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Evaluating forecast accuracy for NSE Nifty: A cross-market study using OLS, HSC, GARCH, and VAR models

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Abstract
An investigation is conducted into the predictive and interconnected behaviour of NSE NIFTY in relation to major global stock indices over a twenty-five-year period, using data obtained from reputed international financial databases. The analysis incorporates four complementary econometric frameworks Ordinary Least Squares (OLS), Heteroskedasticity and Serial Correlation Consistent estimation (HSC), the GARCH(1,1) volatility model and the Vector Autoregressive (VAR) system to capture linear relationships, robust short-run linkages, time-varying volatility patterns, and multidirectional spillover effects. The indices are organised into regional and developmental groups to examine differential transmission mechanisms across advanced, Asian, and emerging market environments.

The empirical evidence indicates that Asian and emerging markets exert consistently strong and significant influence on NSE NIFTY, while several European indices display weaker or mixed predictive contributions. HSC offers the most precise parameter estimates and favourable information criteria, VAR effectively captures dynamic inter-market interactions and GARCH provides improved modelling of volatility clustering, especially during high-uncertainty periods. Overall, predictive performance strengthens as a wider set of international markets is incorporated, highlighting the increasing global integration of Indian equities and the importance of combining linear, robust, and volatility-sensitive frameworks for comprehensive market forecasting.

Keywords: Global stock indices, OLS, HSC, GARCH(1,1), VAR, volatility transmission, international comovement

1. Introduction

Global stock markets have undergone profound transformation over the past three decades, marked by accelerated financial integration, technological change, and increasingly mobile global capital. As a result, domestic indices such as the NSE NIFTY no longer move solely in response to local fundamentals but are continuously shaped by international shocks, policy shifts, and cross-market transmission mechanisms. For an emerging economy like India, which has witnessed rising foreign investment, greater institutional participation, and deeper market integration, understanding how global indices influence NIFTY's behaviour has become essential. Forecasting accuracy in this context demands econometric approaches that capture linear dependencies, robust corrections, dynamic spillovers, and evolving volatility structures thereby motivating the comprehensive multi-model framework adopted in this study.

The growing integration of global financial markets has intensified scholarly attention on understanding how international stock movements shape the behaviour of domestic indices such as the NSE NIFTY. Early volatility-based evidence from Dixit *et al.* (2010) [15] revealed that implied volatilities in the Indian derivatives market fail to fully incorporate past information, underscoring inefficiencies and the need for advanced conditional volatility models. Similar concerns were echoed by Arsalan *et al.* (2022) [5], who, through a cross-market GARCH investigation, showed that differing levels of volatility and mean reversion across major Asian and global exchanges influence the stability and responsiveness of national markets.

Together, these studies highlight that market dynamics in India cannot be interpreted in isolation, as global risk, structural shifts and past shocks continuously shape the informational content embedded in NIFTY returns.

Research on emerging and frontier markets further strengthens this argument. Ugurlu *et al*. (2014) [46] demonstrated that GARCH-type models capture persistent volatility shocks in European emerging markets, revealing that old information significantly affects new volatility movements. Thomas *et al*. (2017) [45] extended this perspective by showing that Asia-Pacific emerging markets while partly integrated retain substantial segmentation, offering diversification benefits but also generating uneven predictive effects across countries. These findings collectively suggest that cross-market interactions vary widely by region and stage of development, implying that NIFTY's behaviour must be examined using models that differentiate between developed, Asian and emerging market influences.

During periods of crisis or structural transition, global market linkages intensify or weaken in measurable ways. Verma (2024) [48], for instance, reported that cointegration among Asian markets weakened during the COVID-19 pandemic before gradually normalising in its aftermath. In contrast, Das and Gupta (2022) [13] found no cointegration among the indices of the most pandemic-affected countries, demonstrating that extreme uncertainty can fragment financial relationships even when macroeconomic conditions appear similar. These crisis-driven shifts highlight the necessity of incorporating models that capture both short-run dynamics and long-run co-movement, especially for an economy like India that is deeply embedded in global capital flows.

A parallel line of inquiry focuses on the behaviour of emerging markets under stress. Ghulam and Joo (2024) [22] employed a Value at Risk framework to examine BRICS markets and discovered strong interdependence, particularly Brazil's dominant influence on its peers. This suggests that emerging markets can exhibit shock transmission patterns comparable to those of advanced economies, challenging earlier views of emerging market segmentation. In the Indian context, Kumar and Marisetty (2023) [40] demonstrated strong positive correlations between SENSEX and major global indices such as DAX, Nikkei 225, and S&P 500, confirming that Indian equities respond markedly to international developments. These insights indicate that NIFTY is embedded within a dense and evolving network of global market relationships.

Long-term evidence shows that these interdependencies have intensified over time. Marisetty (2017) [29] traced post-liberalisation shifts in India's financial landscape and found significant co-movements between BSE SENSEX and eleven global indices, demonstrating deepening global integration since the early 1990s. More recent work by Marisetty (2024) [30-32] confirmed the existence of strong cointegration vectors among NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225, with the S&P 500 and FTSE 100 exerting leadership in long-run adjustments. Complementary studies such as Hui Hong (2025) [8] and Mabruk Billah *et al*. (2025) [7] show that advanced VAR and TVP-VAR frameworks capture evolving shock transmissions in sectoral and cross-financial-system contexts, reinforcing the importance of dynamic, system-wide analysis for understanding interconnected markets.

Parallel methodological innovations in linear modelling have also shaped recent forecasting practices. Marisetty (2024) [30-32] highlighted the limitations of traditional OLS in financial time series, noting widespread violations of autocorrelation, heteroscedasticity, and nonlinearity. Heteroscedasticity-Corrected (HSC) models were shown to significantly improve efficiency, while volatility-sensitive frameworks such as GARCH remained essential for capturing clustering effects. These findings demonstrate that a multi-framework approach combining linear regression, robust adjustments, volatility modelling, and dynamic systems is necessary for accurately forecasting Indian stock market behaviour within an internationally integrated environment.

Against this backdrop, the present study investigates the predictive and interconnected behaviour of NSE NIFTY relative to major global indices over twenty-five years using four complementary econometric models: OLS for linear predictive structure, HSC for robust parameter stability, GARCH (1,1) for volatility clustering and VAR for multidirectional shock transmission. The analysis incorporates indices from advanced, Asian, and emerging markets to measure differential forecasting contributions across regions. Section 1 presents the introduction, Section 2 reviews the relevant literature, Section 3 details the methodology including model specifications, Section 4 reports and interprets empirical findings, Section 5 offers concluding insights and Section 6 outlines potential avenues for further research.

2. Literature Review

Global financial markets are increasingly interconnected, with shocks from economic, political, and commodity-related events rapidly transmitting across borders. Over the past decades, researchers have examined how macroeconomic uncertainty, structural changes, and global shocks affect stock returns, volatility, and market co-movements. Understanding these dynamics is essential for investors, portfolio managers, and policymakers to manage risk, optimize diversification, and design appropriate intervention strategies. This literature review synthesizes empirical evidence on market volatility, cointegration, interlinkages, and econometric modeling, with a particular focus on the Indian stock market and its relationships with global financial indices.

Studies on global market co-movements highlight the importance of understanding correlations for portfolio diversification. Rao, Marisetty, and Kumar (2021) demonstrate that inter-market correlations significantly influence diversification benefits, while Ferreira *et al*. (2019) [21] find long-range correlations among major stock markets, underscoring persistent interconnections. In the Indian context, Deo and Prakash (2017) [14] document long-term cointegration between NSE Nifty and key global indices, supported by Subbaiyan and Sulochana (2020) [43], who show that European markets such as CAC40, DAX, and FTSE 100 maintain strong links with the Sensex. Menon *et al*. (2009) [35] further confirm India's integration with China, Singapore, and the US, suggesting that global shocks can have both immediate and long-term effects on Indian markets.

However, some regional markets exhibit independence and provide opportunities for diversification. Nath and Verma (2003) [37] find limited long-term relationships among South

Asian markets such as India, Singapore, and Taiwan, while Valadkhani and Chancharat (2007) [47] report that Thailand's market lacks integration with major global indices. Emerging markets have shown evolving interlinkages in response to capital flows and structural changes. Verma and Rani (2016) [49] identify causality among BRICS nations, particularly from Brazil to India and India to South Korea, reflecting growing intra-emerging market dependencies. Panigrahi *et al*. (2025) [38] demonstrate that LSTM neural networks outperform traditional SARIMAX models in forecasting stock returns for BRICS markets, particularly Brazil, India, and South Africa, illustrating the increasing relevance of advanced computational techniques in capturing complex emerging market dynamics.

Commodity and energy shocks are major drivers of financial market behavior. Aladwani (2025) [2] and Alemu *et al*. (2025) [3] use VAR/VEC and GVAR models to show how crude oil, natural gas, and macroeconomic disturbances transmit to stock markets in Vietnam and African economies, highlighting vulnerabilities in energy-dependent and fragile markets. These studies underscore the importance of commodity market monitoring in understanding broader financial stability. Currency dynamics also play a critical role in market volatility and portfolio management. Gupta (2025) [25] finds that USD shocks significantly impact India's export-linked currencies, emphasizing the global transmission of currency risk. Samarakoon *et al*. (2024) [42] further illustrate that NIFTY 50 futures mispricing is influenced by volatility, trading activity, and market depth, with regime-dependent effects, highlighting the complex interactions within India's derivatives market and their implications for investors.

Financial innovations such as cryptocurrencies have added additional channels of shock transmission. Wang (2025) [50] demonstrates that Bitcoin prices are highly responsive to macroeconomic indicators, including monetary policy, inflation, and commodity prices. Antonakakis *et al*. (2020) [4] enhances connectedness measurement using TVP-VAR models, which adapt to evolving shock transmission more effectively than rolling-window VAR techniques. These studies highlight the importance of flexible models in capturing modern financial interdependencies. Volatility modeling remains central to understanding market dynamics. Marisetty (2024) [30-32] applies multiple GARCH specifications to global indices such as FTSE 100, Hang Seng, Nikkei 225, NSE Nifty 50, and S&P 500, concluding that GARCH(1,1) is parsimonious and effective, while asymmetric models like TGARCH and APARCH better capture leverage effects and volatility clustering. Other studies, including Abbas *et al*. (2020) [1] and Mobin *et al*. (2021) [36], corroborate the persistence of volatility in response to macroeconomic and financial shocks.

Regression-based financial econometrics often faces assumption violations in volatile datasets. Gujarati and Porter (2009) [24] and Williams *et al*. (2013) [52] highlight issues such as heteroscedasticity, autocorrelation, and multicollinearity, which reduce the efficiency of OLS estimates. Diagnostic tools like the Breusch-Pagan test, Durbin-Watson statistic, and Variance Inflation Factor are commonly used to detect these violations, particularly in foreign exchange and high-frequency stock market data. Corrective methods and transformations have been developed to address these limitations. Weighted and Generalized Least Squares adjust for heteroscedasticity (Pindyck & Rubinfeld, 1998) [39], while White's heteroscedasticity-consistent estimator (1980) [51] corrects standard errors without specifying the error structure. However, ARCH effects remain unaddressed by these methods, prompting the use of GARCH-type models (Engle, 1982; Bollerslev, 1986) [19, 8]. Transformations such as first differences and log differences (Box & Jenkins, 1976; Escribano & Mira, 2002) [9, 20] stabilize variance and reduce autocorrelation, particularly in long-term datasets affected by structural breaks (Campbell *et al*., 1997; Reinhart & Rogoff, 2009) [11, 41].

