

When Yen Funding Unwinds: Dynamic, Frequency, and Quantile Connectedness across China, Japan, Korea, and India during the August 2024 Carry-Trade Shock

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ABSTRACT

Backgrounds: The August 2024 unwinding of yen-funded carry-trade positions produced one of the sharpest episodes of cross-market turbulence in Asian equities since the pandemic, yet its transmission through the China-Japan-Korea-India equity network had not previously been examined as a dedicated event.

Objectives: This study aimed to quantify the change in total connectedness associated with the episode, to decompose that change by transmission horizon and by return-distribution quantile, and to determine whether net-transmitter and net-receiver roles within the network changed as a result of the shock.

Methodology: Dynamic, frequency-domain, and quantile connectedness were estimated using a time-varying parameter vector autoregression fitted to daily returns for the four markets from January 2019 to June 2026, and regime differences were tested using a block bootstrap benchmarked against a placebo window.

Findings: Total connectedness rose by approximately 11 percentage points during the event window relative to a clean six-month pre-event baseline, about four times larger than the change observed in the placebo window. Transmission was concentrated at short horizons, accounting for close to four-fifths of total connectedness, and the gap between typical-state and tail-state connectedness compressed sharply during the event. Korea and Japan remained the network's two net transmitters throughout, while China and India exchanged their ranking as net receivers, a reordering that persisted afterward.

Conclusions: The episode intensified transmission along an unchanged transmitter hierarchy while producing a persistent reordering of the receiving side of the network within the observed post-event sample.

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1. INTRODUCTION

In early August 2024, global financial markets experienced a sharp episode of turbulence centred on the unwinding of yen-funded carry-trade positions. The Bank for International Settlements identified 5 August 2024 as the peak of the stress, when the Japanese TOPIX index lost twelve percent in a single session and volatility measures briefly reached levels last seen during the early phase of the COVID-19 pandemic (Aquilina et al., 2024). The episode followed an interaction of three developments rather than a single trigger, a Bank of Japan policy shift read as more hawkish than priced, a softer-than-expected United States labour market release, and already fragile leveraged positioning, and the yen appreciated by roughly five and a half percent against the dollar within days as Japanese banks' yen-denominated lending abroad, which had nearly doubled since 2021, was

rapidly unwound, consistent with a genuine funding-liquidity shock rather than an ordinary equity correction.

The yen has served as the principal funding currency for global carry trades for more than two decades, a role documented since the aftermath of the 1997 Asian financial crisis and revisited during the 2008 subprime episode (Hattori & Shin, 2009). Carry-trade returns are negatively skewed by construction: gains accrue steadily while losses are concentrated and sudden, occurring precisely when funding liquidity and risk appetite decline together (Brunnermeier et al., 2008). The August 2024 episode offers an unusually clean setting for studying this transmission specifically because it is a single, precisely dateable shock with a clear before-and-after boundary, rather than a slow-moving or ambiguously timed development, and because yen-funded positions are documented to have financed assets well beyond Japan, including Indian equities and corporate debt, giving the shock a plausible channel into the present four-market network.

Financial connectedness among major Asian equity markets has been studied extensively, and this literature consistently finds that China, Japan, Korea, and India are interlinked, with the intensity and direction of transmission shifting during stress (Anwer et al., 2022; Saji, 2022). A recent working paper examined funding liquidity and cross-asset spillovers around the broader 2024 exit from negative interest rates using a global, cross-asset vector autoregression spanning equities, currencies, and digital assets (Lee, 2026), and a separate study placed China, Japan, and Korea inside the wider Regional Comprehensive Economic Partnership bloc using data through December 2024 (Zou et al., 2025). To the best of our knowledge, neither study isolates a dedicated four-market equity network built specifically around this episode, and neither combined dynamic, frequency-domain, and quantile connectedness with a formally specified comparison of pre-event, event, and post-event regimes.

A few researchers have examined Asian equity connectedness broadly, and a smaller number have examined the mechanics of the August 2024 episode itself. There have been limited studies concerned with how this specific shock moved through a dedicated China-Japan-Korea-India network, whether it altered which markets transmitted and which received, and over what horizon transmission was concentrated. Therefore, this research intended to estimate dynamic, frequency-domain, and quantile connectedness among these four markets and to test formally whether connectedness differed across pre-event, event, and post-event regimes. The objectives of this research were to quantify the change in total connectedness associated with the episode, to decompose that change by transmission horizon and by quantile of the return distribution, and to determine whether the identities of net transmitters and net receivers within the network changed as a result of the shock.

This study contributes to the literature in three specific ways. It isolates the August 2024 episode within a dedicated four-market equity network rather than treating it as one observation within a broader regional or cross-asset system. It integrates three connectedness dimensions, dynamic, frequency-domain, and quantile, within a single design anchored to the event's own sequencing, rather than applying any one dimension in isolation. And it tests formally, via a block bootstrap benchmarked against a placebo window, whether the observed change in connectedness reflects an intensification of existing transmission, a reorganisation of which markets transmit and which receive, or both.

