

Multi-Horizon Interdependence between Macroeconomic Conditions and Stock Market Volatility: Comparative Evidence from Developing Economies

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Abstract- This study examines the multi-horizon interdependence between macroeconomic conditions and stock market volatility in two major developing economies, India and China, using annual data for the period 1991 to 2024. The analysis incorporates key macroeconomic indicators, namely Gross Domestic Product (GDP), inflation, exports, imports, and gross capital formation, together with stock market indices represented by the NIFTY 50 and SSE Composite Index. The dataset is obtained from the World Bank DataBank and investing.com, ensuring consistency and reliability across countries. The study adopts a comprehensive econometric framework by first applying Unit Root tests to determine the stationarity properties of the variables, followed by the Johansen Cointegration test to examine the existence of long-run equilibrium relationships between macroeconomic fundamentals and stock market movements. The Vector Error Correction Model (VECM) is subsequently employed to capture both short-run dynamics and long-run adjustments. To further explore time-varying interactions across different frequencies and investment horizons, Wavelet Coherency Analysis is utilized to identify co-movements, lead-lag relationships, and volatility transmission mechanisms between macroeconomic factors and stock markets. The findings are expected to reveal significant long-run integration and heterogeneous time-frequency dependencies, with GDP, trade activities, and capital formation exerting stronger influences over medium- and long-term horizons, while inflation predominantly affects short-term volatility. The study contributes to the literature by providing comparative evidence on macro-financial linkages in developing economies and offers valuable implications for policymakers, investors, and financial market regulators.

Keywords- GDP, Inflation, Export, Volatility, Stock market, Johansen Cointegration, VECM JEL Classification: C32, C58, G15, O53.

I. INTRODUCTION

The intricate relationship between macroeconomic fundamentals and financial market dynamics has long constituted a central preoccupation of both theoretical and empirical finance, yet the temporal complexity of this relationship remain particular across heterogeneous economic environments, which remains insufficiently understood. Classical asset pricing frameworks, from the Capital Asset Pricing Model to the Arbitrage Pricing Theory, posit that systematic macroeconomic forces such as inflation, output growth, interest rates, and monetary policy transmissions are embedded within equilibrium asset valuations; however, these models largely operate under the assumption of homogeneous investor horizons and linear market structures, thereby

obscuring the multi-scale nature of nexus in the macroeconomy volatility (Fama, 1981; Chen, Roll & Ross, 1986). The limitations of such frameworks become especially pronounced when applied to developing economies, where structurally fragile institutions, shallow capital markets, heightened susceptibility to external shocks, and asymmetric information environments collectively generate volatility dynamics that fundamentally diverge from those documented in advanced financial systems (Bekaert & Harvey, 1997; Ang & Bekaert, 2002). Against this backdrop, the need for a multi-horizon analytical lens that can simultaneously capture short-run speculative turbulence and long-run structural co-movements has become increasingly urgent, motivating the methodological innovations undertaken in the present study.

The heterogeneity inherent in developing economies extends beyond market microstructure to encompass the very transmission channels through which macroeconomic shocks propagate into equity markets, rendering cross-country comparative analysis both empirically necessary and methodologically demanding. Extant literature has documented that inflation uncertainty, exchange rate instability, and fiscal imbalances exert disproportionately amplified effects on stock return volatility in emerging and frontier markets relative to their developed counterparts, yet these findings predominantly rely upon time-domain linear econometric techniques that conflate dynamics operating across fundamentally different frequencies (Morales, 2008; Hammoudeh & Li, 2008; Cherif & Gazdar, 2010).

The wavelet decomposition framework and related multi-scale methodologies offer a theoretically coherent alternative by disentangling the covariance structure between macroeconomic variables and market volatility at distinct temporal scales, thereby respecting the heterogeneous investment horizons of market participants ranging from high-frequency traders to long-horizon institutional investors (Gençay, Selçuk & Whitcher, 2005; In & Kim, 2013). Moreover, the interdependence between macroeconomic conditions and stock volatility is not merely unidirectional; feedback mechanisms through the Tobin's q channel, the wealth effect, and forward-looking expectations imply a dynamic simultaneity that standard single-equation frameworks are ill-equipped to accommodate without severe endogeneity bias (Levine & Zervos, 1998; Kilian & Park, 2009). It is precisely this multi-dimensional interdependence like spanning causal direction, temporal horizon, and cross-country heterogeneity through present study systematically interrogates.

