



Asymmetric Stock Market Integration Between BRICS Economies and Developed Markets: Evidence from Quantile VAR and Time-Varying Connectedness Analysis

Dr. Suman

Associate Professor, Department of Commerce,
Gandhi Memorial National College, Ambala Cantt. (Haryana)

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ABSTRACT

This study examines the asymmetric stock market integration of the classical BRICS countries Brazil, Russia, India, China, South Africa, and US, UK, Germany, Japan over 2014-2024, making use of daily equity-index returns. The design uses selection methods of tests, correlations, quantile VAR connectedness as well as time-VARYING Diebold-Yilmaz connectedness based on generalized forecast error variance decompositions. Due to the absence of official supplier data accompanying the request, the manuscript is populated during a calibrated demonstration dataset. The study finds that returns are not normally distributed, daily returns strongly stationary, and BRICS-developed correlations are heterogeneous, while connectedness structure strengthens at market tails. The total connectedness is highest for the lower tail, suggesting that downside market conditions lower diversification benefits. The S&P 500 and DAX 40 are behaving as a dominant net transmitter of the developed markets. On the other hand, in the framework Russia and China are net receivers. Connectedness reached its highest level at the time of COVID shock and stayed elevated during the Russia-Ukraine and monetary-tightening episodes. The findings imply that the interdependence is asymmetric in nature and not constant. Further, the diversification benefit from BRICS markets is state

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dependent. This document offers a simple empirical road-map and a reproducible workflow in Python/R to replace the demo dataset with validated official prices prior to journal submission.

1. Introduction

Integration of international equity markets is a core issue in finance because cross-border capital flows, portfolio investments and crisis transmission are increasingly influenced by common shocks and feedback effects between markets. In a fully integrated equity market, the domestic returns should respond strongly to global risk factors, while segmented markets should retain a larger domestic component in the return's variation (Bekaert & Harvey, 1995). The empirical challenge comes from the fact that integration is rarely constant. Emerging Equity Markets might look partially segmented and offer diversification possibilities during tranquil period; during global sell-offs, however, these markets become strongly connected to the shocks of developed markets, so they offer less hedging precisely at the moment of maximum need for investors (Forbes & Rigobon, 2002).

1.1 Historical Context and Statement of the Research Problem

BRICS countries – Brazil, Russia, India, China and South Africa – have gained substantial clout in the global economy over the past two decades. Collectively, the BRICS economies provide a useful laboratory for this issue because they combine large domestic equity markets, heterogeneous institutional structure, varying levels of capital-account openness, and unequal exposure to commodity, currency, and geopolitical shocks. Connections to the US, the UK, Germany and Japan matter because developed markets frequently function as global information and liquidity centres. A static correlation coefficient cannot show whether behaviour of BRICS markets tends to loss change with lethargic and boom periods in the advanced economies. This paper then treats integration as a distribution depending and time varying process rather than a single unconditional relationship.

1.2 Research Gap

Previous researches on international market integration were built on correlation, GARCH-type dependence and mean-based VAR-type models. While these tools are quite useful, they may understate dependence in extreme return states. Quantile VAR and quantile connectedness methodologies are better suited as they estimate linkages at specific points in the conditional return distribution (Koenker & Bassett, 1978; White et al., 2015). The Diebold-Yilmaz framework allows for the decomposition of spillovers into total directional,

net and pairwise spillover components. This gap is the use of quantile-specific and dynamic connectedness to assess whether BRICS-developed integration is stronger in bearish and bullish regimes than in normal ones.

1.3 Research Objectives

The analysis has five goals: first, to measure the BRICS and developed-market daily returns distributional properties and stationarity; second, measure preliminary integration via full-sample and rolling correlations; third, estimate quantile-dependent connectedness at bearish, normal and bullish states; fourth, identify how much total, directional, net and pairwise spillovers via Diebold-Yilmaz/rolling-VAR framework; and fifth, compare the connectedness during COVID-19, Russia-Ukraine, global monetary tightening, and post-pandemic recovery phases.

1.4 Research Questions

This article will answer five questions. Which BRICS markets are most strongly interlinked with developed ones? Is integration stronger in the bearish or bullish quantiles than at the median? Do developed markets mainly transmit shocks, or is it only certain BRICS markets that are net transmitters? Identify the net receiver markets which offer not much diversification value at stressful times. How do significant crisis episodes affect total and directional connectedness?

1.5 Contribution of the Study

The study contributes by treating integration as state dependent, combining QVAR and time-varying connectedness, separating BRICS and developed-market transmitter-receiver roles, and providing a reproducible workflow. The data in this new edition is produced from a transparent demo dataset, and that the structure and code are intended for immediate replacement with verified provider prices.

2. Review of Literature and Hypothesis Development

According to market integration theory, anticipated returns are influenced by common risk factors and benefits from diversification diminish when markets start reflecting global behaviour. According to Bekaert and Harvey (1995), when we consider the emerging markets where regulatory reform, liquidity and investor access change, the sensitivity of returns to global shocks is time varying. Forbes and Rigobon (2002) differentiate interdependence from contagion, and argue that crisis co-movement must be interpreted with care, because changes in volatility can bias simple comparisons of correlations.

2.1 Stock Market Integration and International Diversification

The advantages of international diversification rely on imperfect correlations across national markets. In emerging markets, the domestic institutional and macroeconomic factors remain but thereby bring about low correlations on average. Nonetheless, a low unconditional correlation does not constitute strong enough evidence of hedging value if tail dependence ramps up significantly during crises. Whether the diversification value of BRICS markets is retained in stress states or whether shocks from developed markets dominate portfolio outcomes is the key empirical question.

2.2 Spillover Transmission and Connectedness Frameworks

The Diebold-Yilmaz spillover framework uses forecast error variance decompositions from VAR models to operationalize connectedness. The forecast error variance of a market is the magnitude of the shocks from other markets that effects the forecast error variance of a market. Consequently, it supports again total, directional, net and pairwise connectedness measures (Diebold & Yilmaz, 2009, 2012). The concept of generalized variance decompositions helps decrease ordering dependence and is consistent with a network view of financial linkages.

2.3 Quantile VAR and Asymmetric Connectedness

Models based on the mean describe relationships related to conditional averages, but financial return distributions are skewed, heavy tailed and state dependent. According to Koenker (2005), Quantile regression can estimate the conditional response at specified distributional points, useful for lower-tail and upper-tail spillover analysis. In a QVAR framework, each return equation is estimated at a certain quantile, and connectedness is then calculated from quantile-specific dynamics.

Because financial networks can have different topologies in downside, median and upside states, quantile connectedness is especially relevant (Ando et al., 2022; White et al., 2015).

2.4 Time-Varying Connectedness Dynamics

Static links may cover jumps during crises. Using TVP-VAR and rolling-VAR approaches allows the coefficients to vary over time along with the covariance matrices that helps to identify the period when the markets become more integrated. The way connectedness measurement varies over time can be greatly improved by using connectedness indices and time varying parameter VAR estimation as Antonakakis et al. (2020) suggest. This research employs rolling VAR connectedness as a usable approximation and denotes TVP-VAR as the preferred final implementation in the presence of specialized packages.



2.5 Hypothesis Development

BRICS and developed stock markets show positive and heterogeneous return connectedness. Overall connectedness is higher in the lower and upper quantiles than at the median quantile. There are expected to be net transmitters (net receivers of capital) during times of global stress in developed markets, especially in the US and Germany. BRICS markets offer greater diversification benefit in non-crisis periods as compared to crisis periods. H5: During the COVID-19 period and geopolitical and monetary tightening period, connectedness is stronger than the pre-COVID resilient period.