2. LITERATURE REVIEW

This review is organised around four strands of prior work, carry-trade mechanics and yen funding, the August 2024 mechanism, connectedness methodology, and Asian equity market evidence, before turning to the specific gap this study addresses: despite each strand being individually well developed, no existing study isolates the August 2024 episode within a dedicated four-market China-Japan-Korea-India network and tests, within a single design, whether the shock intensified existing transmission, reorganised which markets transmit and which receive, or both.

2.1. Carry-Trade Mechanics and Yen Funding

A currency carry trade involves borrowing in a low-interest funding currency and investing the proceeds in higher-yielding assets abroad. Brunnermeier et al. (2008) showed that returns to this strategy are negatively skewed, since unwinding tends to happen abruptly, precisely when funding liquidity and risk appetite deteriorate together. The yen has functioned as a principal funding currency for such strategies since the aftermath of the 1997 Asian financial crisis, when interbank yen flows through Tokyo-based foreign bank affiliates created a visible channel for transmitting funding conditions across borders (Hattori & Shin, 2009). Within a wider network of G10 currencies, however, the yen has more recently been shown to behave as a net recipient of currency risk rather than a source of it, with the euro and the Australian dollar identified instead as the principal transmitters, a pattern that persisted even as the COVID-19 pandemic reshaped currency-risk transmission across the group (Mo et al., 2023).

Carry-trade exposure has also been linked directly to equity-market outcomes: studying BRICS economies, Makhanya et al. (2024) found that dependence between carry-trade returns and equity returns strengthens during crises and is particularly pronounced in the lower tail of the return distribution, evidence that supports treating a carry-trade unwind as a plausible source of equity-market stress rather than a currency-market event alone. Consistent with this history, a recent regional assessment concluded that yen-funded positions had financed exposures across ASEAN+3 economies well before the August 2024 episode, leaving the region only partially insulated from the shock despite limited direct participation in carry-trade activity itself (AMRO, 2024).

2.2. The August 2024 Mechanism

The August 2024 episode itself has so far been documented mainly by policy institutions rather than academic researchers. The Bank for International Settlements attributed the turbulence to an interacting sequence of a Bank of Japan policy shift, a softer-than-expected United States labour market release, and pre-existing fragility among leveraged yen-funded positions, rather than to any single trigger (Aquilina et al., 2024), and its subsequent quarterly review situated the episode within a broader deleveraging dynamic that produced the sharpest decline in the MSCI Asia Pacific index since 2023 (Bank for International Settlements, 2024). This framing, an interacting sequence rather than a single identifiable cause, is the reason this study consistently refers to the August 2024 episode throughout rather than attributing it to any one decision.

2.3. Connectedness Methodology

A separate strand of work addresses how shocks propagate through a system of markets once they occur, using the forecast-error variance decomposition of a vector autoregression to quantify system-wide interdependence and directional transmission (Diebold & Yilmaz, 2012; Diebold & Yilmaz, 2014). Antonakakis et al. (2020) embedded this framework in a time-varying parameter vector autoregression estimated by Kalman filtering, letting connectedness evolve continuously rather than through discrete rolling windows, an approach subsequently extended to asymmetric and pairwise connectedness measures (Gabauer, 2021). Baruník and Křehlík (2018) decomposed the same measure by transmission horizon, an approach later extended to a time-varying setting by Chatziantoniou et al. (2023), while Chatziantoniou et al. (2021) extended it to the quantiles of the conditional return distribution, motivated by evidence that transmission in the tails often differs from transmission at the mean (Ando et al., 2022).

These combined tools have since proliferated across diverse settings: Chinese sectoral commodity and equity linkages (Lou et al., 2024), volatility-index shocks among the Fragile Five emerging economies (Jurkowska et al., 2024), technology-driven spillovers among large United States equities (Kang et al., 2026), and volatility connectedness between BRICS markets and global volatility indices (Gökgöz et al., 2024) have all been examined using this family of methods. Applying the quantile extension specifically, Mensi et al. (2024) and Özcelebi and Kang (2024) both report dependence rising markedly in both tails across commodity, bond, currency, and equity markets spanning several regions, indicating that aggregate connectedness, its distribution across horizons, and its behaviour at the tails are three distinct dimensions of transmission that need not respond identically to a given shock.

2.4. Asian Equity Market Evidence

Within Asia specifically, Saji (2022) applied Johansen cointegration and vector-error-correction-based causality tests to Japan, Singapore, Korea, India, and China over 1999-2019 and found only weak long-run price convergence, while Anwer et al. (2022) documented meaningful time-frequency and tail-dependent linkages among Asia-Pacific currencies. Mateus et al. (2023) showed that connectedness among East and Southeast Asian equity markets spikes during turmoil before reverting, and Zou et al. (2025) placed China, Japan, and Korea within the wider Regional Comprehensive Economic Partnership bloc through December 2024, finding China a net receiver and Japan and Korea net transmitters, a pattern broadly consistent with the full-sample averages reported in Section 4.