This paper contributes to the burgeoning literature on macro-financial linkages in developing economies by offering a rigorously comparative, multi-horizon empirical investigation of the dynamic interdependence between key macroeconomic indicators and stock market volatility across a panel of developing nations. Specifically, the study employs a suite of complementary time-frequency methodologies, such as including wavelet coherence analysis, maximal overlap discrete wavelet transforms (MODWT) decomposition, and wavelet-based Granger causality to disentangle short-, medium-, and long-run interdependencies that are systematically masked by conventional time-domain approaches. The comparative design enables the identification

of both universal cross-country patterns and economy-specific divergences that carry meaningful implications for portfolio risk management, monetary policy formulation, and the design of macroprudential regulatory frameworks in the developing world (Bouri et al., 2018; Rua & Nunes, 2009). Furthermore, by embedding the empirical analysis within a theoretical synthesis that integrates the efficient market hypothesis, behavioral finance perspectives, and macroeconomic uncertainty paradigms, the study advances an integrated analytical narrative rather than a purely data-driven exercise.

The remainder of the paper proceeds as follows: Section 2 reviews the relevant theoretical and empirical literature; Section 3 describes the data and econometric methodology; Section 4 presents and interprets the empirical results; and Section 5 concludes with policy implications and directions for future research.

II. REVIEW OF LITERATURE

The relationship between macroeconomic conditions and stock market volatility has been extensively investigated since the seminal contributions of Fama (1981), who argued that macroeconomic fundamentals significantly influence stock market performance through their effects on expected cash flows and discount rates. Early empirical studies by Chen, Roll and Ross (1986) identified inflation, industrial production, interest rates, and risk premiums as key determinants of stock returns. Subsequently, Mukherjee and Naka (1995) employed Johansen cointegration techniques and reported a positive long-run relationship between stock prices and industrial production, while exchange rates and inflation exhibited negative effects. Similarly, Maysami and Koh (2000) found that stock markets are cointegrated with macroeconomic variables, suggesting that economic fundamentals shape long-term market behavior. These studies collectively established the existence of a positive long-run linkage between economic growth indicators and stock market performance, laying the foundation for later cointegration and error-correction analyses.

Plethora of research work attempted to examine the weak macroeconomic effects of adverse macroeconomic conditions on stock market volatility. Gan, Lee, Yong and Zhang (2006) reported that inflation and interest rate shocks negatively affected stock market returns. Likewise, Humpe and Macmillan (2009) found that inflation exerts a detrimental influence on

stock prices, whereas industrial production contributes positively. In emerging economies, Pal and Mittal (2011) demonstrated that inflation and interest rates increase market uncertainty and volatility. Studies by Tripathi and Kumar (2014) and Khan and Billah (2023) further confirmed that inflationary pressures, exchange-rate depreciation, and monetary instability adversely affect stock market returns and increase volatility, particularly in developing economies. These findings suggest that unfavorable macroeconomic environments can weaken investor confidence and amplify market fluctuations.

A substantial and growing body of empirical scholarship confirms robust long-run cointegrating relationships between macroeconomic fundamentals and stock market volatility, particularly in developing economies using Johansen's multivariate cointegration test and VECM methodology. Adam and Tweneboah (2008) examined the role of macroeconomic variables on stock price movement in Ghana and concluded that cointegration exists between identified macroeconomic variables and stock prices, indicating a long-run relationship. Parallel evidence emerges from South Asian markets, where using monthly time series data and employing the ADF unit root test, Johansen cointegration test, VECM, and Granger causality analysis, results confirm that macroeconomic variables are cointegrated with stock prices, suggesting the presence of a long-run relationship, with the pairwise Granger causality test indicating that exchange rate, money supply, and short-term interest rate Granger-cause stock prices. More recently, (Karki et al. 2024 and Thapa 2023) examined how key macroeconomic variables including exchange rate, money supply, remittances, and GDP significantly influence the Nepalese market, with implications for investors, policymakers, and financial analysts in understanding market behaviour. Collectively, these findings validate the Arbitrage Pricing Theory (APT) and assert that macroeconomic information is systematically priced into equity valuations across developing economies over multiple horizons.

A third stream of literature emphasizes the bidirectional relationship between macroeconomic variables and stock market volatility. Using Vector Error Correction Models (VECM), Mukhopadhyay and Sarkar (2003) found feedback effects between stock prices and macroeconomic indicators. Similarly, Adam and Tweneboah (2008) documented bidirectional causality between stock market development and macroeconomic performance. Later, Pradhan, Arvin and

Bahmani (2015) showed that stock market activity and economic growth reinforce each other through dynamic interactions. More recent evidence from developing and emerging markets by Adekoya and Oliyide (2021) and Maleki (2024) indicates that macroeconomic shocks and stock market volatility exhibit mutual transmission mechanisms across different economic cycles and market conditions. These findings support the view that stock markets not only respond to macroeconomic changes but also serve as leading indicators of future economic performance.

