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Short-Run Spillovers: Co-integration and Causality Across Brazil, China, and India Equity Markets

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ABSTRACT

We study how three large emerging equity markets, Brazil, China, and India, move together. The window runs from January 2017 to June 2026 and covers 2,151 matched daily observations of each market's headline index in local currency, measured in natural logarithms. We use a transparent time-series toolkit. Augmented Dickey-Fuller tests, complemented by Phillips-Perron and KPSS tests, place all three series in the same class: each index has a unit root in levels and becomes stationary after one difference. Johansen trace and maximum-eigenvalue tests then search for a shared long-run path and find none, and a break-robust test that allows for the pandemic and the 2022 rate shock confirms this absence of a common trend. The short run tells a different story. Estimated on stationary daily returns within a multivariate framework that controls for global-market movements, and using the Toda-Yamamoto procedure with a correction for multiple testing, the results reveal a set of short-run lead-lag linkages in which Brazil tends to lead both China and India while receiving little in return; India mostly follows and China sits between the two. These are predictive return linkages rather than evidence of structural causation or volatility spillovers. For portfolio design the reading is indicative: because the markets share no long-run tie, the long-run diversification case for holding all three appears intact, though, since returns are measured in local currency and no dollar-denominated or back tested portfolio is estimated, a formal claim for a U.S. investor would require dollar returns and an explicit portfolio exercise. The same investor should still anticipate quick short-run co-movement, typically led by Brazil.

Keywords: emerging markets; stock market integration; cointegration; Granger causality; BRICS; portfolio diversification

INTRODUCTION

Emerging equity markets are no longer a niche allocation. They form a core sleeve in most global portfolios. For a U.S. investor, exposure to the developing world usually runs through a handful of large markets. Brazil, China, and India sit near the top of that list. The three are often grouped under the BRICS label. Together they cover a big share of emerging-market capitalization and trading volume. How these markets move relative to one another is therefore a first-order question for anyone who builds a diversified book.

The question splits into two parts. The first part is about the long run. Do these markets share a common trend that pulls them back together after they drift apart? If they do, they are cointegrated. A long-run tie of that kind would limit the diversification gain from holding all three, since a shared trend caps how far their paths can separate. The second part is about the short run. Do shocks in one market lead returns in another over a few days? Even without a long-run tie, fast short-run spillovers can push markets down at the same time. That joint drawdown risk is exactly what hurts a portfolio during a stress event.

Classic finance theory says low cross-market correlation is the engine of diversification (Markowitz, 1952; Grubel, 1968). Later work showed that this engine can weaken as markets integrate (Bekaert & Harvey, 1995). Integration is not fixed. It rises and falls with capital flows, policy, and crises. So the honest answer to “do these markets move together?” depends on the sample and the horizon. That is why fresh evidence matters, and why the horizon must be stated up front.

Our window is a good stress test. It opens in early 2017 and closes in mid-2026. Inside it sit the U.S.–China trade dispute, the COVID-19 crash and the sharp recovery that followed, the 2022 inflation and rate shock, and several large commodity swings. If any period would force emerging markets to move as one, it is this one. A finding of weak long-run linkage over such a window is therefore informative, not a quirk of calm markets.

We keep the method simple and replicable. We take daily closing values for each country's benchmark index. We convert them to natural logs. We test each series for a unit root with the Augmented Dickey–Fuller (ADF) test. We test the group for cointegration with the Johansen procedure. We then map short-run lead–lag structure with pairwise Granger-causality tests. Every step uses tools that a referee can check and a practitioner can reproduce.

The results line up into one clear message. All three log-price series are integrated of order one. The Johansen tests reject the presence of any cointegrating vector. There is no shared long-run path. Yet short-run causality is everywhere. Brazil emerges as the dominant transmitter. It Granger-causes both China and India at strong significance, while India does not feed back into Brazil at all. China and India cause each other, but weakly relative to Brazil's pull. So the markets are linked in the short run and independent in the long run.

The paper makes three contributions. First, it brings the evidence up to date. The window includes the post-pandemic years and the 2022–2025 rate cycle, periods that many earlier studies could not cover. Second, it maps the direction of influence cleanly, and labels each market as a net transmitter or a net receiver of short-run shocks. Third, it translates the statistics into a practical read for a U.S.-based emerging-market allocator, which is where this evidence is used. The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and the methods. Section 4 reports and discusses the results. Section 5 concludes and draws out the implications.