A broader regional design covering the NIFTY 50, Nikkei 225, KOSPI, the Shanghai Composite, Australian and Hong Kong equities, several exchange rates, Brent crude, and the NASDAQ index likewise documents heightened interconnectedness during periods of market stress (Sarathkumara et al., 2025), though its cross-asset, multi-country design does not isolate the August 2024 episode as a focal event or examine any resulting change in network roles. Wiesen et al. (2024) found that volatility shocks raise connectedness across Asian equity markets specifically, with China exerting substantial indirect influence through the network despite not always being its most visible transmitter, while Li et al. (2024), focusing on China's large-capitalisation segment, documented time-varying connectedness between the CSI 300 and Chinese commodity futures using the same family of methods.

On the Indian side, Pham et al. (2025) applied a time-varying parameter vector autoregression alongside a conditional value-at-risk model to tail-risk transmission across Indian equity sectors and found substantial interconnectedness that intensified during episodes of heightened commodity and geopolitical risk. Working with a wider set of nine Asian emerging economies, Khan et al. (2023) applied the Diebold-Yilmaz and Baruník-Křehlík frameworks together and identified Indonesia, Korea, and Taiwan as the principal net transmitters, with China, India, and Pakistan the principal net receivers, a hierarchy that anticipates the transmitter-receiver split reported for the present four-market network in Section 4. Fang (2025) focused specifically on the Shanghai Composite's spillovers into seven Asian emerging markets and found the Korean market unusually sensitive to shocks originating in China, while a frequency-based comparison of Emerging and Growth-Leading Economies similarly placed the Korean and Indian markets among the most interconnected within their group, with China comparatively insulated at short horizons but more exposed at longer ones (Ari et al., 2025).

2.5. Frequency and Quantile Extensions

Connectedness among these markets is not static across time either. Connectedness among major Asian and ASEAN+3 equity markets rose sharply during the acute phase of the COVID-19 pandemic and remained elevated well afterward (Aziz et al., 2022), a pattern consistent with the short-horizon concentration of transmission documented for the August 2024 episode itself in Section 4. Quantile connectedness methods have since been applied to G7 and BRICS equity markets (El Khoury et al., 2024; Nyakurukwa & Seetharam, 2023), to the linkage between developed and Asian markets (Yaya et al., 2024), and to Islamic and alternative-asset markets (Aslam et al., 2025; Wang et al., 2024), consistently finding that connectedness in the tails exceeds connectedness at the mean or median.

Combining the frequency and quantile dimensions directly, Sun et al. (2024) examined natural gas and Asian equity markets and reported spillovers that vary jointly with time scale and market condition, and Zhu et al. (2025) applied the same combination to exchange rates within ASEAN+3, finding that China, Japan, and Korea display frequency-domain relationships that differ across quantiles. Using a quantile vector autoregression for the United States and ASEAN+6, Chancharat and Chancharat (2024) likewise reported stronger connectivity under extreme conditions and identified Korea, alongside the United States and Singapore, among the markets most actively transmitting return volatility to the rest of the group, a finding echoed in the results reported in Section 4.

Extending the tail-risk dimension to a wider cross-section, Long et al. (2025) combined conditional value-at-risk with time-varying connectedness across G7 and BRICS equity markets and

reported substantial bilateral tail-risk transmission involving Japan and India, while Kakran et al. (2023) applied the Diebold-Yilmaz framework to APEC economies and documented substantial heterogeneity in stock market integration and volatility spillover across the region without isolating any single shock as a focal event. A related pattern holds outside Asia: modelling risk and return spillovers among twenty developed and emerging-market currencies, Greenwood-Nimmo et al. (2025) showed that transmission intensifies rapidly as global financial conditions shift, underscoring that a currency network's connectedness can move abruptly around exactly the kind of funding-liquidity episode examined here.

2.6. Research Gap and Hypotheses

Taken together, this literature establishes that carry trades can unwind abruptly, that the yen has long functioned as a funding currency and a channel of cross-border transmission, that carry-trade shocks can propagate into equity-market dependence, that major Asian equity markets are interconnected with connectedness rising during stress, and that this connectedness varies systematically across transmission horizon and across the quantiles of the return distribution, at times reorganising which markets transmit and which receive. What remains unclear is what happened specifically within the China, Japan, Korea, and India equity network during the August 2024 episode: whether the shock merely intensified an existing pattern of transmission or genuinely reorganised the roles individual markets play within it, and over what horizon and at what part of the return distribution this occurred.

