically from transmission at the mean or median—an insight foreshadowed by the extreme-dependence evidence of Longin and Solnik (2001) and the contagion literature of Forbes and Rigobon (2002).

2.2 Equity–commodity–currency linkages

The spillovers between equity markets and oil, gold and exchange rates have long been studied in a substantial literature. The channels through which the oil passes to equity markets are production costs, inflation expectations and monetary policy responses–the latter generally having heterogeneous impact depending on sector: energy and materials firms might benefit from increases in prices that harm transport- and consumption-oriented sectors. In the case of gold, Baur and Lucey (2010) provide an influential taxonomy separating a hedge (an asset that is uncorrelated or negatively correlated with equities on average) versus a safe haven (uncorrelated or negatively correlated on net during periods of market stress), while their subsequent work Baur and McDermott (2010) shows that gold's state-dependent and market-dependent safe-haven property. This is especially the case in emerging markets for exchange rates, where global risk aversion leads to foreign portfolio outflows that simultaneously push up equity prices down and currency depreciates, leading to negative equity–currency correlations and making the exchange rate a natural domestic financial system shock absorber.

2.3 Evidence on India and hypotheses

For India specifically, prior studies document significant linkages between the equity market and each of oil, gold and the rupee, as well as time-variation in those linkages around crisis episodes. Relative to that literature, the

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present paper is differentiated by (i) a sectoral rather than aggregate-only equity perspective, (ii) a sample extending through the 2025–2026 trade-policy shock, (iii) the combination of TVP-VAR and quantile connectedness in a single design, and (iv) an explicit mapping from connectedness estimates to hedging and portfolio construction.

The discussion above yields three testable hypotheses. **H1:** total connectedness within the Indian equity–commodity–currency system is time-varying and intensifies during crisis episodes. **H2:** connectedness is stronger in the tails of the conditional return distribution than at the median, and tail connectedness exhibits less time-variation than median connectedness. **H3:** gold acts as a diversifier rather than a hedge for Indian sectoral equities, while the US dollar provides the most effective direct hedge.

3. Data

We use daily closing prices for eleven series from 1 January 2013 to 30 June 2026: the Nifty 50 (NIFTY50) and the Nifty sectoral indices for banking (BANK), information technology (IT), pharmaceuticals (PHARMA), energy (ENERGY), fast-moving consumer goods (FMCG), automobiles (AUTO) and metals (METAL); COMEX gold futures (GOLD); Brent crude oil futures (BRENT); and the US dollar–Indian rupee exchange rate (USDINR), all obtained from publicly available market data. The Indian trading calendar defines the base sample; observations of the globally traded series (gold, Brent, USD/INR) on Indian holidays are carried forward, and residual missing values are removed. The final sample contains 3,295 price observations per series (2 January 2013 to 25 June 2026), yielding 3,294 daily log returns computed as $r_t = 100 \ln(P_t/P_{t-1})$.

Figure 1 plots the normalised price paths with the five major shock events marked—demonetisation (8 November 2016), the WHO pandemic declaration (11 March 2020), the Russian invasion of Ukraine (24 February 2022), the escalation of conflict in the Middle East (7 October 2023) and the US tariff announcement (2 April 2025). Figure 2 plots the corresponding return series, which display the volatility clustering characteristic of daily financial data, with common bursts across markets during the marked episodes.

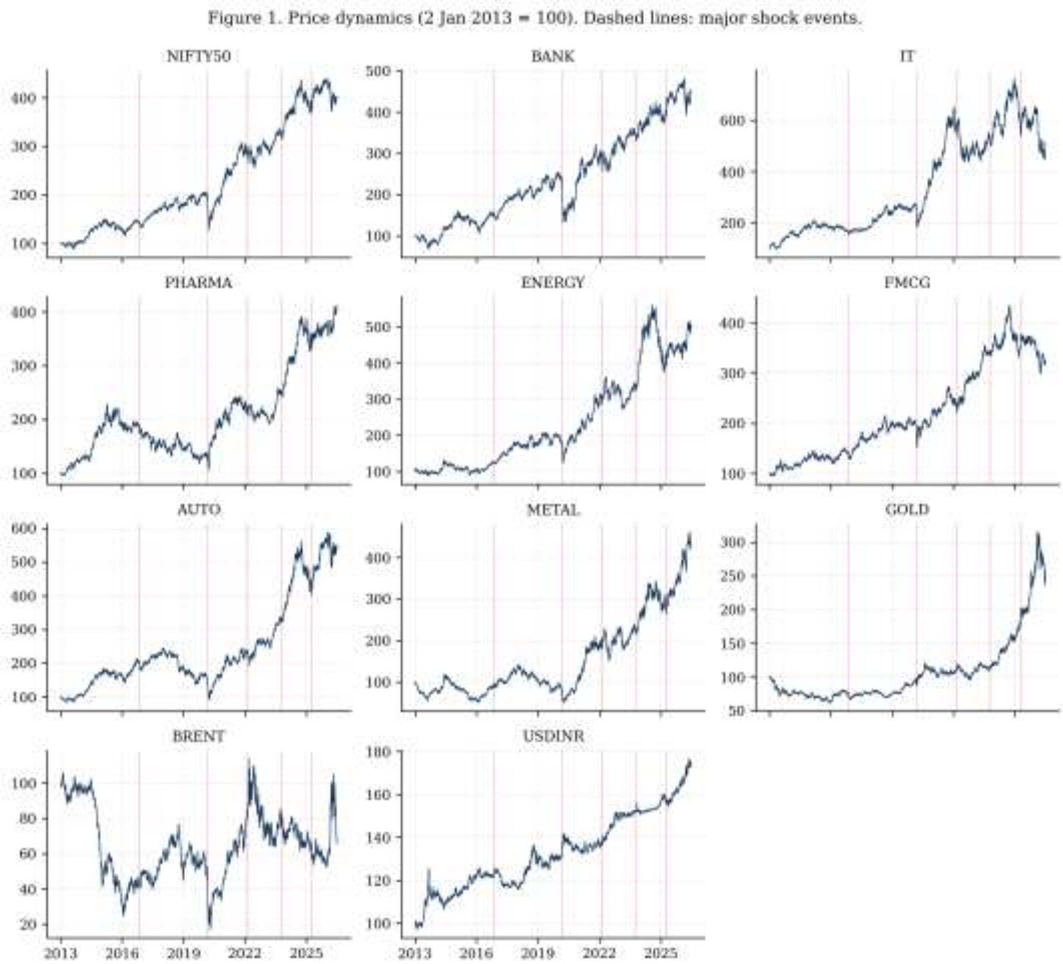

Figure 1. Price dynamics (2 January 2013 = 100). Dashed vertical lines mark major shock events.