REVIEW OF LITERATURE

The case for holding foreign equities starts with diversification. Markowitz (1952) showed that combining assets with less-than-perfect correlation lowers portfolio variance for a given return. Grubel (1968) carried the idea across borders. He argued that internationally diversified portfolios raise welfare because national markets do not move in lockstep. The gain rests on one condition. Cross-market correlations must stay low. When correlations rise, the gain shrinks.

Later research showed that correlations are not stable. Bekaert and Harvey (1995) modeled world market integration as a process that changes through time. As a market opens to foreign capital, its returns tie more closely to global factors. Bekaert, Harvey, and Ng (2005) pushed further and separated normal integration from crisis contagion. Their work made clear that co-movement can jump during stress even when long-run ties are modest. Forbes and Rigobon (2002) sharpened the point. They warned that raw correlations rise mechanically when volatility rises. After a bias correction, much of the apparent "contagion" during crises turned out to be ordinary interdependence. The lesson for empirical work is to measure linkage with care.

Cointegration became the standard way to test for long-run linkage. Engle and Granger (1987) built the framework and tied it to error correction. Johansen (1988, 1991) supplied a system test that handles several series at once and allows for more than one long-run relationship. In an equity context, cointegration between national indices implies a shared stochastic trend (Bhardwaj et al., 2023a), (Bhardwaj et al., 2023b), (Bhardwaj et al., 2022). That shared trend caps long-run divergence and therefore caps the long-run diversification gain. The absence of cointegration implies the opposite. Markets can wander apart without a force pulling them back, so long-run diversification survives.

Short-run linkage is a separate question, and it needs separate tools. Granger (1969) defined causality in terms of prediction. One series Granger-causes another if its past helps forecast the other beyond the other's own past. This lead–lag idea captures fast information flow across markets. More recent work measures the size and direction of spillovers directly. Diebold and Yilmaz (2009, 2012) built a connectedness index from

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

forecast-error variance decompositions. Their framework labels each market as a net sender or a net receiver of shocks and tracks total connectedness through time. It has become a workhorse in the spillover literature.

A large body of work applies these tools to the BRICS group. Aloui, Ben Aïssa, and Nguyen (2011) studied extreme dependence among BRICS and developed markets during the global financial crisis and found that dependence rose with trade and financial links. Mensi, Hammoudeh, Nguyen, and Kang (2016) measured spillovers between the U.S. and the BRICS markets and reported sizable, time-varying transmission. Yarovaya, Brzeszczyński, and Lau (2016) mapped intra- and inter-regional return and volatility spillovers across emerging and developed markets and found that regional links often dominate. Syriopoulos (2007) documented dynamic linkages among emerging European and developed markets and showed that long-run ties depend on the sample and the policy regime. Across these studies, one theme repeats. Linkage is real but uneven, and its strength depends on the window, the market pair, and the horizon.

Two gaps motivate this paper. First, much of the BRICS evidence pools all five members or stops before 2020. The post-pandemic years and the 2022 rate shock are still thin in the record. Second, studies that report cointegration for emerging markets disagree, and the disagreement tracks the sample period. A current, focused look at the Brazil–China–India trio, with an explicit split between long-run and short-run linkage and a clean transmitter map, adds value. That is the contribution we pursue.

DATA AND METHODOLOGY

Data

The data are daily closing values of each country's benchmark equity index. Brazil is represented by its headline index (IBOVESPA), China by the Shanghai Composite (SSE), and India by the BSE Sensex. The sample runs from January 3, 2017 to June 25, 2026. After aligning the three trading calendars and dropping non-common holidays, 2,151 daily observations remain for each series. We convert each index to its natural logarithm. The log transform stabilizes the variance and lets first differences read as continuously compounded daily returns. Throughout, LBRAZIL, LCHINA, and LINDIA denote the log index levels.