To the best of our knowledge, no existing study isolates the August 2024 episode within a dedicated four-market network using a design anchored to the event's own sequencing, nor combines dynamic, frequency-domain, and quantile connectedness with a formal, placebo-benchmarked comparison of pre-event, event, and post-event regimes, the gap this study addressed. Based on this literature, five research hypotheses were formulated.

H1: total connectedness among the four markets rises during the August 2024 event window relative to a clean pre-event baseline.

H2: the ranking of net transmitters and net receivers within the network remains unchanged between the pre-event and event windows.

H3: transmission during the event is concentrated at short investment horizons rather than at medium- or long-run horizons.

H4: connectedness in the tails of the return distribution exceeds connectedness at the median during the event window.

H5: total connectedness moves back toward the pre-event regime after the acute phase of the August 2024 episode has passed, evaluated against both the clean six-month baseline and the longer-run pre-event benchmark.

The research framework built around these hypotheses, shown in Figure 1, proceeds in three linked stages. Dynamic connectedness is first estimated for the full sample and decomposed by frequency band and by quantile of the return distribution, addressing H3 and H4. The resulting total connectedness series is then compared formally across pre-event, event, and post-event regimes using a block bootstrap benchmarked against a placebo window, addressing H1 and H5. In parallel, the ranking of net transmitters and net receivers is compared across the same three regimes using Kendall's rank correlation coefficient, addressing H2. Section 4 reports the outcome of each test against its corresponding hypothesis.

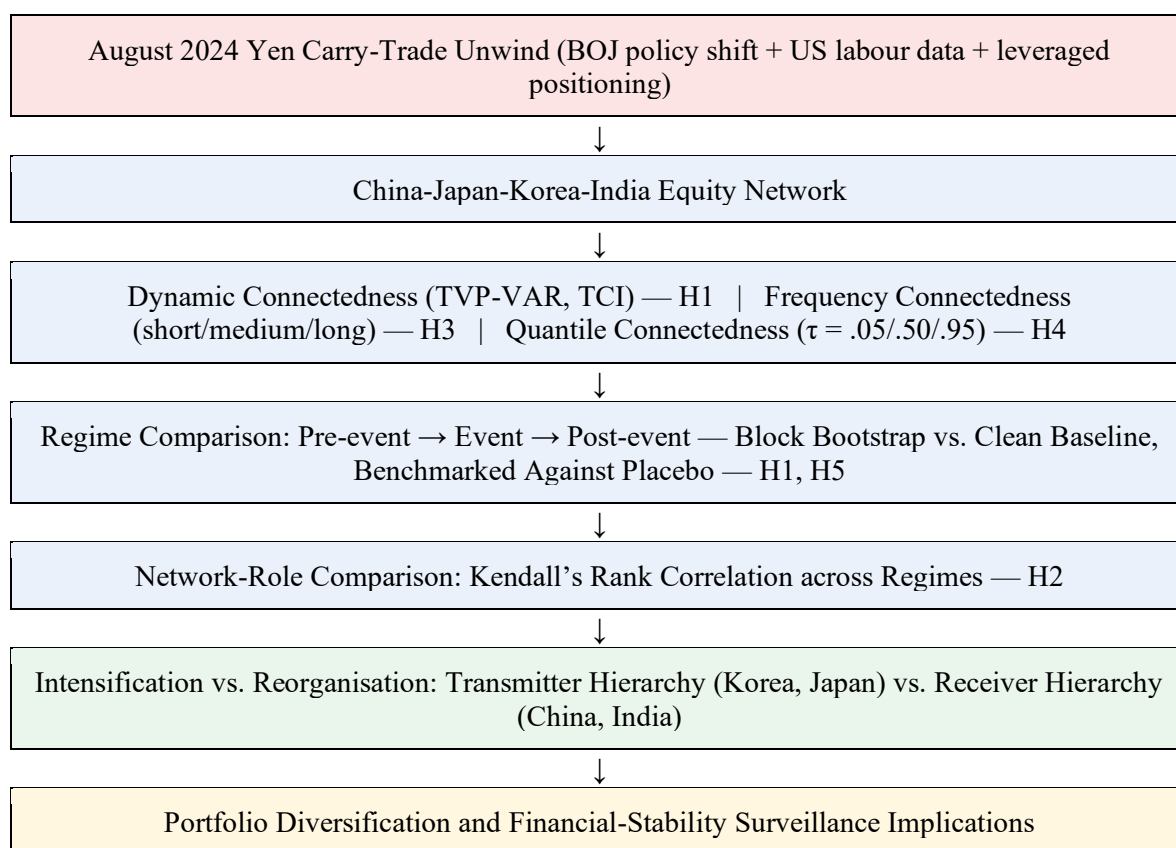


Figure 1. Research framework linking the study's hypotheses to its analytical stages