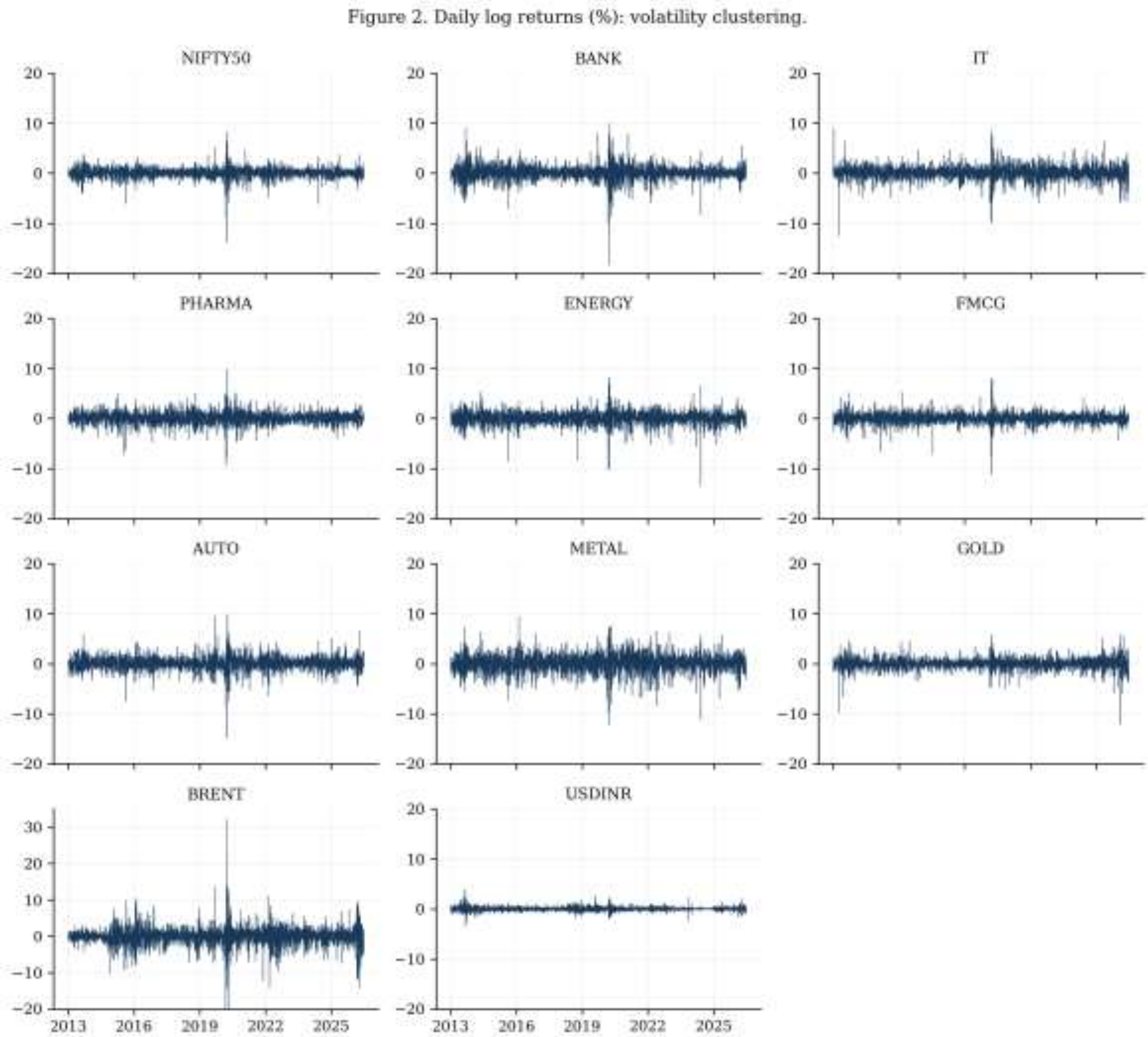

Figure 2. Daily log returns (%), illustrating volatility clustering.

Table 1 reports descriptive statistics and diagnostic tests. Mean daily returns are small and positive for all equity indices and gold, near zero for Brent, and positive for USD/INR (rupee depreciation). Return distributions are non-normal without exception: all equity series are negatively skewed while the exchange rate is positively skewed, and excess kurtosis is severe—most extreme for Brent and the Nifty 50—so the Jarque–Bera test rejects normality at the 1% level for every series. ADF and Phillips–Perron tests reject a unit root in all return series at the 1% level, validating a VAR specification in returns, and Engle's ARCH-LM test detects strong conditional heteroskedasticity in every series, motivating the GARCH-based modelling of Section 5.4.

Table 1. Descriptive statistics and diagnostic tests for daily log returns (%). JB: Jarque–Bera; ADF/PP: unit-root tests; Q(20): Ljung–Box; ARCH(10): Engle LM test. *, **, * denote significance at 1%, 5%, 10%.**

	Mean	Std.Dev.	Min	Max	Skew.	Kurt.	JB	ADF	PP	Q(20)	ARCH(10)
NIFTY 50	0.0422	1.029	-13.9	8.4	-1.141	20.14	41024.745***	-16.032***	-57.822***	83.751***	832.538***
BANK	0.046	1.422	-18.31	10.0	-0.755	16.97	27117.759***	-12.905***	-55.208***	52.013***	586.713***
IT	0.0459	1.343	-12.49	8.92	-0.487	10.28	7400.414***	-20.711***	-57.410***	34.533**	319.013***

PHARMA	0.0429	1.196	-9.35	9.86	-0.172	7.78	3154.627***	-38.567***	-55.303***	26.477	331.213***
ENERGY	0.0485	1.326	-13.31	8.28	-0.806	11.02	9189.330***	-17.159***	-57.400***	39.374***	397.082***
FMCG	0.0357	1.048	-11.2	7.99	-0.407	12.46	12384.374***	-16.520***	-58.001***	63.794***	520.284***
AUTO	0.0517	1.356	-14.91	9.9	-0.418	11.96	11118.838***	-55.704***	-55.875***	23.815	424.830***
METAL	0.0435	1.761	-12.33	9.39	-0.447	6.37	1667.058***	-16.705***	-58.226***	37.125**	297.124***
GOLD	0.0264	1.082	-12.07	5.91	-0.768	13.07	14244.687***	-23.798***	-59.572***	44.602***	170.738***
BRENT	-0.0122	2.49	-27.98	32.12	-0.475	24.27	62213.707***	-10.842***	-57.465***	73.342***	545.750***
USDINR	0.0166	0.428	-3.47	3.92	0.354	11.14	9168.755***	-24.950***	-66.424***	108.989***	649.982***

Table 2 reports unconditional return correlations, visualised in Figure 3. Three features stand out. Sectoral equity returns are strongly positively correlated (0.45–0.84). Gold is essentially uncorrelated with Indian equities (correlations of −0.02 to 0.06), the unconditional signature of a potential diversifier. The rupee correlates negatively with every equity index, consistent with the foreign-flow channel described in Section 2.2.

Table 2. Unconditional return correlations.

	NIFTY 50	**BANK**	**IT**	**PHARMA**	**ENERGY**	**FMCG**	**AUTO**	**METAL**	**GOLD**	**BRENT**	**USDINR**
NIFTY 50	1.0	0.88	0.56	0.53	0.77	0.65	0.8	0.7	0.03	0.07	-0.15
BANK	0.88	1.0	0.31	0.37	0.62	0.48	0.68	0.6	0.01	0.04	-0.15
IT	0.56	0.31	1.0	0.34	0.32	0.32	0.37	0.32	0.03	0.06	-0.06
PHARMA	0.53	0.37	0.34	1.0	0.42	0.42	0.46	0.43	0.02	0.08	-0.01
ENERGY	0.77	0.62	0.32	0.42	1.0	0.45	0.61	0.67	0.03	0.08	-0.1
FMCG	0.65	0.48	0.32	0.42	0.45	1.0	0.52	0.4	-0.0	0.03	-0.11
AUTO	0.8	0.68	0.37	0.46	0.61	0.52	1.0	0.63	0.04	0.03	-0.13
METAL	0.7	0.6	0.32	0.43	0.67	0.4	0.63	1.0	0.08	0.12	-0.08
GOLD	0.03	0.01	0.03	0.02	0.03	-0.0	0.04	0.08	1.0	0.07	-0.02
BRENT	0.07	0.04	0.06	0.08	0.08	0.03	0.03	0.12	0.07	1.0	0.04
USDINR	-0.15	-0.15	-0.06	-0.01	-0.1	-0.11	-0.13	-0.08	-0.02	0.04	1.0

