ISSN 1840-4855
e-ISSN 2233-0046

Original scientific article
http://dx.doi.org/10.70102/afts.2026.1836.380

A GARCH MODEL ANALYSIS OF MACROECONOMIC VOLATILITY AND STOCK MARKET PERFORMANCE IN ASIAN COUNTRIES

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Received: May 13, 2026; Revised: June 24, 2026; Accepted: August 03, 2026; Published: September 29, 2026

SUMMARY

Volatility is one of the most important factors in investment decision-making and financial risk management, and the role of volatility modelling in comprehending market dynamics is crucial. In this study, the volatility behaviour of six major stock markets in Asia—India, China, Japan, South Korea, Singapore and Hong Kong—has been explored with the GARCH (1,1) model. The daily closing price data for six stock indices, the S&P 500, gold, and the price of Brent crude oil from January 2010 to December 2025 (4,166 observations per series) were analysed. The descriptive statistics, Pearson correlation analysis, Augmented Dickey–Fuller (ADF) unit root test, ARCH-LM test, and GARCH (1,1) estimation were used. The ADF test results indicated that all the series were stationary (ADF statistics varied from −9.95 to −66.83 at a p-value < 0.001). The ARCH-LM test results showed that there was significant conditional heteroskedasticity across all the markets (the LR test statistic varied from 155.07 to 1275.50 at a p-value < 0.001). The estimated GARCH models showed that the volatility shocks were very persistent, as the ARCH and GARCH effects were found significant, with the values of the volatility persistence ($\alpha + \beta$) in the range of 0.9451 to 0.9882. A moderate degree of integration was observed across Asian markets, with the highest correlation between Singapore and Hong Kong ($r = 0.5751$), while the equity returns had a weak correlation with gold. The satisfactory forecasting performance of the models was indicated by the results from the model evaluation, where the prediction errors (RMSE and

MAE) for Singapore were the lowest. The results indicate that the GARCH (1,1) model is an appropriate model for volatility modelling and can offer useful information to investors, portfolio managers, financial analysts, and policymakers.

Key words: *GARCH model, stock market volatility, macroeconomic factors, asian markets, financial forecasting, volatility persistence.*

INTRODUCTION

Over the years, the Asian stock market has become one of the fastest-growing financial markets, fulfilling a vital function in mobilizing capital, contributing to the economic development of the country, and luring domestic and foreign investors. In the last ten years, market performance has been more responsive to the economic conditions of the macroeconomic system, including exchange rates, crude oil prices, inflation, interest rates, and global monetary policies. The combination of these economic factors can have a significant impact on investor confidence, company profits, money inflows, and financial stability, leading to large price swings in the stock market. Domestic and foreign financial systems are interlinked, and the overall uncertainty in the markets has increased even more, making it hard to determine the direction of stock returns. This is done in a "calm then voluble" (also known as volatility clustering) fashion. Typical financial return series tend to have non-stationary variance, and thus traditional linear regression methods are not always suitable for the modeling of market risk. Therefore, time-varying conditional volatility estimates are becoming more critical to the study of stock market dynamics and beneficial investment and policy decisions [9].

Volatility of the stock market is one of the major issues for investors, financial institutions, and policymakers, as a sudden change in the macroeconomic conditions can have a significant impact on market behavior within a short period of time [8] [11]. Unpredictability in corporate performance and in returns on investment because of exchange rate fluctuations, commodity price changes, inflation, and monetary policy changes causes equity prices to fluctuate irregularly. The assumption of constant variance is a common one in traditional statistical models and is often violated when modeling the volatility of financial markets because the volatility is more persistent and clustered than would be suggested by this assumption. This means that it remains an empirical challenge to measure market risk and to accurately predict future volatility. To optimize the investment strategy, the risk management of stocks, and financial policy, it is therefore necessary to have a comprehensive study of the macroeconomic variables and the conditional variance of the stock market through an appropriate conditional variance model.

Several research have attempted to quantify the volatility of the stock market by applying various GARCH models, and many of them have also tried to investigate the influence of macroeconomic indicators on the performance of the financial markets [1] [2] [15]. Previous studies, are mostly based on a single economic indicator, market sector, or a limited number of years of study, thereby being unable to provide a complete picture of volatility dynamics. Comparative analyses tend to focus either on domestic economic conditions or on the international financial influences and do not address the effects of a number of macroeconomic factors on stock market behavior [3] [10]. Moreover, not much research has attempted to analyze the exchange rate change, commodity price changes, inflation indicators, and monetary policy variables in an integrated manner in a single volatility modeling framework. However, the limitations show that an empirical investigation is needed in order to understand the impact of macroeconomic uncertainty on stock market performance through an appropriate conditional volatility model [12][17].

This study helps add to the body of literature in a number of significant ways. The first advantage is that it is a comprehensive study of stock market volatility, which combines several macroeconomic variables in a single econometric model, instead of analyzing each of the macroeconomic variables separately. Second, it uses GARCH modeling to calculate the conditional volatility and to assess the persistence of market fluctuations in different economic conditions [5] [13]. Third, the study examines how the exchange rate, commodity prices, inflation, and monetary policy indicators interact together in determining the performance of the stock market, offering a wider picture of the macroeconomic transmission mechanisms [4] [18]. Lastly, the implications of the findings are presented in a practical

sense that assists investment decision-making, portfolio risk management, and financial and monetary policymaking in situations of economic uncertainty.

Objectives

1. The first is to analyse the statistical properties of stock market returns in six Asian stock markets.
2. To test the stationarity and conditional heteroskedasticity of the series of stock market returns using the Augmented Dickey-Fuller and ARCH-LM tests.
3. To perform comparative analysis of the conditional volatility of stock market returns in selected Asian stock markets using the GARCH (1,1) model.
4. To test the persistence of the stock market volatility and the forecasting ability of the GARCH (1,1) model for financial risk management in the Asian equity markets.

Hypotheses

H1: The return series on the stock market are found to be highly volatile and to have conditional heteroskedasticity.