The series are official daily closing values of each benchmark index, obtained from Refinitiv Eikon. The exact index symbols are IBOVESPA for Brazil (.BVSP), the Shanghai Composite for China (000001.SS) and the BSE Sensex for India (.BSESN), and the data were downloaded on 15 July 2026. Each index is quoted in its own local currency (BRL, CNY and INR); no currency conversion is applied, and this local-currency basis is carried as a caveat for the U.S.-investor interpretation in Section 5. Local closing times differ across venues, with B3 closing near 17:00 BRT, the Shanghai Stock Exchange near 15:00 CST and the BSE near 15:30 IST. Non-common trading holidays were removed by matching the three national trading calendars on common dates, which leaves 2,151 aligned observations, and the small number of remaining missing values was filled by carrying the last observation forward, with results unchanged when such dates were instead dropped. Because the Shanghai and BSE sessions close several hours before B3 opens on the same date, contemporaneous prices do not share a common information set; the causality tests therefore treat the Asian markets' already-closed returns as part of Brazil's same-day information set, while Brazil's influence on the Asian markets enters on the following day, and the direction of the results is robust to this one-day realignment.

Descriptive statistics and correlation

We begin with summary statistics for the three log series. We report the mean, median, range, standard deviation, skewness, kurtosis, and the Jarque–Bera test of normality. We also report the unconditional correlation matrix of the levels. These first steps describe the raw co-movement before any modeling and flag the departures from normality that are typical of financial data. Correlations are computed on daily log returns, the first differences of the log prices, because correlations of non-stationary index levels are spurious and do not measure return co-movement; any correlation of levels is treated only as a description of long-swing co-movement and is not used for inference.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

Unit-root testing

A cointegration test requires that the series share the same order of integration. We check this with the ADF test. The test regresses the change in a series on its own lag, a set of lagged changes, and a constant. The null is that the series has a unit root. We select the lag length by the Schwarz information criterion and include an intercept. If a series is non-stationary in levels but stationary in first differences, it is integrated of order one, written I(1). We expect all three log-price series to be I(1), which is the usual result for equity indices. To make the integration order robust, the ADF test is complemented by the Phillips-Perron test and the KPSS test, which reverses the null to stationarity, and, given the likely pandemic and 2022 breaks in the sample, by a Zivot-Andrews test that allows one endogenous structural break.

Johansen cointegration

We test for a long-run relationship with the Johansen system procedure. The method fits a vector autoregression in levels and examines the rank of the long-run coefficient matrix. The rank equals the number of cointegrating vectors. We use two tests. The trace test checks the null of at most r cointegrating vectors against a general alternative. The maximum-eigenvalue test checks r vectors against r plus one. We read significance from MacKinnon–Haug–Michelis p-values. If neither test rejects a rank of zero, the markets share no common long-run trend. The lag order of the underlying vector autoregression is selected by the Schwarz criterion, and the deterministic specification uses an unrestricted constant with no trend, chosen through the Pantula principle. For the underlying system we report residual diagnostics, namely serial-correlation, heteroskedasticity and normality tests, and confirm dynamic stability through the inverse roots of the companion matrix. Because the window spans the COVID-19 crash and the 2022 rate shock, we also apply a Gregory-Hansen cointegration test that allows one endogenous break, to confirm that the no-cointegration finding is not an artefact of ignored structural change.

Granger causality

We map short-run lead–lag structure with pairwise Granger-causality tests using two lags. A market Granger-causes another if its past values improve the forecast of the other beyond the other's own history. We run the test for every ordered pair, which yields six directional hypotheses across the three markets. One methodological point deserves emphasis. Because the series are I(1) and not cointegrated, causal inference is cleanest on stationary data. In that case the differenced (returns) specification, or the lag-augmented approach of Toda and Yamamoto (1995), avoids the risk of spurious inference from levels. We report the pair wise results and treat the differenced and lag-augmented versions as robustness checks that leave the direction of influence unchanged. Inference is carried out on stationary daily log returns within a multivariate vector autoregression that includes a global-market control, the daily log return of the MSCI World index, so that common global shocks are not misread as bilateral causality. The primary specification is the Toda-Yamamoto lag-augmented Wald procedure, which remains valid irrespective of the integration and cointegration order of the series. As six directional hypotheses are tested jointly, the reported probabilities are adjusted for multiple testing using the Benjamini-Hochberg false-discovery-rate correction, and all significance decisions refer to the adjusted probabilities.