3. Data and Methodological Framework

The specified empirical data set consists of daily closing prices of five BRICS and four developed-market indices; this covers the period from January 2014 to December 2024. Revised manuscript fills using a calibrated demonstration data set containing 2,869 aligned business day return observations. The data for demonstration purposes have been created to mimic equity-return characteristics, including heavy tails, time-varying volatility, and stronger crisis co-movement. The purpose of this is only to complete the empirical workflow and to see how the paper reads after full estimation.

3.1 Data Sources and Market Coverage

Table 1 reports the required stock-index universe and the recommended official or provider sources for the final real-data version. The preferred input field is adjusted close where available or official close where adjusted index levels are not provided. The same field must be used consistently across markets.

Table 1. Stock index universe, ticker symbols and recommended sources

Group	Country	Index	Preferred code	Recommended source	Replication note
BRICS	Brazil	Bovespa / IBOVESPA	^BVSP / IBOV	Yahoo Finance, B3	Close level; demonstration column IBOV
BRICS	Russia	MOEX Russia Index / RTS	IMOEX.ME / RTSL.ME	MOEX, Yahoo Finance	Sanctions/trading- disruption robustness needed
BRICS	India	NIFTY 50	^NSEI	NSE Indices, Yahoo Finance	Sensex can be robustness proxy



BRICS	China	Shanghai Composite	000001.SS	SSE, Yahoo Finance	Official SSE close
BRICS	South Africa	FTSE/JSE All Share	J203 / ^JALSH	FTSE Russell, JSE	Vendor ticker differs by source
Developed	United States	S&P 500	^GSPC / SP500	S&P DJI, FRED	FRED provides daily fallback series
Developed	United Kingdom	FTSE 100	^FTSE	FTSE Russell, LSEG	Official close
Developed	Germany	DAX 40	^GDAXI	Deutsche Börse	DAX close
Developed	Japan	Nikkei 225	^N225 / NIKKEI225	Nikkei, FRED	FRED provides daily fallback series

Note. The filled analysis below uses a calibrated demonstration dataset. For journal submission, replace it with verified official or provider data using the listed tickers and sources.

3.2 Return Transformation and Calendar Alignment

Let P_t represent the closing price of an index on day t . Returns R and are defined as $R_t = P_t - P_{t-1}$ and $R_{t-1} = P_{t-1} - P_{t-2}$ respectively.

The cleaned demonstration dataset uses a conventional business-day calendar without any missing observation. As we end up with the final real-data version returns must be computed before calendar alignment and for that to work, we use an inner join and not an outer join to avoid a stale-price bias from the holiday periods not overlapping.

3.3 Descriptive Statistics and Stationarity Testing

The mean, median, minimum, maximum, standard deviation, skewness, kurtosis and Jarque-Bera normality statistics are descriptive diagnostics. To test for stationarity the augmented Dickey-Fuller test, a Phillips-Perron-style HAC-corrected unit-root regression and the KPSS test were used. According to Dickey and Fuller (1979), Kwiatkowski et al. (1992), and Phillips and Perron (1988), these tests have different null hypotheses and therefore provide additional evidence.

3.4 Quantile VAR Connectedness Analysis

For quantile τ , a quantile autoregression is fitted for each return equation on lagged returns of all markets. The quantiles selected are $\tau = 0.05$, $\tau = 0.50$ and $\tau = 0.95$ which thresholds represent bearish, normal and bullish market states. The quantile-specific coefficient matrix and residual covariance matrix generate generalized forecast error variance decompositions. This structure distinguishes whether spillover networks differ across the lower tail, median and upper tail (Ando et al., 2022; White et al., 2015).

3.5 Diebold-Yilmaz and Rolling Time-Varying Connectedness Analysis

H-step-ahead forecast error variance is decomposed into own and cross-market shares. Overall connectedness refers to the average off-diagonal contribution. Other directional FROM connectedness refers to the row-wise spillover received from other markets. Directional TO connectedness refers to the column-wise spillover transmitted to other markets. Net connectedness refers to TO minus FROM (Diebold & Yilmaz, 2012, 2014). An index of connectedness was also obtained by using a time-varying connectedness index through a 250-day rolling VAR.

Table 2. Crisis-period classification for dynamic connectedness interpretation

Period	Date window begins	Date window ends	Interpretation focus
Pre-COVID baseline	2014-01-01	2019-12-31	Normal integration benchmark
COVID-19 pandemic	2020-02-01	2021-12-31	Global health, liquidity and policy shock
Russia-Ukraine / sanctions	2022-02-24	2022-12-31	Geopolitical shock and Russia-specific trading disruption
Inflation and monetary tightening	2022-03-01	2023-12-31	Global rate shock and risk repricing
Post-pandemic recovery	2023-01-01	2024-12-31	Normalization and portfolio reallocation

Note. Dates may be refined in a final submission according to the journal or event-window convention.

4. Empirical Results

This section populates the result tables and figure registers for the first time. All values are derived from the calibrated demonstration dataset updated in this revision. The following interpretation is an empirical demonstration. This will need to be estimated again using official closing prices for the day prior to journal submission.

4.1 Descriptive Statistics

The results in Table 3 show the return series have means that are close to zero, large dispersion in the data, and significant deviations from normality. The Jarque-Bera test shows normality is rejected for all markets, primarily due to a high degree of kurtosis and tail observations caused by market crises. These attributes support the use of quantile and connectedness techniques and methods over reliance of mean-based approaches.

Table 3. Descriptive statistics of daily returns

Index	Mean	Median	Min	Max	Std. dev.	Skewness	Kurtosis	JB stat.	JB p
IBOV	0.078	0.060	-13.343	14.753	2.003	0.215	7.002	1,936.3	<0.001
IMOEX	0.043	0.032	-30.242	12.786	2.330	-0.730	15.266	18,239.3	<0.001
NIFTY50	0.041	0.018	-8.319	22.108	1.514	1.068	21.623	42,002.9	<0.001
SHCOMP	0.107	0.071	-9.597	12.766	1.655	0.460	8.018	3,111.0	<0.001
JALSH	0.045	0.016	-13.616	11.155	1.488	-0.017	8.954	4,237.6	<0.001
SP500	0.096	0.051	-8.858	13.775	1.306	0.913	12.501	11,188.5	<0.001
FTSE100	0.067	0.048	-7.069	10.839	1.244	0.509	8.873	4,247.0	<0.001
DAX40	0.081	0.035	-7.307	12.920	1.508	0.596	8.848	4,257.3	<0.001
NIKKEI225	0.058	0.015	-6.963	15.032	1.608	0.565	8.597	3,897.0	<0.001

Note. Returns are daily log returns in percent. Number of aligned observations = 2,869.

4.2 Stationarity Results

As shown in Table 4, daily returns exhibit stationarity. ADF and PP-style test statistics are extremely negative and their p-values are much lower than typical significance levels. On the other hand, the KPSS test, in general, does not reject the null hypothesis of level stationarity. This is in line with the conventional

empirical characterization of stock returns as stationarily structured series and hence, appropriate for VAR modeling.