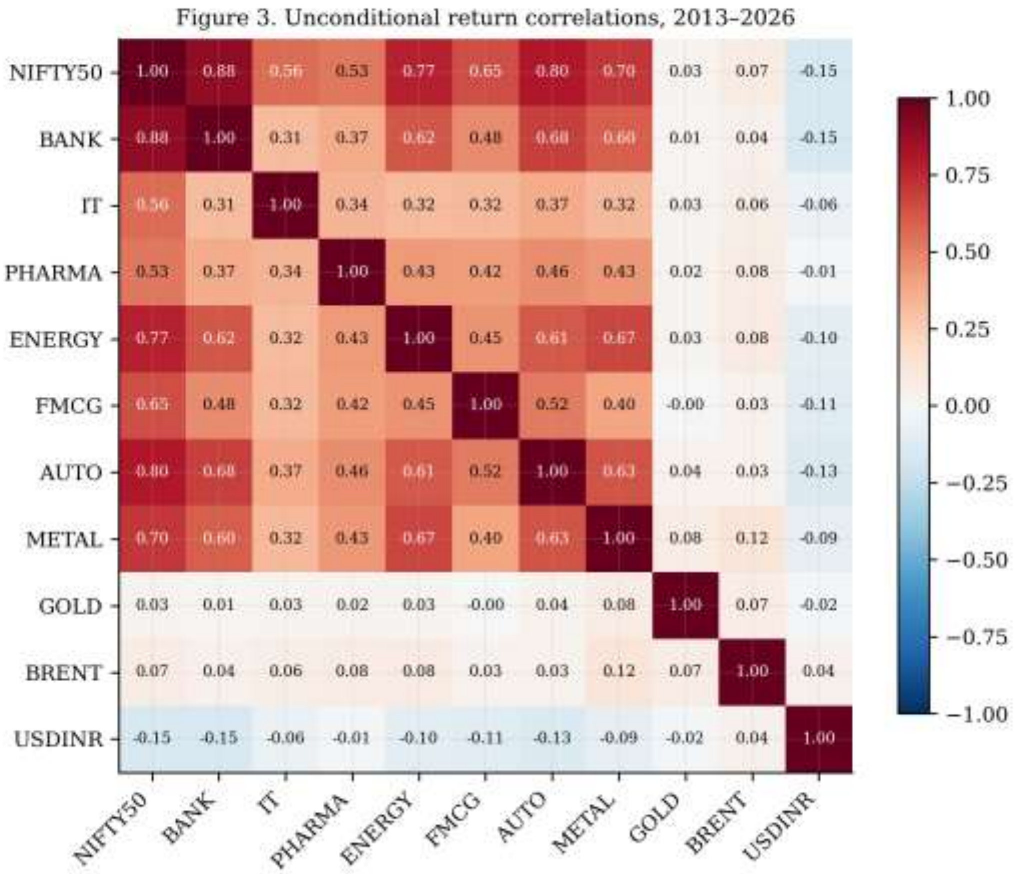

Figure 3. Unconditional return correlations, 2013–2026.

4. Methodology

4.1 TVP-VAR connectedness

Following Antonakakis et al. (2020), we estimate a TVP-VAR(1)—the lag order selected by the AIC, FPE and HQ criteria—written as

$$y_t = B_t' x_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_t),$$

where y_t is the $n \times 1$ return vector ($n = 11$), $x_t = (1, y_{t-1}')'$ stacks an intercept and one lag, and the coefficients follow a random walk, $\mathrm{vec}(B_t) = \mathrm{vec}(B_{t-1}) + v_t$. The system is estimated by a Kalman filter with forgetting factors $\kappa_1 = \kappa_2 = 0.99$ (Koop and Korobilis, 2014), which govern the smoothness of the coefficient and covariance updates, with priors based on ordinary least squares over the first 250 observations. At each date the estimated companion matrix $A_{1,t}$ and covariance Σ_t are used to compute the H-step generalised forecast error variance decomposition ($H = 10$) of Koop et al. (1996) and Pesaran and Shin (1998):

$$\theta_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' A_{h,t} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} e_i' A_{h,t} \Sigma_t A_{h,t}' e_i},$$

normalised so that each row sums to one, $\tilde{\theta}_{ij,t} = \theta_{ij,t} / \Sigma_j \theta_{ij,t}$. From the normalised decomposition we compute the total connectedness index (TCI),

$$TCI_t(H) = \frac{\sum_{i \neq j} \tilde{\theta}_{ij,t}(H)}{n} \times 100,$$

directional connectedness transmitted to others ($TO_{i,t} = \Sigma_{j \neq i} \tilde{\theta}_{ji,t}$), received from others ($FROM_{i,t} = \Sigma_{j \neq i} \tilde{\theta}_{ij,t}$), net connectedness ($NET_{i,t} = TO_{i,t} - FROM_{i,t}$) and net pairwise connectedness.

4.2 Quantile connectedness

To characterise transmission across the conditional distribution we follow Chatziantoniou et al. (2021). For quantile $\tau \in (0, 1)$ the quantile VAR

$$y_t = \mu(\tau) + \Phi_1(\tau) y_{t-1} + u_t(\tau)$$

is estimated equation-by-equation by quantile regression, and the variance–covariance matrix at quantile τ is computed from the second moments of the quantile residuals. The generalised FEVD and all connectedness measures of Section 4.1 are then evaluated at τ. We report full-sample estimates at $\tau \in \{0.05, 0.50, 0.95\}$, the TCI over the grid $\tau \in \{0.05, 0.10, \ldots, 0.95\}$, and dynamic tail and median connectedness from 250-day rolling windows advanced in five-day steps.

4.3 DCC-GARCH, hedge ratios and portfolio weights

Conditional second moments are estimated with the DCC-GARCH model of Engle (2002). Univariate GARCH(1,1) processes, $h_{i,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h_{i,t-1}$, yield standardised residuals z_t whose correlation dynamics follow

$$Q_t = (1 - a - b)\bar{Q} + a z_{t-1} z'_{t-1} + b Q_{t-1}, \qquad R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \, \mathrm{diag}(Q_t)^{-1/2},$$

with $\bar{Q}$ the unconditional correlation of z_t and (a, b) estimated by quasi-maximum likelihood. Writing $h_{sh,t}$ for the conditional covariance between equity s and hedging asset h, the Kroner and Sultan (1993) hedge ratio is $\beta_t = h_{sh,t} / h_{hh,t}$; the Kroner and Ng (1998) optimal weight of the equity in a two-asset portfolio is

$$w_t = \frac{h_{hh,t} - h_{sh,t}}{h_{ss,t} - 2h_{sh,t} + h_{hh,t}},$$

restricted to [0, 1]; and hedging effectiveness (Ederington, 1979) is the proportional variance reduction $HE = 1 - \mathrm{Var}(r_{\text{hedged}})/\mathrm{Var}(r_s)$.

5. Empirical results

5.1 Average connectedness

Table 3 reports the averaged connectedness matrix from the TVP-VAR. The average total connectedness index is 53.2%: over half of the ten-day-ahead forecast error variance in this system is attributable to cross-market spillovers, indicating a tightly integrated system. The diagonal blocks confirm that own-market shocks matter most for the commodities and the currency, whereas the equity indices are heavily exposed to one another.

Table 3. Averaged connectedness table, TVP-VAR (GFEVD, H = 10). Entry (i, j): share of variable i's forecast error variance attributable to shocks in variable j.