H2: The GARCH (1,1) model is a good model of the conditional volatility of stock market returns over the chosen Asian stock markets.

H3: The estimated GARCH persistence coefficient ($\alpha + \beta$) suggests that the stock market volatility is persistent.

H4: There are differences among the selected Asian stock markets in terms of level of volatility persistence.

H5: The GARCH (1,1) model performs well when modelling the volatility of the stock market in the selected Asian stock markets.

The rest of the essay is organized in the following manner. In section 2, previous literature on financial market volatility, macroeconomic factors, and the application of GARCH models is discussed and an outline of the research gap addressed by the study is provided. The methodology of the study comprising the research design, variables used, econometric model, and analytical methods are described in section 3. The outcomes of the statistical tests and GARCH model estimation as well as their implications are explained in section 4. The final section of the paper, section 5, consists of the conclusions drawn from the study and possible directions for future research.

LITERATURE SURVEY

Financial Market Volatility

Volatility in financial markets is the size of fluctuations in returns on assets as a result of a variation in economic conditions, investor expectations, and external financial disturbances [20]. The overall pattern of stock market returns is typically a long period of relatively low volatility, followed by a cluster of more volatile returns, with volatility varying over time [6]. This type of behavior is often referred to as volatility clustering: a large swing in the price of a security is followed by even larger swings, both up and down. Market uncertainty, caused by economic crises, geopolitical tensions, commodity price instability, and monetary policy changes, has further heightened overall market uncertainty, making the return of stocks even more difficult to predict. The knowledge of these volatility patterns can play a crucial role in assessing investment risk, optimizing portfolio allocation, and making informed financial decisions [16].

Macroeconomic Determinants

Macroeconomic variables have a fundamental influence on stock market behaviour because affect the profitability of firms, investment decisions of the firms, and market expectations. International trade competitiveness and foreign capital flows are impacted by exchange rate fluctuations, and fluctuations in crude oil prices directly impact production costs and inflation. Gold is a safe-haven asset that's often ascribed to its ability to change investment flows, typically from commodity and equity markets when times are uncertain. Changes in interest rates impact loan repayments and values of homes, while inflation rates can impact purchasing power, profits of businesses and investor confidence. These macroeconomic indicators interact with each other to form a complicated environment where stock market performance reacts differently in different economic situations, which needs a comprehensive empirical analysis.

GARCH Applications

For a better understanding of how financial market volatility is changing over time, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model has been extensively employed as an important econometric model [7] [14]. In contrast to the traditional regression models with constant variance, GARCH models allow for the inclusion of past shocks in the market as well as past volatility in the estimation process, which allows for the volatility to persist. The model has been frequently applied to analyze the risk in the stock market, the impact of financial crisis, prediction of future volatility, and the influence of macroeconomic uncertainty on financial markets [19]. It is useful for modelling volatility clustering and persistent market volatility, so it is very convenient for a range of financial return time series that are heteroskedastic and subject to a changing market environment.

Research Gap

Despite the extensive literature on the use of GARCH-based models to study volatility in the stock market, a number of important elements have been ignored. The majority of studies consider a small number of macroeconomic variables or only a particular financial sector, which limits a proper comprehension of the market behaviour. Familiar studies also tend to focus on the volatility phenomena on rather short time spans, which are inadequate to assess changing economic conditions and major global disturbances. Moreover, empirical evidence that tests the joint effects of exchange rates, commodity prices, inflation and monetary policy variables in a joint conditional volatility model is limited. These limitations may be overcome to gain a more complete picture of macroeconomic uncertainty and of stock market performance.

METHODOLOGY

Research Design

The methodology of this research paper involves an empirical approach because it involves collecting factual information from real life and using methods that are derived from observation and experience. To investigate the relationship between macroeconomic factors and stock market returns over time, a time-series econometric approach is adopted. The GARCH model has been chosen to analyze the varying volatility due to clustered volatility and varying variance in financial returns. The research methodology can be divided into two broad parts and two analyses. The second part of the research concentrates on analyzing the varying volatility in the collected data set using the GARCH (1,1) model along with the impact of macroeconomic factors on stock market performance.

Study Area

This study is centered around six prominent economies in Asia: India, China, Japan, South Korea, Singapore, and Hong Kong, having varied financial systems in South Asia, East Asia, and Southeast Asia, respectively. These benchmark indices for the stock market are the NIFTY 50 in India, the Shanghai Composite Index in China, the Nikkei 225 in Japan, the KOSPI in South Korea, the Straits

Times Index in Singapore, and the Hang Seng Index in Hong Kong. These indices taken together account for a significant percentage of the market cap and activities in Asian stock markets and represent a broad spectrum of developed and developing economies.

The timeline for this study ranges from January 2010 till December 2025. This allows examining the behavior of the stock market in varying macroeconomic conditions such as global financial crises, changes in commodity prices, exchange rates, inflation, monetary policy changes, and recovery after a pandemic. The chosen countries have geographical and economic diversification that will allow comparing volatility in Asian financial markets.

Data Collection

Data for this study has been sourced from open, secondary sources from January 2010 to December 2025. The six major Asian stock market indices that were used were the NIFTY 50 (India), Shanghai Composite Index (China), Nikkei 225 (Japan), KOSPI (South Korea), Straits Times Index (Singapore), and the Hang Seng Index (Hong Kong), and the daily data for these indices were collected from Yahoo Finance. Furthermore, daily closing levels of the S&P 500 Index, gold, and Brent crude oil were added as global financial indicators for the analysis of the relation between Asian equity market performances. The daily logarithmic returns were calculated from the closing prices and were then analyzed descriptively, correlated, tested for stationarity, tested for ARCH-LM effects, and modeled as GARCH (1,1). In order to maintain the methodological consistency and to prevent the mixed-frequency estimation bias, the economic variables available at daily frequency only were included in the econometric analysis. To provide a context for the interpretation of the macroeconomic indicators, such as inflation, interest rates, exchange rates, and unemployment, they were drawn from sources such as the World Bank and Federal Reserve Economic Data (FRED) for this purpose, but they were not directly analyzed in the GARCH estimation, as they are reported at monthly frequency. The final data consists of 4166 daily observations for each of the financial series, which gives a thorough foundation for studying the volatility dynamics of the 6 selected Asian stock markets. To ensure a strictly balanced panel dataset and eliminate structural misalignment caused by varying country-specific market holidays, trading calendars were synchronized using a forward-fill interpolation technique for missing non-trading day asset values, resulting in an identical sample size ($N = 4{,}166$) across all series.