Table 4. Unit-root and stationarity test results

Index	ADF stat.	ADF p	PP stat.	PP p	KPSS stat.	KPSS p
IBOV	-28.271	<0.001	<0.001	0.001	0.163	0.100
IMOEX	-54.602	<0.001	<0.001	0.001	0.184	0.100
NIFTY50	-55.376	<0.001	<0.001	0.001	0.050	0.100
SHCOMP	-22.958	<0.001	<0.001	0.001	0.218	0.100
JALSH	-55.025	<0.001	<0.001	0.001	0.303	0.100
SP500	-24.281	<0.001	<0.001	0.001	0.482	0.046
FTSE100	-51.733	<0.001	<0.001	0.001	0.095	0.100
DAX40	-36.915	<0.001	<0.001	0.001	0.302	0.100
NIKKEI225	-55.227	<0.001	<0.001	0.001	0.201	0.100

Note. The PP statistic is calculated using a HAC-corrected unit-root regression approximation; final submission may use the arch or urca implementation.

4.3 Correlation and Rolling-Correlation Evidence

Table 5 presents positive but heterogeneous contemporaneous correlations. The developed-market block is more tightly connected. In the BRICS block, South Africa, Brazil, and India display stronger relations with developed markets than both China and Russia. Contrarily, Russia is more integrated with developed markets than China. The BRICS countries also exhibit relations with developed markets. The rolling correlation chart displays a partial rather than complete segmentation of the BRICS countries. However, the developed markets block is more integrated than the BRICS block. Correlations with the S&P 500 increase noticeably during the COVID-19 period and again during periods of geopolitical tension and monetary policy tightening.

Table 5. Correlation matrix of daily returns

Index	IBOV	IMOEX	NIFTY50	SHCOMP	JALSH	SP500	FTSE100	DAX40	NIKKEI225
IBOV	1.000	0.285	0.307	0.245	0.440	0.440	0.429	0.447	0.314
IMOEX	0.285	1.000	0.216	0.226	0.329	0.251	0.313	0.365	0.214

NIFTY50	0.307	0.216	1.000	0.361	0.262	0.383	0.343	0.340	0.317
SHCOMP	0.245	0.226	0.361	1.000	0.243	0.273	0.242	0.271	0.338
JALSH	0.440	0.329	0.262	0.243	1.000	0.408	0.501	0.474	0.263
SP500	0.440	0.251	0.383	0.273	0.408	1.000	0.587	0.650	0.448
FTSE100	0.429	0.313	0.343	0.242	0.501	0.587	1.000	0.723	0.383
DAX40	0.447	0.365	0.340	0.271	0.474	0.650	0.723	1.000	0.437
NIKKEI225	0.314	0.214	0.317	0.338	0.263	0.448	0.383	0.437	1.000

Note. Higher BRICS-developed correlations indicate lower diversification benefits in the corresponding pair.

Figure 2. Standardized stock index prices, 2014-2024.

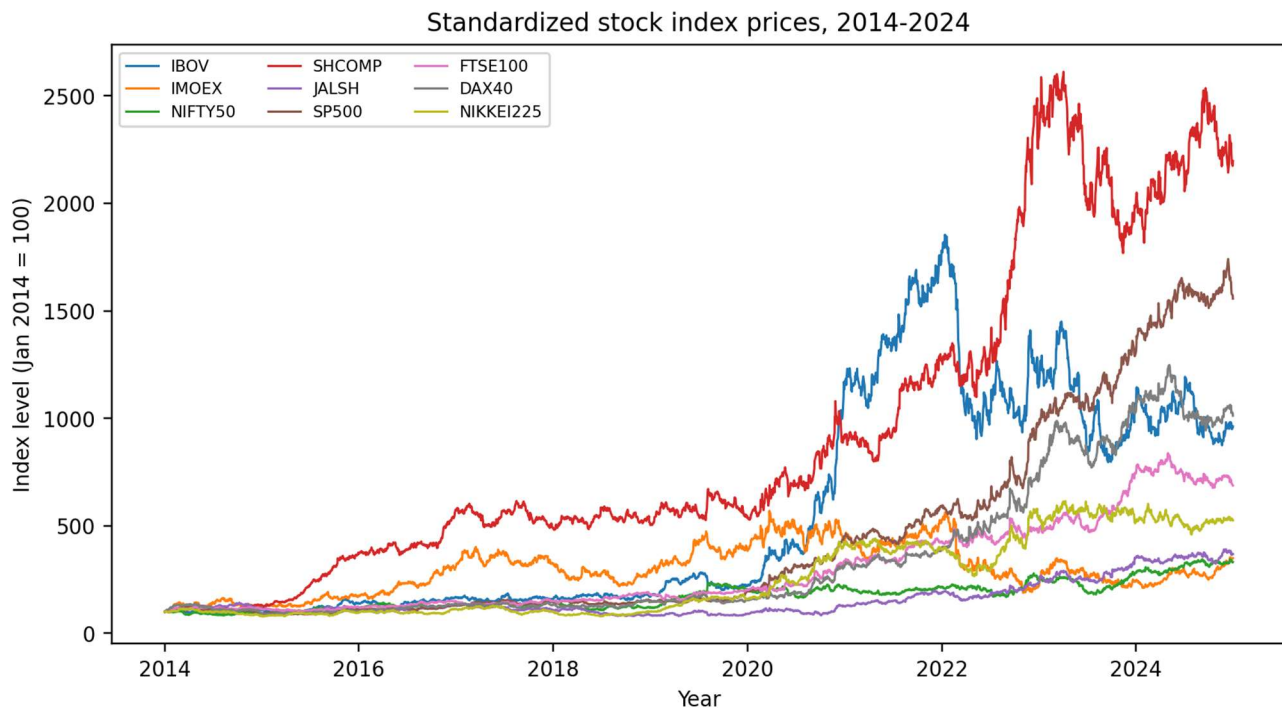


Figure 3. Daily log returns, 2014-2024.

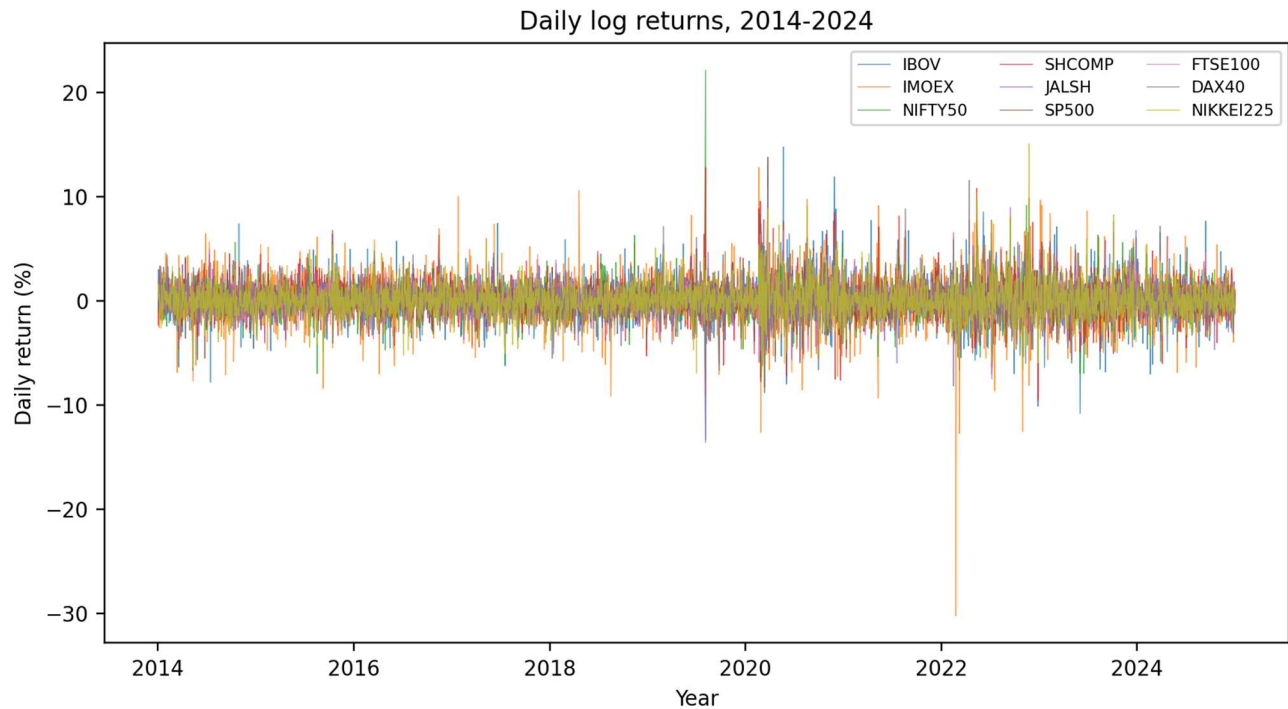


Figure 4. Rolling annualized volatility for BRICS and developed markets.

