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Dynamic Integration, Granger Causality and Volatility Spillovers between Indian and Global Stock Markets

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Abstract

This study examines dynamic integration, predictive precedence, long-run co-movement, and volatility dependence between the Indian stock market and nine major global and regional markets over 1991–2023. Using 8,318 synchronized daily observations, the analysis combines correlation, Granger predictive-precedence tests, Johansen cointegration, generalized method of moments (GMM), and DCC-GARCH(1,1).

The results show positive unconditional correlations and significant positive DCC trends across all market pairs. Granger tests indicate bidirectional predictive precedence between India and Australia, Belgium, Hong Kong, Japan, Singapore, and the United States; France and Germany precede India, whereas India precedes Indonesia. Johansen tests identify two cointegrating relations, indicating long-run common stochastic trends. GMM estimates reveal significant positive conditional associations with seven markets, while Germany and the United States are statistically insignificant. DCC-GARCH estimates further indicate highly persistent conditional dependence. Overall, the findings demonstrate multidimensional integration between India and international equity markets, suggesting more limited diversification benefits over the long run and supporting cross-border surveillance and systemic-risk monitoring.

Keywords: stock market integration, volatility spillovers, DCC-GARCH, Granger causality, cointegration, portfolio diversification, India.

JEL Classification: C32; F36; G11; G15.

Introduction

Financial-market integration is an important dimension of the international financial system because capital mobility, common information, foreign institutional investment (FII), and cross-border trade can strengthen the transmission of asset-price information across countries. India's economic liberalization, initiated in the early 1990s, substantially increased its connections with international capital markets and provides an important setting for examining whether domestic equity-market movements have become progressively more closely related to major global and regional markets. At the same time, stronger integration can reduce the effectiveness of international diversification when markets respond to common shocks or when contagion intensifies.

The portfolio-diversification implications of integration are not unequivocal. If international markets remain sufficiently segmented, investors may benefit from combining assets across countries. Conversely, persistent common stochastic trends and strong time-varying correlations can reduce long-horizon diversification opportunities. The distinction between short-run dependence and long-run equilibrium relationships is therefore central to international portfolio analysis (Hassan & Naka, 1996; Kearney & Lucey, 2004).

Evidence on stock-market integration in the Indian context remains mixed. Previous studies report both substantial integration and periods of weak or absent long-run relationships, while the empirical setting has evolved alongside changes in India's financial openness, cross-border capital flows, and the global market architecture. Recent research has increasingly emphasized dynamic dependence and volatility transmission (Octavia & Wijaya, 2020; Panda & Nanda, 2017), but many studies rely on shorter samples or focus on a limited set of markets. The present study addresses this gap by using daily observations from January 1991 to December 2023 and combining complementary methods that capture distinct dimensions of interdependence. The applied relevance lies in determining whether integration affects diversification opportunities, market surveillance, and cross-border risk monitoring.

The present study addresses four interconnected questions. First, how strong is the unconditional and dynamic dependence between the Indian market and selected global and regional markets? Second, which markets demonstrate predictive precedence relative to India in the short run? Third, is there evidence of long-run cointegration in the system of international equity indices? Fourth, how persistent is the conditional volatility dependence between India and the selected markets?

The study is empirical rather than causal in the structural sense. Correlation and DCC-GARCH are used to characterize dependence; Granger tests identify predictive precedence; Johansen analysis identifies long-run stochastic co-movement; and GMM estimates conditional associations under the specified dynamic structure. This distinction avoids treating statistical predictability as evidence of an identified structural transmission mechanism.

The remainder of the paper is organized as follows. Section 2 reviews the literature thematically and identifies the research gap. Section 3 describes the data and empirical strategy. Section 4 presents the results. Section 5 discusses the findings in relation to the literature and their implications for diversification and financial stability. Section 6 develops policy and governance implications, followed by the conclusion, which also addresses study limitations and avenues for future research.

1. Review of Existing Literature and Research Gap

Research on stock-market integration has examined the extent to which national equity markets move together, transmit information, and share long-run trends. In the Indian context, this question became particularly relevant after the economic reforms initiated in the early 1990s. To identify the research gap systematically, the literature is organized around four themes: international stock-market integration; Indian stock-market integration with global and regional markets; volatility spillovers and dynamic dependence; and methodological approaches.

International Stock-Market Integration

The theoretical foundations of international stock-market integration can be linked to the law of one price, portfolio-selection theory, the capital asset pricing model, and arbitrage-pricing theory. These perspectives imply that common risk factors, capital mobility, and arbitrage can generate linkages among asset prices across countries (Lintner, 1965; Markowitz, 1952; Ross, 1976; Sharpe, 1964). Early empirical evidence documented international transmission of stock-market movements, including the prominent role of the United States in transmitting information to other markets (Eun & Shim, 1989). Subsequent studies showed that integration can vary across regions and crisis periods (Chong et al., 2003; Diranzo et al., 2002; Malliaris & Urrutia, 1992).

Cointegration studies have produced heterogeneous findings. Gilmore and McManus (2004) and Aggarwal and Kyaw (2005) reported long-run integration in North American markets, whereas other studies identified weaker associations during or after financial crises. This evidence suggests that international integration is not necessarily constant over time and that common trends may coexist with substantial short-run deviations.