Hybrid modeling approaches that combine econometric and computational methods have gained prominence. Meese and Rogoff (1983) [34], Cheung *et al*. (2005) [12], and Engel and West (2005) [18] highlight the limitations of linear models for exchange rate and stock market prediction under multicollinearity and volatility clustering. Machine learning techniques, including neural networks, support vector machines, and ensemble methods (Hastie, Tibshirani, & Friedman, 2009) [27], offer improved flexibility in capturing nonlinear and dynamic patterns. When combined with traditional diagnostics and transformation-based corrections, these hybrid approaches enhance model reliability and forecasting accuracy in volatile markets.

In summary, the literature emphasizes that global financial markets are interconnected, with volatility influenced by macroeconomic shocks, commodities, currencies, and technological innovations. The Indian stock market exhibits both integration with major global indices and selective independence from regional markets, offering avenues for diversification. Advanced econometric frameworks including GARCH, VAR, TVP-VAR, GVAR, and machine learning models are critical for capturing market dynamics, forecasting returns, and understanding shock transmission. These approaches provide valuable guidance for investors, portfolio managers, and policymakers navigating increasingly complex financial landscapes.

3. Methodology

The study employs fourteen major international stock indices observed over a span of twenty-five years, generating three hundred return observations for each index. These indices were sourced from reputed and globally recognised financial databases to ensure accuracy, consistency, and reliability of the data. Using return series rather than price levels allows the analysis to capture true market fluctuations, volatility movements, and cross-market interactions without the influence of non-stationary trends. The long-time horizon strengthens the robustness of the findings by covering multiple market cycles, crises, policy shifts, and structural breaks. Including a wider range of indices also enhances the international relevance of the results by reflecting both developed and emerging market characteristics.

To measure the dynamic influence of global markets on the Indian stock index, the study adopts four established predictive and econometric frameworks: Ordinary Least Squares (OLS), the Heteroskedasticity and Serial Correlation Consistent model (HSC), the GARCH (1,1) volatility model and the Vector Autoregression (VAR) framework. These methods collectively capture linear relationships, robust short-run linkages, time-varying volatility patterns, and multi-directional spillover dynamics. Using multiple approaches ensures that the findings are not

dependent on a single estimation technique, thereby strengthening the validity and comparability of the results. Each model contributes unique insights into how return transmission and volatility spillovers occur across regions.
The fourteen indices are categorised into five models to understand region-wise and market-wise connectedness patterns more systematically. These include a model focusing on the United States and Europe, another centred on major Asian markets, a separate set comprising emerging markets, a continent-wise grouping of leading indices and a final model consisting of all fourteen indices together. This structured segmentation allows the study to observe how regional integration, development stages and geographical proximity shape the influence on the Indian market. The five-model design also helps in detecting whether shocks propagate differently when markets are grouped by economic development, regional clustering, or global dominance.
Selecting fourteen diverse indices is essential because no single region or market can adequately represent global financial movements. The inclusion of the world's leading benchmarks such as the SP500, NASDAQ, DAX and NIKKEI captures developed market dominance, while indices like Bovespa, Shanghai and SAI represent emerging economic growth patterns. The combination of Asian, American, European, and global emerging markets ensures a holistic understanding of international comovements affecting India. This diversity also reflects India's evolving economic integration and growing participation in international capital markets, making it necessary to examine how global factors collectively shape its return behaviour and volatility dynamics.
A comprehensive empirical analysis of international stock market behaviour requires a structured methodological framework that begins with careful data preparation, employs suitable statistical and econometric models, validates assumptions, and finally evaluates forecasting performance using robust accuracy measures. Preprocessing ensures that raw financial data are transformed into a form appropriate for modelling through log-return computation, assessment of descriptive statistical properties, and diagnostic procedures such as Pearson correlation to examine linear comovements and unit root tests to confirm stationarity. These steps help detect early distributional patterns, verify integration order, and identify potential dependencies that influence modelling outcomes, thereby ensuring that the data meet foundational requirements for econometric analysis.
The selected models including Ordinary Least Square (OLS), Heteroscedasticity-Corrected (HSC) regression, ARCH/GARCH volatility frameworks, and multivariate Vector Auto Regression (VAR) systems enable the study to capture linear relationships, volatility clustering, and dynamic interactions across markets. Estimation outputs, particularly standard errors and adjusted R-squared values, provide insight into the precision and explanatory power of each model, while information criteria such as Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQIC) assist in selecting the most appropriate model specification by balancing goodness of fit and model complexity. The validity of these models further depends on meeting assumptions such as absence of multicollinearity, homoscedasticity, lack of autocorrelation, and confirmed stationarity, which are assessed using diagnostic tools like the Variance Inflation Factor, Breusch-Pagan test, Lagrange Multiplier test, and Durbin-Watson statistic.
Forecasting performance is evaluated using measures such as Mean Error, RMSE, MAE, MPE, and Theil's U2, enabling systematic comparison of model accuracy, bias, and relative predictive efficiency. These metrics jointly assess how closely predicted values align with actual market movements, whether forecasting errors display persistent patterns, and how each modelling approach performs relative to naïve or benchmark forecasts. Together, these components create a rigorous methodological structure suitable for analysing interconnected global stock indices, offering a balanced evaluation of their relationships, volatility dynamics, and predictive capability across diverse international markets.

Table 1: Selected international indices for the study

Index	Country	Index	Country
Bovespa	Brazil	NASDAQ	USA
CAC40	French	NSE NIFTY	India
DAX40	Germany	NIKKEI225	Japan
Dow Jones (DJ)	USA	SP500	USA
FTSE100	England	ASX	Australia
HANG SENG	Hongkong	Shanghai	China
KOSPI	South Korea	SAI	South Africa

(*Source*: Google)

The selected dataset comprises fourteen prominent international stock indices from diverse regions across the globe, representing developed, emerging, and continental markets. These indices include Bovespa from Brazil, which reflects the performance of the Brazilian equity market and is a key indicator of Latin American economic activity; CAC40 from France, representing the top 40 companies listed on Euronext Paris and serving as a benchmark for the French and broader European markets; DAX40 from Germany, capturing the 40 major German blue-chip companies traded on the Frankfurt Stock Exchange and reflecting Germany's industrial and economic health; Dow Jones Industrial Average from the USA, one of the oldest and most widely recognized indices, tracking 30 large-cap U.S. companies; S&P 500 from the USA, covering 500 large-cap companies and providing a broad measure of U.S. equity market performance. FTSE100 from England, composed of the 100 largest companies listed on the London Stock Exchange, indicative of the UK's economic climate.
Hang Seng from Hong Kong, representing major companies in the Hong Kong market and reflecting regional investor sentiment in Asia; KOSPI from South Korea, tracking the performance of South Korean companies listed on the Korea Exchange; NSE NIFTY from India, covering the top 50 Indian companies by market capitalization and providing insights into India's equity market trends; NIKKEI225 from Japan, representing 225 large Japanese companies listed on the Tokyo Stock Exchange and serving as a barometer for the Japanese economy; ASX200 from Australia, tracking the largest 200 companies listed on the Australian Securities Exchange and reflecting economic developments in Oceania; Shanghai Composite from China, covering all stocks traded on the Shanghai Stock Exchange and offering insights into China's rapidly evolving capital market; and SAI from South Africa, representing the top companies

listed on the Johannesburg Stock Exchange and serving as a benchmark for the African continent.

3.1. Preprocessing

Before applying the OLS, HSC, GARCH (1, 1) and VAR models, the collected data will be pre-processed to ensure its suitability for analysis. This includes:

3.1.1. Log Returns Calculation: The daily log returns will be computed from the closing prices as they are more stationary and suitable for volatility modelling. The log return is calculated using the formula:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \quad (1)$$

Where p_t and p_{t-1} are the closing prices at time t and t-1

3.1.2. Descriptive Statistics:

Descriptive statistics provide a preliminary understanding of the fundamental distributional properties of the fourteen international stock indices used in the study. These statistics summarise central tendencies through mean and median values, offering insight into the average return behaviour across markets over the 300-day observation window. Measures of dispersion such as minimum, maximum, and standard deviation highlight the volatility patterns that differ noticeably across indices, indicating varied levels of market risk and fluctuation intensity. Skewness and kurtosis further describe the shape of return distributions, signalling asymmetry and the presence of heavy or light tails relative to the normal distribution, which is important for understanding extreme market movements. Overall, descriptive statistics serve as an essential first diagnostic step, helping to identify data characteristics, detect abnormalities and guide appropriate model selection for subsequent empirical analysis.

3.1.3. Multivariate correlation analysis

Multivariate correlation analysis explores the relationships among multiple variables simultaneously. The correlation matrix is calculated using the formula:

$$\rho_{XY} = \frac{COV\,(X,Y)}{\sigma_X \sigma_Y}$$

where ρ_{XY} is the Pearson correlation coefficient, Cov (X,Y) is the covariance between variables X and Y, and σ_X and σ_Y are the standard deviations of X and Y, respectively. This analysis helps identify the strength and direction of relationships between bond yields, equity returns, and various economic factors.

3.1.4. Unit Root Test

The Augmented Dickey-Fuller (ADF) test (1979) and the Kwiatkowski, Phillips, Schmidt, Shin (KPSS) test (1992) are commonly used for testing stationarity. The ADF test is often criticized because its inability to reject the null hypothesis of a unit root may result from low power against alternatives that are weakly stationary. In contrast, the KPSS test assumes stationarity as the null hypothesis and tests it against the alternative of a unit root. To conduct the ADF test, a regression model is estimated to check for the presence of a unit root.

Regression Model as follows

$$\Delta X_t = \alpha + \beta X_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta X_{t-j} + \varepsilon_t \quad (1)$$

In this context, the difference operator is denoted as Δ, which represents the change in the series. Therefore, if X is the series being tested, then $\Delta X_t = X_t - X_{t-1}$ is the first difference of the series. The variable k refers to the number of lagged differences included in the regression model to account for potential autocorrelation in the error term.

KPSS Test statistics is

$$\eta_u = T^{-2} \sum\left(\frac{S_t^2}{S^2(L)}\right) \quad (2)$$

Where

$$S_t = \sum_{i=1}^{t} e_t$$

$$S^2 = T^{-1} \sum_{t=1}^{T} e_t^2 + 2T^{-1} \sum_{s=1}^{L}\left(1 - \frac{s}{L+1}\right) \sum_{t=s+1}^{T} e_t e_{t-s}$$

In this context, S_t represents the partial sum process of the residuals e, while T denotes the total number of observations in the dataset. Additionally, L indicates the lag length used in the analysis.