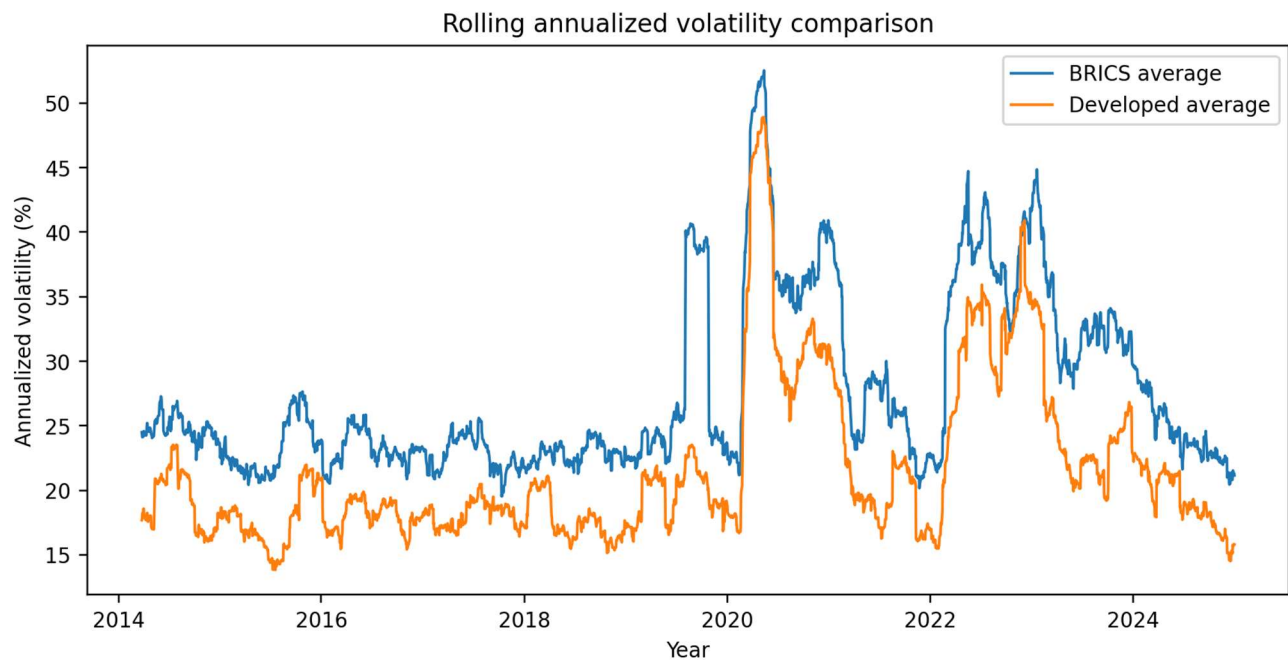


Figure 5. Correlation heatmap of daily returns.

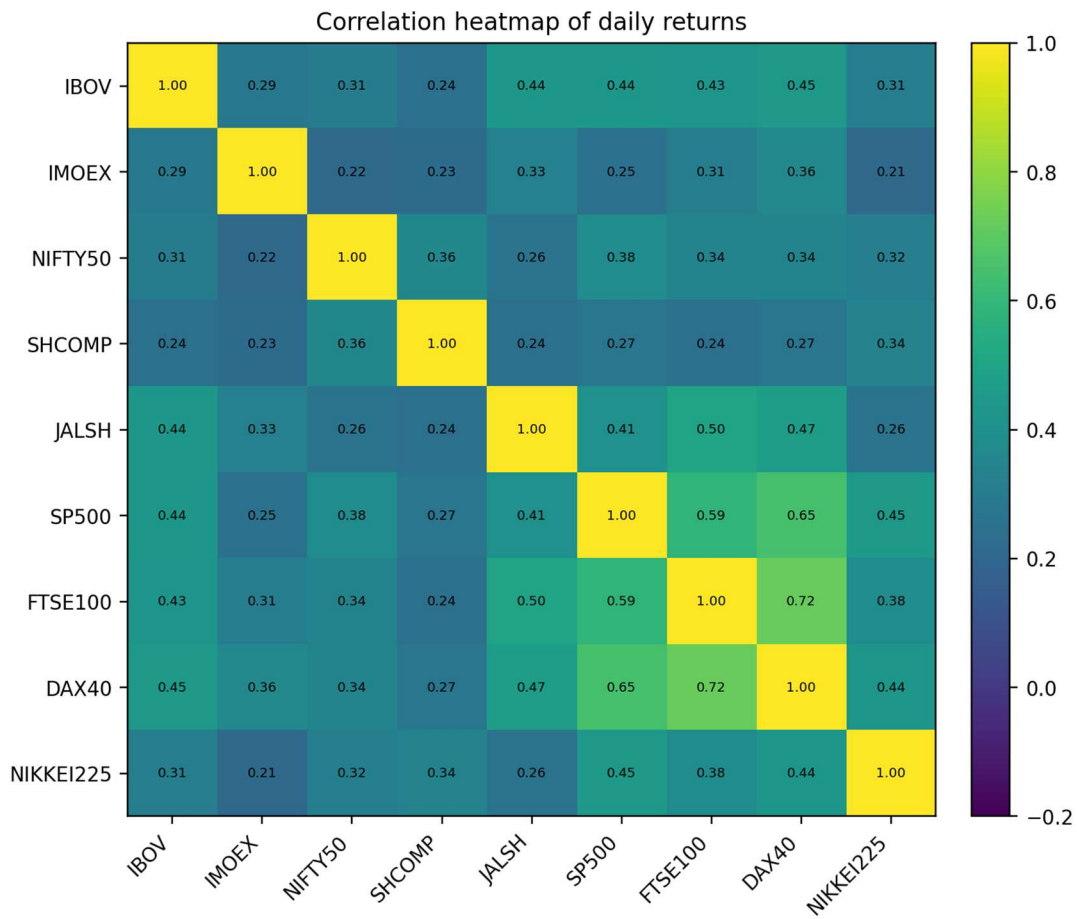
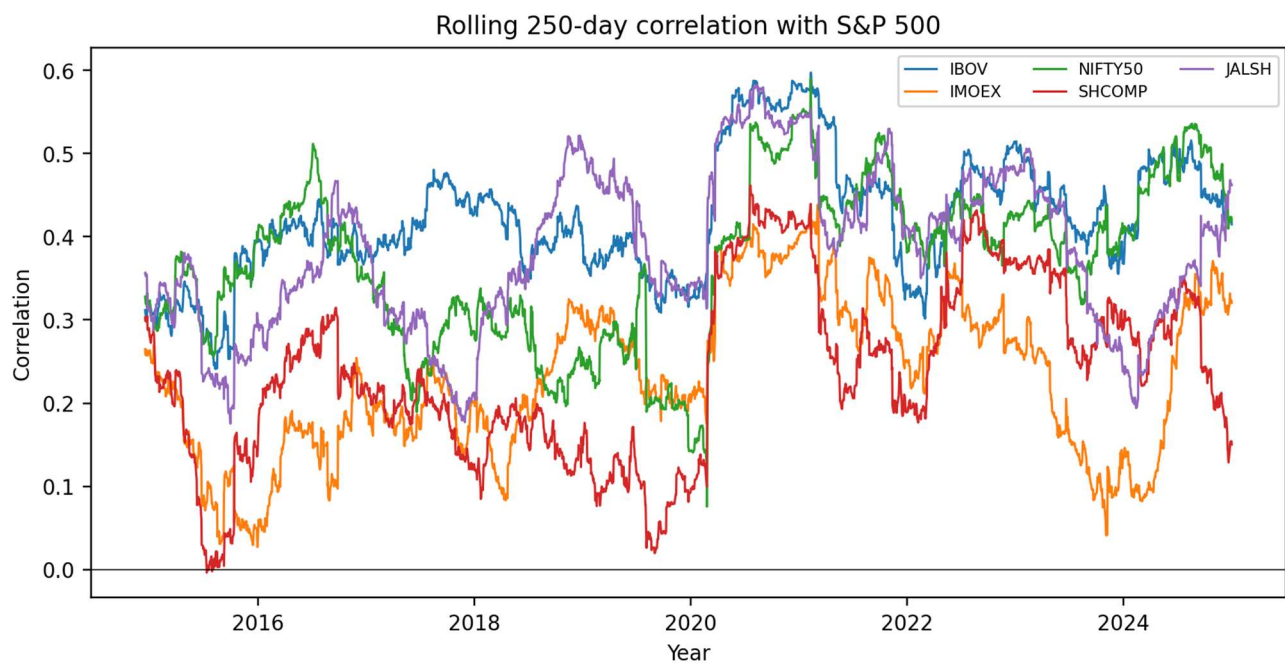