	NIFTY50	**BANK**	**IT**	**PHARMA**	**ENERGY**	**FMCG**	**AUTO**	**METAL**	**GOLD**	**BRENT**	**USDINR**	**FROM others**
NIFTY50	22.38	17.09	6.4	6.13	13.01	8.87	13.46	10.83	0.51	0.65	0.67	77.62
BANK	22.16	29.22	2.88	4.22	11.07	6.15	12.14	10.14	0.56	0.69	0.77	70.78
IT	13.72	4.43	54.43	5.49	4.26	4.61	5.61	4.33	1.04	1.16	0.91	45.57
PHARMA	11.8	6.3	4.99	43.79	7.46	7.04	8.69	7.89	0.58	0.89	0.56	56.21
ENERGY	17.67	11.56	2.86	5.36	31.05	5.74	10.72	12.81	0.6	0.95	0.69	68.95
FMCG	15.59	8.12	3.96	6.25	7.47	40.91	9.96	5.77	0.53	0.71	0.72	59.09
AUTO	17.71	12.38	3.46	6.01	10.41	7.5	29.44	10.96	0.68	0.79	0.65	70.56
METAL	15.3	11.06	3.01	5.9	13.43	4.74	11.79	31.81	1.02	1.3	0.64	68.19
GOLD	1.26	1.13	1.64	0.87	1.16	0.84	1.38	1.7	85.93	2.76	1.33	14.07
BRENT	1.59	1.39	1.25	1.51	1.59	1.13	1.48	2.0	2.4	84.79	0.87	15.21

USDINR	6.81	6.01	1.91	2.12	5.16	3.09	4.89	3.75	2.98	1.86	61.41	38.59
TO others	123.63	79.47	32.36	43.85	75.03	49.71	80.12	70.18	10.91	11.77	7.83	584.85
NET	46.01	8.68	-13.2	-12.36	6.07	-9.38	9.55	1.99	-3.16	-3.44	-30.77	
TCI = 53.17 %												

The NET row identifies the transmission hierarchy, visualised as a network in Figure 6. The Nifty 50 is the dominant net transmitter (+46.0), as expected for the aggregate market factor (Section 6 shows that all qualitative conclusions survive its exclusion). Among sectors, automobiles (+9.6), banking (+8.7), energy (+6.1) and metals (+2.0) are net transmitters—cyclical sectors whose fortunes embody the macroeconomic news that drives the whole system. The defensive, export-oriented sectors—IT (−13.2), pharmaceuticals (−12.4) and FMCG (−9.4)—are net receivers, consistent with revenues that are partly insulated from the domestic cycle. Gold (−3.2) and Brent (−3.4) are mild net receivers, indicating that at the daily frequency the Indian equity system reacts to global commodity prices without materially feeding back into them. The rupee is by far the largest net receiver (−30.8): the exchange rate is the shock absorber of the system, exactly as the foreign-flow channel predicts.

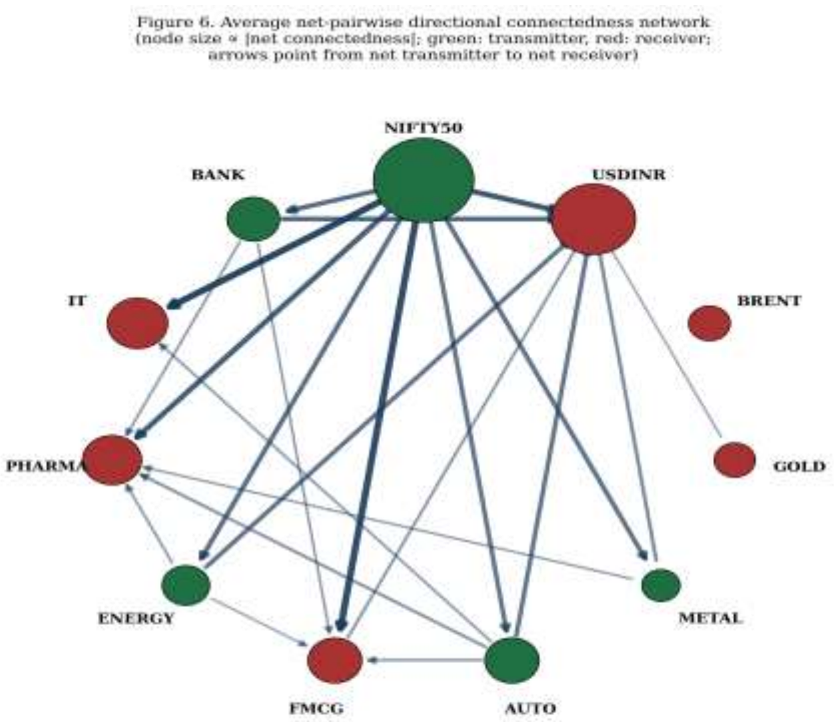

Figure 6. Average net-pairwise directional connectedness network. Node size is proportional to absolute net connectedness; green nodes are net transmitters, red nodes net receivers.

5.2 Dynamic connectedness

Figure 4 plots the dynamic TCI. Connectedness is strongly event-driven, supporting H1. From a calm-period average of 48.7% over 2017–2019, the TCI jumps to its sample maximum of 77.9% at the COVID-19 outbreak in March 2020, rises to 62.1% following the Russian invasion of Ukraine, and climbs again to 60.4% around the April 2025 tariff announcement—evidence that trade-policy shocks propagate through emerging-market asset systems with an intensity comparable to a major geopolitical event. Elevated connectedness decays only gradually after each episode, so crisis-level integration persists for months. Figure 5 shows the corresponding net directional series: the transmitter role of the cyclical sectors and the absorber role of the rupee are stable features rather than crisis artefacts, though the magnitude of the rupee's net-receiving position deepens sharply in every stress episode.

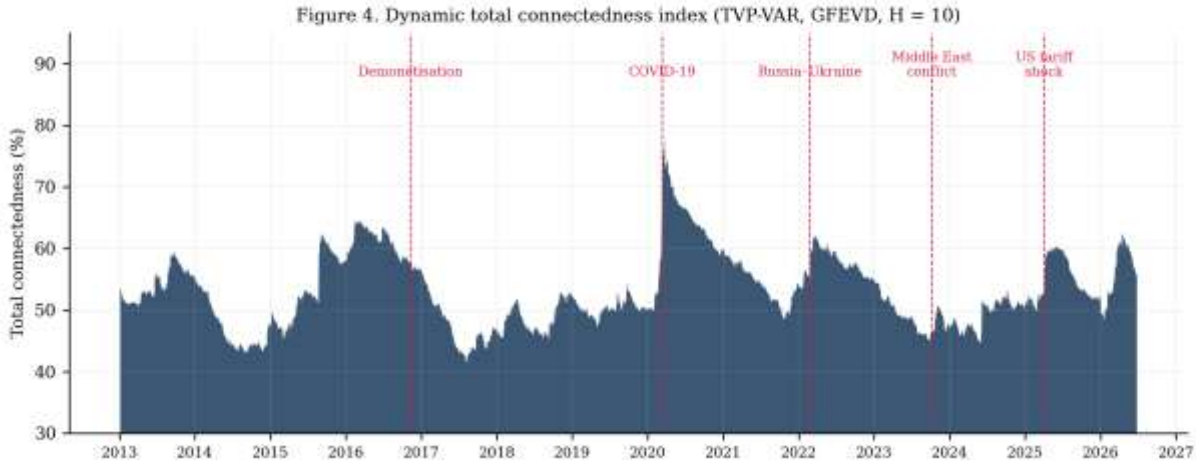

Figure 4. Dynamic total connectedness index (TVP-VAR, generalised FEVD, H = 10).