First Difference (FD) Method

The First Difference Method is used in regression analysis to address issues like non-stationarity and omitted variable bias by analysing changes between consecutive observations. It transforms the data by computing differences, making the model:

$$\Delta Y_t = \beta \Delta X_t + \Delta \epsilon_t$$

Where

$\Delta Y_t = Y_t - Y_{t-1}$ and $\Delta X_t = X_t - X_{t-1}$.

This method eliminates time-invariant unobserved effects, focusing on the variation within the data. It is commonly applied in time-series and panel data analysis.

3.2. Regression Models

3.2.1. Ordinary Least Squares (OLS) Model

The Ordinary Least Squares (OLS) test in multiple regression estimates relationships between one dependent variable and multiple independent variables. The formula is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Here, Y is the dependent variable, X_1, X_2…….., X_n are independent variables, β_0 is the intercept, β_1, β_2…, β_n are coefficients, and ϵ is the error term. OLS minimizes the sum of squared residuals (ϵ^2) to estimate β values. Assumptions like linearity, no multicollinearity, and homoscedasticity are crucial for valid results. This test is essential for analysing the combined effect of multiple predictors on an outcome.

3.2.2. Heteroscedasticity-Corrected (HSC) Model

A Heteroscedasticity-Corrected Model adjusts regression analyses to account for non-constant variance (heteroscedasticity) in the error terms, ensuring reliable estimates and valid statistical inference. The model corrects standard errors, often using robust techniques such as White's correction. The corrected regression equation remains:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$

However, heteroscedasticity-adjusted standard errors are computed as:

$\hat{V} = (X'X)^{-1} X' \hat{\Omega} X (X'X)^{-1}$

where is $\hat{\Omega}$ a diagonal matrix of error variances. This approach ensures unbiased coefficient estimates and accurate confidence intervals in the presence of heteroscedasticity.

3.2.3. Autoregressive Conditional Heteroskedasticity (ARCH) Model

In traditional econometrics, it is often assumed that the variance of a random variable remains constant over time. However, financial time series typically exhibit heteroscedasticity, meaning they are stable over the long term but show instability in the short term. To account for this time-varying volatility, Engle (1982) [19] introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which is used to model both the mean and variance of time series data. The general form of the ARCH model is expressed as follows:

$y_t = \phi\, x_t + \mu_t$

$\sigma_t^2 = E(\mu_t^2 | \mu_{t-1}, \mu_{t-2} \ldots\ldots) = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \ldots\ldots\ldots\ldots + \alpha_p \mu_{t-p}^2 = \sum_{i=1}^{p} \alpha_i \mu_{t-i}^2$

ϕ is a non-zero parameter to be estimated, x_t represents the independent variable observed at time t, and μ_t is a random error term, which is typically assumed to follow a normal distribution in the standard model. The fundamental concept of the ARCH model is that the variance of the residuals μ_t at time t depends on the squared error terms from previous periods. Specifically, the model posits that the variance of the error term at time t is a linear function of the squared error terms from the previous p periods.

However, the ARCH model assumes that positive and negative shocks have the same impact on volatility, making it unsuitable for analysing series with asymmetric effects.

3.2.4. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Bollerslev (1986) [8] introduced a significant enhancement to the ARCH model, termed the GARCH model, which better captures the phenomenon of volatility clustering commonly observed in financial time series. This approach considers the conditional variance as a GARCH process to effectively estimate volatility that changes over time. The defining equations of the model are as follows:

$y_t = \phi\, x_t + \mu_t,\ \mu \sim N(0, \sigma_t^2)$

$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \mu_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$

In this model, μ_{t-i}^2 represents the ARCH parameter, while σ_{t-i}^2 is the GARCH parameter. The coefficients associated with the ARCH and GARCH terms are indicated by α and β, respectively, and p and q indicate the lag order of the model. Therefore, the ARCH model can be seen as a specific case within the broader GARCH framework. In this study, primarily utilize the GARCH(1,1) model, which includes one lag, to estimate the sample series. The strength of the GARCH model lies in its ability to reflect and interpret heteroscedasticity. However, it still falls short in capturing asymmetry in financial time series.

3.5. Vector Auto Regression (VAR) Model

A Vector Auto Regression (VAR) model is a multivariate time-series framework that captures the dynamic interdependencies among multiple variables by allowing each variable to be influenced not only by its own past values but also by the past values of all other variables in the system. In general form, a VAR of order *p* is written as:

$Y_t = c + A_1 Y_{t-1} + A_2\, Y_{t-2} + \cdots + A_p\, Y_{t-p} + \varepsilon_t$

Where Y_t is a vector containing all variables at time *t*, c is a vector of intercept terms, A_1 to A_p are coefficient matrices capturing lagged interactions, and ε_t represents the vector of error terms. This structure makes VAR particularly useful for studying jointly evolving financial markets, as it identifies how shocks originating in one index propagate across others over time. By relying on minimal theoretical restrictions and focusing on empirical relationships, the VAR framework provides a flexible and powerful tool for modelling spillovers, forecasting returns, and analysing market connectedness across global equity indices.

3.3. Estimation Output

3.3.1. Standard Error (SE)

Standard Error (SE) measures the precision of a sample statistic, such as the mean, relative to the population parameter. It is calculated as:

$SE = \frac{\sigma}{\sqrt{n}}$

where σ is the population standard deviation and n is the sample size. A smaller SE indicates greater accuracy of the sample estimate, making it critical in hypothesis testing and confidence interval calculation.

3.3.2. Adjusted R-squared

The Adjusted R-squared adjusts the R-squared value for the number of predictors in a regression model, providing a more accurate measure of goodness-of-fit, especially with multiple predictors. The formula is:

$\bar{R}^2 = 1 - \frac{(1 - R^2)\,(n-1)}{n - p - 1}$

where R^2 is the R-squared value, n is the number of observations, and pp is the number of predictors. Unlike R-squared, the Adjusted R-squared penalizes unnecessary variables, preventing overfitting and giving a more reliable evaluation of model performance.

3.3. Information Criteria

3.3.1. Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is used to evaluate and compare the goodness of fit of statistical models, balancing model complexity and fit. The formula for AIC is:

AIC =2k − 2ln (L)

where k is the number of parameters in the model, and L is the likelihood of the model. A lower AIC value indicates a better-fitting model, while penalizing excessive complexity. It is widely used in model selection, especially when comparing models with different numbers of parameters.

3.3.2. Schwarz Information Criterion (SIC)

The Schwarz Information Criterion, often referred to as the Bayesian Information Criterion, is a statistical measure used to compare and select among competing models by balancing model fit with model complexity. It is defined as

SIC = -2 ln(L) + k ln(n)

where L is the maximised likelihood of the model, k is the number of estimated parameters and n is the sample size. The criterion increases as more parameters are added, thereby penalising overfitting and encouraging the choice of more parsimonious models that achieve a good fit with fewer parameters. When comparing models, the one with the lowest SIC value is preferred because it indicates the most efficient trade-off between explanatory power and simplicity. The SIC is widely applied in time-series, econometric, and forecasting frameworks to guide lag-length selection, model structure choices, and overall model adequacy assessment.

3.3.3. Hannan-Quinn Information Criterion (HQIC)

The Hannan-Quinn Information Criterion (HQIC) is an information-theoretic measure used to select optimal model specifications by balancing goodness of fit with model parsimony. It penalizes additional parameters more moderately than the Schwarz (BIC) criterion but more strongly than the Akaike (AIC) criterion, making it a middle-ground option when avoiding both overfitting and underfitting is essential. The HQIC is calculated as

HQIC = −2 ln(L) + 2k ln(ln(T))

Where L is the likelihood of the estimated model, k is the number of estimated parameters, and T is the sample size. Because the penalty term grows slowly with sample size, HQIC is particularly useful in large datasets where AIC may favour overly complex models and BIC may be too restrictive. The model yielding the lowest HQIC value is preferred, as it indicates an efficient trade-off between explanatory power and simplicity.

3.4. Validity Tests

3.4.1. Durbin-Watson (DW) Test

The Durbin-Watson (DW) Test checks for autocorrelation in the residuals of a regression model, particularly for first-order correlation. The test statistic is:

$$DW = \frac{\sum_{t=2}^{n} (\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{n} \hat{\varepsilon}_t^2}$$

where $\hat{\varepsilon}_t$ are the residuals at time t. The DW statistic ranges from 0 to 4; a value near 2 indicates no autocorrelation, values < 2 suggest positive autocorrelation, and values > 2 indicate negative autocorrelation. This test is critical for ensuring the validity of regression assumptions in time-series data.

3.4.2. Variance Inflation Factor (VIF)

The Variance Inflation Factor (VIF) is used to detect multicollinearity in regression models by measuring how much the variance of a regression coefficient is inflated due to correlation with other predictors. The formula for VIF is:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where R_i^2 is the coefficient of determination obtained by regressing the i-th predictor on all other predictors. A high VIF (typically > 10) indicates significant multicollinearity, which may distort the regression results and reduce the reliability of the coefficients.

3.4.3. Breusch-Pagan (BP) Test Heteroscedasticity

The Breusch-Pagan (BP) Test detects heteroscedasticity in regression models by assessing whether error variances depend on independent variables. It involves regressing the squared residuals ($\hat{\varepsilon}^2$) on the predictors:

$$\hat{\varepsilon}^2 = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_k X_k + u$$

The test statistic is: $BP = \frac{1}{2} R_{aux}^2 n$

where R_{aux}^2 is the coefficient of determination from the auxiliary regression. The BP statistic follows a chi-squared distribution, with higher values indicating heteroscedasticity.

3.4.4. Lagrange Multiplier (LM) Test Autocorrelation

The Lagrange Multiplier (LM) Test for autocorrelation detects serial correlation in residuals of a regression model. It involves regressing residuals ($\hat{\varepsilon}_t$) on lagged residuals and independent variables. The auxiliary regression is:

$$\hat{\varepsilon}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 \hat{\varepsilon}_{t-2} + \cdots + \alpha_p \hat{\varepsilon}_{t-p} + ut$$

The test statistic is: $LM = nR^2$

where n is the sample size, and R^2 is the auxiliary regression's determination coefficient. The LM statistic follows a chi-squared distribution, with significance indicating autocorrelation.

3.4.5. Lagrange Multiplier (LM) Test for ARCH Effect

The Lagrange Multiplier (LM) Test for ARCH Effect identifies autoregressive conditional heteroscedasticity (ARCH) in time-series data. It involves regressing squared residuals ($\hat{\varepsilon}_t$) on their lagged values. The auxiliary regression is:

$$\hat{\varepsilon}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 \hat{\varepsilon}_{t-2} + \cdots + \alpha_p \hat{\varepsilon}_{t-p} + ut$$

The test statistic is: $LM = nR^2$

where n is the sample size, and R^2 is from the auxiliary regression. A significant LM statistic indicates ARCH effects, essential for volatility modelling.

3.5. Forecasting Accuracy Evaluating Measures

Five measures Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Theil's U2 (TU2) are commonly used to evaluate forecasting accuracy and compare model performance. Mean Error captures the average signed difference between predicted and actual values, indicating whether a model tends to over-forecast or under-forecast on average. RMSE measures the square root of the average squared forecast errors, giving more weight to large deviations and highlighting the presence of large mistakes. MAE measures the average absolute magnitude of forecast errors, offering a more balanced view that is less sensitive to extreme values than RMSE. Together, these measures help quantify how close a model's predictions are to real observations from different perspectives and reveal whether errors are concentrated or dispersed. By comparing them, researchers can detect complementary strengths and weaknesses across forecasting models. This integrated evaluation helps determine whether model performance remains consistent under different data patterns.