Despite substantial empirical evidence, several research gaps remain. First, most earlier studies concentrated on single-country analyses and conventional time-domain approaches, limiting cross-country comparability among developing economies. Second, the majority of research examined either stock returns or stock prices rather than stock market volatility as a distinct measure of market uncertainty. Third, although Unit Root Tests, Johansen Cointegration, and VECM models have been widely employed, limited attention has been given to comparing long-run equilibrium and short-run adjustment dynamics simultaneously across multiple developing economies over extended periods. Fourth, recent studies have largely focused on post-crisis episodes or individual macroeconomic indicators, overlooking the multi-dimensional interactions among inflation, interest rates, exchange rates, money supply, and economic growth. Finally, evidence up to 2024 remains fragmented regarding whether positive, negative, and bidirectional relationships vary across different developing economies and economic regimes. Therefore, the present study contributes to the literature by examining the multi-horizon interdependence between macroeconomic conditions and stock market volatility in developing economies using Unit Root Tests, Johansen Cointegration, and VECM models, thereby providing a comprehensive understanding of both long-run equilibrium relationships and short-run adjustment mechanisms over an extended period.

III. DATA AND METHODOLOGY

This study investigates the multi-horizon interdependence between macroeconomic conditions and stock market volatility in two major developing economies, India and China, over the period 1991-2024 using annual time-series data. The macroeconomic variables considered include Gross Domestic Product (GDP), Inflation, Exports of Goods and Services, Imports of Goods and Services, and Gross Capital Formation,

while stock market performance is represented by the NIFTY 50 Index for India and the SSE Composite Index for China. Macroeconomic data are collected from the official World Bank DataBank database, whereas stock market index data are obtained from www.investing.com.

The selected variables are widely recognized as key indicators of economic activity, external sector performance, investment behavior, and market development. Prior to empirical estimation, all variables are transformed into their natural logarithmic form, except inflation, to reduce heteroscedasticity and improve normality. Stationarity properties of the series are examined using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to determine their order of integration. Following confirmation of non-stationarity at levels and stationarity at first differences, the Johansen Cointegration Test is employed to identify the existence of long-run equilibrium relationships among macroeconomic variables and stock market indices. Where cointegration is established, a Vector Error Correction Model (VECM) is estimated to capture both the short-run dynamic adjustments and long-run causal interactions among the variables. The combined application of Unit Root Tests, Johansen Cointegration, and VECM provides a comprehensive framework for understanding the dynamic and time-varying interactions between macroeconomic fundamentals and stock market behavior in developing economies.

Methodology

One of the prominent methods adopted in any time series data is to check the stationary or non-stationary of the series by employing Augmented Dickey Fuller test and Phillip Perron test. Since, the estimated errors should be statistically significant and not heteroscedasticity in nature. Therefore, the barriers in calculating the residuals ϵ_t should be risk free from the autocorrelation function and lead to invalidate the test.

Johansen Cointegration test

The present work tries to explore the presence of casual nexus between macroeconomic variable and stock market volatility for India and China by using Johansen Cointegration Maximum likelihood approach for testing the presence of the Cointegrating vector of the series Johansen (1991). The method adopted for estimating the equation is given below

$$X_t = A_0 + \sum_{i=1}^P A_i X_{t-i} + \epsilon_t$$

Where, X_t is a vector of the non-stationarity series in the variables A_0 is the constant terms associated with the variable. The disseminated information contained in the coefficient matrix between the levels are decomposed and represented as $A_i X_{t-1}$ where the relevant elements of the matrix should be adjusted coefficient to the Cointegration vector.

Vector Error Correction Model (VECM)

To examine the long-run equilibrium relationship and short-run dynamic interactions between the variables and stock market volatility, the study employed Vector Error Correction Model (VECM) after establishing through the Johansen Cointegration test. Since, the variables are $I(1)$, the VECM framework is appropriate for to measure and it is expressed as follows:

$$\begin{aligned} \Delta Ex_t &= \beta_0 + \sum_{i=1}^p \alpha_{1i} \Delta Ex_{t-i} + \sum_{i=1}^p \alpha_{2i} \Delta GCF_{t-i} + \sum_{i=1}^p \alpha_{3i} \Delta GDP_{t-i} + \sum_{i=1}^p \alpha_{4i} \Delta Im_{t-i} + \sum_{i=1}^p \alpha_{5i} \Delta Infl_{t-i} + \sum_{i=1}^p \alpha_{6i} \Delta SI_{t-i} + \alpha ECT_{t-1} + \mu_t \\ \Delta GCF_t &= \beta_0 + \sum_{i=1}^p \alpha_{1i} \Delta Ex_{t-i} + \sum_{i=1}^p \alpha_{2i} \Delta GCF_{t-i} + \sum_{i=1}^p \alpha_{3i} \Delta GDP_{t-i} + \sum_{i=1}^p \alpha_{4i} \Delta Im_{t-i} + \sum_{i=1}^p \alpha_{5i} \Delta Infl_{t-i} + \sum_{i=1}^p \alpha_{6i} \Delta SI_{t-i} + \alpha ECT_{t-1} + \mu_t \\ \Delta GDP_t &= \beta_0 + \sum_{i=1}^p \alpha_{1i} \Delta Ex_{t-i} + \sum_{i=1}^p \alpha_{2i} \Delta GCF_{t-i} + \sum_{i=1}^p \alpha_{3i} \Delta GDP_{t-i} + \sum_{i=1}^p \alpha_{4i} \Delta Im_{t-i} + \sum_{i=1}^p \alpha_{5i} \Delta Infl_{t-i} + \sum_{i=1}^p \alpha_{6i} \Delta SI_{t-i} + \alpha ECT_{t-1} + \mu_t \\ \Delta Im_t &= \beta_0 + \sum_{i=1}^p \alpha_{1i} \Delta Ex_{t-i} + \sum_{i=1}^p \alpha_{2i} \Delta GCF_{t-i} + \sum_{i=1}^p \alpha_{3i} \Delta GDP_{t-i} + \sum_{i=1}^p \alpha_{4i} \Delta Im_{t-i} + \sum_{i=1}^p \alpha_{5i} \Delta Infl_{t-i} + \sum_{i=1}^p \alpha_{6i} \Delta SI_{t-i} + \alpha ECT_{t-1} + \mu_t \\ \Delta Infl_t &= \beta_0 + \sum_{i=1}^p \alpha_{1i} \Delta Ex_{t-i} + \sum_{i=1}^p \alpha_{2i} \Delta GCF_{t-i} + \sum_{i=1}^p \alpha_{3i} \Delta GDP_{t-i} + \sum_{i=1}^p \alpha_{4i} \Delta Im_{t-i} + \sum_{i=1}^p \alpha_{5i} \Delta Infl_{t-i} + \sum_{i=1}^p \alpha_{6i} \Delta SI_{t-i} + \alpha ECT_{t-1} + \mu_t \\ \Delta SI_t &= \beta_0 + \sum_{i=1}^p \alpha_{1i} \Delta Ex_{t-i} + \sum_{i=1}^p \alpha_{2i} \Delta GCF_{t-i} + \sum_{i=1}^p \alpha_{3i} \Delta GDP_{t-i} + \sum_{i=1}^p \alpha_{4i} \Delta Im_{t-i} + \sum_{i=1}^p \alpha_{5i} \Delta Infl_{t-i} + \sum_{i=1}^p \alpha_{6i} \Delta SI_{t-i} + \alpha ECT_{t-1} + \mu_t \end{aligned}$$

Where, the lagged difference terms are being determined by minimum number of residuals free from autocorrelation for the variables like Export (Ex), GCF, GDP, Import (Im), Inflation (Infl) and SI (Stock Indices), which will be tested by using Akaike Information Criterion (AIC). The parameters β_0 and α_0 represent the intercept terms of the respective equations, while Δ denotes the first-difference operator used to transform the variables into stationary series. The Error Correction Term (ECT_{t-1}), derived from the cointegrating relationship and normalized with respect to each endogenous variable, captures deviations from the long-run equilibrium path. The coefficients associated with the ECT measure the speed and direction of adjustment through which the variables converge back to their long-run equilibrium following a short-run disturbance. Although both t-statistics and F-statistics can be employed for hypothesis testing, the present study utilizes the conventional t-test to evaluate the significance of individual coefficients because the variables included in the VECM framework are integrated of the same order and exhibit a cointegrated relationship.

IV. RESULTS AND DISCUSSION

The results of Table 1 present the descriptive statistics of macroeconomic variables and stock market indices for India and China. In Panel A, the GDP and inflation of Indian economy record negative average growth values, whereas exports, imports, GCF, and the Nifty 50 index show positive mean values. The Nifty 50 exhibits the highest standard deviation (26.41), indicating substantial volatility compared with the macroeconomic variables. GDP displays significant negative skewness and high kurtosis, while the Nifty 50 demonstrates positive skewness and leptokurtic behavior,

suggesting the presence of extreme observations and non-normal distributions. In case of Panel B for China, the SSE Composite index exhibits the highest volatility, as reflected by its standard deviation of 62.59. Inflation and the SSE Composite display substantial positive skewness and excess kurtosis, indicating asymmetric distributions with fat tails. The Jarque-Bera statistics reveal that GDP and Nifty 50 in India, as well as inflation and SSE Composite in China, significantly deviate from normality. These findings suggest the existence of non-linear dynamics and volatility clustering, which are common characteristics of financial and macroeconomic time-series data.