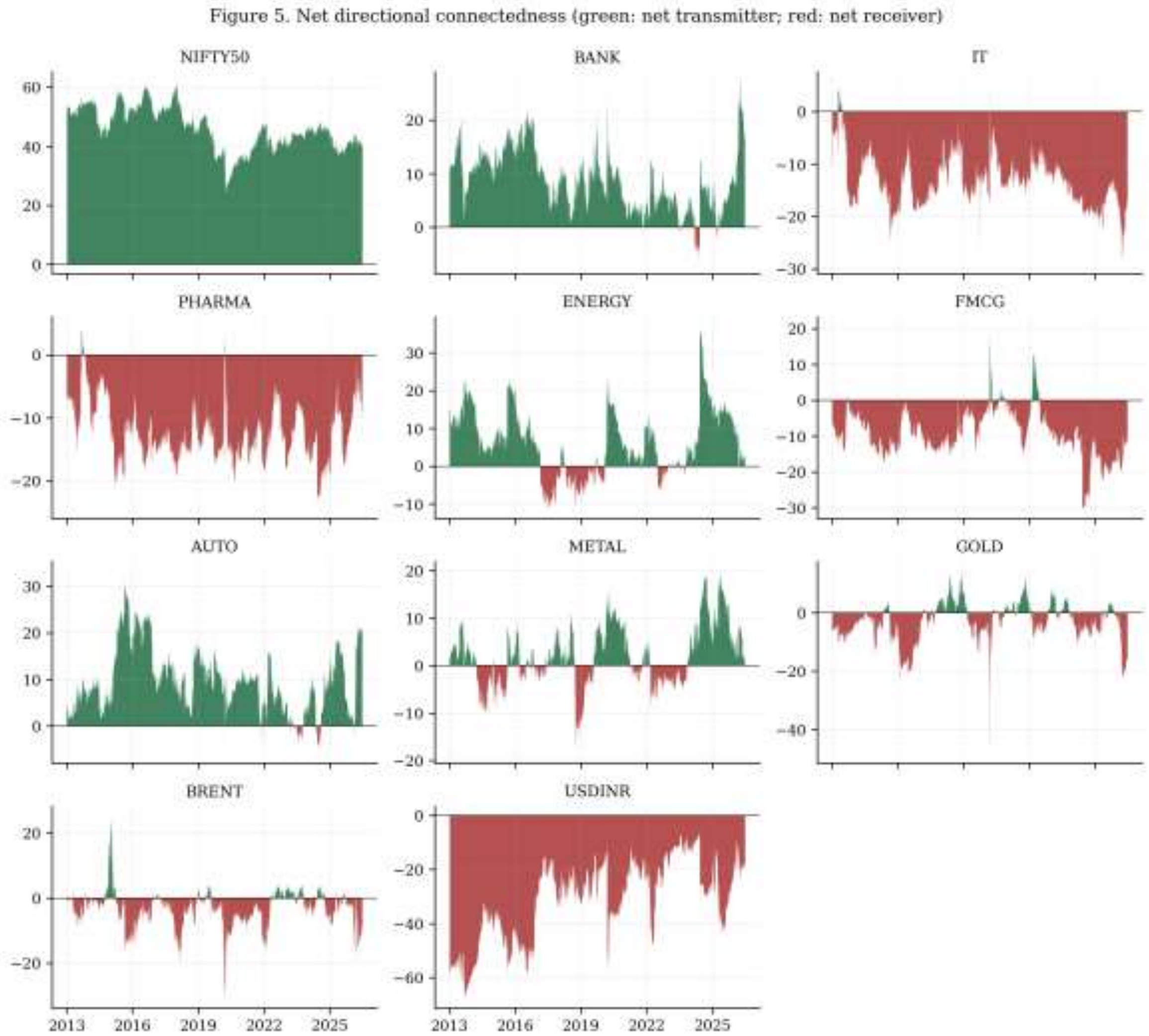

Figure 5. Net directional connectedness (green: net transmitter; red: net receiver).

5.3 Connectedness across quantiles

Table 4 reports full-sample connectedness at the fifth percentile, the median and the ninety-fifth percentile, and Figure 7 traces the TCI across the full quantile grid. The pattern is a pronounced U-shape: total connectedness is 50.5% at the median but 86.2% at $\tau = 0.05$ and 85.8% at $\tau = 0.95$. Shock transmission in extreme market states is therefore roughly 35 percentage points stronger than in normal states, and mean- or median-based estimates—the bulk of the existing evidence—substantially understate systemic linkages precisely where they matter most for risk management. This strongly supports the first part of H2.

Table 4, Panel A. Quantile connectedness at τ = 0.05 (extreme losses).

	NIFTY50	**BANK**	**IT**	**PHARMA**	**ENERGY**	**FMCG**	**AUTO**	**METAL**	**GOLD**	**BRENT**	**USDINR**	**FROM others**
NIFTY50	12.2	11.28	9.14	8.99	10.49	9.65	10.66	10.01	6.25	6.27	5.06	87.8
BANK	11.94	12.98	8.21	8.41	10.02	9.11	10.48	9.95	6.68	6.59	5.63	87.02
IT	10.56	8.74	14.13	9.17	8.93	8.91	9.26	9.16	7.4	7.31	6.44	85.87
PHARMA	10.04	8.93	8.92	13.33	9.49	9.13	9.55	9.56	7.26	7.23	6.55	86.67
ENERGY	11.0	10.13	8.34	8.9	12.45	8.91	10.08	10.32	6.82	7.15	5.88	87.55
FMCG	10.81	9.51	8.59	9.29	9.52	13.63	9.91	9.22	6.85	6.83	5.85	86.37
AUTO	11.27	10.42	8.44	9.05	9.98	9.39	12.77	10.14	6.54	6.44	5.58	87.23
METAL	10.35	9.71	8.23	9.05	10.22	8.79	10.06	12.32	7.52	7.55	6.19	87.68
GOLD	8.29	8.1	8.36	8.52	8.56	8.4	8.34	8.96	15.82	8.53	8.12	84.18
BRENT	8.32	8.04	8.33	8.57	8.6	8.19	8.11	8.96	8.61	16.33	7.94	83.67
USDINR	8.4	8.38	8.14	8.72	8.6	8.22	8.42	8.71	8.62	8.36	15.43	84.57
TO others	100.97	93.23	84.7	88.65	94.41	88.7	94.89	94.99	72.54	72.28	63.25	948.61
NET	13.17	6.22	-1.17	1.98	6.86	2.33	7.66	7.31	-11.64	-11.39	-21.33	

Table 4, Panel B. Quantile connectedness at τ = 0.50 (median).

	NIFTY50	**BANK**	**IT**	**PHARMA**	**ENERGY**	**FMCG**	**AUTO**	**METAL**	**GOLD**	**BRENT**	**USDINR**	**FROM others**
NIFTY50	22.06	17.21	6.86	6.18	12.92	9.31	14.01	10.82	0.03	0.16	0.43	77.94
BANK	22.44	28.83	2.79	4.01	11.05	6.56	13.4	10.28	0.02	0.06	0.56	71.17
IT	15.81	4.92	50.9	5.74	4.99	5.2	6.74	5.11	0.06	0.33	0.19	49.1
PHARMA	12.26	6.06	4.94	43.47	7.85	7.57	9.24	8.22	0.08	0.29	0.0	56.53
ENERGY	17.87	11.7	2.98	5.49	30.34	6.17	11.43	13.39	0.05	0.34	0.24	69.66
FMCG	16.37	8.82	3.96	6.73	7.9	38.78	10.61	6.16	0.05	0.09	0.52	61.22
AUTO	18.14	13.29	3.78	6.02	10.71	7.81	28.45	11.28	0.04	0.08	0.4	71.55
METAL	15.49	11.28	3.17	5.97	13.85	5.01	12.48	31.51	0.37	0.68	0.19	68.49

GOLD	0.11	0.05	0.11	0.08	0.1	0.01	0.16	0.65	98.1	0.52	0.11	1.9
BRENT	0.6	0.22	0.42	0.63	0.65	0.12	0.13	1.44	0.49	95.1	0.2	4.9
USDINR	4.86	4.68	0.45	0.71	3.08	2.47	3.37	2.12	0.99	0.27	76.99	23.01
TO others	123.95	78.23	29.46	41.56	73.11	50.24	81.58	69.47	2.19	2.82	2.84	555.46
NET	46.01	7.06	-19.64	-14.96	3.45	-10.98	10.03	0.98	0.29	-2.08	-20.17	

Table 4, Panel C. Quantile connectedness at τ = 0.95 (extreme gains).