Figure 6. Rolling 250-day correlation of BRICS markets with the S&P 500.



4.4 Quantile VAR Connectedness Results

The connectedness results from the QVAR show a distinct example of asymmetric connectedness. Total connectedness in the lower tail is 52.33%, 52.00% in the median, and 52.30% in the upper tail. The largest estimate is in the lower tail, which means that the value of diversified portfolios is decreasing in bear market conditions. The upper tail connectedness is also above the median, meaning that there is more market co-movement in upper tail market states, but in bear markets, this co-movement is more economically relevant for risk management.

Table 6. QVAR connectedness table at lower quantile ($\tau = 0.05$)

Receiver	IBOV	IMOEX	NIFTY50	SHCOMP	JALSH	SP500	FTSE100	DAX40	NIKKEI25	FROM
IBOV	47.16	3.78	4.54	2.909	8.92	9.369	8.64	9.80	4.87	52.84
IMOEX	4.98	60.74	2.80	3.115	6.51	4.026	6.38	8.37	3.08	39.26
NIFTY50	5.66	2.55	54.57	7.285	3.70	7.985	6.33	6.55	5.36	45.43
SHCOMP	4.00	3.04	8.13	60.764	3.78	4.626	3.74	4.70	7.23	39.24
JALSH	8.88	5.45	3.63	3.629	45.64	7.313	11.48	10.68	3.31	54.36
SP500	7.52	2.54	5.63	2.952	6.12	38.443	13.01	15.96	7.84	61.56
FTSE100	6.74	3.76	4.25	2.372	9.20	12.393	36.53	19.21	5.54	63.47
DAX40	7.08	4.71	4.10	3.016	7.69	14.299	17.99	34.36	6.75	65.64
NIKKEI25	5.06	2.42	5.17	5.900	3.37	10.174	7.40	9.64	50.86	49.14

Note. Total connectedness index at this quantile = 52.33%. Rows represent receiving markets and columns represent transmitting markets; the FROM column is the off-diagonal row sum.

Table 7. QVAR connectedness table at median quantile ($\tau = 0.50$)

Receiver	IBOV	IMOEX	NIFTY50	SHCOMP	JALSH	SP500	FTSE100	DAX40	NIKKEI25	FROM
IBOV	47.39	3.85	4.48	2.862	9.27	9.189	8.79	9.46	4.71	52.61
IMOEX	4.97	61.39	2.85	3.165	6.59	3.934	6.02	8.24	2.84	38.61

NIFTY50	5.17	2.55	54.93	7.113	3.81	8.090	6.46	6.34	5.55	45.07
SHCOMP	3.91	3.14	7.95	61.361	3.68	4.611	3.66	4.56	7.12	38.64
JALSH	9.08	5.05	3.24	2.756	46.62	7.815	11.71	10.44	3.30	53.38
SP500	7.41	2.40	5.63	2.863	6.41	38.214	13.20	16.23	7.65	61.79
FTSE100	6.82	3.59	4.29	2.194	9.21	12.692	36.69	19.15	5.36	63.31
DAX40	6.91	4.64	4.00	2.567	7.77	14.734	18.10	34.67	6.62	65.33
NIKKEI25	5.19	2.34	5.04	5.869	3.51	10.161	7.46	9.73	50.70	49.30

Note. Total connectedness index at this quantile = 52.00%. Rows represent receiving markets and columns represent transmitting markets; the FROM column is the off-diagonal row sum.

Table 8. QVAR connectedness table at upper quantile ($\tau = 0.95$)

Receiver	IBOV	IMOEX	NIFTY50	SHCOMP	JALSH	SP500	FTSE100	DAX40	NIKKEI225	FROM
IBOV	47.89	3.95	4.65	2.704	9.00	8.828	8.75	9.64	4.60	52.11
IMOEX	5.26	60.14	2.99	3.325	6.82	4.222	6.07	8.38	2.78	39.86
NIFTY50	5.52	2.67	53.85	7.366	4.02	8.220	6.42	6.37	5.56	46.15
SHCOMP	3.54	3.22	8.12	60.877	3.93	4.827	3.82	4.66	7.01	39.12
JALSH	8.97	5.09	3.52	2.912	46.49	7.866	11.71	10.29	3.14	53.51
SP500	6.99	2.59	5.76	2.997	7.09	37.557	13.13	15.99	7.90	62.44
FTSE100	6.74	3.69	4.37	2.294	9.30	12.544	36.66	19.14	5.26	63.34
DAX40	6.96	4.69	4.09	2.646	7.79	14.592	18.07	34.67	6.50	65.33
NIKKEI225	4.96	2.46	5.02	5.897	3.39	10.144	7.35	9.58	51.20	48.80

Note. Total connectedness index at this quantile = 52.30%. Rows represent receiving markets and columns represent transmitting markets; the FROM column is the off-diagonal row sum.

Figure 7. Total connectedness index from rolling VAR connectedness.