Mean Percentage Error expresses forecast errors as percentages, which helps compare performance across datasets with different scales, although it may be sensitive to very small actual values. Theil's U2 is a relative accuracy measure that compares a model's performance to a naïve benchmark such as the previous period's value. A value less than one indicates that the forecasting model performs better than the benchmark, while a value greater than one indicates weaker predictive ability. Together, these metrics provide a comprehensive understanding of forecast bias, error magnitude, percentage-based performance, and relative efficiency. They also help analysts judge whether errors arise from systematic bias or random fluctuations and offer a holistic basis for comparing competing forecasting frameworks. Ultimately, these indicators guide the selection of robust models that remain reliable under varying data conditions and volatility structures. This comprehensive evaluation is crucial for identifying models that maintain stability even during periods of heightened uncertainty. Such insights help practitioners choose forecasting techniques that align with both statistical accuracy and practical relevance.

4. Results analysis

Table 2: Descriptive statistics of international stock indices

Index	N	Mean	Median	Minimum	Maximum	Std. Dev.	C.V.	Skewness	kurtosis
Bovespa	300	0.8968	0.7121	-29.9040	17.9170	6.9421	7.7410	-0.3558	1.1260
CAC40	300	0.1998	0.7764	-17.4900	20.1190	5.0455	25.2570	-0.2725	1.2374
DAX	300	0.5209	0.9579	-25.4220	21.3780	5.7719	11.0800	-0.5256	2.1936
DJ	300	0.5305	0.8320	-14.0600	13.9510	4.3114	8.1279	-0.3436	0.9021
FTSE100	300	0.1836	0.5319	-13.8080	12.3520	3.7497	20.4180	-0.5767	1.3485
HS	300	0.2622	0.8168	-22.4660	26.6240	6.4327	24.5320	0.1282	1.7470
KOSPI	300	0.4705	0.7449	-23.1340	22.4510	6.1095	12.9850	-0.1533	1.1714
NASDAQ	300	0.7205	1.1399	-22.9020	19.1950	6.2735	8.7069	-0.4790	1.1763
NSE 50	300	1.1284	1.1623	-26.4100	28.0660	6.3006	5.5837	-0.3500	2.5362
NIKKEI225	300	0.3944	0.6950	-23.8270	15.0430	5.3580	13.5840	-0.4860	0.8066
SP500	300	0.5619	1.1045	-16.9410	12.6840	4.4177	7.8627	-0.4894	0.7690
ASX	300	0.3964	0.9947	-21.1820	9.9568	3.8339	9.6726	-1.0084	3.1150
Shanghai	300	0.5490	0.4463	-24.6310	27.4460	7.0492	12.8390	-0.0444	1.8661
SAI	300	0.8736	0.7949	-14.9070	14.6670	4.9679	5.6871	0.0303	0.3956

(**Source:** Author's computations)

Table 2 presents the descriptive statistics of fourteen major international stock indices, highlighting their distributional properties and volatility patterns. The means across indices show that NSE50 and Bovespa record relatively higher average returns, while markets like CAC40 and FTSE100 exhibit lower average movements, reflecting their comparatively stable market environments. Standard deviations reveal that Shanghai, Bovespa, and HS experience the highest volatility, suggesting greater sensitivity to global shocks and domestic policy changes. Most indices show negative skewness, indicating a higher probability of extreme negative returns, while kurtosis values below three for many markets point to distributions with thinner tails than a normal curve. These characteristics collectively suggest that the return series are non-normally distributed, reinforcing the need for robust econometric models. The coefficients of variation further highlight clear distinctions in relative volatility, with CAC40, HS, and FTSE100 demonstrating higher variability compared to their mean returns, whereas NSE50 shows the lowest relative dispersion, implying relatively stable performance despite occasional large shocks. The minimum and maximum values reveal wide return ranges for indices like Shanghai, Bovespa, and HS, emphasizing their exposure to large fluctuations during global events. Meanwhile, ASX and FTSE100 show narrower ranges, supporting their classification as more stable developed markets. The combined descriptive metrics underline substantial heterogeneity across global markets, indicating that their risk-return profiles differ widely. This variability underscores the importance of accounting for market-specific features in predictive modeling.

Overall, Table 2 demonstrates that international indices display diverse statistical behaviours shaped by regional market dynamics, global spillovers, and domestic economic conditions. Indices such as Shanghai and Bovespa exhibit higher volatility and extreme price shifts, while FTSE100 and ASX reflect steadier performance, signalling structural differences in liquidity and investor behaviour. The presence of negative skewness across many markets highlights the prevalence of downside risks, which must be considered in forecasting frameworks. These descriptive insights form a crucial foundation for subsequent empirical analysis, guiding the selection of appropriate econometric methods for modeling connectedness and return predictability across global markets.

Table 3: Correlation matrix of international indices

Index	Bovespa	CAC40	DAX	DJ	FTSE100	HS	KOSPI	NASDAQ	NSE 50	NIKKEI225	SP500	ASX	Shanghai	SAI
Bovespa	1.000	0.559*	0.564*	0.588*	-0.025	0.529*	0.577*	0.573*	0.581*	0.430*	0.606*	0.576*	0.301*	0.542*
CAC40	0.559*	1.000	0.916*	0.780*	-0.006	0.507*	0.593*	0.714*	0.514*	0.617*	0.804*	0.720*	0.254*	0.578*
DAX	0.564*	0.916*	1.000	0.778*	-0.021	0.511*	0.629*	0.746*	0.535*	0.608*	0.801*	0.669*	0.281*	0.550*
DJ	0.588*	0.780*	0.778*	1.000	-0.094	0.492*	0.615*	0.748*	0.513*	0.586*	0.950*	0.707*	0.275*	0.600*
FTSE100	-0.025	-0.006	-0.021	-0.094	1.000	-0.109	-0.071	-0.036	-0.042	0.076	-0.065	-0.074	-0.111	-0.010
HS	0.529*	0.507*	0.511*	0.492*	-0.109	1.000	0.524*	0.538*	0.512*	0.438*	0.532*	0.473*	0.506*	0.553*
KOSPI	0.577*	0.593*	0.629*	0.615*	-0.071	0.524*	1.000	0.642*	0.597*	0.568*	0.653*	0.592*	0.279*	0.627*
NASDAQ	0.573*	0.714*	0.746*	0.748*	-0.036	0.538*	0.642*	1.000	0.524*	0.621*	0.865*	0.655*	0.251*	0.540*
NSE 50	0.581*	0.514*	0.535*	0.513*	-0.042	0.512*	0.597*	0.524*	1.000	0.533*	0.542*	0.578*	0.281*	0.531*
NIKKEI225	0.430*	0.617*	0.608*	0.586*	0.076	0.438*	0.568*	0.621*	0.533*	1.000	0.637*	0.582*	0.288*	0.460*
SP500	0.606*	0.804*	0.801*	0.950*	-0.065	0.532*	0.653*	0.865*	0.542*	0.637*	1.000	0.739*	0.286*	0.615*
ASX	0.576*	0.720*	0.669*	0.707*	-0.074	0.473*	0.592*	0.655*	0.578*	0.582*	0.739*	1.000	0.287*	0.615*
Shanghai	0.301*	0.254*	0.281*	0.275*	-0.111	0.506*	0.279*	0.251*	0.281*	0.288*	0.286*	0.287*	1.000	0.282*
SAI	0.542*	0.578*	0.550*	0.600*	-0.010	0.553*	0.627*	0.540*	0.531*	0.460*	0.615*	0.615*	0.282*	1.000

(**Source:** Author's computations)
(* 5 percent significance)

The correlation matrix from Table 3 reveals several clear patterns of interdependence among the fourteen international indices, beginning with the consistently strong positive associations observed between the major developed markets. The CAC40 and DAX show a high correlation of 0.916, reflecting the integrated nature of the Eurozone financial environment. Similarly, SP500 and DJ exhibit a very strong correlation of 0.950, confirming the close co-movement within US markets. The NASDAQ also moves closely with SP500 at 0.865, emphasizing the dominance of US-led market influence. These high correlations indicate that shocks within one major developed market are quickly transmitted to others, leading to a high degree of synchronicity in global equity movements. The analysis extends to cross-continental relationships, where Asian markets also demonstrate significant integration with Western markets. For instance, the KOSPI shows strong correlations above 0.600 with DAX, SP500, NASDAQ, and CAC40, suggesting that South Korea's market is heavily influenced by global economic factors. Similarly, Japan's NIKKEI225 demonstrates correlations in the range of 0.586 to 0.637 with DJ, NASDAQ, SP500, and CAC40, reinforcing Japan's deep integration with major global financial systems. Even Hong Kong's HS maintains strong associations above 0.500 with Bovespa, CAC40, KOSPI, NASDAQ, and SP500, illustrating its position as a key gateway for international investment flows.

India's NSE 50 presents a similar pattern of interconnection, with moderately strong correlations in the 0.513 to 0.581 range with CAC40, DAX, DJ, SP500, and NASDAQ, indicating India's increasing integration with global markets. These relationships are particularly noteworthy given India's emerging market status, which traditionally might exhibit weaker ties with developed markets. The correlation of 0.597 between NSE 50 and KOSPI, and 0.578 with ASX, further highlights regional interconnectedness within the Asia-Pacific zone, reflecting shared exposure to global risk factors and synchronized trading behaviors. Bovespa, representing Brazil, also exhibits significant connections with most global indices, showing correlations between 0.529 and 0.606 with HS, NASDAQ, SP500, CAC40, and DAX. This suggests substantial co-movement between Brazil and developed economies, likely due to commodity price links and global investor sentiment. The strongest Bovespa relationship is with SP500 at 0.606, emphasizing the influence of US economic conditions on Latin American markets. At the same time, Bovespa shows relatively weaker ties with FTSE100, recording a negative correlation of -0.025, indicating differentiated market behavior in the UK relative to Brazil.

One of the most distinctive features of the correlation matrix is the consistently low association of FTSE100 with most markets, with several correlations near zero and even negative values such as -0.094 with DJ and -0.111 with Shanghai. This suggests that the UK market behaves more independently, potentially due to domestic policy factors, Brexit-driven structural changes, and differing sectoral compositions. Shanghai also shows comparatively weaker correlations with other indices, generally ranging from 0.251 to 0.301, signalling China's partially segmented financial landscape, capital controls, and differentiated trading patterns that limit its short-term comovement with global markets. The overall structure of the correlation results underscores a global financial environment where developed markets particularly the US and Europe form a highly interconnected core with correlations often above 0.700, while emerging markets like India, Brazil, and South Korea show moderately strong but slightly lower co-movements in the range of 0.500 to 0.600. In contrast, markets like FTSE100 and Shanghai register relatively lower correlations, suggesting either structural independence or unique domestic influences. These patterns collectively highlight the presence of global financial integration, regional clustering, and selective market segmentation shaping contemporary international equity dynamics.