	NIFTY50	**BANK**	**IT**	**PHARMA**	**ENERGY**	**FMCG**	**AUTO**	**METAL**	**GOLD**	**BRENT**	**USDINR**	**FROM others**
NIFTY50	12.28	11.38	9.16	9.01	10.46	9.71	10.72	10.11	5.96	5.9	5.31	87.72
BANK	12.03	13.04	8.16	8.61	9.98	9.23	10.57	9.96	6.41	6.19	5.81	86.96
IT	10.56	8.93	14.2	9.17	8.74	8.96	9.18	8.98	7.17	7.15	6.95	85.8
PHARMA	10.13	9.14	8.92	13.65	9.28	9.29	9.57	9.54	6.86	6.75	6.87	86.35
ENERGY	11.29	10.21	8.21	8.88	13.23	9.0	10.12	10.51	6.29	6.34	5.92	86.77
FMCG	10.91	9.71	8.67	9.34	9.35	13.83	9.98	9.15	6.6	6.33	6.13	86.17
AUTO	11.34	10.53	8.38	9.07	9.95	9.4	12.97	10.14	6.44	5.98	5.81	87.03
METAL	10.78	10.04	8.26	9.07	10.39	8.67	10.21	13.09	6.79	6.65	6.05	86.91
GOLD	8.24	8.36	8.51	8.42	7.99	8.16	8.4	8.8	16.97	8.13	8.01	83.03
BRENT	8.29	8.28	8.34	8.6	8.14	7.95	8.06	8.79	8.31	16.86	8.39	83.14
USDINR	8.38	8.51	8.28	8.8	8.58	8.21	8.42	8.5	8.47	7.99	15.86	84.14
TO others	101.95	95.09	84.89	88.97	92.87	88.58	95.24	94.47	69.31	67.4	65.25	944.01
NET	14.23	8.14	-0.92	2.62	6.1	2.41	8.21	7.57	-13.72	-15.74	-18.89	

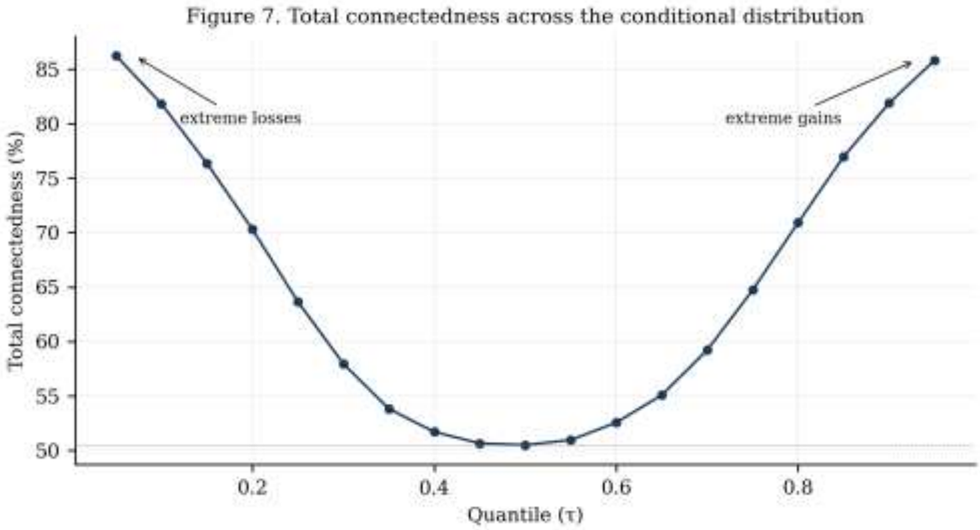

Figure 7. Total connectedness across the conditional distribution of returns.

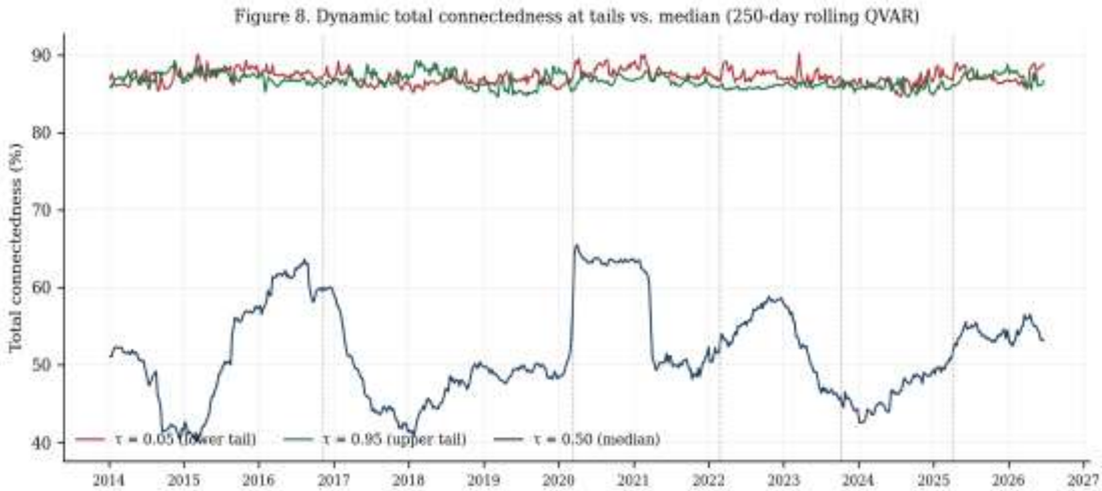

Figure 8. Dynamic total connectedness at the tails versus the median (250-day rolling quantile VAR).

Figure 8 delivers the second part of H2 and, we believe, the most striking result of the paper. Rolling median connectedness varies widely—between 40.1% and 65.5% (mean 51.6%, standard deviation 6.2)—spiking around COVID-19, the Russia–Ukraine war and the 2025 tariff shock. Tail connectedness, by contrast, is uniformly extreme and almost time-invariant: the lower-tail TCI averages 87.2% with a standard deviation of only 0.9, and the upper tail behaves symmetrically. Crisis events, in other words, move connectedness at the *centre* of the distribution; the tails of the system are always tightly coupled, whether or not a crisis is under way. The economic takeaway is sobering: cross-market diversification within this system is a true fair-weather game, dependable in normal states and largely an illusion in extreme ones.

Tail tables also show some reshuffling of roles. At τ = 0.05 gold (−11.6) and Brent (−11.4) change to considerably stronger net receivers than on average, while even the more defensive FMCG (+2.3) and pharmaceutical (+2.0) sectors flip into net transmitters, with the rupee still by far the strongest absorber at (−21.3). To summarize the second bullet point: no market is insulated from each other in crash states, and moreover, it appears that assets that appear disconnected from one another at the mean become connected at some point by a spider-like web of a transmission network.