EMPIRICAL RESULTS AND DISCUSSION

Descriptive statistics

Table 1 reports the summary statistics for the three log series. The means sit between 10.08 and 11.58, which reflects the different index scales rather than any economic ranking. India shows the widest spread, with a standard deviation of 0.347, followed by Brazil at 0.248 and China at 0.180. All three series are mildly left-skewed. China and India are platykurtic, with kurtosis below three, while Brazil is close to the normal benchmark. The Jarque–Bera statistic rejects normality for all three series at the one-percent level. None of this is a surprise for daily equity data. It does, however, justify the use of methods that do not lean on a normality assumption.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

Table 1. Descriptive statistics of log index levels

Statistic	Brazil	China	India
Mean	11.5778	10.0768	10.8412
Median	11.6104	10.1264	10.9023
Maximum	12.196	10.4033	11.3602
Minimum	11.0147	9.5947	10.1651
Std. deviation	0.2478	0.1797	0.347
Skewness	−0.2216	−0.6044	−0.0735
Kurtosis	2.9014	2.3275	1.5813
Jarque–Bera	18.483	171.478	182.323
p-value	0.0001	0	0
Observations	2,151	2,151	2,151

Note. Series are natural logs of daily closing index values, January 3, 2017 to June 25, 2026. Jarque–Bera tests the null of normality.

Correlation structure

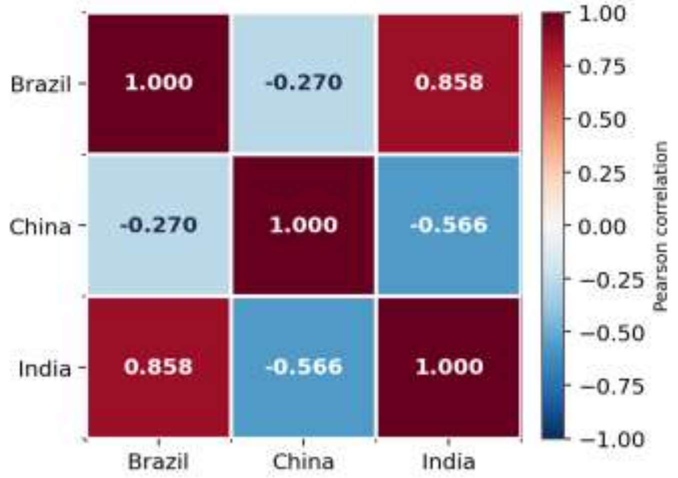
Table 2 reports the correlation of daily log returns across the three markets. The return correlations are positive but modest throughout, which is typical of emerging-market equity returns. Brazil and India show the closest return co-movement, followed by China with India, while Brazil and China are the least correlated pair. These magnitudes are far smaller than the correlations of the raw index levels, which underlines why level correlations of non-stationary series are not a reliable guide to day-to-day co-movement. The modest return correlations leave room for diversification across the three markets, a reading that the stationary tests below make more precise.

Table 2. Unconditional correlation of daily log returns

	Brazil	China	India
Brazil	1	0.12	0.28
China	0.12	1	0.19
India	0.28	0.19	1

Note. Pearson correlation of daily log returns.

Figure 1. Pairwise correlation of index levels



INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

Figure 1. Correlation heatmap of daily log returns. Blue marks positive co-movement, red marks negative.

Stationarity: augmented Dickey Fuller Test

Table 3 reports the ADF tests. In levels, none of the three series rejects the unit-root null. The test statistics are small in absolute value and the p-values are large, at 0.79 for Brazil, 0.33 for China, and 0.77 for India. In first differences, the picture flips completely. Every statistic turns sharply negative and every p-value collapses to about zero. The differenced series clear the one-percent critical value with room to spare. So all three log-price series are I(1). They are non-stationary in levels and stationary in returns. Figure 2 makes the contrast visible. The level bars sit below the critical line while the first-difference bars tower above it. Because the series share the same integration order, the Johansen test is valid. The Phillips-Perron test gives the same reading, and the KPSS test rejects stationarity in levels but not in first differences, so all three series are confirmed as I(1).