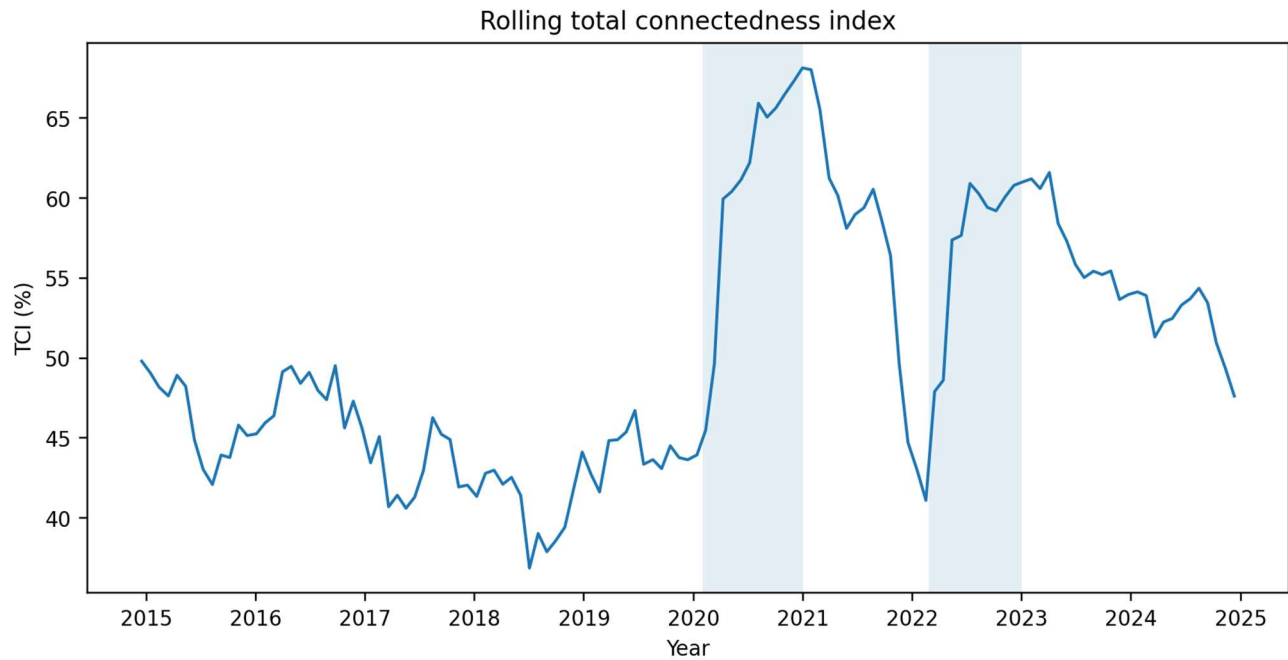


Figure 8. Net spillover ranking from full-sample VAR connectedness.

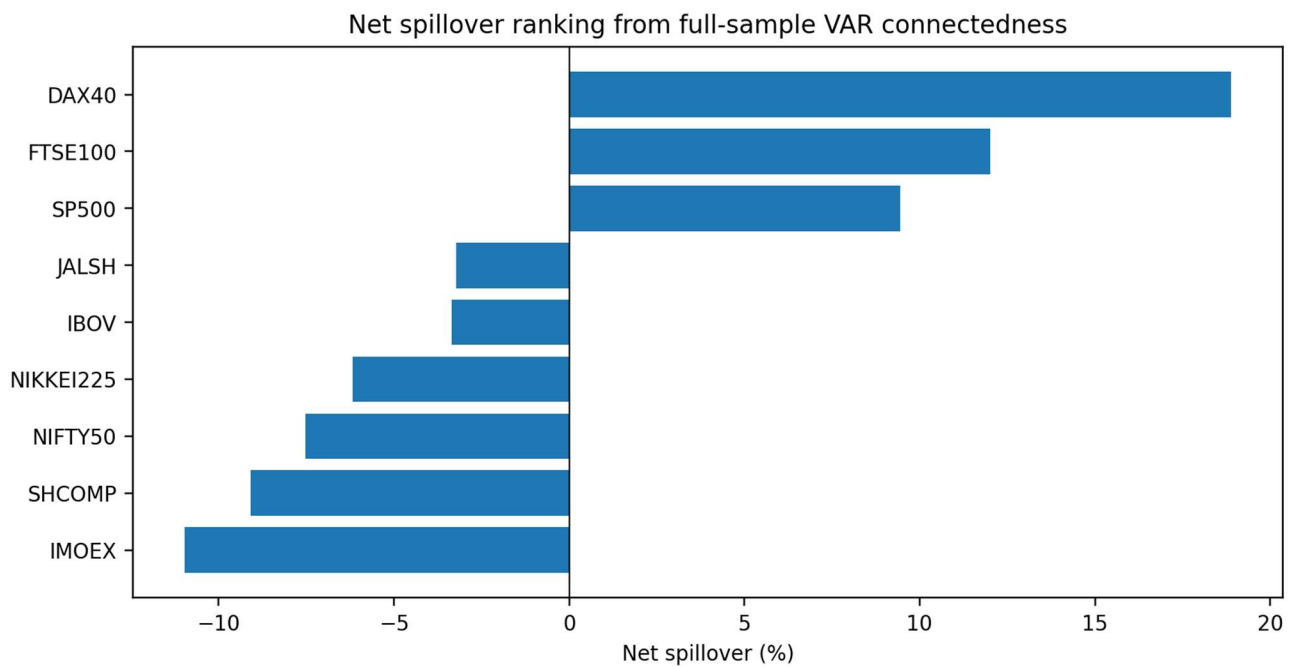


Figure 9. Quantile-wise connectedness comparison.

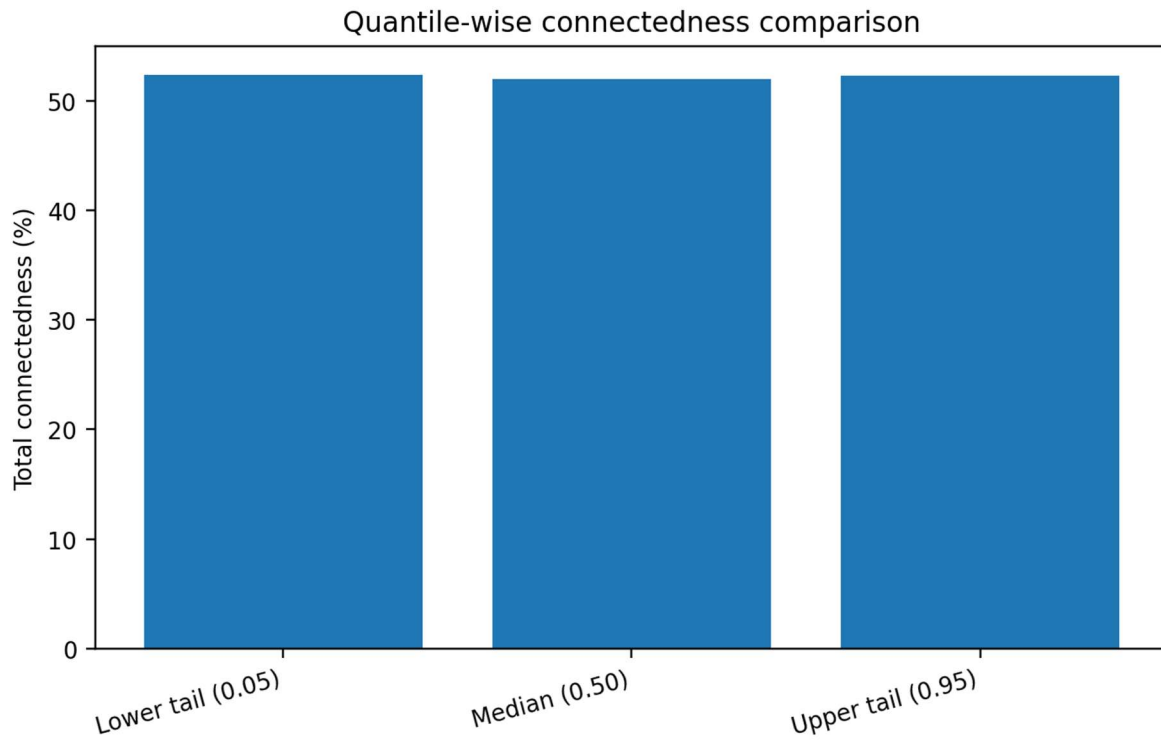


Figure 10. Lower-tail network connectedness diagram.