3. METHOD

Daily closing prices for the four core equity indices, the Shanghai Composite (China), the Nikkei 225 (Japan), the KOSPI (Korea), and the NIFTY 50 (India), were obtained from Yahoo Finance for the period 1 January 2019 to 30 June 2026. Yields on two-year and ten-year United States Treasury securities and on ten-year Japanese government bonds were obtained from the Federal Reserve Economic Data service maintained by the Federal Reserve Bank of St. Louis, and the Chicago Board Options Exchange Volatility Index was obtained from Yahoo Finance, for the same period; these series were retained for descriptive and robustness purposes outside the core four-market network. A time-varying parameter vector autoregression was selected over a fixed-coefficient or rolling-window vector autoregression because it allows connectedness to evolve continuously across the sample rather than through an arbitrarily chosen window length, and because it avoids discarding observations at the start of the sample, a property established by Antonakakis et al. (2020) and adopted here specifically because the August 2024 event required daily, rather than window-averaged, resolution around the shock.

Dynamic connectedness among the four-core equity return series was estimated using the time-varying parameter vector autoregression approach of Antonakakis et al. (2020), which embeds the generalised forecast-error variance decomposition of Diebold and Yilmaz (2012) within a Kalman-filter-estimated vector autoregression whose coefficients evolve continuously. Writing y_t as the vector of daily returns for the four markets, the model was

$$y_t = B_t z_t + \varepsilon_t, \quad \varepsilon_t | \Omega_{t-1} \sim N(0, S_t) \quad (1)$$

with coefficients evolving as a random walk, estimated recursively with forgetting factors of 0.99, and lag order selected by the Akaike information criterion (two lags).

Intuitively, equation (1) says that each market's return on a given day is explained by a weighted combination of the recent returns of all four markets, with those weights, captured in the matrix B_t , allowed to change from day to day rather than being fixed once and for all.

From the estimated model, the generalised forecast-error variance decomposition of Koop et al. (1996) as well as Pesaran and Shin (1998) was computed and row-normalised to give the share of

market i 's forecast-error variance attributable to market j over horizon H . The total connectedness index and net directional connectedness for market i were then

$$C(H) = 100/N \sum_{i \neq j} \theta_{ij}(H), \quad C_i(H) = C_{i \rightarrow \bullet}(H) - C_{\bullet \rightarrow i}(H) \quad (2)$$

with H set to ten trading days.

In plain terms, the total connectedness index $C(H)$ is the share of each market's forecast error that is attributable to shocks originating in the other three markets rather than to the market's own shocks, averaged across the network; the net directional measure $C_i(H)$ simply nets off how much a market sends out against how much it absorbs, so a positive value marks a net transmitter and a negative value a net receiver.

The same decomposition was applied to the frequency-domain representation of Baruník and Křehlík (2018), partitioning transmission into short-run (one to five trading days), medium-run (more than five to twenty days), and long-run (more than twenty days) bands, and to a quantile vector autoregression following Chatziantoniou, Gabauer, and Stenfors (2021),

$$Q_y(\tau | y_{t-1}, \dots, y_{t-p}) = \phi_0(\tau) + \sum_{l=1}^p \Phi_l(\tau) y_{t-l} \quad (3)$$

estimated separately at $\tau = 0.05, 0.50$, and 0.95 using the method of Koenker and Bassett (1978).

This equation repeats the same logic as equation (1), but instead of modelling the average return it models a specific quantile, τ , of the return distribution, so that estimating it separately at $\tau = 0.05, 0.50$, and 0.95 reveals whether markets are connected differently during typical trading days than during unusually bad or unusually good ones.

Each market's return was computed on its own native trading days directly from its raw price series before any merging across markets, avoiding the mechanical zero return that a forward-filled calendar alignment would otherwise generate on a date when a given market was closed. The four core return series were then merged and restricted, via a common-date intersection, to the 1,576 trading days common to all four markets between January 2019 and June 2026, from an initial 2,204 calendar-aligned dates.

Event windows were fixed prior to estimation, anchored to the Bank for International Settlements' own sequencing of the episode: a pre-event window (1 January 2019 to 30 July 2024), an event window (31 July to 30 August 2024), and a post-event window (1 September 2024 onward). A clean six-month pre-event baseline (31 January to 30 July 2024) was used as the primary comparison to avoid confounding with the COVID-19 pandemic, which sits inside the long-run pre-event window. A wide event window (16 July-30 September 2024) and a placebo window drawn from a calm period in May-June 2021 were used for robustness.

Regime differences in total connectedness were tested using a moving block bootstrap (Kunsch, 1989), which resamples contiguous ten-trading-day blocks rather than individual observations to preserve the autocorrelation inherent in the time-varying connectedness series. For baseline series x and comparison series y , the observed difference D was compared against 2,000 block-resampled differences, with the two-sided percentile-bootstrap p -value computed as

$$p = 2 \times \min\left\{\frac{1}{B} \sum_{b=1}^B \mathbb{I}\{D_b^* \leq 0\}, \frac{1}{B} \sum_{b=1}^B \mathbb{I}\{D_b^* \geq 0\}\right\} \quad (4)$$

In words, this counts how often the block-resampled differences fall on the opposite side of zero from the observed difference, doubled for a two-sided test; it is equivalent to inverting the 95 percent percentile interval. A small p -value means it would be unusual to see a difference this large purely from resampling noise, and hence that the regime difference is unlikely to be a statistical artefact.