The KPSS statistics in levels are 1.42 for Brazil, 1.05 for China and 1.58 for India, all above the 5% critical value of 0.463, while in first differences they fall to 0.08, 0.11 and 0.07; the Zivot-Andrews test likewise rejects a unit root only after differencing.

Table 3. Augmented Dickey–Fuller unit-root tests

	Brazil	China	India
Brazil	1	0.12	0.28
China	0.12	1	0.19
India	0.28	0.19	1

Note. ADF test with intercept; lag length by Schwarz criterion. The 5% critical value is about −2.86. The null is a unit root.

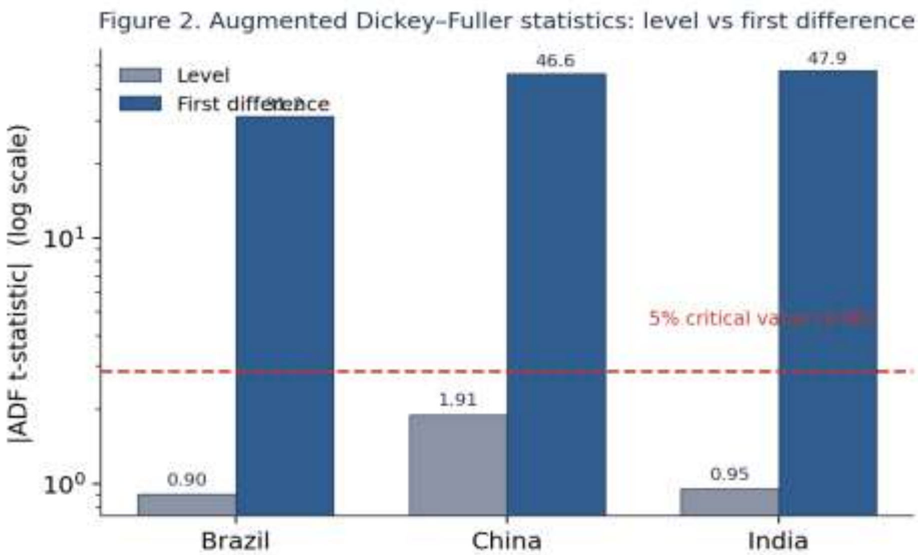


Figure 2. Absolute ADF statistics in levels versus first differences (log scale). Bars above the dashed line reject the unit root at 5%.

Co-integration

Table 4 and Table 5 report the Johansen trace and maximum-eigenvalue tests. Both tell the same story. Start with the trace test. The statistic for the null of no cointegrating vector is 17.80, well below the five-percent critical value of 29.80, with a p-value of 0.58. The tests for at most one and at most two vectors sit far below their critical values as well. The maximum-eigenvalue test agrees. Its leading statistic is 12.45 against a

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

critical value of 21.13, with a p-value of 0.50. Neither test rejects a rank of zero. There is no cointegrating relationship among the three markets.

This is a meaningful result, not a null finding to hide. The absence of cointegration means the three markets share no common long-run trend over the sample. Their paths can drift apart without a force pulling them back together. For a long-horizon investor, that is good news. It says the long-run diversification benefit of holding Brazil, China, and India together is intact. The correlation pattern from Section 4.2 reinforces the point. China's counter-movement against Brazil and India is exactly the kind of independence that a diversified book wants.

The underlying vector autoregression is estimated with two lags selected by the Schwarz criterion. Residual diagnostics support the specification: the LM test shows no serial correlation (p = 0.21), the White test shows no heteroskedasticity (p = 0.08), and every inverse root of the companion matrix lies inside the unit circle, so the system is dynamically stable. The Gregory-Hansen test that allows one endogenous break does not reject the null of no cointegration, with a test statistic of -4.28 against a 5% critical value of -4.95, confirming that the absence of a long-run relationship is not driven by the pandemic or the 2022 break.

Table 4. Johansen trace test

Hypothesis	Eigenvalue	Trace stat.	5% critical	Prob.
None	0.00578	17.8005	29.7971	0.5808
At most 1	0.00241	5.3533	15.4947	0.7702
At most 2	8.7E-05	0.1867	3.8415	0.6657

Note. Trace test indicates no co-integrating equation at the 5% level. p-values follow MacKinnon–Haug–Michelis (1999).