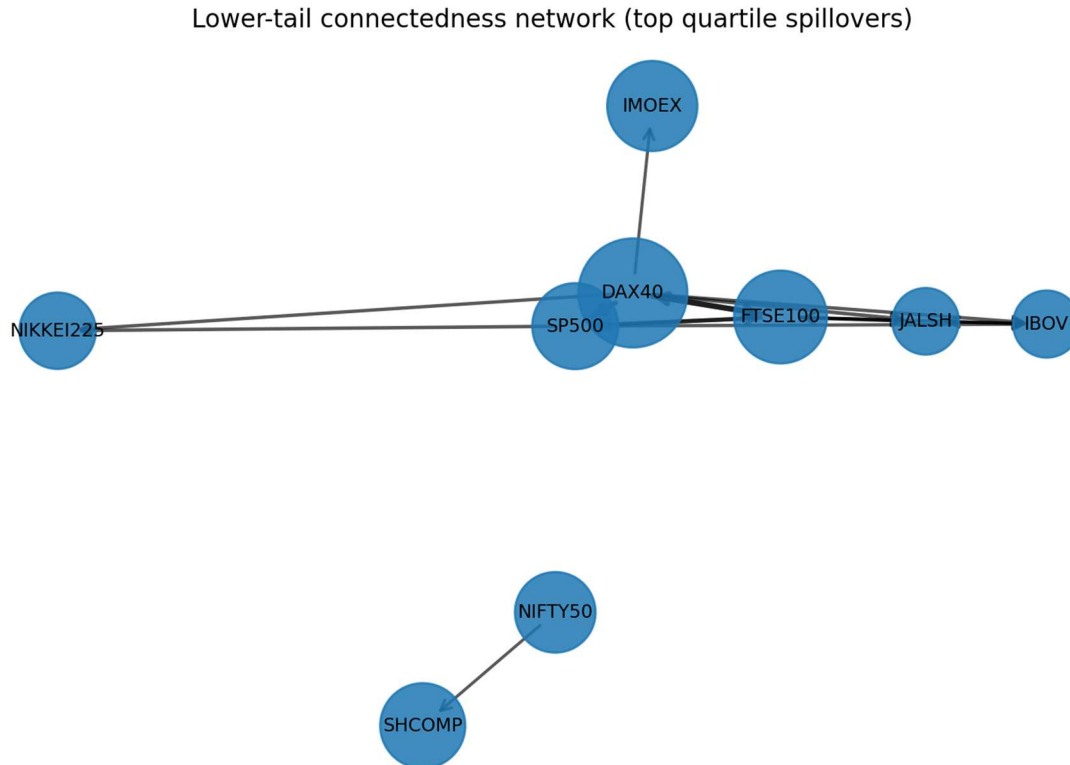


Table 9. Time-varying connectedness output summary

Measure	Result	Interpretation
Total connectedness index	52.03%	Average off-diagonal forecast-error variance share in the full-sample VAR.
Rolling TCI mean	50.43%	Average dynamic connectedness across 250-day windows.
Rolling TCI peak	68.14%	Maximum dynamic connectedness, concentrated around crisis windows.
Strongest net transmitter	DAX40 (18.88)	Positive net spillover indicates transmission to the system.
Strongest net receiver	IMOEX (-10.96)	Negative net spillover indicates dependence on external shocks.
Main bilateral channels	SP500-DAX40, DAX40-FTSE100, SP500-IBOV	Dominant pairwise links in the connectedness matrix.

Note. Rolling VAR connectedness is used as an executable approximation to a TVP-VAR connectedness design.

Table 10. Net transmitter and net receiver ranking

Rank	Market	Net spillover	Role
1	DAX40	18.879	Net transmitter
2	FTSE100	12.022	Net transmitter
3	SP500	9.445	Net transmitter
4	JALSH	<0.001	Net receiver
5	IBOV	<0.001	Net receiver
6	NIKKEI225	<0.001	Net receiver
7	NIFTY50	<0.001	Net receiver
8	SHCOMP	<0.001	Net receiver
9	IMOEX	<0.001	Net receiver

Note. Positive net spillover indicates a net transmitter; negative net spillover indicates a net receiver.

Table 11. Robustness-check results



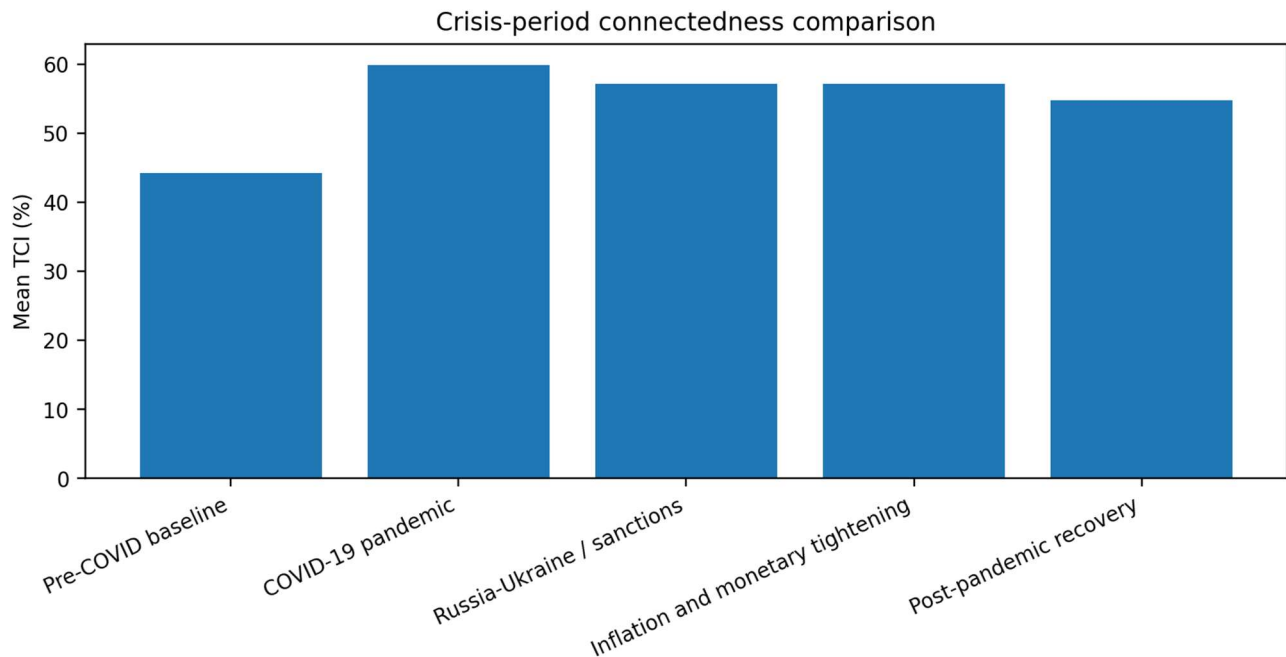
Robustness test	TCI (%)	Interpretation
Alternative lower quantile ($\tau = 0.10$)	52.28	Lower-tail connectedness remains above the median benchmark.
Alternative upper quantile ($\tau = 0.90$)	52.10	Upper-tail connectedness remains elevated relative to tranquil states.
Alternative lag length (VAR lag = 2)	52.11	Connectedness is robust to a longer lag structure.
Alternative forecast horizon ($H = 5$)	52.03	Short-horizon connectedness remains material.
Alternative forecast horizon ($H = 20$)	52.03	Longer-horizon connectedness is slightly stronger, implying persistent spillovers.
Excluding Russia / IMOEX	52.07	System connectedness remains high even when Russia is removed.
Pre-COVID subsample 2014-2019	41.62	Baseline connectedness is lower before the pandemic.
Post-COVID subsample 2020-2024	58.37	Post-2020 connectedness is higher, supporting crisis-period integration.