Conceptual Framework

The main assumption of the conceptual framework is that the changes in the above-mentioned macroeconomic variables affect the investor's expectations and therefore the financial uncertainty, which in turn affects the stock market returns. These fluctuations lead to volatility clustering, which is estimated using the GARCH (1,1) model for studying the stock market performance.

The conceptual framework for this research is shown in figure 1. In the current research, the key attention is paid to the impact of macroeconomic factors on the stock market performance. It should be mentioned that such macroeconomic variables as exchange rate, Brent crude oil price, gold price, Consumer Price Index, Federal Funds Rate, unemployment rate, and Treasury yield are vital for understanding the state of investors' confidence and financial market mood. When changes occur in macroeconomic variables, there is economic uncertainty that can have an effect on stock market performance and cause financial volatility. The period of time when financial volatility lasts can be estimated using the GARCH (1,1) model.

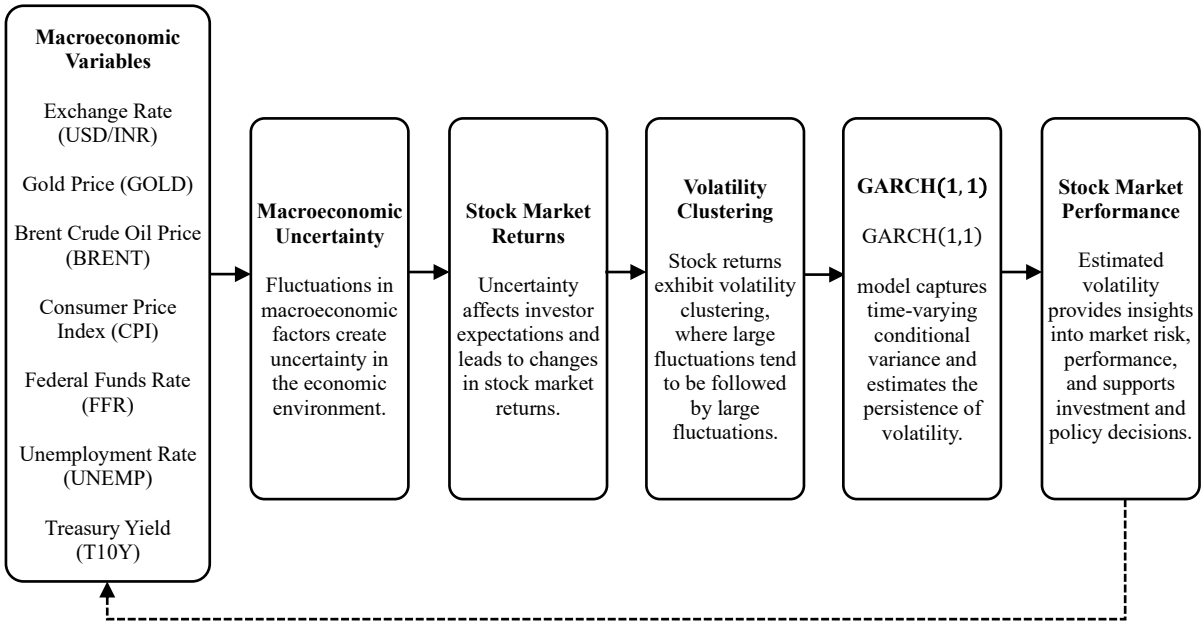

Figure 1. Conceptual framework of the proposed GARCH-based macroeconomic volatility analysis

Data Pre-processing

For econometric analysis, the collected financial data is pre-processed. The daily stock prices are converted to continuously compounded logarithmic returns to avoid scale effects and to stabilize the variance. Observations that are missing are deleted, and all variables are ordered chronologically. Descriptive statistics are calculated to provide a summary of the financial series' attributes. After that, the stationarity test using the Augmented Dickey Fuller (ADF) test is done to ascertain whether the data is stationary. Furthermore, the ARCH-LM test is done to determine the presence of conditional heteroskedasticity. The following is a set of diagnostics to check that the assumptions underpinning GARCH modeling are met.

Using equation (1), the stock return for the day is calculated as the log return.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

Were

R_t= stock return at time t;

P_t= closing stock price at time t;

P_{t-1}= closing stock price at time $t-1$.

Analysis I: Preliminary Statistical Analysis

The first process entails assessing the statistical dispersion of the financial return series. This is achieved by calculating descriptive statistics such as mean, standard deviation, minimum and maximum value, skewness, and kurtosis in order to observe the behavior of the stock return series. Following this is an analysis on the stationarity of the return series through the Augmented Dickey Fuller (ADF) unit root test.

The ADF regression model is presented in equation (2):

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{k} \delta_i \, \Delta Y_{t-i} + \varepsilon_t \qquad (2)$$

Where

ΔY_t represents the first difference of the return series;

α denotes the intercept;

β measures the presence of a unit root;

δ_i represents lag coefficients;

ε_t is the white-noise error term.

The ARCH-LM test is conducted to check if volatility clustering exists; it is done based on equation (3):

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + u_t \qquad (3)$$

where

ε_t^2 denotes the squared residuals;

α_0 is the constant term;

α_i represents ARCH coefficients;

u_t is the random disturbance term.

The presence of conditional heteroskedasticity is confirmed by a statistically significant ARCH-LM statistic, which is used to justify the use of the GARCH model.