Indian Stock-Market Integration with Global and Regional Markets

Evidence for India is similarly mixed. Dhal (2009) found long-run integration between India and global and regional markets, whereas Subha and Nambi (2010) found no cointegration between the Indian and US markets. Saha and Bhunia (2012), Siddiqui (2009), Veerappa (2016), and Shah et al. (2015) documented different combinations of short-run dependence, long-run relationships, and lead–lag effects. More recent studies continue to report heterogeneous results, reflecting differences in market selection, sample periods, data frequency, and econometric methodology (Keshari & Gautam, 2024; Sachdeva et al., 2021).

The mixed evidence is important because India's financial integration has deepened during a period of substantial institutional and macro-financial transformation. A long sample can therefore provide useful evidence on the average pattern of integration, while also increasing the likelihood of structural breaks and regime heterogeneity.

Volatility Spillovers and Dynamic Dependence

A further strand of the literature focuses on volatility rather than only price-level co-movement. DCC-GARCH models are useful because they allow conditional correlations to vary over time and can therefore capture changes in cross-market dependence that are not visible in unconditional correlations (Engle, 2002). Evidence for India and international markets also documents time-varying volatility dependence and stronger linkages during periods of market stress (Alam et al., 2020).

It is important, however, to distinguish dynamic conditional correlation from a directional spillover measure. DCC-GARCH characterizes time-varying conditional covariance and correlation; by itself, it does not establish the direction or magnitude of variance transmission in the sense of a forecast-error variance decomposition. Accordingly, this study uses the term "volatility spillover" in the broader sense of time-varying volatility dependence and avoids claims about directional transmission.

Methodological Approaches and Research Gap

The existing literature applies correlation analysis, unit-root and cointegration tests, Granger causality, VAR/VECM frameworks, GARCH-family models, wavelet methods, and copula-based approaches. Each method addresses a different empirical question. Correlation summarizes average linear dependence; Granger testing evaluates incremental predictive content; cointegration identifies common long-run stochastic trends; GMM estimates conditional associations under specified moment conditions; and DCC-GARCH models time-varying conditional dependence.

The present study addresses a gap through the combination of long daily coverage and multiple complementary dimensions of integration. It covers 33 years, from 1991 to 2023, and simultaneously evaluates unconditional dependence, dynamic conditional correlation, predictive precedence, long-run cointegration, and conditional associations. Existing studies report inconsistent findings and differ substantially in market selection and methodology. The empirical contribution of this study is therefore to provide an integrated assessment of India's market interdependence without claiming a structural causal mechanism.

The study aims to investigate the short-run and long-run dependence of the Indian stock market on nine major global and regional markets: Australia, Belgium, France, Germany, Hong Kong, Indonesia, Japan, Singapore, and the United States. More specifically, it evaluates unconditional and dynamic dependence, Granger predictive precedence, long-run cointegration, and the persistence of conditional correlations.

2. Methodology

2.1. Data, Market Selection and Synchronization

Daily stock-index data for India and the selected comparator markets from 1 January 1991 to 31 December 2023 were obtained primarily from Prowess IQ, with supplementary market-price data drawn from the sources reported by the authors. Daily data are appropriate for capturing rapid information diffusion and both short-run and long-run market linkages (Hassan & Naka, 1996; Voronkova, 2004). The Indian market is represented by the BSE Sensex; the comparator indices are the S&P/ASX 200 (Australia), BEL 20 (Belgium), CAC 40 (France), DAX (Germany), Hang Seng Index (Hong Kong), Jakarta Composite Index (Indonesia), Nikkei 225 (Japan), Straits Times Index (Singapore), and Dow Jones Industrial Average (United States).

Because national markets observe different holidays and trading hours, the raw series are not perfectly synchronous. Observations that could not be aligned across markets were removed, resulting in a synchronized sample of 8,318 observations used in the descriptive, correlation, GMM, and Granger analyses. The sample period was selected primarily on the basis of data availability and spans several major episodes of international financial stress.

For return analysis, continuously compounded returns are defined as $r_{it} = 100 \times [\ln(P_{it}) - \ln(P_{i,t-1})]$, where P_{it} is the closing index level. Log index levels, rather than returns, are the appropriate objects for the Johansen cointegration analysis because cointegration concerns non-stationary price-level processes and their stationary linear combinations. This distinction is important for avoiding an inappropriate application of cointegration tests to stationary return series.

2.2. Empirical Strategy

The empirical strategy proceeds in five stages. First, descriptive statistics and unconditional correlations characterize the sample. Second, ADF tests establish the integration properties of the series used in the short-run and long-run analyses. Third, pairwise Granger tests assess predictive precedence using stationary return series. Fourth, the Johansen procedure evaluates long-run cointegration among the log index levels. Fifth, GMM and DCC-GARCH are used to characterize conditional associations and time-varying volatility dependence. The methods are complementary rather than interchangeable.

ADF Test

The Augmented Dickey–Fuller (ADF) test is used to establish the integration properties of the series. The regression is represented in Equation (1).

$$\Delta Y_t = \alpha + \pi t + \delta Y_{t-1} + \sum_{i=1}^{m} \beta_i \, \Delta Y_{t-1} + \varepsilon_t \qquad \text{eq. (1)}$$

The null hypothesis is H0: ρ = 0 (unit root) against H1: ρ < 0 (stationarity), with lag length selected using the Schwarz Information Criterion. Rejection of H0 implies stationarity. The interpretation reported below is based on the first-difference results.