Table 4: Unit root test for international indices

Indexes	ADF Test (15 lag)	ADF GLS Test (15 lag)	KPSS Test (5 lag)
Bovespa	-15.4624 (0.0000)***	-11.8753 (0.0000)***	0.0801 (>0.1000)
CAC40	-16.6481 (0.0000)***	-2.2339 (0.0240)***	0.1868 (>0.1000)
DAX	-16.6571 (0.0000)***	-3.9776 (0.0000)***	0.0572 (>0.1000)
DJ	-14.2294 (0.0000)***	-24.3346 (0.0000)@***	0.0333 (>0.1000)
FTSE100	-17.5822 (0.0000)***	-3.1184 (0.0210)***	0.0473 (>0.1000)
HS	-17.8227 (0.0000)***	-8.8037 (0.0000)***	0.0623 (>0.1000)
KOSPI	-8.5533 (0.0000)***	-4.6389 (0.0000)***	0.0524 (>0.1000)
NASDAQ	-17.0053 (0.0000)***	-3.7550 (0.0030)***	0.0668 (>0.1000)
NSE 50	-16.7309 (0.0000)***	-7.1758 (0.0000)***	0.0538 (>0.1000)
NIKKEI225	-15.7556 (0.0000)***	-7.6952 (0.0000)***	0.0527 (>0.1000)
SP500	-17.2679 (0.0000)***	-3.5403 (0.0050)***	0.0386 (>0.1000)
ASX	-16.7529 (0.0000)***	-5.1400 (0.0000) ***	0.0360 (>0.1000)
Shanghai	-5.3383 (0.0000)***	-29.8326 (0.0000)@***	0.0320 (>0.1000)
SAI	-18.3193 (0.0000)***	-7.6810 (0.0000)***	0.0393 (>0.1000)

(**Source:** Author's computations)
(* 10 percent significance, ** 5 percent significance and *** 1 percent significance)
(@ First difference)

The results of the unit root tests presented in Table 4 provide strong and consistent evidence that all international stock indices used in the study are stationary after transformation, confirming their suitability for further time-series modelling. The ADF test statistics are highly significant at the one-percent level across all indices, indicating rejection of the null hypothesis of a unit root. This suggests that the return series are mean-reverting and free from long-term stochastic trends. For indices such as Shanghai and DJ, the ADF-GLS test indicates stationarity after first differencing, but this does not contradict the overall stationarity of the return series since return transformations commonly introduce stability even when price series are integrated. The very low p-values across the ADF and ADF-GLS results strengthen the reliability of these findings and ensure that the datasets are appropriate for multivariate modelling techniques such as VAR, GARCH, and HSC.
The KPSS test complements these results by failing to reject the null hypothesis of stationarity for all indices, as indicated by KPSS statistics well below the critical threshold. This further reinforces that each index behaves as a stable series around a mean, with no evidence of level-based non-stationarity. The combination of ADF, ADF-GLS, and KPSS outcomes provides robust cross-validation, confirming that the return series are structurally sound for predictive modelling, volatility estimation, and spillover analysis. The convergence of outcomes across all three tests eliminates concerns about misleading inferences caused by non-stationary data, thereby ensuring that subsequent econometric estimates such as coefficients, diagnostics, and predictive accuracy are statistically meaningful. Overall, the unit root diagnostics highlight that the international financial markets represented in the dataset exhibit consistent statistical properties suitable for comparative and interconnected analysis. With all series confirmed as stationary, the study is able to confidently proceed with evaluating cross-market linkages, volatility behaviour, and forecast performance without the distortions that arise from non-stationarity. This foundation strengthens the empirical credibility of the later models and results, ensuring that any observed comovements, predictive relations, or causal interactions among global markets and NSE NIFTY reflect genuine economic dynamics rather than artefacts of unstable data.

Table 5: NSE NIFTY with USA and European Markets for Various predictive measures (Model - I)

Particulars	Ordinary Least Square (OLS)			HSC		GARCH (1, 1)		VAR	
	Coefficients	p-value	Collinearity	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Const	0.7280	0.0182**	--	0.7576	0.0068***	0.5045	0.0604*	0.9845	0.0131**
SP500	0.2544	0.1158	5.6080	0.1067	0.4345	0.3259	0.0322**	0.4227	0.0850*
NASDAQ	0.1702	0.0833*	4.1700	0.2314	0.0079***	0.0959	0.3392	0.0480	0.7699
CAC40	0.0476	0.7614	6.8820	0.0273	0.8521	−0.0011	0.9931	0.0062	0.9696
DAX	0.2518	0.0683*	6.9670	0.3440	0.0113**	0.2775	0.0274**	0.3248	0.0451**
FTSE100	−0.0318	0.6942	1.0120	−0.0335	0.7008	−0.0050	0.9471	−0.0569	0.5224
Standard Error	5.2039	--	--	2.0991$	--	--	--	5.0597	--
Adjusted R-squared	0.3178	--	--	0.2854	--	--	--	0.3481#	--
F Stat	28.8609	0.0000***	--	24.8849	0.0000***	--	--	7.7917	0.0000***
Akaike criterion	1846.95	--	--	1302.20	--	1827.93	--	6.1410$	--
Schwarz criterion	1869.17	--	--	1324.43	--	1864.97	--	6.3699$	--
Hannan-Quinn	1855.84	--	--	1311.10	--	1842.76	--	6.2327$	--
Durbin-Watson	2.1110	--	--	2.1229	--	--	--	2.1573	--
BP Test HSD	18.9484	0.0001***	--	--	--	--	--	--	--
LM Test ACR (12 Lag)	1.5356	0.1108	--	--	--	--	--	1.1310	0.3353
LM Test ARCH (12 Lag)	14.4529	0.2727	--	15.6124	0.2096	--	--	8.5010	0.7449
Mean Error	0.0000	--	--	-0.0344$	--	0.2283	--	--	--
Root Mean Squared Error	5.1516$	--	--	5.1646	--	5.1661	--	--	--
Mean Absolute Error	3.8386	--	--	3.8198$	--	3.8695	--	--	--
Mean Percentage Error	105.060	--	--	99.988	--	97.352$	--	--	--
Theil's U2	0.8669	--	--	0.8508	--	0.8355$	--	--	--

(**Source:** Author's computations)
(* 10 percent significance, ** 5 percent significance and *** 1 percent significance)
(# Highest value and $ Lowest value)

Table 5 explains the predictive relationship between NSE NIFTY and major US-European markets across four econometric models, beginning with the OLS results. The constant term is positive and significant, suggesting a stable baseline influence. The SP500 and NASDAQ show positive coefficients, with NASDAQ being significant at the ten-percent level, while DAX also shows a marginally significant positive effect. CAC40 and FTSE100 display negligible influence with high p-values. The Variance Inflation Factors reported for SP500, NASDAQ, CAC40 and DAX remain below the common threshold of ten, indicating no collinearity issues among the explanatory variables. The AIC for OLS is 1846.95, which is higher relative to the alternative models, signalling weaker model efficiency. The adjusted R-squared indicates that OLS explains a moderate proportion of the variation in NIFTY, while diagnostics such as BP test indicate heteroskedasticity, though the DW statistic reflects no major autocorrelation concerns. The HSC model strengthens the explanatory power of the constant and continues to show a positive influence from SP500, though it remains statistically insignificant. NASDAQ and DAX again display positive effects, but without significance, while CAC40 shows a statistically relevant coefficient. The standard error decreases considerably compared to OLS, suggesting improved precision. The AIC falls to 1302.20, representing a notable improvement in model fit compared to OLS. The adjusted R-squared shows a slight decline relative to OLS, but the model benefits from more stable variance estimation. Mean error becomes marginally negative, indicating slight underprediction. Taken together, the HSC model improves efficiency but does not dramatically change the significance profile of the predictors. The GARCH(1,1) model provides a different perspective by capturing volatility clustering. The constant term becomes marginally significant, showing structural persistence in returns. NASDAQ exhibits strong significance with a very small coefficient, implying small but statistically reliable influence, while DAX remains significant at the five-percent level. SP500 and CAC40 do not contribute significantly, and FTSE100 retains its weak and negative coefficient. The model performs strongly in terms of information criteria, with the AIC at 1827.93, lower than OLS but higher than the HSC specification. Volatility-based diagnostics such as the LM-ARCH test suggest no remaining ARCH effects, indicating that the model successfully captures conditional variance behaviour. Error measures such as RMSE and MAE are close to the minimum values across models, reflecting better predictive stability. The VAR model provides a dynamic, system-based assessment of how markets jointly influence NIFTY. The constant remains highly significant and larger than in the other models, reflecting a strong baseline level in the multivariate structure. SP500 and DAX show significant positive relationships, with DAX maintaining consistent influence across the models. NASDAQ and CAC40, however, remain statistically weak. The adjusted R-squared reaches the highest value among the models, indicating that the VAR framework captures more joint information and interdependencies. The information criteria values around six remain the lowest among all models, marking VAR as the most efficient specification. The DW statistic indicates acceptable residual independence, while the LM-ACR test confirms the absence of autocorrelation issues.

Comparing the predictive error metrics, VAR consistently produces lower information criteria values, indicating superior performance. GARCH follows with moderately low AIC and stable error distribution, while OLS shows the highest information criterion, confirming it as the least efficient. HSC improves efficiency compared to OLS but does not outperform GARCH or VAR in adjusted R-squared or significance consistency. Theil's U2 is lowest in GARCH and VAR, highlighting better forecasting accuracy in these frameworks. The patterns across models show that market interactions are best captured in dynamic or volatility-sensitive structures rather than static linear estimation. Overall, the table reveals that DAX exerts consistent influence on NIFTY across nearly all model structures, while SP500 shows significance only in the VAR model and NASDAQ becomes significant under volatility modelling. CAC40 and FTSE100 contribute minimally in all specifications. The comparative evaluation of AIC, significance levels, and error measures shows clear superiority of the VAR and GARCH models, which better accommodate market interdependencies and volatility behaviour. The absence of high VIF values ensures reliability of coefficient interpretation, and the combined evidence highlights that dynamic and conditional-variance models provide the strongest basis for understanding NIFTY's linkages with US and European indices.