Analysis II: GARCH Model Estimation

The return volatility for stock market return data was estimated with the use of the conventional Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) model. The reason for choosing such a method is the fact that it is quite a popular method in financial econometrics due to its ability to explain volatility clustering and conditional heteroskedasticity. The GARCH model uses the approach of estimating current conditional variance as a function of previous shock and previous conditional variance in order to evaluate short-term and long-term impacts of market disturbances on it. Logarithmic daily stock returns based on closing price values of the stock market benchmark index were used as an input series in the model estimation. Stationarity and conditional heteroskedasticity of the return series were first tested using the Augmented Dickey-Fuller (ADF) and ARCH-LM tests, respectively; only then was the GARCH (1,1) model estimated using Maximum Likelihood Estimation (MLE).

The conditional mean equation is written as equation 4.

$$R_t = \mu + \varepsilon_t \qquad (4)$$

In the equation above, R_t is the daily log-return on the stock, μ is the constant mean log-return, and ε_t is the random error.

The conditional variance equation is expressed as equation 5

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (5)$$

Where σ_t^2 denotes the conditional variance at time t,

- ω represents the constant variance component,
- α measures the short-run impact of recent market shocks (ARCH effect),
- β captures the persistence of previous volatility (GARCH effect), and
- ε_{t-1}^2 represents the squared residual from the previous period.

The persistence of volatility is evaluated using equation 6

$$P = \alpha + \beta \quad (6)$$

where values near one suggest a very high persistence in the volatility, indicating that the shocks will fade away slowly over time. The estimated GARCH parameters were then interpreted for assessing the degree of volatility clustering, persistence, and dynamics of volatility in general. The output from the model is therefore the basis of studying the behavior of volatility in financial markets during the study period.

In this study, the GARCH (1,1) model is used to estimate the volatility of stocks and assess its persistence through time. The GARCH (1,1) model estimates conditional heteroskedasticity in a way that the current volatility is dependent on the market shocks experienced in the past as well as the conditional variance in the past. The daily logarithm of stock returns was used as the data for estimating the volatility of stocks. Before the estimation of the model, the series of returns was tested for stationarity using the Augmented Dickey-Fuller (ADF) test as well as testing for conditional heteroskedasticity using the ARCH-LM test.

Model Evaluation

Performance of the GARCH model that has been estimated is analyzed using the root mean square error (RMSE) and mean absolute error (MAE).

The RMSE is calculated as per equation (7):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (7)$$

The MAE is calculated using equation (8):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (8)$$

Where

y_i denotes the observed stock return;

$\hat{y}_i$ denotes the predicted stock return;

n represents the total number of observations.

Low values of both RMSE and MAE indicate a higher degree of forecast accuracy, thus indicating that the GARCH model can efficiently predict stock market volatility in diverse macroeconomic scenarios.

RESULTS AND DISCUSSION

Sample Details

A large financial and macroeconomic database of the six major Asian stock markets, India, China, Japan, South Korea, Singapore, and Hong Kong, was used for the empirical analysis. After data cleaning and preprocessing, 4,166 synchronized daily observations were obtained from the daily stock market price data from 5 January 2010 to 31 December 2025. In addition to the six benchmark stock market indices, the dataset also covered internationally recognized financial indicators such as the S&P 500 Index, gold futures, and Brent crude oil prices to account for the global financial market conditions' impact on Asian stock markets. Additionally, monthly macroeconomic data, such as the Consumer Price Index (CPI), the Federal Funds Rate, the Ten-Year Government Bond Yield, and the Unemployment Rate, were added and resampled to daily frequencies using forward-fill interpolation to match the financial data.

The financial observations were fully observed after the pre-processing, and the missing observations in the macroeconomic variables were filled with forward-fill procedures in table 1. All financial variables were calculated using daily log returns before the statistical modeling to remove scale effects and fulfill the stationarity condition of volatility modeling.

The data set is balanced and includes the main markets of the Asian region along with other commodities and macroeconomic indicators globally to study the volatility transmission and persistence in the GARCH framework.

Table 1. Sample characteristics of the financial and macroeconomic dataset

Attribute	Value
Study Period	05 January 2010 – 31 December 2025
Countries Included	India, China, Japan, South Korea, Singapore, Hong Kong
Daily Observations	4,166
Stock Market Indices	6
Global Financial Variables	S&P 500, Gold, Brent Crude Oil
Macroeconomic Variables	CPI, Federal Funds Rate, 10-Year Treasury Yield, Unemployment Rate
Total Variables	22
Missing Values after Preprocessing	0

Analysis 1: Preliminary Statistical Analysis

To understand the distributional properties, interrelationships, stationarity, and volatility clustering of financial time series, a number of preliminary statistical tests were performed before estimating the GARCH (1,1) models. These diagnostic analyses are important because the assumption of GARCH models is that return series are stationary with great conditional heteroskedasticity. Hence, descriptive statistics, Pearson correlation analysis, ARCH-LM tests, and Augmented Dickey–Fuller (ADF) unit root tests are conducted on all the return series.

Descriptive Statistics

Table 2 shows the descriptive statistics of the stock indices, indices of global financial markets, and their logarithmic return series for the period under study. Differences in average index values and market volatility are all seen across the six Asian markets, with the highest average index values being seen in Hong Kong and Japan and the highest market growth over the long term seen in India.

The average values of the returns for the markets are close to zero, and the volatility of the markets ranges from the least volatile in Singapore to the most volatile in Japan. Moreover, all return distributions are negative-skewed, high- kurtosed, and have statistically significant Jarque–Bera statistics ($p < 0.001$), which suggests that these return distributions are non-normal and have high kurtosis. These features are characteristics that will be used to justify the use of GARCH-family models in modeling the dynamic volatility of the Asian stock markets and that confirm the presence of volatility clustering. The six Asian stock market indices' performance during the study period is presented in figure 2. Asian equity markets

are dynamic, with all markets showing long-term growth with several sharp declines, especially in times of significant global financial disruptions.