Granger Causality as Predictive Precedence

For two stationary return series Xt and Yt, the pairwise test evaluates whether lagged values of X provide statistically significant incremental information for predicting Y after controlling for lags of Y. The null hypothesis is that the relevant lag coefficients of X are jointly zero. Rejection is described as “X Granger-causes Y” only in the conventional econometric sense; substantively, it means that X exhibits predictive precedence over Y. It does not establish structural causality, contemporaneous causation, or an identified economic transmission mechanism. Equations (2) and (3) represent the corresponding predictive-precedence specifications.

$$Y_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i \, Y_{t-1} + \sum_{j=1}^{n} \beta_j \, X_{t-1} + \varepsilon_t \qquad \text{eq. (2)}$$

$$Y_t = \omega_0 + \sum_{i=1}^{m} \gamma_i \, Y_{t-1} + \sum_{j=1}^{n} \theta_j \, X_{t-1} + \varepsilon_t \qquad \text{eq. (3)}$$

If the lagged coefficients of *X* are jointly significant in the equation for Y, the null hypothesis that *X* does not Granger-predict *Y* is rejected. This result is interpreted as predictive precedence rather than structural causality.

Johansen Cointegration Test

The Johansen trace and maximum-eigenvalue statistics are used to determine the number of cointegrating relations in the multivariate system of log index levels. If the individual price-level series are I(1), a cointegrating vector represents a stationary linear combination and therefore indicates a long-run equilibrium relation. The trace test evaluates H0: r ≤ r0 against H1: r > r0, while the maximum-eigenvalue test evaluates H0: r = r0 against H1: r = r0 + 1.

The trace and maximum-eigenvalue statistics are reported in Equations (4) and (5), respectively.

$$Trace(r, k) = -T \sum_{i=r+1}^{k} \ln(1 - \ddot{e}_i) \qquad \text{eq. (4)}$$

In the trace test, *T* denotes the number of observations and the ordered eigenvalues are used to test the null hypothesis that the number of cointegrating relations does not exceed *r*.

The maximum-eigenvalue statistic compares the null hypothesis of exactly *r* cointegrating relations with the alternative of r + 1 relations.

$$\ddot{e}_{max}(r, r+1) = -Tln(1 - \ddot{e}_{r+1}) \quad \text{eq. (5)}$$

GMM Estimation and Diagnostic Interpretation

GMM is used to estimate conditional associations under specified moment conditions and to obtain inference that is robust to heteroskedasticity and autocorrelation in financial returns. The Hansen J-statistic is interpreted as a test of the over-identifying restrictions: failure to reject the null means that these restrictions are not rejected by the data. It should not be interpreted as proof that the entire model or every instrument is valid. The estimated GMM specification is reported in Equation (6) (Hansen, 1982).

$$G(\emptyset) = 1/n \sum_{i=1}^{n} g(W_i, \emptyset)' W_i g(W_i, \emptyset) \quad \text{eq. (6)}$$

In Equation (6), the parameter vector is estimated from the sample moment conditions using the specified weighting matrix.

Diagnostic tests are reported to assess residual serial correlation and conditional heteroskedasticity. These diagnostics inform the interpretation of the GMM estimates and provide an econometric rationale for modelling volatility with a GARCH-family specification.

2.3. DCC-GARCH(1,1)

The DCC-GARCH framework models time-varying conditional correlations. In the first stage, each return series is assigned a univariate GARCH(1,1) variance equation, as reported in Equation (7).

In the second stage, standardized residuals are used to estimate the dynamic correlation matrix according to the recursion in Equation (8).

$$\sigma(i,t)^{\wedge 2} = \omega_{(i)} + \alpha_{(i)}\varepsilon_{(i,t-1)}^{\wedge 2} + \beta_{(i)}\sigma_{(i,t-1)}^{\wedge 2} \quad \text{eq. (8)}$$

The conditional correlation matrix Rt is obtained by standardizing Qt. The estimated αDCC and βDCC parameters describe the sensitivity of conditional dependence to new information and its persistence. Under the standard specification, αDCC + βDCC < 1 indicates a mean-reverting, non-explosive dynamic-correlation process.

The DCC model in the analysis is symmetric. Therefore, statistically significant α_{DCC} and β_{DCC} coefficients do not, by themselves, demonstrate an asymmetric response of volatility to positive and negative shocks. Any claim of leverage or asymmetric effects would require an explicitly asymmetric specification such as ADCC-GARCH. The revised interpretation therefore treats the reported estimates as evidence of dynamic dependence and persistence, not as evidence of asymmetry.

3. Empirical Results

3.1. Descriptive Statistics and Unconditional Correlations

Appendix Table A1 summarizes the descriptive statistics of stock-market returns over the selected period. The sample mean return is positive for all ten markets, with India recording the highest mean and Japan the lowest. Hong Kong, India, and Japan exhibit comparatively high standard deviations, whereas Belgium and Indonesia show lower dispersion.

Skewness and kurtosis indicate substantial departures from Gaussianity. In particular, all Jarque–Bera p-values are effectively zero; therefore, the null hypothesis of normality is rejected for every series. This pattern is consistent with the heavy-tailed behaviour commonly observed in daily equity returns.

Appendix Table A2 presents the unconditional correlation matrix of daily returns. Pairwise correlations are positive throughout the sample. The strongest correlation is between Singapore and the United States (0.90), while the lowest is between Indonesia and the United States (0.07). India's unconditional correlations with the selected markets are positive but generally lower than the strongest correlations observed among some developed-market pairs. These unconditional statistics motivate the use of DCC-GARCH to examine whether dependence varies over time.