Table 6: NSE NIFTY with Asian Markets for Various predictive measures (Model - II)

Particulars	Ordinary Least Square (OLS)			HSC		GARCH (1, 1)		VAR	
	Coefficients	p-value	Collinearity	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Const	0.7926	0.0040***	--	0.7816	0.0038***	0.7399	0.0039***	0.7995	0.0167***
NIKKEI225	0.2821	<0.0001***	1.5480	0.2357	<0.0001***	0.2527	<0.0001***	0.2413	0.0003***
HANG SENG	0.2233	<0.0001***	1.7450	0.2693	<0.0001***	0.2249	<0.0001***	0.2401	<0.0001***
KOSPI	0.3512	<0.0001***	1.7130	0.3398	<0.0001***	0.3561	<0.0001***	0.4089	<0.0001***
Shanghai	0.0014	0.9755	1.3540	−0.0118	0.7851	−0.0366	0.4426	−0.0202	0.6671
Standard Error	4.7115	--	--	2.1102	--	--	--	4.6866	--
Adjusted R-squared	0.4408	--	--	0.4107	--	--	--	0.4407	--
F Stat	59.9261	0.0000***	--	53.1025	0.0000***	--	--	15.1341	0.0000***
Akaike criterion	1786.33	--	--	1304.38	--	1785.40	--	5.9845	--
Schwarz criterion	1804.85	--	--	1322.90	--	1818.73	--	6.2007	--
Hannan-Quinn	1793.74	--	--	1311.79	--	1798.74	--	6.0712	--
Durbin-Watson	2.1269	--	--	2.1309	--	--	--	2.1717	--
BP Test HSD	15.4702	0.0038***	--	--	--	--	--	--	--
LM Test ACR (12 Lag)	1.2539	0.2460	--	--	--	--	--	1.1010	0.3593
LM Test ARCH (12 Lag)	13.2834	0.3488	--	16.5651	0.1667	--	--	13.7420	0.3175
Mean Error	0.0000	--	--	0.0298	--	0.0825	--	--	--
Root Mean Squared Error	4.6721	--	--	4.6813	--	4.6844	--	--	--
Mean Absolute Error	3.5324	--	--	3.5453	--	3.5287	--	--	--
Mean Percentage Error	56.255	--	--	57.410	--	63.020	--	--	--
Theil's U2	1.1194	--	--	1.0858	--	1.0609	--	--	--

(**Source:** Author's computations)

(* 10 percent significance, ** 5 percent significance and *** 1 percent significance)

(# Highest value and $ Lowest value)

Table 6 provides the relationship between NSE NIFTY and major Asian markets using four predictive models and shows that all models consistently produce statistically significant constants, suggesting a stable baseline influence on NIFTY movements. The VIF values for all regressors are below 10, indicating no collinearity among the Asian indices and confirming that each contributes independent information to the model. The AIC values show that the HSC model records the lowest value (1304.38), followed closely by the GARCH model (1785.40), whereas OLS displays the highest AIC (1786.33), implying that HSC provides the most efficient model fit among the alternatives. Overall, the descriptive indicators suggest that the Asian market variables collectively offer strong explanatory power, particularly under the HSC and VAR frameworks.

The OLS model results reveal that NIKKEI 225, HANG SENG, and KOSPI exert strong and highly significant positive effects on NIFTY, each with coefficients above 0.22 and p-values less than 0.0001, highlighting their strong contemporaneous linkages with the Indian market. The Shanghai Composite shows no meaningful contribution, indicated by its near-zero coefficient (0.0014) and very high p-value (0.9755). With an adjusted R-squared of 0.4408 and a very strong F-statistic, the OLS results confirm that the combined Asian indices account for a substantial proportion of NIFTY's variations. The BP test shows heteroskedasticity, but the LM tests indicate no autocorrelation or ARCH problems, making OLS reliable except for variance instability.

The HSC model provides reinforced results with highly significant coefficients for NIKKEI 225, HANG SENG, and KOSPI, again showing clear predictive influence. Shanghai remains statistically insignificant with a negative but negligible coefficient. The lowest AIC among all models further signals that HSC is the most efficient in capturing NIFTY's variation relative to the Asian indices. The standard error is comparatively low (2.1102), and the adjusted R-squared of 0.4107 remains close to the OLS value, confirming strong predictive performance within a volatility-sensitive framework. The GARCH (1,1) model continues the same pattern where NIKKEI 225, HANG SENG, and KOSPI strongly influence NIFTY returns, all bearing very strong significance levels, indicating that these markets transmit substantial volatility-adjusted spillovers. Shanghai again contributes insignificantly, showing persistent weak linkage with NIFTY. The error metrics show slightly higher RMSE and MAE compared with HSC, but the model maintains a strong explanatory capacity under high-volatility settings. Mean error values remain small, indicating well-centred predictions.

The VAR results show that the dynamic interrelationship framework also identifies NIKKEI 225, HANG SENG, and KOSPI as major contributors to NIFTY movements with very high significance levels, while Shanghai remains weak and insignificant. The adjusted R-squared of 0.4407 is almost identical to OLS, suggesting that past values of all indices collectively enhance predictive power without drastically altering the strength of relationships. The LM test for autocorrelation at 12 lags shows no serial correlation, confirming that the VAR specification is well structured. Across all models, the performance metrics affirm that the predictive quality is consistently highest for NIKKEI 225, HANG SENG, and KOSPI, while Shanghai fails to exhibit meaningful influence under any specification. Theil's U2 values show improvement across models, with GARCH achieving the lowest value (1.0609), indicating superior predictive accuracy compared to OLS and HSC. The overall results demonstrate that NIFTY has strong connectedness with major Asian markets especially Japan, Hong Kong, and South Korea while China's Shanghai Composite contributes very little to return predictability under any modeling framework.

Table 7: NSE NIFTY with Emerging Markets for Various predictive measures (Model - III)

Particulars	Ordinary Least Square (OLS)			HSC		GARCH (1, 1)		VAR	
	Coefficients	p-value	Collinearity	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Const	0.4717	0.0890*	--	0.4764	0.0875*	0.5106	0.0348**	0.6933	0.0358**
Bovespa	0.2800	<0.0001***	1.6660	0.2969	<0.0001***	0.2543	<0.0001***	0.2838	<0.0001***
ASX	0.4485	<0.0001***	1.8720	0.4229	<0.0001***	0.4216	<0.0001***	0.4029	<0.0001***
Shanghai	0.0530	0.1984	1.1340	0.0506	0.2699	0.0319	0.4549	0.0438	0.3053
SAI	0.2274	0.0020***	1.7730	0.2061	0.0037***	0.2190	0.0022***	0.2893	0.0001***
Standard Error	4.7098	--	--	2.1227$	--	--	--	4.6343	--
Adjusted R-squared	0.4412	--	--	0.3994	--	--	--	0.4531#	--
F Stat	60.0234	0.0000***	--	50.7031	0.0000***	--	--	15.8625	0.0000***
Akaike criterion	1786.11	--	--	1307.93	--	1769.43	--	5.9621$	--
Schwarz criterion	1804.63	--	--	1315.35	--	1802.77	--	6.1783$	--
Hannan-Quinn	1793.52	--	--	1315.35	--	1782.77	--	6.0487$	--
Durbin-Watson	2.1170	--	--	2.1188	--	--	--	2.1449	--
BP Test HSD	1.8339	0.7663	--	--	--	--	--	--	--
LM Test ACR	1.1664	0.3070	--	--	--	--	--	1.1830	0.2953
LM Test ARCH	17.0412	0.1481	--	17.0591	0.1474	--	--	15.0540	0.2385
Mean Error	0.0000$	--	--	0.0103	--	0.0139	--	--	--
Root Mean Squared Error	4.6704$	--	--	4.6727	--	4.6843	--	--	--
Mean Absolute Error	3.5060	--	--	3.4933	--	3.4908$	--	--	--
Mean Percentage Error	63.5710	--	--	61.0590$	--	73.6900	--	--	--
Theil's U2	0.6319$	--	--	0.6363	--	0.6510	--	--	--

(**Source:** Author's computations)
(* 10 percent significance, ** 5 percent significance and *** 1 percent significance)
(# Highest value and $ Lowest value)

The discussion on Table 7 shows how the NIFTY index responds to major emerging markets under four predictive models, with consistent evidence of strong interactions. The constant term remains positive across all models, increasing from 0.4717 in OLS to 0.6933 in VAR, indicating a stable baseline effect on NIFTY even after accounting for market influences. Variance Inflation Factor values for all predictors remain below 10, confirming no collinearity issues and validating the stability of the coefficient estimates. When comparing AIC values, the HSC model records 1307.93 and VAR shows the lowest normalized AIC value (5.9621), indicating better model fit in relative terms.

Across all specifications, Bovespa emerges as a consistently significant predictor of NIFTY. The coefficients remain stable around 0.28 in OLS and 0.2969 in HSC while p-values stay below 0.0001, demonstrating a highly robust relationship. The GARCH(1,1) estimate of 0.2543 and VAR value of 0.2838 support the same conclusion, suggesting that movements in the Brazilian market strongly influence NIFTY regardless of model complexities or volatility adjustments. This consistency shows that Bovespa remains an important emerging-market driver of NIFTY returns.

ASX also demonstrates a strong and stable impact on NIFTY. The OLS coefficient of 0.4485 and similar values in HSC and GARCH models confirm a positive and highly significant association at the 1 percent level. Even under VAR, the coefficient remains high at 0.4029, showing that Australian market dynamics maintain explanatory power even when accounting for system-wide feedback effects. The uniformity of these results highlights the economic and financial interlinkages between India and Australia.

The Shanghai index behaves differently from the other emerging markets. In OLS, its coefficient of 0.0530 is insignificant, and HSC continues this insignificance with a p-value of 0.2699. The GARCH model produces a small positive effect of 0.0319 but again without significance. VAR detects a positive coefficient of 0.0438, yet still statistically weak. These results indicate that Shanghai does not meaningfully influence NIFTY within this model set, suggesting weaker short-run or volatility-adjusted linkages between the two markets.

SAI, in contrast, consistently demonstrates strong explanatory power. The OLS and HSC models produce coefficients of 0.2274 and 0.2061, both significant at the 1 percent and 5 percent levels respectively. GARCH reinforces the relationship with a coefficient of 0.2190, again highly significant. VAR increases the magnitude to 0.2893, indicating stronger dynamic interactions when market interdependencies are incorporated. This consistent significance shows that SAI contributes substantial predictive information for NIFTY, likely reflecting deeper financial or regional ties.

Model comparison-based diagnostics support these findings. The adjusted R-squared remains high across OLS (0.4412), HSC (0.3994), and VAR (0.4531), indicating solid explanatory performance. The lowest mean error and RMSE values appear in OLS and HSC, while GARCH features the lowest Theil's U2 value at 0.6319, highlighting superior forecasting accuracy under volatility considerations. Residual diagnostics, including BP, LM-ACR, and LM-ARCH tests, confirm that the models are free from serial correlation and heteroskedasticity problems. Overall, the outcomes reflect strong and consistent relationships between NIFTY and major emerging markets especially Bovespa, ASX, and SAI while Shanghai contributes minimally, and volatility-based measures strengthen the precision of these insights.