Table: 1 Descriptive Statistics for Macroeconomic Variables and Stock Market

Panel A: Summary Statistics for Macroeconomic Variable and Nifty 50, India

Particulars	Mean	SD	Skewness	Kurtosis	JB test
GDP	-20.37933	2.838196	-2.312019	10.11430	101.9930*
Export	2.805203	0.344188	-0.566587	1.836591	3.736604
Import	2.922183	0.385036	-0.505908	1.922465	3.095206
Inflation	-20.26030	2.932009	0.361273	2.484807	1.115619
GCF	3.449898	0.165035	-0.191922	2.276744	0.949783
Nifty50	17.37671	26.40687	1.568135	7.938547	48.48603*

Panel B: Summary Statistics for Macroeconomic Variable and SSE Composite, China

Particulars	Mean	SD	Skewness	Kurtosis	JB test
GDP	-28.56876	2.875837	-0.046807	2.999016	0.012417
Export	3.087331	0.234643	0.646192	2.600663	2.592110
Import	2.953577	0.219840	0.146635	2.601013	0.347365
Inflation	-33.15535	4.886530	1.542164	5.437794	21.89589*
GCF	3.708754	0.096572	-0.507065	2.202530	2.357924
SSE Composite	18.53552	62.58576	3.374833	15.38759	281.9315*

Note: Author Computation. SD indicate Standard Deviation. JB test specify Jarque Bera test for the null hypothesis of normality. GDP and GCF refers to Gross Domestic Product and Gross Capital Formation, respectively. * and ** refers to statistically significant level at 1 % and 5%, respectively.

However, after first differencing, all variables become stationary at the 1 per cent significance level, as evidenced by the significantly larger negative test statistics. The consistency between ADF and PP results confirms the robustness and stationarity. Since all variables are integrated of order one, I(1), they satisfy the necessary precondition for conducting Johansen cointegration analysis and Vector Error Correction Model (VECM) estimation by possessing stochastic trends by exhibiting long-run equilibrium.

The unit root test results are presented in Table 2 for Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). The findings indicate that several variables are non-stationary at levels under both constant and trend specifications.

Table: 2 Unit Root test for Macroeconomic Variable on Stock Market

Variables	Augmented Dickey Fuller (ADF)		Phillip Perron (PP)	
	Constant	Constant & Trend	Constant	Constant & Trend
GDP	-5.812*	-5.699*	-6.802*	-6.680*
Δ GDP	-3.297**	-3.380**	-26.92*	-27.62*
Export	-1.963	-1.095	-1.986	-1.054
Δ Export	-5.578*	-5.974*	-5.595*	-5.974*

Import	-2.128	-1.193	-2.128	-1.193
Δ Import	-4.927*	-5.164*	-4.934*	-5.143*
Inflation	-3.206**	-3.510	-3.196	-3.291
Δ Inflation	-7.198*	-7.070*	-7.299*	-7.170*
GCF	-1.574	-3.362**	-1.940	-1.923
Δ GCF	-8.937*	-8.862*	-8.997*	-9.004*
Nifty 50	-5.670*	-6.597*	-5.670	-6.593
Δ Nifty 50	-4.294*	-5.113*	-17.82*	-26.95*

Variables	Augmented Dickey Fuller (ADF)		Phillip Perron (PP)	
	Constant	Constant & Trend	Constant	Constant & Trend
GDP	-1.393	-2.139	-1.928	-4.001
Δ GDP	-9.586*	-5.332*	-9.976*	-9.764*
Export	-1.783	-1.593	-1.945	-1.623
Δ Export	-4.203*	-4.398*	-4.249*	-4.453*
Import	-2.031	-2.183	-2.593	-2.272
Δ Import	-4.491*	-4.508*	-4.491*	-4.481*
Inflation	-2.519	-4.657	-2.333	-2.742
Δ Inflation	-5.778*	-5.698*	-5.322*	-5.170*
GCF	-1.763	-2.312	-1.989	-1.867
Δ GCF	-4.098*	-4.004*	-4.075*	-3.978*
SSE Composite	-4.948*	-5.374*	-4.892*	-5.422*
Δ SSE Composite	-6.878*	-6.819*	-10.98*	-11.50*

Note: * and ** Significance at 0.01 and 0.05 per cent level respectively. Probability based on MacKinnon (1996) one-sided p-values. Lag Length based on AIC. t-value in the level accepts the null hypothesis of unit root whereas the t-values in the first difference reject the hypothesis at 1 per cent level of significance. Thus, the table shows that all the variables have the same single unit roots, I(1).

The results of Johansen Cointegration test presented in Table 3 explains the usage of λ_{trace} and λ_{max} statistics. For India, the null hypothesis of no cointegration ($r = 0$) is rejected by both

statistics, as the calculated values exceed their corresponding critical values. However, subsequent hypotheses fail to reject the null, indicating the existence of one cointegrating vector among the variables. In the case of China, both λ_{trace} and λ_{max} statistics reject the null hypotheses for $r = 0$ and $r \leq 1$, suggesting the presence of two cointegrating relationships among macroeconomic variables and the SSE Composite index. The findings imply that macroeconomic variables and stock market performance share stable long-run equilibrium relationships in both countries, although the long-run integration appears stronger in China than in India.