3.2. Dynamic Conditional Correlation

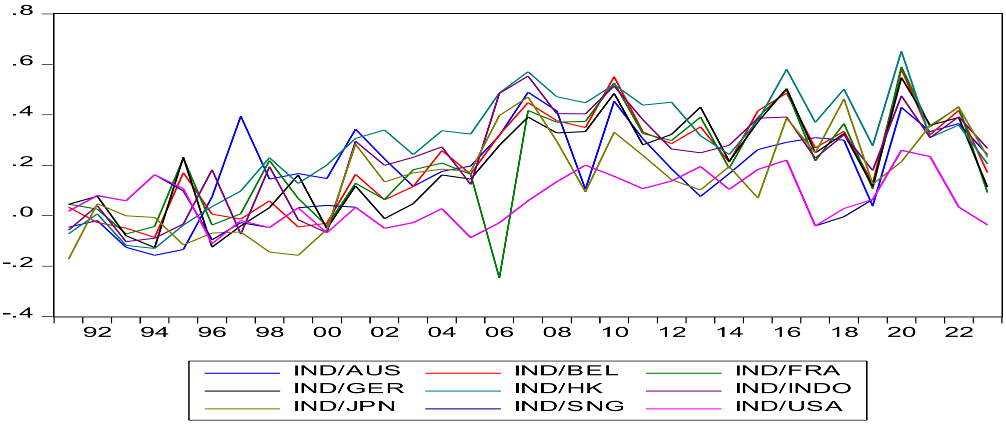
The DCC trend coefficients are positive and statistically significant for all nine India-market pairs. The largest reported trend coefficient is associated with Hong Kong, while the remaining coefficients are positive and comparatively small. The appropriate interpretation is that the conditional correlation between India and each comparator market exhibits a statistically significant upward trend over the sample, not that either market structurally causes the other to move. DCC is a measure of conditional dependence rather than a structural causal parameter. Trade integration and the evolution of bilateral trade may provide contextual explanations, but these mechanisms are not directly tested in the present study. Figure 1 illustrates the co-movement patterns underlying these estimates.

Table 1: Trend Estimates for Dynamic Conditional Correlations between India and Partner Markets

DCC	Co-efficient	Std. Error	t-statistics	Prob.
IND/AUS	0.012954	0.002546	5.088169	0.0000
IND/BELG	0.015251	0.002402	6.349210	0.0000
IND/JPN	0.012431	0.002480	5.011615	0.0000
IND/SING	0.008416	0.001585	5.311732	0.0000
IND/FRANCE	0.013421	0.002600	5.162047	0.0000
IND/GER	0.014173	0.002450	5.784830	0.0000
IND/HK	0.300959	0.010392	28.96147	0.0000
IND/INDO	0.011636	0.002337	4.978799	0.0000
IND/USA	0.008638	0.001656	5.214906	0.0000

Source: Authors' estimate

Figure 1: Co-movement of global and regional stock markets: India and selected partner markets



Source: Authors' elaboration based on the study dataset.

3.3. Stationarity and Predictive Precedence

Table 2 presents the ADF results used to establish the stationarity properties of the selected series.

Table 2: Augmented Dickey–Fuller Test at First Difference

Countries	t- statistics	Prob.
India (Dependent Variable)	-30.01171	0.0000*
Australia	-29.34532	0.0000
Belgium	-30.84081	0.0000
France	-29.26045	0.0000
Germany	-30.12193	0.0000
Hong Kong	-30.78313	0.0000
Indonesia	-30.50410	0.0000
Japan	-30.85291	0.0000
Singapore	-29.93961	0.0000
USA	-30.09271	0.0000
Test Critical Value	1% Level	-3.959143
	5% level	-3.410345
	10% level	-3.126925

Note: MacKinnon (1996) one-sided p-values. H_0: the series has a unit root; H_1: the series is trend-stationary. Lag selection was automatic using SIC. Results are reported at first difference, consistent with I(1) price-level series.

Source: Authors' estimate

The ADF statistics reported at first difference are strongly significant for all ten markets. Thus, the null hypothesis of a unit root is rejected for the first-differenced log index series, supporting I(1) behaviour for the price-level series used in the long-run analysis. The results also justify the use of stationary return series for pairwise Granger testing.

The pairwise Granger results in Table 3 show a heterogeneous pattern of predictive precedence. Bidirectional predictive precedence is observed between India and Australia, Belgium, Hong Kong, Japan, Singapore, and the United States. France and Germany exhibit predictive precedence toward India, while the reverse null is not rejected. Indonesia displays the opposite pattern: the null that Indonesia does not predict India is not rejected, whereas the null that India does not predict Indonesia is rejected. These findings indicate heterogeneous predictive-information patterns across markets rather than a uniform causal hierarchy.