Table 2. Descriptive statistics of financial variables

Variable	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	Jarque–Bera	p-value
India	11815.555	6217.882	4544.200	26216.051	0.828	-0.526	524.536	<0.001
China	2977.736	506.162	1950.012	5166.350	0.066	0.498	46.125	<0.001
Japan	21730.059	9612.759	8160.010	52411.340	0.660	-0.047	303.220	<0.001
South Korea	2278.793	435.662	1457.640	4221.870	1.371	2.400	2304.808	<0.001
Singapore	3184.045	341.282	2233.480	4655.380	1.177	3.369	2932.484	<0.001
Hong Kong	23217.470	3529.050	14687.020	33154.121	0.199	-0.500	70.841	<0.001
S&P 500	2948.402	1492.168	1022.580	6932.050	0.770	-0.347	432.880	<0.001
Gold	1663.988	583.954	1050.800	4529.100	2.156	5.370	8231.883	<0.001
Brent Crude Oil	77.724	23.541	19.330	127.980	0.126	-0.903	152.599	<0.001
India Return	0.000384	0.010134	-0.139038	0.084003	-0.929	14.677	37990.235	<0.001
China Return	0.000048	0.012129	-0.088732	0.077550	-0.872	7.931	11446.713	<0.001
Japan Return	0.000373	0.013000	-0.132341	0.097366	-0.501	8.364	12318.365	<0.001
South Korea Return	0.000218	0.010516	-0.091761	0.082513	-0.450	7.196	9129.506	<0.001
Singapore Return	0.000114	0.008099	-0.077515	0.058946	-0.630	9.058	14517.296	<0.001
Hong Kong Return	0.000041	0.012827	-0.141833	0.086928	-0.374	6.933	8440.932	<0.001
S&P 500 Return	0.000434	0.010752	-0.127652	0.090895	-0.622	14.143	34988.208	<0.001
Gold Return	0.000327	0.010100	-0.098206	0.057775	-0.599	5.790	6067.575	<0.001
Brent Return	-0.000062	0.021980	-0.279761	0.190774	-0.959	17.563	54183.770	<0.001

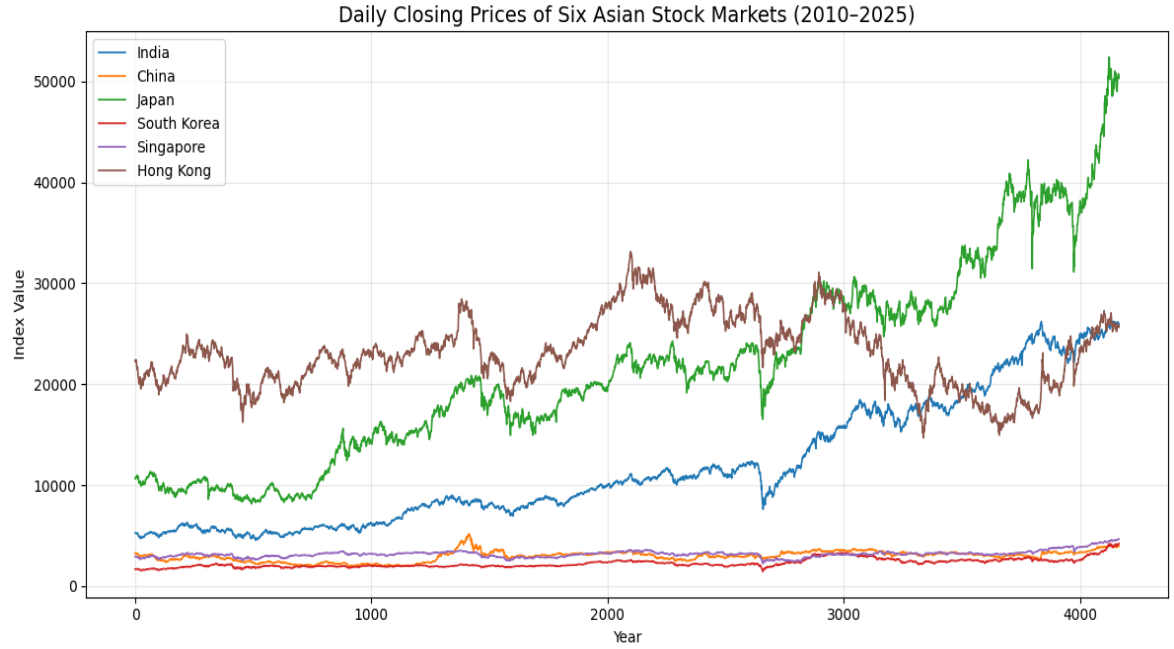

Figure 2. Daily closing prices of six asian stock markets (2010–2025)

Correlation Analysis

The Pearson correlation matrix of the daily logarithmic return series of the six Asian stock markets and the global financial variables is displayed in table 3. The results show moderate positive relationships between the Asian equity markets, with the highest relationships found between Singapore and Hong Kong, South Korea and Singapore, and Japan and South Korea, which is indicative of market integration

in the region. The correlations are also relatively low with the other Asian markets and moderate and positive with the indexes of the other countries, reflecting limited spillover effects across countries.

The correlation of gold returns with equity market returns is very weak, while the correlation between returns on crude oil, with Brent, is moderately positive. The overall correlation coefficients are excellent, suggesting financial integration without a high level of multicollinearity; hence, these variables are used in the following GARCH volatility analysis. A correlation heatmap is given in figure 3, and darker color intensities indicate a stronger positive correlation. Asian equity markets appear to be more integrated than equity and commodity returns, with this relationship very clearly visible in this figure.