5.4 Hedging and portfolio implications

The DCC-GARCH estimates (a = 0.013, b = 0.966; parameter estimates for the univariate GARCH processes are reported in Appendix Table A1) imply highly persistent conditional correlations, plotted for the Nifty 50 in Figure 10. Table 5 reports hedge ratios, optimal weights and hedging effectiveness for each equity–hedge pair, and Figure 9 plots the dynamic hedge ratios for the aggregate index.

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Table 5. Hedge ratios (HR), optimal portfolio weights, and hedging effectiveness (HE). HE is the variance reduction from the direct hedge; HE_portfolio from the optimal-weight portfolio.

Equity	Hedge	HR mean	HR sd	Weight mean	HE (%)	Corr mean	HE_portfolio (%)
NIFTY50	GOLD	0.008	0.06	0.555	-0.811	0.011	45.949
NIFTY50	BRENT	0.036	0.037	0.836	0.059	0.078	9.545
NIFTY50	USDINR	-0.384	0.178	0.195	1.122	-0.151	86.923
BANK	GOLD	0.002	0.081	0.415	-0.681	0.004	62.486
BANK	BRENT	0.029	0.053	0.723	-0.098	0.043	21.367
BANK	USDINR	-0.457	0.233	0.127	1.358	-0.133	92.471
IT	GOLD	0.037	0.076	0.382	-1.835	0.028	59.417
IT	BRENT	0.048	0.039	0.709	-0.143	0.072	16.063
IT	USDINR	-0.208	0.194	0.105	0.14	-0.055	91.104
PHARMA	GOLD	-0.003	0.064	0.441	-0.412	-0.0	53.88
PHARMA	BRENT	0.04	0.035	0.754	0.811	0.07	10.902
PHARMA	USDINR	-0.094	0.187	0.119	-0.224	-0.028	88.69
ENERGY	GOLD	0.008	0.072	0.404	-0.422	0.008	59.006
ENERGY	BRENT	0.033	0.041	0.719	0.699	0.055	14.387
ENERGY	USDINR	-0.39	0.234	0.121	0.331	-0.112	91.147
FMCG	GOLD	-0.019	0.053	0.51	-0.627	-0.018	48.61
FMCG	BRENT	0.021	0.029	0.8	-0.096	0.043	10.939
FMCG	USDINR	-0.263	0.141	0.161	0.12	-0.095	86.877
AUTO	GOLD	0.012	0.085	0.404	-0.022	0.012	59.643
AUTO	BRENT	0.035	0.044	0.723	0.801	0.054	19.443
AUTO	USDINR	-0.414	0.226	0.122	1.324	-0.119	91.718
METAL	GOLD	0.101	0.109	0.262	0.446	0.063	70.755
METAL	BRENT	0.101	0.062	0.595	1.671	0.117	23.74
METAL	USDINR	-0.486	0.322	0.074	0.816	-0.099	94.665

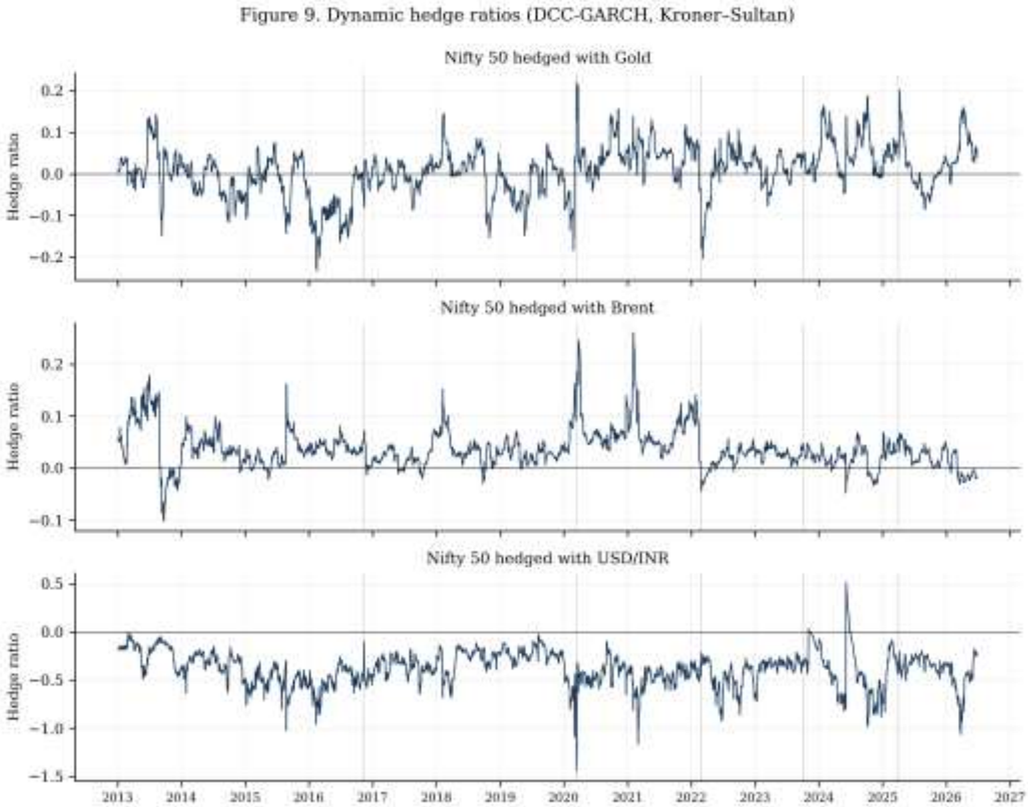

Figure 9. Dynamic hedge ratios for the Nifty 50 (DCC-GARCH, Kroner–Sultan).

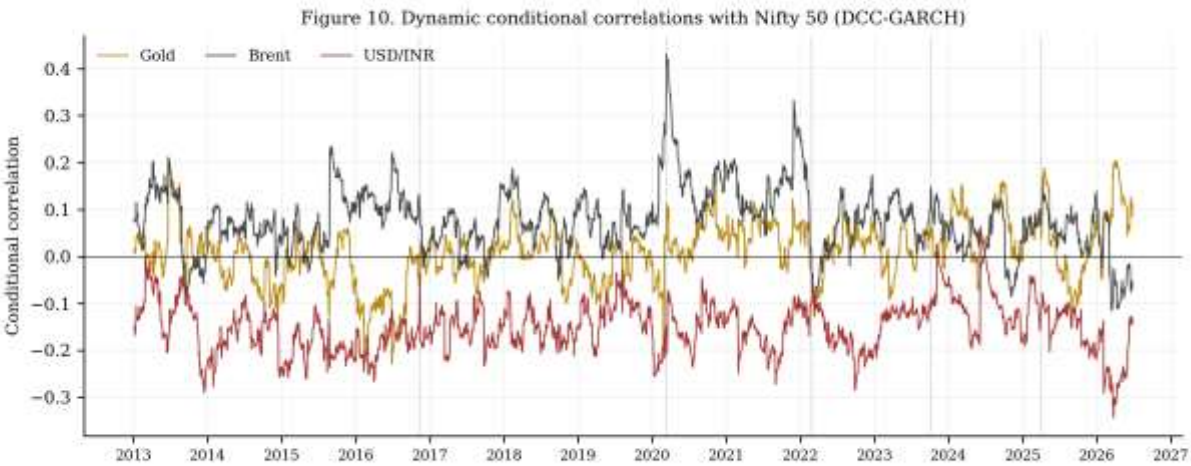

Figure 10. Dynamic conditional correlations with the Nifty 50.