Table 3: Pairwise Granger Predictive-Precedence Tests (Two Lags)

Null Hypothesis:	Sign	F-Statistic	Prob.	Decision
Australia (AUS) does not granger causes India	AUS→IND	3.45089	0.0318	Reject H_0
India (IND) does not granger cause Australia	IND→AUS	34.9672	0.0000	Reject H_0
Belgium (BEL) does not granger cause India	BEL→IND	32.5148	0.0000	Reject H_0
India (IND) does not granger cause Belgium	IND→BEL	3.50049	0.0302	Reject H_0
France (FRN) does not granger cause India	FRN→IND	42.2040	0.0000	Reject H_0
India (IND) does not granger cause France	IND↛FRN	0.04861	0.9526	Accept H_0
Germany (GER) does not granger cause India	GER→IND	44.3779	0.0000	Reject H_0
India (IND) does not granger cause Germany	IND↛GER	0.66256	0.5156	Accept H_0

Null Hypothesis:	Sign	F-Statistic	Prob.	Decision
Hong Kong (HK) does not granger cause India	HK→IND	3.04490	0.0477	Reject H_0
India (IND)does not granger cause Hong Kong	IND→HK	17.3201	0.0000	Reject H_0
Indonesia (INDO) does not granger cause India	INDO↛IND	0.59969	0.5490	Accept H_0
India (IND) does not granger cause Indonesia	IND→INDO	6.46734	0.0016	Reject H_0
Japan (JPY) does not granger cause India	JPY→IND	6.05170	0.0024	Reject H_0
India (IND) does not granger cause Japan	IND→JPY	62.4855	0.0000	Reject H_0
Singapore (SING) does not granger cause India	SING→IND	88.0718	0.0000	Reject H_0
India (IND)does not granger cause Singapore	IND→SING	4.26018	0.0142	Reject H_0
USA does not granger cause India	USA→IND	90.2223	0.0000	Reject H_0
India (IND) does not granger cause USA	IND→USA	4.50250	0.0111	Reject H_0

Note: 8316 Observations were made

Source: Authors' estimates. H_0: *X* does not Granger-predict *Y*. Rejection is interpreted as predictive precedence, not structural causality.

3.4. Long-Run Cointegration

The Johansen trace statistic rejects the null of no cointegration and the null of at most one cointegrating relation at the 5% level, while the null of at most two is not rejected. The maximum-eigenvalue statistic produces the same rank decision. Thus, the reported multivariate system contains two cointegrating relations at the 5% level. This provides evidence of long-run common stochastic trends among the selected index levels. The complete Johansen rank-test output is reported in Appendix Table A3.

The presence of cointegration has an important portfolio interpretation. Although short-run price deviations may create diversification opportunities, the existence of common long-run trends means that the selected markets cannot be treated as permanently independent sources of risk. Cointegration should not, however, be interpreted as proof that all markets move in the same direction on every day or that a particular market structurally causes another.

The two cointegrating relations indicate common long-run stochastic trends among the selected equity indices. This result suggests that the markets are not permanently independent sources of risk and that long-horizon diversification benefits may be constrained when common trends dominate. The finding is consistent with studies reporting stronger integration of the Indian market with international markets (Dhankhar et al., 2025; Siddiqui, 2009), but differs from studies reporting no long-run equilibrium relationship (Patel, 2013). Cointegration itself does not identify the direction of influence or establish that one market structurally causes another.

Table 4: GMM Estimates for the Indian Stock-Market Return Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.049403	0.015368	3.214784	0.0013
AUSTRALIA	0.140167	0.030336	4.620541	0.0000
BELGIUM	0.082236	0.028395	2.896159	0.0038
FRANCE	0.068465	0.023834	2.872555	0.0041
GERMANY	0.031623	0.023368	1.353248	0.1760
HONG_KONG	0.148194	0.017434	8.500504	0.0000
INDONESIA	0.138284	0.018531	7.462333	0.0000
JAPAN	0.036375	0.016546	2.198418	0.0279

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SINGAPORE	0.049722	0.022028	2.257276	0.0240
USA	-0.021737	0.022131	-0.982179	0.3260
AR (1)	0.052261	0.020788	2.514026	0.0120
R-squared	0.151634		Mean dependent var	0.062321
Adjusted R-squared	0.150613		S.D. dependent var	1.521418
S.E. of regression	1.402173		Sum squared resid	16330.33
Durbin-Watson stat	2.018391		J-statistic	14.31933
Instrument rank	20		Prob(J-statistic)	0.111411
			Inverted AR Roots	0.05

Source: Authors' estimates. Hansen J-test p-value = 0.111411; failure to reject the over-identifying restrictions is treated as a specification diagnostic, not as proof of overall model validity.

3.5. GMM Estimates

Table 4 reports the GMM estimates for the Indian stock-market return equation. The Hansen J-statistic is used as a diagnostic for the over-identifying restrictions rather than as a general measure of model fit.

The GMM estimates show statistically significant positive coefficients for Australia, Belgium, France, Hong Kong, Indonesia, Japan and Singapore. Germany has a positive but statistically insignificant coefficient, while the United States has a negative but statistically insignificant coefficient. The coefficient signs should be interpreted as conditional associations within the specified GMM equation and not as structural causal effects.

The Hansen J-statistic is 14.31933 with a p-value of 0.111411. Therefore, the null hypothesis associated with the over-identifying restrictions is not rejected at conventional significance levels. This result is consistent with the maintained moment restrictions, but it does not establish that every instrument is individually valid or that the specification is immune to all forms of misspecification. The reported serial-correlation diagnostics also indicate that residual dependence remains in the estimated equation, which reinforces the importance of robust inference and cautious interpretation.

The negative US coefficient is statistically insignificant and therefore should not be assigned a substantive economic mechanism on the basis of this regression alone. Possible explanations include differences in trading hours, common global factors, model specification, or time-varying transmission; however, these hypotheses are not directly tested in the present model.