Table 3. Correlation matrix of financial return series

Variables	**India**	**China**	**Japan**	**South Korea**	**Singapore**	**Hong Kong**	**S&P500**	**Gold**	**Brent**
India Return	1.000	0.211	0.311	0.416	0.488	0.409	0.266	0.039	0.136
China Return	0.211	1.000	0.260	0.304	0.320	0.517	0.128	0.048	0.099
Japan Return	0.311	0.260	1.000	0.554	0.472	0.423	0.165	-0.005	0.104
South Korea Return	0.416	0.304	0.554	1.000	0.558	0.549	0.195	0.050	0.118
Singapore Return	0.488	0.320	0.472	0.558	1.000	0.575	0.241	0.025	0.148
Hong Kong Return	0.409	0.517	0.423	0.549	0.575	1.000	0.187	0.062	0.141
S&P500 Return	0.266	0.128	0.165	0.195	0.241	0.187	1.000	0.045	0.300
Gold Return	0.039	0.048	-0.005	0.050	0.025	0.062	0.045	1.000	0.128
Brent Return	0.136	0.099	0.104	0.118	0.148	0.141	0.300	0.128	1.000

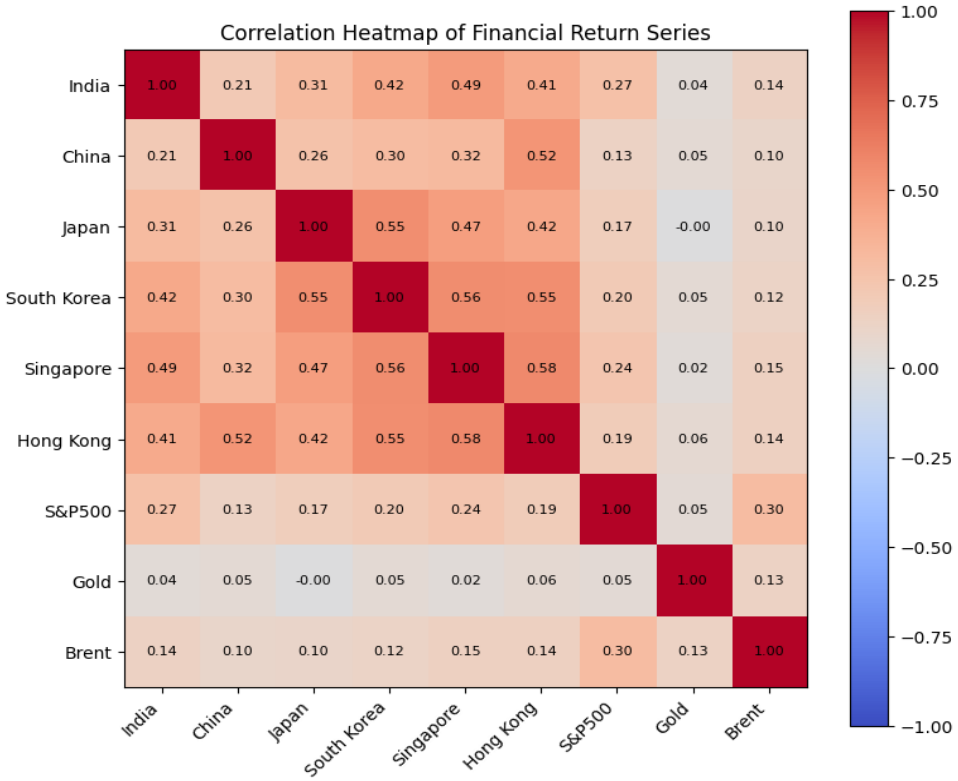

Figure 3. Correlation heatmap of financial return series

Stationarity and ARCH Effect Analysis

All financial return series have been tested for a unit root using the Augmented Dickey–Fuller (ADF) test, and the results are presented in table 4. The ADF statistics are very negative with values ranging from −9.95 to −66.83 and p-values less than 0.001 in all cases. The results reject the null hypothesis of a unit root, indicating that all the logarithmic return series are stationary and thus meet the requirement of stationarity for the next GARCH modeling of volatility.

The results of the ARCH-LM tests for all financial return series are listed in table 5. The LM and F tests are highly significant in all the markets, validly proving the existence of conditional heteroskedasticity and volatility clustering. The highest ARCH effects are found in Singapore, South Korea, and India, suggesting that the volatility shocks are the most persistent in these countries, whereas Hong Kong and gold are also characterized by important ARCH effects. The results obtained confirm the applicability of the GARCH (1,1) model to the study of the time-varying volatility of the stock markets and other financial indicators in the Asian region.

Table 4. Augmented dickey–fuller test results

Variable	ADF Statistic	p-value	Lags	Observations	Decision
India Return	-19.335	<0.001	10	4155	Stationary
China Return	-13.225	<0.001	23	4142	Stationary
Japan Return	-33.387	<0.001	3	4162	Stationary
South Korea Return	-20.700	<0.001	8	4157	Stationary
Singapore Return	-19.241	<0.001	10	4155	Stationary
Hong Kong Return	-14.307	<0.001	22	4143	Stationary
S&P500 Return	-12.913	<0.001	31	4134	Stationary
Gold Return	-66.835	<0.001	0	4165	Stationary
Brent Return	-9.951	<0.001	30	4135	Stationary

Table 5. ARCH-LM test results

Variable	LM Statistic	LM p-value	F Statistic	F p-value	Decision
India Return	809.442	<0.001	100.256	<0.001	ARCH Effect Present
China Return	449.548	<0.001	50.274	<0.001	ARCH Effect Present
Japan Return	637.129	<0.001	75.050	<0.001	ARCH Effect Present
South Korea Return	816.286	<0.001	101.311	<0.001	ARCH Effect Present
Singapore Return	937.133	<0.001	120.677	<0.001	ARCH Effect Present
Hong Kong Return	159.344	<0.001	16.526	<0.001	ARCH Effect Present
S&P500 Return	1275.502	<0.001	183.543	<0.001	ARCH Effect Present
Gold Return	155.067	<0.001	16.065	<0.001	ARCH Effect Present
Brent Return	391.341	<0.001	43.088	<0.001	ARCH Effect Present

Analysis 2: GARCH-Based Volatility Analysis

After stationarity was confirmed and significant ARCH effects were found, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH (1,1)) model was estimated for each of the six Asian stock markets. The GARCH framework was adopted because it provides a good representation of the two essential features of financial return time series: volatility clustering and persistence. The model also captures the conditional variance as a function of past market shocks (ARCH effect) and past conditional volatility (GARCH effect), which allows for a full description of the dynamic response of stock market volatility. The estimation was carried out independently for each country considered, namely India, China, Japan, South Korea, Hong Kong, and Singapore, and under the assumption that the innovations were normally distributed.