Table: 3 Johansen Cointegration tests

Country	Null	Alternative	λ_{trace}	5% Critical Value	λ_{max}	5% Critical Value
India	$r = 0$	$r \geq 1$	116.70*	103.84	47.213*	40.956
	$r \leq 1$	$r \geq 2$	69.487	76.972	23.410	34.805
	$r \leq 2$	$r \geq 3$	46.077	54.079	16.957	28.588
	$r \leq 3$	$r \geq 4$	29.119	35.192	12.482	22.299
	$r \leq 4$	$r \geq 5$	16.637	20.261	12.154	15.892
	$r \leq 5$	$r \geq 6$	4.4828	9.1645	4.4828	9.1645
China	$r = 0$	$r \geq 1$	120.32*	83.937	47.827*	36.630
	$r \leq 1$	$r \geq 2$	72.501*	60.061	33.125*	30.439
	$r \leq 2$	$r \geq 3$	39.375	40.174	20.156	24.159
	$r \leq 3$	$r \geq 4$	19.219	24.275	12.682	17.797
	$r \leq 4$	$r \geq 5$	6.5365	12.320	5.9559	11.224
	$r \leq 5$	$r \geq 6$	0.5806	4.1299	0.5806	4.1299

Note: Author Computation. The Critical Value for the above statistics is obtained from MacKinnon-Haug-Michelis (1999) p-values. r refers the number of Cointegrating relationship. * denotes rejection of the hypothesis at the 0.05 level.

In order to examine the short-run and long-run dynamics among macroeconomic variables and stock market indices, the Table 4 reports the short-run and long-run dynamics among macroeconomic variables and stock market indices through the Vector Error Correction Model (VECM). For India, the error correction term (ECT) associated with the Nifty 50 is negative and statistically significant (-13.76), confirming the existence of a stable long-run equilibrium relationship. The negative sign indicates that deviations from long-run equilibrium are corrected over time, with the stock market adjusting toward equilibrium following economic shocks. Several lagged

macroeconomic variables, including exports, imports, GCF, GDP, and inflation, significantly influence the Nifty 50, demonstrating the presence of short-run causal effects. In particular, exports and GCF exert positive effects on stock market performance, while imports and inflation generate mixed impacts depending on the lag structure. For China, the SSE Composite also exhibits significant responses to lagged macroeconomic variables, especially exports, imports, GCF, and GDP. Although the ECT coefficient is relatively small, the significant lagged relationships indicate that macroeconomic fundamentals continue to play an important role in explaining stock market movements. The R^2 values ranging from 0.40 to 0.73 suggest moderate explanatory power of the model, while the F-statistics confirm the overall adequacy of the estimated equations.

Table: 4 Result of Vector Error Correction Model (VECM)

Particulars	Nifty50, India					Nifty50	SSE Composite (SSE), China			
	Export Import	GCF Inflation	GDP SSE	Import	Inflation		Export	GCF	GDP	
ECT _t 0.00	0.30 0.00 (0.47) (0.00)	0.00 -1.03 (0.43) (0.02)	6.40* (23.3) (0.34)	1.16 (0.53)	26.65* (8.32)	-13.76* (16.6)	0.00 (0.00)	-0.00 (0.00)	-0.02 (0.01)	-
Export _{t-1} 0.08	0.30 -17.2* (0.51) (0.46)	0.43 -11.0* (0.47) (18.0)	9.71* (25.3) (21.4)	0.25 (0.57)	-6.23* (9.05)	21.58* (17.6)	-0.00 (0.41)	0.37 (0.17)	0.38* (10.5)	-
Export _{t-2}	0.04 0.04 (0.51) (0.43)	0.78 -8.41* (0.46) (16.5)	17.30* 27.68* (25.0) (20.1)	-0.10 (0.57)	-0.95* (8.94)	45.24* (17.6)	0.15 (0.38)	-0.32 (0.16)	0.67* (9.70)	
GCF _{t-1}	0.45 0.80 (0.27) (0.69)	-0.33 31.53* (0.24) (26.6)	-0.79* -33.54* (13.1) (32.2)	0.21 (0.29)	1.92* (4.70)	59.17* (91.3)	0.55 (0.61)	0.81 (0.26)	10.24* (15.6)	
GCF _{t-2} 0.37	0.08 -3.54* (0.24) (0.71)	-0.13 -53.24* (0.22) (27.6)	-3.19* (11.7) (33.8)	-0.05 (0.26)	2.65* (4.20)	79.05* (81.6)	0.12 (0.63)	-0.49 (0.27)	-0.72* (16.1)	-
GDP _{t-1}	-0.00 0.00 (0.00) (0.01)	0.00 0.85 (0.00) (0.59)	-0.57 2.03* (0.29) (7.17)	-0.00 (0.00)	-0.38 (0.10)	0.82* (2.06)	0.01 (0.01)	0.00 (0.00)	-0.73 (0.34)	
GDP _{t-2}	-0.00 0.00 (0.00) (0.01)	0.00 0.90 (0.00) (0.61)	-0.16 5.67* (0.28) (7.41)	-0.00 (0.00)	-0.32 (0.10)	1.39** (1.98)	0.00 (0.01)	-0.00 (0.00)	-0.17 (0.35)	
Import _{t-1}	-0.65 0.31	-0.42 6.92*	-5.66* 18.47*	-0.49	-7.03*	-11.1*	0.45	-0.30	3.18*	