3.6. Diagnostic Tests

The Breusch–Godfrey LM test rejects the null hypothesis of no serial correlation up to order two. The Ljung–Box statistics are also significant at the reported lags. The ARCH test strongly rejects the null of homoskedasticity. These diagnostics confirm that serial dependence and conditional heteroskedasticity are relevant features of the data.

Table 5: Breusch-Godfrey Serial Correlation LM Test:

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	11.43442	Prob. F(2,8306)	0.0000
Obs*R-squared	22.83901	Prob. Chi-Square(2)	0.0000

H_0: There is no serial correlation in the residuals up to the specified order;

H_1: There is serial correlation in the residuals up to the specified order

The test rejects the null hypothesis of no serial correlation up to order two ($p < 0.05$). The LM and Ljung–Box diagnostics therefore indicate residual serial dependence.

Table 6: Ljung–Box Autocorrelation Diagnostics

Lag	AC	PAC	Q-Stat(k)	Prob*
1	0.042	0.042	14.554	0.000
5	0.005	0.005	22.247	0.000
10	0.030	0.027	66.931	0.000
15	0.022	0.025	75.855	0.000
20	0.005	0.010	90.374	0.000
25	-0.029	-0.032	98.499	0.000
30	-0.009	-0.009	101.88	0.000
35	-0.016	-0.015	107.91	0.000

Note: Q(k) denotes the Ljung–Box statistic at lag k after adjustment for the number of estimated parameters.

In each case, 36 lags are taken into account, and only the Q-Stat (k) values accompanied by lags 7, 10, 15, 20, 25, 30, and 35 have been reported. From the Ljung-Box statistic values in the above Table, we see that significant autocorrelation has been noticed for standardised residuals in the entire period. The reported Ljung–Box statistics are statistically significant at the reported lags, indicating residual autocorrelation over the sample period.

Table 7: ARCH Heteroscedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	464.7662	Prob. F(1,8315)	0.0000
Obs*R-squared	440.2692	Prob. Chi-Square (1)	0.0000

Source: Authors’ estimate

H_0: There is no heteroscedasticity i.e., variance for the errors is equal.

In math terms, that's:

$H_0 = \sigma^2{}_1 = \sigma^2$;$H_1$: There is heteroscedasticity i.e., variance for the errors is not equal. In math terms, that's:$H_1 = \sigma^2{}_1 \neq \sigma^2$

The ARCH test rejects the null hypothesis of homoskedasticity ($p < 0.05$), indicating conditional heteroskedasticity and volatility clustering. This provides an econometric rationale for using GARCH-family models for volatility dynamics and for avoiding reliance on conventional homoskedastic OLS standard errors.

The ARCH Heteroskedasticity Test rejects the null hypothesis of no heteroscedasticity because the p-value is smaller than 0.05. [$p<0.05$]. So, we reject null hypothesis of no heteroscedasticity. The Q-statistic and also LM test both indicate that the residuals are heteroskedastic and therefore variances for the errors are not equal. So, there exists volatility clustering. This provides an econometric rationale for using GARCH-family models for volatility dynamics and for avoiding reliance on conventional homoskedastic OLS standard errors.

3.7. DCC-GARCH(1,1) Estimates

Table 8 shows the results of DCC-GARCH (1.1) model estimated to evaluate whether there is time-varying conditional correlation between the Indian stock market and other 9 global stock markets' volatility. All reported αDCC and βDCC estimates are positive and statistically significant. The sums of αDCC and βDCC range from 0.9841 to 0.9976, remaining below one for every India-market pair. The estimates therefore indicate strong persistence in dynamic conditional dependence: shocks to the conditional correlation decay slowly rather than disappearing immediately. The United States pair has the largest reported αDCC (0.09021), suggesting relatively greater sensitivity of the conditional correlation to recent standardized innovations, whereas the Hong Kong pair has the smallest αDCC (0.05803).

The β_{DCC} coefficients are high across all pairs, ranging from 0.89872 to 0.93660. This indicates that the conditional-correlation process is dominated by persistence. Because the model is symmetric, however, the estimates do not establish that positive and negative shocks have different effects.

Table 8: DCC-GARCH(1,1) Estimates

Stock exchange (Country)	αdcc	αdcc: t value	αdcc: p value	βdcc	βdcc: t value	βdcc: p value	Sum of estimates
IND/AUS	0.07989	10.3852	0.0000	0.91775	130.7774	0.0000	0.9976
IND/BELG	0.08202	13.4371	0.0000	0.91416	159.8766	0.0000	0.9962
IND/JPN	0.08061	13.2604	0.0000	0.91589	161.1540	0.0000	0.9965
IND/SING	0.08304	24.3839	0.0000	0.91423	293.7074	0.0000	0.9973
IND/FRANCE	0.08129	24.9255	0.0000	0.91627	311.2199	0.0000	0.9976
IND/GER	0.08275	19.1044	0.0000	0.90138	177.1358	0.0000	0.9841
IND/HK	0.05803	20.2084	0.0000	0.93660	291.2517	0.0000	0.9946
IND/INDO	0.07688	24.0911	0.0000	0.92069	324.1646	0.0000	0.9976
IND/USA	0.09021	20.5996	0.0000	0.89872	191.3627	0.0000	0.9889

Source: Authors' estimate; α_{DCC} and β_{DCC} are the DCC persistence parameters; $\alpha_{DCC} + \beta_{DCC} < 1$ for all reported pairs

4. Discussion

The findings provide a multidimensional picture of India's integration with global and regional equity markets. Positive unconditional correlations and positive DCC trends indicate that the Indian market is connected to the selected international markets in terms of both average and conditional dependence. This result is consistent with studies documenting growing international financial integration, although the magnitude and direction of specific relationships vary across studies and sample periods.