Three conclusions follow, jointly supporting H3. First, gold is a diversifier rather than a hedge in the taxonomy of Baur and Lucey (2010): average equity–gold hedge ratios are statistically and economically negligible (0.01 for the Nifty 50), so direct hedging with gold achieves essentially nothing, yet mixed equity–gold portfolios at the Kroner–Ng optimal weights—which allocate roughly 26–56% to equities depending on the sector—reduce portfolio variance by 46–71% relative to an unhedged equity position. Second, the currency market offers the most effective direct hedge: equity–USDINR hedge ratios are consistently negative (−0.38 for the Nifty 50, reaching −0.49 for metals), so a long US dollar position against the rupee offsets Indian equity exposure, and Figure 9 shows this hedge intensifying in every crisis episode—exactly when it is needed. Third, against metals exposure (hedge ratio 0.10), Brent offers protection through hedging value (largest oil beta in the system) biased in accordance with input-cost; i.e. The Section 5.3 quantile results provide an important caveat to the gold conclusion: as tail connectedness nears 86%, we should expect that average correlations used for diversification will weaken materially in extreme market states.

6. Robustness

Figure 11 overlays the baseline dynamic TCI with four alternatives: excluding the Nifty 50 (removing any mechanical aggregate–constituent overlap), forecast horizons of $H = 5$ and $H = 20$, and forgetting factors of 0.98. The horizon variations are indistinguishable from the baseline (correlation 1.000), the alternative forgetting factors yield a correlation of 0.915 with identical crisis dating, and the ten-variable system excluding the aggregate index shifts the level down (average TCI 45.3%) while preserving the dynamics almost exactly (correlation 0.997). Table 6 reports the averaged connectedness matrix for the ten-variable system: automobiles (+15.0), energy (+11.4), banking (+11.2) and metals (+8.3) remain the net transmitters and the rupee the dominant net receiver (−26.4), confirming that the transmission hierarchy of Section 5.1 is not an artefact of including the aggregate index. The quantile U-shape is likewise preserved in the ten-variable system.

Table 6. Averaged connectedness table excluding the Nifty 50 (robustness).

	BANK	IT	PHARMA	ENERGY	FMCG	AUTO	METAL	GOLD	BRENT	USDINR	FROM others
BANK	37.68	3.63	5.37	14.25	7.88	15.6	13.02	0.72	0.89	0.98	62.32
IT	5.2	62.54	6.45	5.02	5.44	6.61	5.17	1.2	1.33	1.04	37.46
PHARMA	7.18	5.67	49.47	8.5	7.97	9.92	8.97	0.66	1.0	0.65	50.53
ENERGY	14.09	3.43	6.47	37.79	6.96	13.03	15.53	0.73	1.15	0.83	62.21
FMCG	9.68	4.68	7.4	8.88	48.34	11.83	6.87	0.64	0.83	0.85	51.66
AUTO	15.09	4.19	7.31	12.63	9.09	35.79	13.31	0.83	0.96	0.81	64.21
METAL	13.07	3.57	6.96	15.85	5.59	13.93	37.59	1.2	1.53	0.73	62.41
GOLD	1.16	1.66	0.89	1.19	0.87	1.4	1.74	86.93	2.8	1.37	13.07

BRENT	1.46	1.28	1.54	1.63	1.16	1.52	2.05	2.44	86.01	0.91	13.99
USDINR	6.56	2.07	2.36	5.62	3.37	5.38	4.06	3.17	1.99	65.42	34.58
TO others	73.49	30.17	44.74	73.57	48.34	79.21	70.72	11.57	12.48	8.17	452.46
NET	11.16	-7.29	-5.79	11.36	-3.32	14.99	8.31	-1.5	-1.51	-26.41	

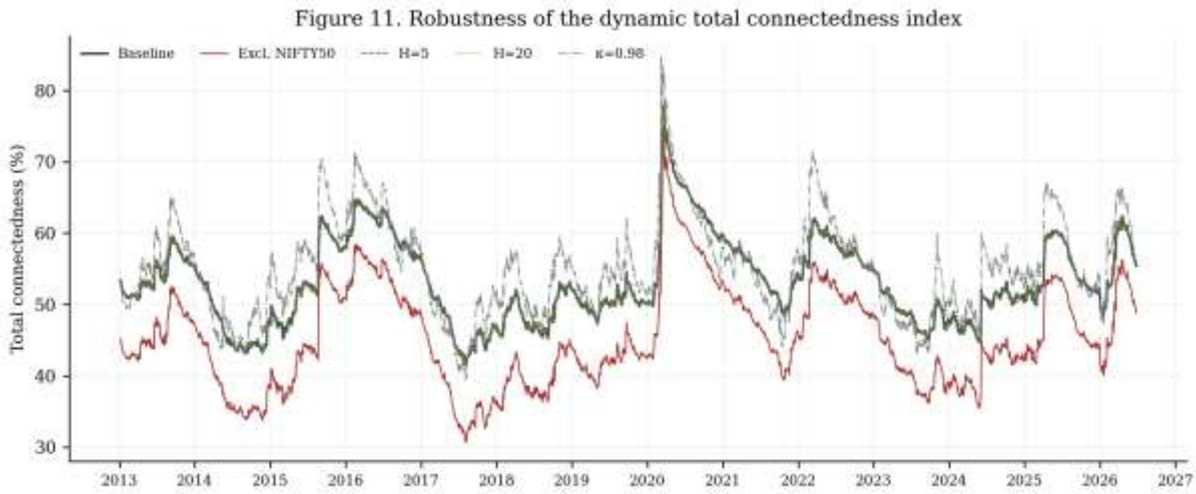

Figure 11. Robustness of the dynamic total connectedness index.

7. Conclusion

This paper studies time-varying and distribution-dependent connectedness in a system comprising Indian sectoral equities, gold, Brent crude oil and the rupee over January 2013 to June 2026, and translates the evidence into portfolio prescriptions. Average total connectedness of 53.2% masks two forms of state dependence. Over time, connectedness surges in crises—reaching 77.9% during COVID-19 and 60.4% after the 2025 tariff shock—and decays slowly. Across the return distribution, connectedness rises from 50.5% at the median to approximately 86% in both tails, and rolling estimates show that this tail coupling is a permanent feature of the system rather than a crisis phenomenon. Cyclical sectors transmit shocks; defensive sectors, the commodities and above all the rupee absorb them; and in crash states even the apparent diversifiers are drawn into the network.

The practical implications are direct. Gold merits a concentrated long-term strategic allocation from an investor standpoint, serving as the best portfolio diversifier (at optimal weights, gold is expected to halve to two-thirds the variance of most portfolios) but one should not look at it as a tail insurance; direct hedging of Indian equity exposure may be better served by long US dollar positions which heighten roughly endogenously in stress. Models that are fitted to means will greatly underestimate co-movement during crisis by risk managers, and stress tests should find structure in tail-state dependence. The rupee's position as the main shock absorber in the system indicates that for policymakers, the exchange rate should be a crucial focus of financial stability surveillance and shows that trade policy is an intermediary systemic risk factor for emerging markets with the aforementioned 2025 tariff episode generating connectedness levels comparable to those seen in major geopolitical shocks.

Several extensions merit future work: intraday data would sharpen the identification of crisis transmission; adding Bitcoin or Indian sovereign bonds would test alternative safe-haven candidates; and asymmetric or frequency-domain connectedness decompositions would reveal whether the tail coupling documented here is driven by short- or long-horizon components.

CrediT author contribution statement:

Deepak Kumar Aggarwal: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing.

Mini Srivastava: Methodology, Validation, Writing – review & editing.

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Declaration of generative AI and AI-assisted technologies in the writing process:
During the preparation of this work we used a generative AI assistant in order to support exploratory data analysis, drafting, and formatting of the manuscript. After using the tool, we reviewed and edited the content as needed, verified all reported statistics against the underlying data, and take full responsibility for the content of the publication..

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