Table 8: NSE NIFTY with leading (Continental) Markets for Various predictive measures (Model - IV)

Particulars	Ordinary Least Square (OLS)			HSC		GARCH (1, 1)		VAR	
	Coefficients	p-value	Collinearity	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Const	0.4888	0.0726*	--	0.5103	0.0634*	0.4339	0.0709*	0.6777	0.0390**
DJ	−0.0420	0.6998	3.1300	−0.0197	0.8439	−0.0160	0.8677	0.0854	0.4728
NIKKEI	0.2851	<0.0001***	1.7640	0.2518	0.0002***	0.2387	0.0002***	0.2203	0.0020***
Bovespa	0.2744	<0.0001***	1.7530	0.2973	<0.0001***	0.2427	<0.0001***	0.2644	<0.0001***
AXI	0.3209	0.0050***	2.6880	0.2827	0.0148**	0.3272	0.0010***	0.2380	0.0443**
SFI	0.2066	0.0050***	1.8680	0.2018	0.0036***	0.2250	0.0014***	0.2558	0.0007***
CAC40	−0.0214	0.8194	3.1980	−0.0248	0.7989	−0.0514	0.5415	−0.0063	0.9509
Standard Error (SE)	4.5873	--	--	2.0149$^{\$}$	--	--	--	4.5459	--
Adjusted R-squared (R^2)	0.4699	--	--	0.4339	--	--	--	0.4738$^{\#}$	--
F Stat	45.1766	0.0000***	--	39.1973	0.0000***	--	--	15.3554	0.0000***
Akaike criterion (AIC)	1772.25	--	--	1278.63	--	1759.02	--	5.9300$^{\$}$	--
Schwarz criterion (SIC)	1798.18	--	--	1304.55	--	1799.77	--	6.1717$^{\$}$	--
Hannan-Quinn (HQC)	1782.63	--	--	1289.00	--	1775.33	--	6.0269$^{\$}$	--
Durbin-Watson (DW)	2.1320	--	--	2.1345	--	--	--	2.1550	--
BP Test HSD	0.8317	0.9912	--	--	--	--	--	--	--
LM Test ACR	1.2831	0.2278	--	--	--	--	--	1.0980	0.3617
LM Test ARCH	15.9953	0.1915	--	16.0784	0.1877	--	--	11.9000	0.4547
Mean Error (ME)	0.0000	--	--	-0.0207$^{\$}$	--	0.0754	--	--	--
Root Mean Squared Error (RMSE)	4.5335$^{\$}$	--	--	4.5389	--	4.5494	--	--	--
Mean Absolute Error (MAE)	3.4676	--	--	3.4501	--	3.4441$^{\$}$	--	--	--
Mean Percentage Error (MPE)	63.8280	--	--	62.6550$^{\$}$	--	71.5470	--	--	--
Theil's U2 (TU2)	0.7528	--	--	0.7418	--	0.7369$^{\$}$	--	--	--

(**Source:** Author's computations)

(* 10 percent significance, ** 5 percent significance and *** 1 percent significance)

(# Highest value and $ Lowest value)

Table 8 explains the predictive relationship between NSE NIFTY and the leading continental markets by presenting results from OLS, HSC, GARCH(1,1), and VAR models, and the set of estimates shows consistent significance across several markets. The constant term remains positive across all four models, and its significance at the 10 percent level in OLS, HSC, and GARCH, and at the 5 percent level in VAR, reflects a stable baseline effect in NIFTY returns. The variance-inflation factors for all predictors are below ten, confirming that multicollinearity is not a concern in this model. AIC comparison shows that the VAR framework provides the lowest value, indicating superior model fit relative to OLS, HSC, and GARCH.

The coefficient behaviour across the predictors demonstrates that NIKKEI, Bovespa, AXI, and SFI consistently exert strong positive and highly significant effects on NIFTY in every model specification. The magnitude of NIKKEI's impact moves from around 0.29 in OLS to 0.22 in VAR, showing stability and robustness. Bovespa also exhibits a closely aligned pattern, with highly significant coefficients across all models, confirming its influential role in explaining Indian market movements. AXI and SFI maintain strong positive effects, with significance at the 1 percent or 5 percent levels throughout, supporting the idea that these markets transmit substantial informational and structural influences to NIFTY.

The DJ and CAC40 indices show no meaningful explanatory power across any of the four models, with consistently insignificant coefficients. Their weak influence is further reinforced by the small magnitudes of their coefficients and the absence of statistical significance in each framework. This indicates that while these markets are important globally, they do not play a substantial role in the short-run predictability of NIFTY compared to the more regionally and economically connected indicators such as NIKKEI, Bovespa, AXI, and SFI.

The diagnostic statistics provide strong support for model adequacy. Durbin-Watson values across models' cluster around two, confirming an absence of autocorrelation. BP tests show no heteroskedasticity problems, with OLS displaying a very high p-value. ARCH tests likewise show no volatility clustering concerns for OLS, HSC, or VAR. The LM tests for autocorrelation also indicate well-specified models, as none of the p-values suggest the presence of serial correlation.

In terms of overall model performance, the adjusted R-squared values reveal that VAR explains the largest proportion of NIFTY variability, followed closely by OLS and HSC, while GARCH offers a slightly lower but still strong explanatory capability. AIC, SIC, and HQC values are consistently lowest for the VAR model, confirming it as the preferred specification among the four. Prediction accuracy measures, including RMSE, MAE, and Theil's U2, show GARCH delivering the lowest forecast error values, while VAR provides competing efficiency with a better global fit.

Together, these results highlight that continental markets represented by NIKKEI, Bovespa, AXI, and SFI are highly integrated with NIFTY, serving as reliable predictors across all model frameworks. Their significance aligns with global trading linkages and the increasing synchronicity of cross-market movements. The collective diagnostic and information-criterion evidence position VAR as the strongest structural model and GARCH as the most accurate forecasting model, reinforcing the depth of interconnectedness between Indian equity markets and the broader leading continental markets.

Table 9: NSE NIFTY with leading Markets for Various predictive measures (Model - V)

Particulars	Ordinary Least Square (OLS)			HSC		GARCH (1, 1)		VAR	
	Coefficients	**p-value**	**Collinearity**	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
Const	0.5546	0.0398**	--	0.5608	0.0291**	0.5102	0.0340**	0.6308	0.0524*
NIKKEI	0.2269	0.0011***	2.0380	0.1530	0.0179**	0.1797	0.0077***	0.1708	0.0184**
KOSPI	0.1863	0.0051***	2.4240	0.2169	0.0010***	0.1685	0.0101**	0.1970	0.0101**
HS	0.1330	0.0238**	2.1100	0.1336	0.0289**	0.1227	0.0247**	0.1435	0.0168**
Shanghai	−0.0173	0.6895	1.3970	−0.0465	0.2983	−0.0476	0.2908	−0.0371	0.4123
ASX	0.3363	0.0032***	2.8100	0.2814	0.0095***	0.3392	0.0006***	0.2515	0.0326**
SAI	0.0990	0.2028	2.2140	0.1148	0.1124	0.1306	0.0860*	0.1393	0.0850*
DAX	0.1843	0.1307	7.3400	0.2501	0.0315**	0.1912	0.0939*	0.2050	0.1135
CAC40	−0.2059	0.1491	7.6920	−0.2397	0.0655*	−0.2331	0.0619*	−0.2292	0.1204
FTSE100	−0.0188	0.7882	1.0770	−0.0554	0.4336	0.0335	0.6161	−0.0333	0.6436
NASDAQ	−0.0126	0.8855	4.5230	0.0492	0.6022	−0.0187	0.8291	−0.0884	0.4865
SP500	−0.1388	0.3462	6.2980	−0.1823	0.1856	−0.0823	0.5600	0.0730	0.7035
Bovespa	0.2092	<0.0001***	1.9450	0.2108	0.0001***	0.1932	<0.0001***	0.2075	0.0001***
Standard Error	4.4791	--	--	1.9232$^{\$}$	--	--	--	4.4301	--
Adjusted R-squared	0.4946	--	--	0.4663	--	--	--	0.5002$^{\#}$	--
F Stat	25.3858	0.0000***	--	22.7715	0.0000***	--	--	12.9701	0.0000***
Akaike criterion	1763.73	--	--	1256.46	--	1754.52	--	5.8975$^{\$}$	--
Schwarz criterion	1811.88	--	--	1304.61	--	1817.49	--	6.2155$^{\$}$	--
Hannan-Quinn	1783.00	--	--	1275.73	--	1779.72	--	6.0250$^{\$}$	--
Durbin-Watson	2.1159	--	--	2.1119	--	--	--	2.1145	--
BP Test HSD	25.6836	0.0119**	--	--	--	--	--	--	--
LM Test ACR	1.5828	0.0961*	--	--	--	--	--	0.9330	0.5144
LM Test ARCH	15.1938	0.2310	--	13.8731	0.3089	--	--	14.4830	0.2709
Mean Error	0.0000	--	--	-0.0094$^{\$}$	--	0.0403	--	--	--
Root Mean Squared Error	4.3810	--	--	4.4095	--	0.4056$^{\$}$	--	--	--
Mean Absolute Error	3.3811$^{\$}$	--	--	3.3589	--	3.3489	--	--	--
Mean Percentage Error	50.8590$^{\$}$	--	--	58.0860	--	59.4630	--	--	--
Theil's U2	0.7542	--	--	0.7196	--	0.6690$^{\$}$	--	--	--

(**Source:** Author's computations)

(* 10 percent significance, ** 5 percent significance and *** 1 percent significance)

(# Highest value and $ Lowest value)

Table 9 presents the predictive relationship between NSE NIFTY and a broad set of leading global markets under Model V across OLS, HSC, GARCH(1,1), and VAR approaches. Across all models, the coefficients of several Asian and emerging markets appear consistently significant, while major US and European indicators show weaker explanatory power. The collinearity values reported as VIF are all below the threshold of ten, indicating no concerning multicollinearity and confirming the reliability of the estimated coefficients. This broad model brings together leading markets, allowing for a consolidated view of global influences on Indian equity movements.

The OLS results show that NIKKEI, KOSPI, Hang Seng, ASX, and Bovespa are all positively significant, indicating strong contemporaneous associations with NIFTY. Shanghai, DAX, CAC40, FTSE100, NASDAQ, and SP500 remain insignificant, suggesting their daily changes do not exert a direct measurable influence when all markets are included jointly. The adjusted R^2 of 0.4946 is one of the stronger fits among the models, reflecting that nearly half of NIFTY's variation is explained by these global indices. Error diagnostics indicate stable residual behaviour but highlight some heteroskedastic tendencies through the BP test.

Under the HSC model, the significance pattern largely mirrors OLS, with NIKKEI, KOSPI, HS, ASX, and Bovespa again emerging as strong contributors. Shanghai continues to be insignificant, while SAI shows mild significance. The adjusted R^2 (0.4663) is slightly lower but remains robust, and the Akaike Information Criterion (AIC) value of 1256.46 is the lowest among all four models, implying the best model fit in terms of information efficiency. The stability in coefficient signs between OLS and HSC reinforces the strength of Asian market linkages with NIFTY.

The GARCH(1,1) model introduces volatility adjustments and shows even clearer dominance of Asian and Latin American influences. NIKKEI, KOSPI, HS, ASX, SAI, and Bovespa are all strongly significant at conventional levels. This indicates that volatility-adjusted movements in NIFTY are highly sensitive to shocks in these markets. The RMSE and MAE values are among the lowest, showing that the model handles error minimization effectively, and Theil's U2 of 0.6690 registers the lowest value among the predictive setups, highlighting superior forecast accuracy under volatility-based modelling. The VAR model offers dynamic multi-directional insights and reveals that NIKKEI, KOSPI, HS, ASX, SAI, and Bovespa remain significant influences even after accounting for interdependencies. The adjusted R^2 (0.5002) is the highest across all models, demonstrating the strongest explanatory ability when allowing lagged interactions among variables. The AIC value of 5.8975 is also the lowest in the VAR column, signalling that the VAR provides the most efficient model structure overall. Durbin-Watson statistics close to two confirm absence of autocorrelation, and the ARCH and ACR tests show well-behaved residuals.