The Granger results add an important short-run dimension. Bidirectional predictive precedence involving Australia, Belgium, Hong Kong, Japan, Singapore, and the United States suggests that information in these markets contains incremental predictive content for Indian returns and that Indian returns also contain predictive content for those markets within the chosen lag structure. The unidirectional patterns involving France, Germany, and Indonesia show that integration is heterogeneous. These findings are broadly consistent with literature reporting varied lead–lag relationships across international markets.

The two cointegrating relations indicate that the markets share common long-run stochastic trends. This supports studies that find long-run integration between India and international markets but differs from studies reporting no cointegration. Differences may arise from the sample period, index choice, data frequency, treatment of non-synchronous observations, and structural changes. The result should therefore be interpreted as evidence of long-run co-movement over the full sample rather than evidence that the relationship is stable in every sub-period.

The DCC-GARCH results reinforce this interpretation by showing that conditional dependence is highly persistent. For investors, persistent cross-market dependence means that diversification benefits can be state-dependent: opportunities may exist when conditional correlations are relatively low, but they can diminish when common volatility rises. For financial stability, persistent conditional dependence means that shocks in one major market may coincide with or be followed by elevated dependence elsewhere, although DCC estimates alone do not identify a directional structural transmission channel. Overall, the evidence depicts Indian financial integration as substantial but heterogeneous. The study extends earlier work by showing that average correlation, predictive precedence, long-run cointegration, and dynamic volatility dependence are related but empirically distinct dimensions of integration.

5. Policy and Governance Implications

The findings have several implications for regulators and market institutions. First, persistent dynamic dependence supports continuous cross-market surveillance. Indian regulators and market institutions should monitor international market indicators alongside domestic measures of volatility, liquidity, and market stress rather than treating domestic risk as fully isolated.

Second, the existence of long-run cointegration and high DCC persistence suggests that systemic-risk monitoring should incorporate cross-border dependence. Stress-testing frameworks can include scenarios involving simultaneous or sequential shocks in major global markets, particularly the United States and Asian markets with which India exhibits strong predictive and dynamic interactions.

Third, the findings support stronger information-sharing and coordination among financial authorities, exchanges, and market infrastructures. Cross-border surveillance arrangements can help identify rapid changes in conditional correlations and potential amplification of volatility. Macroprudential authorities may also use such indicators as complementary early-warning measures, while recognizing that correlation does not establish the direction of contagion.

Fourth, portfolio and risk-management institutions should avoid relying exclusively on unconditional historical correlations when assessing international diversification. Dynamic correlation measures provide a more informative assessment of how diversification benefits may change across market conditions. The evidence also supports stress scenarios in which correlations rise sharply during crisis periods.

Finally, policy analysis should distinguish statistical predictability from structural causation. Granger results can inform forecasting and surveillance, but they should not be used alone to support claims about the economic mechanism through which one market affects another.

Conclusion

This study assesses India's integration with nine major global and regional equity markets over 1991–2023 using complementary measures of unconditional dependence, predictive precedence, long-run cointegration, and dynamic conditional correlation. The results show positive unconditional correlations and positive DCC trends for all India-market pairs. Pairwise Granger tests reveal heterogeneous predictive-precedence patterns, including bidirectional relationships with Australia, Belgium, Hong Kong, Japan, Singapore, and the United States. The Johansen procedure indicates two long-run cointegrating relations in the multivariate system. GMM estimates show significant positive conditional associations for seven markets, while Germany and the United States are statistically insignificant. DCC-GARCH estimates show very high persistence in conditional dependence across all pairs.

The central implication is that India's stock market is substantially integrated with the selected international markets, but integration is neither uniform nor equivalent across econometric dimensions. Long-run common trends and persistent conditional dependence may constrain international diversification during periods of elevated common risk, while short-run predictive relationships may still provide forecasting and portfolio-allocation opportunities.

The study contributes by combining a long daily sample with several complementary econometric approaches and by explicitly separating correlation, predictive precedence, cointegration, and dynamic volatility dependence. For regulators, the findings support cross-border market surveillance, stress testing, and systemic-risk monitoring. For investors, they emphasize the importance of state-dependent correlation rather than reliance on unconditional historical correlation alone. These conclusions should nevertheless be interpreted in light of structural breaks, non-synchronous trading, market selection, and the absence of a directional volatility-spillover model.

The findings should be interpreted in light of several limitations. The 1991–2023 sample spans major institutional and financial regime changes, including the Asian financial crisis, the global financial crisis, the COVID-19 shock, and subsequent market restructuring; full-sample estimates may therefore mask structural breaks and regime-dependent relationships. Although non-aligned observations were removed, residual non-synchronous trading and time-zone effects may remain. The analysis is also limited to nine comparator markets and a symmetric DCC-GARCH specification, which does not test asymmetric responses to positive and negative shocks. Finally, Granger predictive precedence should not be interpreted as structural causality, and the DCC framework used here does not identify directional volatility transmission.

Future research should examine formal structural breaks, regime shifts, crisis-specific dependence, and lag-adjusted or overlapping trading-window measures. Extending the market set to other emerging markets, commodity and bond markets, exchange rates, and sectoral indices would provide a broader assessment of connectedness. Asymmetric volatility responses could be evaluated using ADCC-GARCH, while directional transmission could be examined through Diebold–Yilmaz connectedness measures, VAR-GARCH systems, or related variance-decomposition frameworks. Identified structural VARs, high-frequency event studies, external instruments, and network-based systemic-risk measures could further clarify transmission mechanisms beyond predictive precedence.