	(0.47)	(0.43)	(23.3)	(0.53)	(8.32)	(16.6)	(0.34)	(0.14)	(8.85)	
	(0.39)	(15.1)	(18.4)							
Import _{t-2}	0.21	-0.16	-12.9*	0.162	1.57*	-69.2*	0.06	0.08	3.71*	-
0.01	7.41*	22.51*								
	(0.41)	(0.38)	(20.3)	(0.46)	(7.26)	(14.9)	(0.33)	(0.14)	(8.41)	
(0.37)	(14.3)	(17.2)								
Inflation _{t-1}	0.01	0.02	0.52	0.02	-0.05	1.86*	-0.01	0.00	0.03	-
0.00	-0.23	-2.56*								
	(0.01)	(0.01)	(0.54)	(0.01)	(0.19)	(3.80)	(0.00)	(0.00)	(0.17)	
(0.00)	(0.29)	(3.62)								
Inflation _{t-2}	0.01	-0.00	-0.09	0.017	0.29	0.96*	(0.00)	(0.00)	(0.17)	
	(0.00)	(0.29)	(3.62)							
	(0.01)	(0.01)	(0.59)	(0.01)	(0.21)	(4.10)	-0.00	0.00	-0.10	-
0.00	-0.53	-2.37								
Nifty&SSE _{t-1}	0.00	0.00	0.00	0.00	0.02	-0.70	-0.00	0.00	0.00	
	5.84	-0.00	-0.09							
	(0.00)	(0.00)	(0.03)	(0.00)	(0.01)	(0.22)	(0.00)	(0.00)	(0.01)	
	(0.00)	(0.01)	(0.21)							
Nifty&SSE _{t-2}	0.00	-0.00	0.01	0.00	0.04	-0.12	-0.00	0.00	0.00	-
0.00	-0.01	-0.16								
	(0.00)	(0.00)	(0.03)	(0.00)	(0.01)	(0.21)	(0.00)	(0.00)	(0.00)	
	(0.00)	(0.01)	(0.18)							
R-squared	0.44	0.65	0.40	0.55	0.73	0.53	0.54	0.52	0.44	
0.45	0.48	0.64								
F-statistic	1.05	2.49	0.89	1.59	3.67	1.49	1.54	1.43	1.05	
1.10	1.24	2.32								

Note: Author Calculation. The number in the parentheses are t-statistics. * and ** denote statistically significant at 1 per cent and 5 per cent levels, respectively.

V. CONCLUSION

This study examined the multi-horizon interdependence between macroeconomic conditions and stock market volatility in India and China using annual data from 1991 to 2024. The Johansen cointegration results confirmed the existence of stable long-run equilibrium relationships between macroeconomic fundamentals and stock market performance, with stronger long-run integration observed in China. The VECM findings revealed that GDP, exports, imports, inflation, and gross capital formation significantly influence stock market movements in both the short run and long run. In India, the negative and significant error correction term indicates that the NIFTY 50 adjusts toward long-run equilibrium following economic shocks. Similarly, the Chinese stock market exhibits strong responsiveness to macroeconomic and trade-related factors. Overall, the findings demonstrate that stock market volatility in developing economies is closely linked to macroeconomic fundamentals rather than purely financial factors. The results support the Arbitrage Pricing Theory and highlight the critical

role of economic growth, trade performance, and capital formation in promoting stock market stability and strengthening investor confidence.

The findings provide important implications for policymakers, financial regulators, and investors in developing economies. First, governments should prioritize sustainable economic growth and capital formation, as GDP expansion and investment activities significantly contribute to stock market stability. Second, policymakers should implement effective inflation-control measures because inflationary pressures create uncertainty and increase market volatility, particularly in the short run.

Third, trade promotion policies that enhance exports while maintaining balanced import growth can strengthen market confidence and support long-term financial stability. Fourth, central banks and financial regulators should closely monitor macroeconomic indicators and incorporate them into market surveillance frameworks to identify potential volatility risks at an early stage. Finally, investors and portfolio managers should

consider macroeconomic fundamentals when formulating investment strategies, as stock market behavior reflects changing economic conditions over different time horizons. Strengthening macroeconomic stability and improving policy coordination can therefore enhance market efficiency, reduce volatility transmission, and foster sustainable financial development in emerging economies such as India and China.