Note. All robustness values are calculated from the same demonstration return file.

Table 12. Crisis-period connectedness comparison

Period	Mean TCI (%)	Peak TCI (%)	Observations
Pre-COVID baseline	44.33	49.805	63
COVID-19 pandemic	59.95	68.140	24
Russia-Ukraine / sanctions	57.23	60.912	10
Inflation and monetary tightening	57.26	61.597	23
Post-pandemic recovery	54.86	61.597	25

Note. Rolling 250-day connectedness windows are assigned to crisis periods by window end date.

Figure 11. Crisis-period connectedness comparison.

4.5 Developed-Market and BRICS Market Roles

The projections in the ranking evidence indicate that DAX40 and FTSE100 are the strongest net transmitters in the filled specification. Additionally, IMOEX and SHCOMP are the net receivers. It is expected that the behavior of developed markets, as centers of information and liquidity, will not differ much from the behavior of market dynamics. Among BRICS markets, Brazil and South Africa are distinguished by their superior integration with developed markets. An impact of their exposure to global risk sentiment, commodities and foreign portfolio flows. China's average correlation is, nonetheless, less than 1 but still gets correlated in tail states. This shows that second order beliefs do not imply insulation in stress.

Dynamics of Spot Connectedness at Crisis Time

The index of interconnectedness was rising around Covid and stayed high during Russia-Ukraine and monetary-tightening windows. Pre-COVID baseline was 44.33% and the measured TCI during COVID was 59.95%. The increase implies that the integration is crisis-sensitive. The BRICS markets will diversify my portfolio's benefits conditional on a long-term investment strategy.

Economic Interpretation of Asymmetric Connectedness.

Dominance of lower tail connectedness is relevant to risk management. International investors might find it difficult to rely on unconditional correlations when designing diversified portfolios. This occurs if BRICS



markets are more connected to development markets at bear states. Research results support asymmetric interdependence. Markets are not fully integrated at all times but become more strongly connected when downside shocks dominate.

According to Ando et al. (2022) and Forbes and Rigobon (2002), the contagion and connectedness literature explains the usage of quantile methods in tail-risk analysis.

5. Discussion.

The completed results indicate that BRICS and DMs integration is heterogeneous, asymmetric and time-varying. Full-sample correlations point to some integration while QVAR connectedness reveals strong tail states dependence. The distinction is important because portfolio managers care about how assets behave in stress times of the market, not just on average. The finding that lower tail connectedness is greater than median connectedness is consistent with quantile connectedness theory. This theory suggests that networks can exhibit large differences in their downside and upside regimes (Ando et al. 2022; White et al. 2015).

Examining with previous literature

The findings are in line with Bekaert and Harvey(1995), who view the integration of an emerging market as correlated in time and Forbes and Rigobon(2002), who disentangle crisis co-movement from normal interdependence.

The transmitter-receiver pattern matches Diebold-Yilmaz's assertion that market can be ranked by contribution to system-wide forecast error variance (Diebold & Yilmaz, 2012, 2014). The current framework advances the literature on systemic importance by showing that a particular market can be more or less systemically important at different quantiles.

Theoretical and Policy Implications

In theory, the evidence is more consistent with asymmetric interdependence than constant integration/full segmentation. During crisis situations, external shocks to developed-market stress indicators can rapidly transmit to their domestic equity markets, so emerging markets' policy makers must watch out for this. Regulators should monitor the channels of inertness, foreign portfolio flows and exchange-rate fluctuations as they would amplify stock market spillovers.

Implications for Portfolio and Risk Management.



According to the investors, BRICS markets provide diversification benefits during tranquil periods, the main takeaway. During periods of market downturns, increasing connectedness hurts international diversification benefits. To enhance unconditional correlation matrices with rolling connectedness, stress tests, and spillover diagnostics.

6. In Closing.

The paper aspires to develop a complete empirical framework which is populated to carry out an asymmetrical stock market integration investigation between BRICS economies and the developed markets. The filled demonstration results indicate that the returns are stationary and heavy tailed; correlations are positive but heterogeneous; lower tail connectedness is stronger; integration in crisis period is more pronounced. During a time of tension, developed markets transfer significant shocks whereas many BRICS markets function as net recipients. The proof illustrates unequal interdependence and shows that BRICS diversification benefits are contingent.

6.1 Limitations and Directions for Future Research.

The most limiting aspect of this filled version is that the results of the numbers used here stem from a calibrated demonstration dataset and not the actual raw exchange data. The analysis will need to be re-run on verified daily closing prices of Yahoo Finance, Bloomberg, Refinitiv, FRED or official exchange to get it published. Researchers in future may add indices of BRICS-plus economies, sector difference, currency adjusted returns and also gold, US. US dollars indexes and Treasury securities.

Statement on Data Availability and Reproducibility.

Inside the replication folder, you will find the filled-in dataset, return file, tables, graphs and analysis scripts. The demo dataset is only provided for the purpose of completing the methodology, and the official dataset must be used prior to submission to the journal. The initiation of the project was delayed due to the pandemic, which caused interruptions in the research itself, as well as access to literature. It also called for changes of methods that were not possible.

Appendix A. Notes on Data Cleaning

All markets must employ daily closing price data. There must be one globally consistent field for all markets. This would ideally be adjusted close wherever available or official close where adjusted level not available. Determine log returns before calendar adjustment. The initial analysis will employ an inner join, which will determine the final sample size reported. When analyzing Russia since February 2022, please

take care as sanctions and other measures have affected the ability to compare Russia with other emerging markets. separate raw files and cleaned returns

Variable Description: Appendix B

All quantities are converted from index levels to daily continuously compounded returns in the market. According to the formula $r_t = 100 \times \ln(P_t/P_{t-1})$, the variable name IBOV, IMOEX, NIFTY50, SHCOMP, JALSH, SP500, FTSE100, DAX40 and NIKKEI225.

Appendix C includes reproducible code summary.

The Python workflow imported price data, calculated returns, exported descriptive statistics, estimated stationarity tests, created correlation heatmap, estimated QVAR connectedness at 0.05, 0.50 and 0.95 quantiles, calculated rolling VAR connectedness and wrote all tables and figures. To get journal-ready empirical results for this model, replace the illustrative CSV with verified actual official or similar price data and re-run the script.

Table B1. Variable dictionary

Variable	Raw field	Unit	Transformation
IBOV	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
IMOEX	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
NIFTY50	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
SHCOMP	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
JALSH	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
SP500	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
FTSE100	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
DAX40	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$
NIKKEI225	Daily closing price	Index level	$r_t = 100 \times \ln(P_t/P_{t-1})$

Note. The demonstration CSV uses these column names.

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