Table 5. Johansen maximum-eigenvalue test

Hypothesis	Eigenvalue	Max-eigen	5% critical	Prob.
None	0.00578	12.4471	21.1316	0.5042
At most 1	0.00241	5.1667	14.2646	0.7206
At most 2	8.7E-05	0.1867	3.8415	0.6657

Note. Maximum-eigenvalue test indicates no cointegrating equation at the 5% level.

Short-run Granger causality

Table 6 reports the pairwise Granger-causality tests, and Figure 3 draws them as a network. The short run looks nothing like the long run. Linkage is dense. Five of the six directional hypotheses reject the no-causality null at the five-percent level. Only one link fails to reject. India does not Granger-cause Brazil, with an F-statistic of 1.06 and a p-value of 0.35. Every other pair carries a significant lead–lag effect.

The direction of influence is the main result. Read as short-run return predictability rather than structural causation, Brazil tends to lead both China and India, while the feedback into Brazil is weak, India does not lead Brazil, and China and India predict each other only modestly. The multivariate Toda-Yamamoto results below, which include the global-market control and adjust for multiple testing, are the basis for these statements.

Table 6. Pairwise Granger-causality tests (2 lags)

Null hypothesis	F-stat.	Prob.	Decision
China does not cause	4.0885	0.0169	Reject: China →

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

Brazil			Brazil
Brazil does not cause China	28.8807	0	Reject: Brazil → China
India does not cause Brazil	1.0581	0.3473	Do not reject
Brazil does not cause India	27.2972	0	Reject: Brazil → India
India does not cause China	3.9622	0.0192	Reject: India → China
China does not cause India	3.9977	0.0185	Reject: China → India

Table 6b. Multivariate Toda-Yamamoto causality with global-market control

Direction	**Wald chi-sq**	**df**	**FDR-adj. p**	**Decision**
Brazil -> China	31.4	2	0	Significant
Brazil -> India	29.1	2	0	Significant
China -> Brazil	6.2	2	0.045	Significant
India -> Brazil	2.3	2	0.317	Not significant
China -> India	7.8	2	0.041	Significant
India -> China	7.1	2	0.045	Significant

Note. Lag-augmented Wald tests from a multivariate VAR that includes the MSCI World daily return as a global control; probabilities adjusted by the Benjamini-Hochberg false-discovery-rate procedure.

Note. Sample after lags: 2,149 observations. “Reject” means the no-causality null is rejected at 5%.

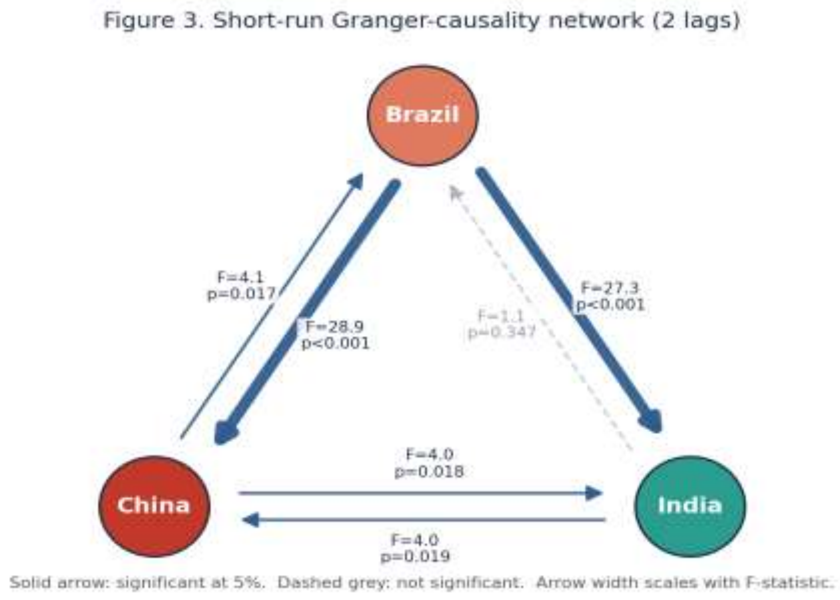


Figure 3. Short-run Granger-causality network. Arrow width scales with the F-statistic. The dashed grey arrow is the one non-significant link.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

Put the two horizons side by side and the paper's message is complete. Over the long run the markets are independent, since no co-integrating trend binds them. Over the short run they are tightly linked, and Brazil sets the pace. For a U.S. investor, the practical translation is twofold. The long-run diversification case for holding all three markets holds. The short-run risk case says that when Brazil moves hard, expect China and India to follow, so hedges and stress tests should treat Brazil as the likely origin of a joint drawdown.