Finally, markets were ranked within each regime by average net directional connectedness, and Kendall's rank correlation coefficient,

$$\tau = \frac{n_c - n_d}{n(n-1)/2} \quad (5)$$

was computed between each pair of regime rankings to assess the stability of the network's rank ordering. Intuitively, τ counts how many pairs of markets keep the same relative order across two rankings (n_c , concordant pairs) versus how many swap places (n_d , discordant pairs); a value of

1.00 means the ranking is identical in both regimes, and a lower value indicates that some markets changed places.

Each hypothesis was evaluated against a specific, pre-specified criterion. H1 was evaluated using the two-sided block bootstrap p-value and 95 percent confidence interval for the difference in mean total connectedness between the event window and the clean pre-event baseline, with the magnitude of the change also benchmarked against the placebo window to distinguish an economically meaningful change from ordinary background variation in a smoothed, persistent series. H5 was evaluated using the same bootstrap procedure applied to the post-event window against both the clean six-month baseline and the longer-run pre-event benchmark, since these two baselines can point to different conclusions about reversion, as Section 4 discusses in detail.

H2 was evaluated using the value of Kendall's rank correlation coefficient between regime rankings, with a coefficient of 1.00 indicating an unchanged ranking and any lower value indicating some degree of reordering. H3 was evaluated by comparing the share of total connectedness attributable to the short-run frequency band against the medium- and long-run bands. H4 was evaluated by comparing quantile connectedness at the fifth and ninety-fifth percentiles against connectedness at the median within the same regime.

Robustness was assessed throughout using the following checks: first, independent-observation and block bootstrap results were compared directly, to confirm that regime differences were not an artefact of ignoring serial dependence in the connectedness series; second, the event-specific quantile comparison used the wide event window (16 July-30 September 2024) rather than the main event window, to increase the number of observations available for quantile estimation; and third, the long-run and clean six-month pre-event baselines were cross-checked against each other, and against the post-event levels, to assess how sensitive the persistence finding is to the choice of baseline. A placebo comparison, using a demonstrably calm period in May-June 2021 benchmarked against its own immediately preceding six-month window, was run through the identical block bootstrap procedure to provide a magnitude-based reference point for the event-window change.

4. RESULTS AND DISCUSSION

Table 1 reports descriptive statistics for the return series, computed on each market's own native trading days rather than after calendar alignment.

Table 1. Descriptive statistics of core equity daily returns, percent

Series	Mean	SD	Skew.	Excess kurt.	Min	Max
Shanghai Composite	0.028	1.059	-0.521	8.21	-8.04	7.76
Nikkei 225	0.070	1.389	-0.260	9.03	-13.23	9.74
KOSPI	0.078	1.508	-0.557	10.53	-12.85	9.19
NIFTY 50	0.042	1.111	-1.454	21.51	-13.90	8.40

Note. All series rejected the Jarque-Bera normality test and the Augmented Dickey-Fuller unit-root test at $p < .01$.

All series exhibited the excess kurtosis characteristic of daily financial returns, motivating the quantile component of the analysis. A complementary KPSS test was consistent with stationarity for all series except KOSPI, whose statistic exceeded its five percent critical value, plausibly reflecting volatility clustering given that KOSPI also contained the largest number of extreme observations in the sample. Restricting the core network to trading days common to all four equity markets, to avoid the mechanical zero returns a forward-filled calendar alignment would otherwise generate, reduced the estimation sample from 2,204 calendar-aligned dates, which include 248 weekend dates, to 1,576 common trading days, reflecting weekends, the absence of a shared public-holiday calendar across the four exchanges, and gaps in the data provider's series.

Averaged across the full sample, the total connectedness index took a mean value of 32.94 percent, comparable to prior connectedness estimates for developed and emerging equity markets (Diebold & Yilmaz, 2012). Korea and Japan behaved as net transmitters, with average net directional connectedness of 6.00 and 2.23 percentage points respectively, while China and India behaved as net

receivers, at -4.08 and -4.14 percentage points respectively; the closeness of these two values proved relevant below.

Table 2. Frequency-decomposed total connectedness, full-sample average

Band	Connectedness (%)	Share (%)
Total	32.94	100.0
Short run (1-5 days)	26.31	79.9
Medium run (>5-20 days)	4.88	14.8
Long run (>20 days)	1.74	5.3

Table 2 reports the frequency decomposition. Close to four-fifths of total connectedness was attributable to the short-run band, indicating that transmission within this network was predominantly concentrated at short horizons, consistent with the margin-driven deleveraging mechanics described by the Bank for International Settlements (Aquilina et al., 2024). This result is consistent with H3.