GARCH Model Estimation

The estimated GARCH (1,1) parameters of the six Asian stock markets are shown in table 6. The results indicate that the variance constant (ω), ARCH coefficient (α_1), and GARCH coefficient (β_1) are all positive and statistically significant for all markets, indicating that there is time-varying conditional volatility. There are no significant differences among the ARCH and GARCH coefficients across countries, except that Japan and Singapore have relatively higher ARCH coefficients, suggesting that the two countries have a higher short-term volatility reaction to new market shocks, while Hong Kong, China, and India have relatively higher GARCH coefficients, signifying that the two countries have a greater persistence of historical volatility. The volatility persistence values ($\alpha_1 + \beta_1$) are between 0.9451 and 0.9882, indicating that a volatility shock is persistent and stays in the markets for long periods of time. In addition, log-likelihood, AIC, and BIC statistics indicate that the GARCH (1,1) model fits the data well in all of the six markets, suggesting that the GARCH (1,1) model is effective in modeling

the volatility dynamics for the Asian equity markets.

It can be seen from figure 4 that the conditional volatility of the six Asian stock markets varies across different markets. High levels of volatility are easily discerned during global financial crises, suggesting that volatility clustering exists in all markets. The volatility dynamics are seen to be more volatile in India, China, and Hong Kong compared to Singapore. Long periods of high volatility are observed in the case of India, China, and Hong Kong, while comparatively smooth dynamics can be observed in the case of Singapore.

Table 6. GARCH (1,1) estimation results

Country	μ	ω	α_1	β_1	$\alpha_1+\beta_1$	Log-Likelihood	AIC	BIC
India	0.0636	0.0172	0.0797	0.9038	0.9836	-5447.50	10903.00	10928.34
China	0.0091	0.0183	0.0574	0.9303	0.9877	-6184.85	12377.69	12403.03
Japan	0.0682	0.0922	0.1249	0.8202	0.9451	-6598.54	13205.09	13230.43
South Korea	0.0314	0.0269	0.0949	0.8809	0.9757	-5618.57	11245.14	11270.48
Singapore	0.0325	0.0320	0.1180	0.8291	0.9471	-4520.66	9049.32	9074.66
Hong Kong	0.0291	0.0210	0.0571	0.9312	0.9882	-6639.68	13287.35	13312.69

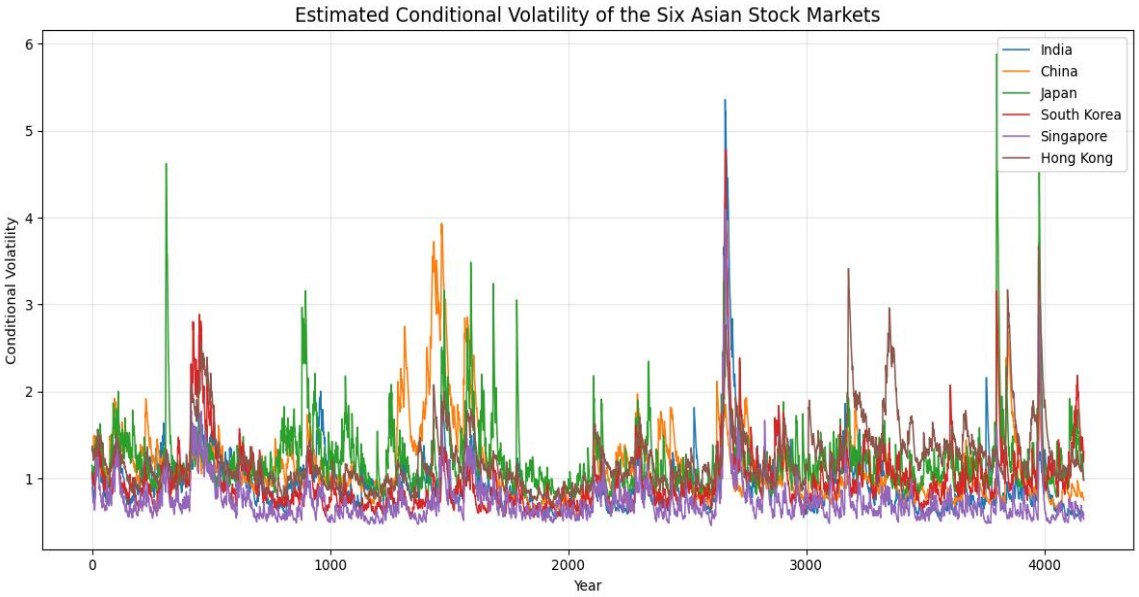

Figure 4. Estimated conditional volatility of the six asian stock markets

Hypothesis Testing

Table 7. Hypothesis testing results

Hypothesis	Statistical evidence	Decision
H1	ARCH-LM Test (Table 5), $p < 0.001$ for all markets; significant α and β coefficients in table 6	Supported
H2	Statistically significant log-likelihood, AIC, and BIC indicators showing appropriate model fit across all six series	Supported
H3	Sum of estimated GARCH parameters $(\alpha_1 + \beta_1)$ approaching unity, ranging from 0.9451 to 0.9882 (Table 6).	Supported
H4	GARCH estimates (Table 6): α+β = 0.945–0.988 (<1 and close to 1)	Supported
H5	Significant ARCH and GARCH coefficients ($p < 0.001$ in most markets), ARCH-LM results and satisfactory RMSE/MAE (Table 8)	Supported

Table 7 gives a summary of the interpretation of GARCH (1,1) estimation results. All the six Asian markets have highly significant ARCH and GARCH coefficients, which are indicative of the existence of volatility clustering and persistent conditional heteroskedasticity. The estimated persistence values ($\alpha_1 + \beta_1$) range from 0.9451 to 0.9882, showing that volatility shocks last a long time, particularly in the

case of Hong Kong and China. The results are generally consistent with the time-varying volatility and long memory properties of stock market returns found in the Asian markets and validate the proposed GARCH (1,1) model as an adequate framework for modeling these properties.