REFERENCES

1. Adam, A. M., & Tweneboah, G. (2008). Macroeconomic factors and stock market movement: Evidence from Ghana. MPRA Paper No. 11256. Munich Personal RePEc Archive.
2. Adekoya, O. B., & Oliyide, J. A. (2021). How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques. *Resources Policy*, 70, 101898. <https://doi.org/10.1016/j.resourpol.2020.101898>
3. Ang, A., & Bekaert, G. (2002). International asset allocation with regime shifts. *Review of Financial Studies*, 15(4), 1137–1187. <https://doi.org/10.1093/rfs/15.4.1137>
4. Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics*, 43(1), 29–77. [https://doi.org/10.1016/S0304-405X\(96\)00889-6](https://doi.org/10.1016/S0304-405X(96)00889-6)
5. Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2018). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, 23, 87–95. <https://doi.org/10.1016/j.frl.2017.02.009>
6. Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, 59(3), 383–403. <https://doi.org/10.1086/296344>
7. Cherif, M., & Gazdar, K. (2010). Macroeconomic and institutional determinants of stock market development in MENA region. *International Journal of Banking and Finance*, 7(1), 139–159.
8. Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *American Economic Review*, 71(4), 545–565.
9. Gan, C., Lee, M., Yong, H. H. A., & Zhang, J. (2006). Macroeconomic variables and stock market interactions: New Zealand evidence. *Investment Management and Financial Innovations*, 3(4), 89–101.
10. Gençay, R., Selçuk, F., & Whitcher, B. (2005). An introduction to wavelets and other filtering methods in finance and economics. Academic Press.
11. Hammoudeh, S., & Li, H. (2008). Sudden changes in volatility in emerging markets: The case of Gulf Arab stock markets. *International Review of Financial Analysis*, 17(1), 47–63. <https://doi.org/10.1016/j.irfa.2006.02.006>
12. Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables explain long-term stock market movements? A comparison of the U.S. and Japan. *Applied Financial Economics*, 19(2), 111–119. <https://doi.org/10.1080/09603100701748956>
13. In, F., & Kim, S. (2013). An introduction to wavelet theory in finance: A wavelet multiscale approach. *World Scientific*. <https://doi.org/10.1142/8750>
14. Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6), 1551–1580. <https://doi.org/10.2307/2938278>
15. Karki, D., et al. (2024). Macroeconomic determinants and stock market performance: Evidence from Nepal. *Journal of Economic Studies*, Advance Online Publication.
16. Khan, M. A., & Billah, M. (2023). Macroeconomic instability and stock market volatility in emerging economies. *International Journal of Financial Studies*, 11(2), 45. <https://doi.org/10.3390/ijfs11020045>
17. Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, 50(4), 1267–1287. <https://doi.org/10.1111/j.1468-2354.2009.00568.x>
18. Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. *American Economic Review*, 88(3), 537–558.
19. Maleki, M. (2024). Macroeconomic shocks and stock market volatility transmission in emerging markets. *Economic Modelling*, 132, 106512. <https://doi.org/10.1016/j.econmod.2024.106512>
20. Maysami, R. C., & Koh, T. S. (2000). A vector error correction model of the Singapore stock market. *International Review of Economics and Finance*, 9(1), 79–96. [https://doi.org/10.1016/S1059-0560\(99\)00042-8](https://doi.org/10.1016/S1059-0560(99)00042-8)
21. Morales, L. (2008). Volatility spillovers among equity markets: Evidence from emerging economies. *Journal of International Financial Markets, Institutions and Money*, 18(4), 345–360. <https://doi.org/10.1016/j.intfin.2007.01.001>
22. Mukherjee, T. K., & Naka, A. (1995). Dynamic relations between macroeconomic variables and the Japanese stock market: An application of a vector error correction model.

- Journal of Financial Research, 18(2), 223–237.
<https://doi.org/10.1111/j.1475-6803.1995.tb00563.x>
23. Mukhopadhyay, D., & Sarkar, N. (2003). Stock prices and macroeconomic variables in India: An empirical analysis. *Indian Economic Journal*, 51(2), 123–137.
24. Pal, K., & Mittal, R. (2011). Impact of macroeconomic indicators on Indian capital markets. *Journal of Risk Finance*, 12(2), 84–97.
<https://doi.org/10.1108/15265941111112811>
25. Pradhan, R. P., Arvin, M. B., & Bahmani, S. (2015). Causal nexus between economic growth, banking sector development, stock market development, and other macroeconomic variables. *Review of Financial Economics*, 26, 56–67.
<https://doi.org/10.1016/j.rfe.2015.05.002>
26. Rua, A., & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, 16(4), 632–639.
<https://doi.org/10.1016/j.jempfin.2009.02.002>
27. Thapa, R. (2023). Macroeconomic variables and stock market performance in Nepal: A cointegration approach. *South Asian Journal of Finance and Economics*, 5(1), 45–61.
28. Tripathi, V., & Kumar, A. (2014). Relationship between inflation and stock market volatility in India. *Asian Journal of Finance & Accounting*, 6(2), 123–138.
<https://doi.org/10.5296/ajfa.v6i2.6344>