Overall, Table 8 confirms that Asian markets particularly NIKKEI, KOSPI, Hang Seng, and ASX along with Bovespa, exert dominant and consistent influences on NIFTY across all modelling approaches. In contrast, major US, and European markets (SP500, NASDAQ, DAX, CAC40, FTSE100) do not demonstrate significant predictive strength when evaluated within a comprehensive global model. The comparative evidence from AIC, R^2, and error measures collectively indicates that VAR and GARCH provide superior predictive efficiency, while HSC offers the best information-criterion-based fit. These findings reinforce the growing integration between India and major Asian and emerging markets rather than traditional Western financial hubs.

Table 10: Comparison between various models and various predictive measures for various models

Model	Particulars	OLS	HSC	GARCH (1, 1)	VAR
Model - I	Standard Error	5.2039	2.0991	--	5.0597
	Adjusted R-squared	0.3178	0.2854	--	0.3481
	Akaike criterion	1846.95	1302.20	1827.93	6.1410
	Mean Error	0.0000	-0.0344	0.2283	--
	Root Mean Squared Error	5.1516	5.1646	5.1661	--
	Mean Absolute Error	3.8386	3.8198	3.8695	--
	Mean Percentage Error	105.060	99.988	97.352	--
	Theil's U2	0.8669	0.8508	0.8355	--
Model - II	Standard Error	4.7115	2.1102	--	4.6866
	Adjusted R-squared	0.4408	0.4107	--	0.4407
	Akaike criterion	1786.33	1304.38	1785.40	5.9845
	Mean Error	0.0000	0.0298	0.0825	--
	Root Mean Squared Error	4.6721	4.6813	4.6844	--
	Mean Absolute Error	3.5324	3.5453	3.5287	--
	Mean Percentage Error	56.255	57.410	63.020	--
	Theil's U2	1.1194	1.0858	1.0609	--
Model - III	Standard Error	4.7098	2.1227	--	4.6343
	Adjusted R-squared	0.4412	0.3994	--	0.4531
	Akaike criterion	1786.11	1307.93	1769.43	5.9621
	Mean Error	0.0000	0.0103	0.0139	--
	Root Mean Squared Error	4.6704	4.6727	4.6843	--
	Mean Absolute Error	3.5060	3.4933	3.4908	--
	Mean Percentage Error	63.5710	61.0590	73.6900	--
	Theil's U2	0.6319	0.6363	0.6510	--
Model - IV	Standard Error	4.5873	2.0149	--	4.5459
	Adjusted R-squared	0.4699	0.4339	--	0.4738
	Akaike criterion	1772.25	1278.63	1759.02	5.9300
	Mean Error	0.0000	-0.0207	0.0754	--
	Root Mean Squared Error	4.5335	4.5389	4.5494	--
	Mean Absolute Error	3.4676	3.4501	3.4441	--
	Mean Percentage Error	63.8280	62.6550	71.5470	--
	Theil's U2	0.7528	0.7418	0.7369	--
Model - V	Standard Error	4.4791	1.9232	--	4.4301
	Adjusted R-squared	0.4946	0.4663	--	0.5002

	Akaike criterion	1763.73	1256.46	1754.52	5.8975
	Mean Error	0.0000	-0.0094	0.0403	--
	Root Mean Squared Error	4.3810	4.4095	0.4056	--
	Mean Absolute Error	3.3811	3.3589	3.3489	--
	Mean Percentage Error	50.8590	58.0860	59.4630	--
	Theil's U2	0.7542	0.7196	0.6690	--

(**Source:** Author's computations)

Table 10 provides a consolidated comparison of various models and predictive measures for NSE NIFTY. Observing standard errors across models, HSC consistently shows the lowest values, indicating greater precision in predictions compared to OLS, GARCH, and VAR. OLS generally exhibits higher standard errors, suggesting less precise forecasts, while VAR maintains moderate levels but shows improvements in models with broader market inclusion, reflecting its ability to capture variation when multiple predictors are considered.

Adjusted R-squared values reveal that explanatory power increases from Model I to Model V, with VAR often showing the highest values, particularly in later models, indicating that it effectively captures the variation in NSE NIFTY returns when multiple markets are included. OLS shows moderate explanatory power, while HSC, despite slightly lower adjusted R-squared than VAR, balances explanatory ability with lower standard errors and better fit, as seen in the AIC comparisons. Across all models, HSC consistently presents the lowest AIC, confirming its superior goodness-of-fit relative to other measures.

Mean error values are generally close to zero for all measures, suggesting unbiased predictions. Mean absolute error and root mean squared error are lowest in HSC across most models, reinforcing its reliability in forecasting. Mean percentage error is highest in Model I and gradually decreases in subsequent models, reaching the lowest values in Model V for OLS, reflecting improved predictive performance as more global and regional market indices are included. GARCH shows slightly higher root mean squared errors in most models, except in Model V, where it provides its best forecast performance.

Theil's U2 values further illustrate the comparative predictive accuracy among measures. HSC consistently yields lower Theil's U2 values than OLS in most models, indicating better forecast reliability. GARCH occasionally shows the lowest Theil's U2, particularly in later models, highlighting its ability to capture volatility dynamics more effectively. VAR does not report Theil's U2 in Table 10, but its higher adjusted R-squared values suggest strong explanatory capability, even if forecasting performance cannot be directly compared.

Overall, Table 10 demonstrates that HSC strikes the best balance between precision, model fit, and forecast reliability, reflected in low standard errors, AIC, and mean absolute errors. VAR excels in explaining variation across multiple markets but may not always provide the most precise predictions. OLS provides a baseline with moderate accuracy, and GARCH performs well in volatility-sensitive models. The comparison indicates that as more comprehensive market information is included from Model I to Model V, predictive performance improves across all measures, with HSC consistently offering optimal model fit and reliability.

Tables 5 to 9 collectively explore the predictive relationship of NSE NIFTY with different global markets using OLS, HSC, GARCH, and VAR models. Table 5 focuses on USA and European markets, where SP500, NASDAQ, and DAX show some significance, while CAC40 and FTSE100 are largely insignificant. The adjusted R-squared is moderate, and AIC is relatively high, indicating limited explanatory power when only these markets are considered. Collinearity is not an issue as variance inflation factors are below ten. Standard errors are generally higher in OLS and VAR compared to HSC, suggesting that HSC provides more precise predictions. Theil's U2 values show reasonable forecast accuracy, but model performance improves when more diverse markets are included in later tables.

Tables 6 and 7 extend the analysis to Asian and emerging markets, respectively. In Table 6, NIKKEI225, HANG SENG, and KOSPI consistently show highly significant positive coefficients, while Shanghai remains insignificant. Table 7 highlights Bovespa, ASX, and SAI as strong predictors, with Shanghai again largely insignificant. Across these models, adjusted R-squared values increase compared to Table 5, reflecting better explanatory power when regional markets are considered. HSC consistently shows the lowest AIC and standard errors, confirming superior model fit and predictive precision. Forecast errors, including root mean squared and mean absolute errors, are lower in these tables, demonstrating that inclusion of regional market indices enhances prediction accuracy for NSE NIFTY.

Tables 8 and 9 analyze leading and combined markets, including Continental, Asian, and emerging indices. Significant positive influences are observed in NIKKEI, Bovespa, KOSPI, ASX, and SAI, while some European indices such as CAC40, DAX, and FTSE100 show mixed or insignificant results. Adjusted R-squared values are the highest among all tables, indicating the best explanatory power, while HSC consistently exhibits the lowest AIC, standard errors, and mean absolute errors, confirming optimal model fit. GARCH occasionally improves Theil's U2, reflecting better handling of volatility in dynamic markets. Overall, comparing Tables 5 to 9 shows that predictive performance improves with the inclusion of a broader set of global markets, with HSC offering consistently strong fit and VAR capturing variation effectively, while OLS provides baseline estimates.

5. Conclusion

The analysis of NSE NIFTY across multiple global markets using OLS, HSC, GARCH, and VAR models highlights the intricate interconnections between domestic and international financial markets. When focusing on USA and European markets, indices such as SP500, NASDAQ, and DAX demonstrate measurable positive effects on NSE NIFTY returns, while CAC40 and FTSE100 generally remain insignificant. Although the explanatory power of these models is moderate, HSC consistently exhibits lower standard errors and better Akaike Information Criterion values compared to OLS, GARCH, and VAR. This indicates that HSC provides more precise and reliable predictions, while VAR models capture slightly more variation.

Collinearity is minimal across variables, ensuring stable coefficient estimates and trustworthy results.

Including Asian markets strengthens the predictive capability of the models. Indices like NIKKEI225, KOSPI, and HANG SENG show highly significant positive influence on NSE NIFTY across all modeling approaches, while Shanghai's effect remains negligible. Similarly, emerging markets such as Bovespa, ASX, and SAI consistently exhibit strong positive relationships. The explanatory power of these models increases with the inclusion of regional indices, reflected in higher adjusted R-squared values. HSC continues to perform well, providing the lowest standard errors and AIC values, demonstrating its robustness in capturing the impact of regional markets on NSE NIFTY. Forecasting accuracy improves across models, with reduced root mean squared errors, mean absolute errors, and Theil's U2 values, indicating more precise and reliable predictions.

When the analysis is extended to leading Continental markets alongside Asian and emerging markets, predictive performance further improves. Indices such as NIKKEI, Bovespa, KOSPI, ASX, and SAI show consistently significant positive coefficients, while European indices like CAC40, DAX, and FTSE100 show mixed or limited significance. VAR models often achieve the highest explanatory power in these comprehensive settings, reflecting their strength in capturing variations across interconnected markets. HSC continues to provide the lowest AIC, standard errors, and mean absolute errors, confirming its optimal fit and predictive precision. GARCH models occasionally show better Theil's U2 values, emphasizing their effectiveness in modeling volatility within dynamic market conditions.

Overall, the analysis demonstrates that predictive accuracy for NSE NIFTY improves as a broader set of global markets is considered. HSC emerges as the most balanced modeling approach, providing precise forecasts, low standard errors, and superior model fit. VAR effectively explains variation, particularly when multiple markets interact, while GARCH enhances the modeling of volatility and dynamic dependencies. The results underline the importance of including both regional and leading international markets to capture the full spectrum of influences on NSE NIFTY, suggesting that a combined approach leveraging HSC for precision, VAR for explanatory power, and GARCH for volatility provides the most comprehensive and reliable framework for market prediction.

6. Scope for further research

Future research can expand this analysis by incorporating high-frequency intraday data, which may capture short-term volatility spillovers more accurately than daily observations. Additional global markets, sector-specific indices, and alternative asset classes such as commodities, cryptocurrencies, and bond markets could also be included to better understand cross-market transmission mechanisms. Machine learning and nonlinear models may further enhance predictive accuracy, especially during periods of structural breaks or financial crises where traditional models often underperform. Integrating macroeconomic variables, investor sentiment indicators, and geopolitical risk measures would deepen insights into the fundamental drivers of NIFTY movements. Overall, broadening datasets, exploring advanced methodologies, and considering structural dynamics present valuable opportunities for more comprehensive and robust forecasting in future studies.

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