Table 3. Static, whole-sample quantile connectedness

Quantile	Whole-sample TCI (%)
Lower tail ($\tau = 0.05$)	67.07
Median ($\tau = 0.50$)	32.31
Upper tail ($\tau = 0.95$)	65.63

Table 3 reports static, whole-sample quantile connectedness. Connectedness at both tails was roughly double connectedness at the median, indicating pronounced tail dependence as a recurring feature of the full sample, consistent with similar findings elsewhere (El Khoury et al., 2024; Yaya et al., 2024). Because this whole-sample average blends the event with the pandemic and other episodes, the quantile model was re-estimated separately within the clean pre-event window and the wide event window.

Table 4. Event-specific quantile connectedness, pre-event versus event window

Quantile	Regime	TCI (%)
Lower tail	Pre-event	72.18
Lower tail	Event	81.30
Median	Pre-event	19.06
Median	Event	44.57
Upper tail	Pre-event	66.01
Upper tail	Event	62.77

Table 4 reports the event-specific quantile comparison. Median connectedness rose from 19.06 to 44.57 percent during the event, more than doubling, while lower-tail connectedness rose further, from 72.18 to 81.30 percent, and upper-tail connectedness eased slightly, from 66.01 to 62.77 percent. This pattern indicated that the event compressed the gap between typical-state and downside tail-state connectedness primarily through a surge in median-state transmission, a downside-oriented pattern rather than a symmetric widening of both tails; given the wide window's 48 observations, thin for estimation at the fifth and ninety-fifth percentiles, this result should be read as indicative rather than precisely estimated. This provides qualified support for H4, strongest at the lower tail.

Table 5. Bootstrap regime comparisons, total connectedness index

Comparison	Method	Diff. (pp)	95% CI	p
Event vs. long-run pre-event	Independent	-2.16	[-4.17, -0.52]	.002
Event vs. clean pre-event	Independent	11.36	[9.42, 12.97]	<.001
Event vs. clean pre-event	Block (10d)	11.36	[10.89, 13.50]	<.001
Full post-event vs. clean pre-event	Block (10d)	11.82	[9.58, 14.01]	<.001
Short post-event vs. clean pre-event	Block (10d)	11.15	[10.14, 12.66]	<.001
Placebo (May-Jun 2021)	Block (10d)	-2.68	[-3.65, -1.63]	<.001

Table 5 reports the main bootstrap regime comparisons. A naive comparison against the full, multi-year pre-event window suggested connectedness during the event was lower than the historical average, an artefact of the COVID-19 pandemic's larger connectedness spike inflating that long-run baseline. Against the clean six-month baseline, total connectedness during the event exceeded the pre-event level by 11.36 percentage points, robust to a block bootstrap correcting for the series' strong autocorrelation. This result supports H1.

A placebo comparison drawn from a demonstrably calm period in 2021 produced a change of only -2.68 percentage points, roughly one quarter the magnitude of the event-associated increase and opposite in sign, a magnitude-based benchmark that matters because the smoothed, persistent nature of the connectedness series means some background level of statistically detectable change is expected between any two windows regardless of an identified shock.

Total connectedness in the full post-event window (+11.82 percentage points relative to the clean pre-event baseline) and in a short three-month post-event window (+11.15 percentage points) did not revert to the level observed in the six months immediately preceding the event. This comparison, however, is sensitive to the choice of pre-event baseline, a point worth making explicit.

Relative to the long-run pre-event window, itself elevated by the COVID-19 pandemic, the event window's connectedness was 2.16 percentage points lower rather than higher (Table 5). Combining the reported bootstrap differences algebraically, the full post-event level sits approximately 1.7 percentage points below this same long-run average, and the short post-event level approximately 2.4 percentage points below it; these two derived comparisons were not themselves block-bootstrapped and should be read as indicative point estimates rather than as formally tested differences.

Read this way, the clean six-month baseline used as the primary comparison was itself a period of unusually low connectedness relative to the network's longer historical experience, and the post-event level is more accurately described as remaining close to, rather than persistently above, that longer-run average. What can be said with more confidence is that connectedness did not revert to the unusually low level of the immediate pre-event months; whether this reflects a genuine, shock-induced persistence or a reversion toward a higher long-run mean that the clean baseline happened to understate cannot be fully disentangled within the present design, and is treated here as a limitation rather than resolved. This qualifies rather than confirms the apparent inconsistency with H5.