Credit Authorship Contribution Statement

Firdous, A: data collection; econometric and statistical analysis; visualization. Ray, B.: conceptualization; literature review; writing - original draft; writing - review and editing. Both authors approved the final revised version. Both authors contributed substantially to the study, reviewed the final manuscript, and approved it for submission.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval Statement

Not applicable. This study uses secondary financial-market data and does not involve human participants, personal data, animals, or interventions requiring ethical approval.

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Appendix A. Supplementary Statistical Results

Table A1: Descriptive Statistics of Stock-Market Returns, 1991–2023

Statistic	India	Australia	Belgium	France	Germany	Hongkong	Indonesia	Japan	Singapore	USA
Mean	0.061751	0.022269	0.017918	0.024749	0.032705	0.022777	0.039401	0.016082	0.051564	0.050742
Median	0.020058	0.028334	0.013093	0.013358	0.035247	0.000000	0.000000	0.000000	0.073177	0.071744
Maximum	17.33933	6.561077	9.783475	11.17617	11.40195	18.82360	14.02833	14.15031	14.17320	14.17320
Minimum	-13.15258	-9.524746	-14.21066	-12.27677	-12.23861	-13.70044	-11.95493	-11.40637	-12.32133	-12.32133
Std. Dev.	1.522214	0.925278	1.139246	1.347378	1.367080	1.530966	1.354156	1.402026	1.467128	1.474572
Skewness	0.093215	-0.624809	-0.139758	-0.046300	-0.067468	0.295186	0.057337	-0.053582	-0.012254	-0.004561
Kurtosis	11.82972	11.06853	12.41987	9.071858	9.301355	13.41279	13.82337	8.822848	9.889143	9.765155
Jarque-Bera	27,033.07	23,104.18	30,780.81	12,780.62	13768.12	37,699.48	40,605.17	11,755.08	16,449.15	15,862.22
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	513.6426	185.2358	149.0413	205.8635	272.0366	189.4614	327.7394	133.7711	428.9105	422.0761
Sum Sq. Dev.	19,271.61	7,120.508	10,794.48	15,098.92	15,543.72	19,493.86	15,251.20	16,348.55	17,902.05	18,084.17
Observations	8,318	8,318	8,318	8,318	8,318	8,318	8,318	8,318	8,318	8,318

Source: Authors' estimates from the study dataset.

Table A2: Unconditional Correlation Matrix of Daily Returns, 1991–2023

Countries	India	Australia	Belgium	France	Germany	Hongkong	Indonesia	Japan	Singapore	USA
India	1.00									
Australia	0.27	1.00								
Belgium	0.26	0.31	1.00							
France	0.26	0.31	0.71	1.00						
Germany	0.24	0.29	0.75	0.77	1.00					
Hongkong	0.30	0.51	0.30	0.32	0.28	1.00				

Countries	India	Australia	Belgium	France	Germany	Hongkong	Indonesia	Japan	Singapore	USA
Indonesia	0.24	0.29	0.21	0.18	0.19	0.36	1.00			
Japan	0.19	0.42	0.25	0.21	0.24	0.35	0.19	1.00		
Singapore	0.13	0.13	0.35	0.38	0.42	0.14	0.08	0.09	1.00	
USA	0.12	0.13	0.35	0.38	0.42	0.13	0.07	0.08	0.90	1.00

Source: Authors' estimates from the study dataset.

Table A3: Johansen Cointegration Rank Test

Unrestricted Co-integration Rank Test (Trace)					Unrestricted Co-integration Rank Test (Maximum Eigen value)				
Hypothesized No. of CE(s)	Eigen value	Max-Eigen Statistic	0.05 Critical Value	Prob.**	Hypothesized No. of CE(s)	Eigen value	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.977168	316.5912	179.509	0.0000	None *	0.97716	117.1678	54.96577	0.0000
At most 1 *	0.905095	199.4234	143.669	0.0000	At most 1 *	0.90509	73.00126	48.87720	0.0000
At most 2	0.712178	126.4222	111.780	0.0742	At most 2	0.71217	38.60779	42.77219	0.1342
At most 3	0.639309	87.81439	83.9371	0.1255	At most 3	0.63930	31.61174	36.63019	0.1716
At most 4	0.537522	56.20266	60.0614	0.1014	At most 4	0.53752	23.90586	30.43961	0.2609
At most 5	0.356760	32.29680	40.1749	0.2463	At most 5	0.35676	13.67833	24.15921	0.6308
At most 6	0.269238	18.61846	24.2759	0.2189	At most 6	0.26923	9.723708	17.79730	0.5147
At most 7	0.242240	8.894753	12.3209	0.1753	At most 7	0.24224	8.599040	11.22480	0.1397
At most 8	0.009494	0.295713	4.12990	0.6479	At most 8	0.00949	0.295713	4.129906	0.6479
Trace test indicates 2 cointegrating eqn(s) at the 0.05 level					Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level					* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values					**MacKinnon-Haug-Michelis (1999) p-values				

Note: H_0 specifies the cointegration rank indicated in the table. The trace and maximum-eigenvalue tests indicate two cointegrating relations at the 5% significance level.

Source: Authors' estimate