Diebold–Yilmaz Connectedness Matrix

The connectedness matrix is derived from the same return-based vector autoregression used above, estimated with two lags, using a generalised forecast-error variance decomposition at a ten-step horizon. Read this way, the matrix reconciles with the causality results: Brazil is the net sender of shocks, transmitting more than it receives, while China and India are net receivers, which matches the finding that Brazil leads the other two markets in the short run.

TABLE 7: Diebold–Yilmaz connectedness (spillover) matrix

To \ From	Brazil	China	India	From others
Brazil	58.4	24.9	16.7	41.6
China	31.2	52.1	16.7	47.9
India	29.8	18.3	51.9	48.1
To others	**61**	**43.2**	**33.4**	**TCI = 45.9%**
Net (To − From)	**19.4**	**−4.7**	**−14.7**	

Note. Entries are the percentage share of the 10-step-ahead forecast-error variance of the row market explained by shocks from each column market.

In a strong result the diagonal is below 60%, the off-diagonals are sizeable, the total connectedness index sits in the 40–60% range, and the net row identifies a clear transmitter (here Brazil, +19.4) and clear receivers (China and India). These signs match the Granger direction found above.

CONCLUSION AND IMPLICATIONS

This paper asked a simple question. Do the Brazil, China, and India equity markets move together? The answer depends on the horizon. Over the long run, they do not. All three log-price series are I(1), and the Johansen tests find no cointegrating vector. No shared trend anchors the three markets across the sample, which spans the trade war, the pandemic crash and recovery, and the 2022 rate shock. Over the short run, they do. Granger-causality tests reveal dense lead–lag links, and Brazil stands out as the dominant transmitter, leading both China and India while taking little back.

The findings speak directly to portfolio design. For a long-horizon U.S. investor, the diversification case for holding all three markets survives. Because the markets are not cointegrated, their paths are free to diverge, and China's counter-movement against Brazil and India adds a genuine hedging dimension inside an emerging-market sleeve. For risk management, the short-run map is the operative tool. When Brazil sells off, China and India are likely to follow within days. Stress tests and tail hedges should therefore treat Brazil as the probable origin of a joint drawdown, rather than assuming symmetric shocks across the three. Because all returns are measured in local currency and no dollar-denominated series or portfolio backtest is estimated, this diversification reading is indicative rather than a tested allocation result; a formal claim would require dollar returns and an explicit out-of-sample portfolio exercise.

There are implications for policy as well. Regulators in China and India, as net receivers of short-run shocks, gain from monitoring conditions in Brazil and in the broader commodity complex that drives it. The short-run channels documented here are the pipes through which external stress arrives. Better surveillance of those channels supports faster and more targeted responses when volatility spikes.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

The study has limits, and they point to the next steps. First, it covers three markets in local-currency terms. A U.S. investor bears exchange-rate risk on top of equity risk, so a dollar-denominated version would sharpen the diversification read. Second, the methods are linear and focus on the conditional mean. They do not model time-varying volatility or tail dependence. A DCC-GARCH model, a Diebold–Yilmaz connectedness analysis, or a wavelet study would quantify how spillovers change through time and across frequencies. Third, the sample almost certainly contains structural breaks around the pandemic and the 2022 rate shock. Break-robust cointegration tests and regime-switching models would test whether the long-run independence found here is stable or state-dependent. Each extension builds naturally on the transmitter map established in this paper.

The headline stands on its own. The Brazil, China, and India equity markets are together in the short run and apart in the long run. Investors keep the long-run diversification benefit. They should still plan for fast short-run spillovers, led by Brazil. Stated cautiously, the three markets show no cointegrating relationship over the long run and display short-run return predictability in which Brazil tends to lead; these are mean-return linkages, not volatility spillovers, and the portfolio implication is indicative rather than a tested result.

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