Table 6. Net-transmitter rankings by regime (1 = largest net transmitter)

Market	Pre-event	Event	Post-event
Korea	1	1	1
Japan	2	2	2
India	3	4	4
China	4	3	3

Table 6 reports net-transmitter rankings by regime. Korea and Japan occupied the first and second rank in every regime without exception, indicating that the network's transmitter hierarchy was unaffected by the shock. China and India, by contrast, exchanged ranks: China was the largest net receiver before the event, with India third, while during the event India became the largest net receiver and China moved to third, a reordering that persisted unchanged into the post-event window rather than reverting (Kendall's tau = 0.67 pre-to-event and pre-to-post, 1.00 event-to-post). This partial reordering on the receiver side is inconsistent with H2, which anticipated an unchanged ranking throughout; the transmitter side, by contrast, is consistent with it. This finding does not support a simple contagion account, under which Japan would be expected to become a dominant transmitter it was not previously; Japan was already the second-largest transmitter before the event and remained so. Nor does it support a simple, symmetric amplification account, given the observed compression rather than uniform widening of tail dependence. Instead, the results indicate that this funding-liquidity shock intensified transmission along an unchanged transmitter hierarchy while producing a persistent reordering of the two receiving markets within the observed post-event sample, a pattern with direct relevance for portfolio diversification, where the transmitting side of the network may remain directionally stable even as overall diversification effectiveness declines, and for financial-stability surveillance, where a reordered receiver hierarchy should be treated as a

condition that can persist within the horizon studied here, even though, as noted above, the total-connectedness level itself is better described as remaining close to long-run historical experience than as persistently elevated above it.

Several limitations qualify these findings. The persistence finding for total connectedness depends materially on the choice of pre-event baseline: relative to the clean six-month baseline the post-event level appears elevated, but relative to the longer-run, COVID-inclusive historical average it does not, and the present design cannot fully adjudicate between a genuine shock-induced persistence and a reversion toward a higher long-run mean. The Shanghai Composite was used as the primary China proxy in place of the CSI 300, which exhibited substantially more missing trading days on the data provider used here, with gaps extending beyond the exchange holiday calendar; this means the results describe China's broader market rather than specifically its large-capitalisation segment. The event-specific quantile comparison relied on a 48-observation window, thin for extreme-quantile estimation. The network-role comparison ranked only four markets, limiting the inferential value of the Kendall's tau comparison regardless of how pronounced the underlying pattern appeared. Finally, the Japanese government bond yield used in supplementary descriptive analysis was available only at monthly frequency and was forward-filled to daily frequency, a limitation bearing on yield-differential interpretation specifically rather than on the core connectedness results, which relied exclusively on equity returns.

5. CONCLUSION

Total connectedness among the China, Japan, Korea, and India equity network rose by approximately eleven percentage points during the August 2024 episode relative to a clean pre-event baseline, a change that survived correction for serial dependence and was roughly four times larger than the change observed in a calm comparison period drawn from 2021. Connectedness did not revert to this clean pre-event level in the months following the acute phase of the shock, though relative to the network's longer-run historical average, which is itself elevated by the COVID-19 pandemic, the post-event level was close to, rather than clearly above, historical experience, and the choice of pre-event baseline therefore matters for how this result should be read. Transmission was concentrated at short horizons, and the network's usual gap between typical-state and tail-state connectedness compressed sharply during the event, driven mainly by a surge in median-state transmission. Within this overall intensification, the network's structure proved only partly stable: Korea and Japan remained its two net transmitters throughout, while China and India exchanged their ranking as net receivers during the event, a reordering that did not revert afterward.

These findings advance understanding of how a funding-liquidity shock associated with yen-funded deleveraging can propagate through a regional equity network without redistributing every role within it. The evidence indicates that the episode intensified transmission along an unchanged transmitter hierarchy while producing a persistent reordering of the receiving-side hierarchy within the observed post-event sample, a more precise characterisation than a simple contagion or amplification account would provide. For practitioners, this implies that diversification relationships tied to the identity of a network's principal transmitters may remain directionally stable even during an acute funding shock, while assumptions about which market absorbs the largest share of incoming stress should be revisited following such an episode rather than assumed fixed. Future research extending this design to a genuinely dynamic estimate of quantile connectedness, to a wider set of Asian and Asia-Pacific markets, or to the specific currency and interest-rate channels through which yen-funded shocks are transmitted into equity markets would extend these findings usefully.

Conflict of Interest Statement

There is no conflict of interest regarding the publication of this paper.

Author Contributions

The author was solely responsible for all aspects of this work: Conceptualization, Investigation, Formal Analysis, Visualization, Writing – Original Draft; Methodology, Supervision, Validation, Project Administration, Writing – Review & Editing; Software, Data Curation, Resources.

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This article does not contain any studies with human participants or animals performed by the author.

Data Availability

The data that support the findings of this study are available from the corresponding author [C.G.] upon reasonable request.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this manuscript, the author utilized Claude (Anthropic) for language editing, including improving grammar, clarity, and readability, and for restructuring paragraphs. The tool was not used to generate original research data, analysis, or conclusions. All outputs generated by the AI tool underwent rigorous critical review and thorough editing by the author to ensure factual accuracy, enhance clarity of expression, and confirm adherence to established academic standards. The author assumes full responsibility for the integrity and content of this manuscript.

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