The statistical procedures used in the study were used to test the hypotheses. The ARCH-LM test and the GARCH parameter estimates were used to test for volatility clustering; Pearson correlation analysis was used to analyze market relationships; the sum of ARCH and GARCH coefficients ($\alpha + \beta$) was used to test for volatility persistence; and statistical significance and forecasting accuracy measures (RMSE and MAE) were used to test model adequacy.

Model Evaluation

The predictive performance of the estimated GARCH (1,1) models are summarized in table 8 in terms of RMSE and MAE. The results show promising forecasting accuracy for all six Asian stock markets, where the forecasting accuracy in Singapore is the lowest, with RMSEs and MAEs of 0.5719 and 0.4428, respectively, followed by India and South Korea. Despite the comparatively larger prediction errors for the Chinese, Japanese, and Hong Kong markets, their RMSE and MAE values are within acceptable limits because of the relatively higher market volatility of these markets. Overall, low forecasting errors indicate that the suggested GARCH (1,1) model has the ability to deliver reliable and stable volatility forecasts in both the emerging and developed Asian equity markets.

Table 8. Model evaluation results

Country	RMSE	MAE
India	0.7466	0.5638
China	0.9387	0.7178
Japan	0.9738	0.7592
South Korea	0.7683	0.5986
Singapore	0.5719	0.4428
Hong Kong	0.9537	0.7521

Discussion

The empirical results show that the GARCH (1,1) model has a good ability to log the volatility dynamics of the 6 Asian stock markets. After checking the stationarity of all the return series using the Augmented Dickey–Fuller (ADF) test (with p-value < 0.001), also employed the ARCH-LM test to confirm that the return series were not homoscedastic across all the markets (with p-value < 0.001) for the application of the GARCH model in this study. The estimated GARCH parameters reveal statistically significant ARCH (α) and GARCH (β) effects for all the markets, suggesting significant effects of recent market shocks as well as the previous volatility on the current market risk. The persistence of volatility (α + β) varies from 0.9451 in Japan to 0.9882 in Hong Kong, China, indicating that volatility shocks fade slowly and are well integrated in Asian equity markets for long periods of time, especially in Hong Kong, China, and India. The correlation analysis also shows moderate positive interdependence between the Asian equity markets, with the highest being between Singapore and Hong Kong (r = 0.5751) and relatively low correlations between commodity returns and equity returns, which provide diversification benefits. Model evaluation also shows good forecasting performance, with the lowest prediction errors recorded by the models from Singapore (RMSE = 0.5719; MAE = 0.4428), and other markets also have fairly good forecasting accuracy, though they have relatively higher volatility. In conclusion, the results indicate that the GARCH (1,1) model can be used as a useful tool for modeling the time-varying volatility in the Asian financial markets and is useful for financial risk management and market uncertainty for investors, financial analysts, and portfolio managers in understanding financial risk and the persistence of market uncertainty.

Limitations

There are some limitations to this study. The analysis was based on a symmetric GARCH (1,1) model, which explicitly reflects the persistence of volatility but fails to consider the asymmetric reactions of

market volatility to positive and negative market shocks (leverage effects). Second, empirical analysis was carried out for six Asian stock markets for daily financial variables, although monthly macroeconomic indicators were also included in the analysis for context only and were not used to estimate volatility to avoid mixed frequency bias.

Future Work

The present study can be expanded in the future by using asymmetric volatility models, which consider the different impact of positive and negative market shocks, like EGARCH, GJR-GARCH (TGARCH), or APARCH. Moreover, multivariate tools like DCC-GARCH and GARCH-X can be used to study the spillover effects of volatility and to explicitly analyze the macroeconomic determinants of stock market volatility among the Asian financial markets.

CONCLUSION

In this study, the volatility dynamics of six leading Asian stock markets, namely India, China, Japan, South Korea, Singapore, and Hong Kong, have been studied under the framework of the GARCH (1,1) model. The strength of the results gained from the empirical analysis confirms that the extent of non-normality, clustering of volatility, and time-varying conditional variance are stylized features of the financial return series, as are the stock market return series. The results of descriptive statistics showed significant differences between markets, and the correlation analysis showed moderate financial integration between the equity markets of Asia, with the highest correlation found between Singapore and Hong Kong ($r = 0.5751$). Return on commodities, including gold, showed relatively low correlations with the stock market, indicating that they can be diversified from stocks.

The stationarity hypothesis was tested before estimating the GARCH model, and all the return series were stationary ($p < 0.001$, ADF statistics = −9.95 to −66.83). The ARCH-LM test also indicated that there was significant conditional heteroskedasticity in each market (LM statistics = 155.07 – 1275.50, $p < 0.001$), which confirmed the appropriateness of the GARCH (1,1) approach. All markets showed positive values for the ARCH and GARCH coefficients, which were statistically significant, and the volatility persistence ($\alpha + \beta$) ranged from 0.9451 (Japan) to 0.9882 (Hong Kong). The results suggest that volatility shocks are slow to fade and have a long impact on the Asian financial markets.

The model evaluation showed that the model performs well in predicting the output, with the lowest prediction errors from the model (RMSE = 0.5719; MAE = 0.4428) indicated to be for Singapore, while the rest of the markets had satisfactory predictive accuracy. The results illustrate that the GARCH (1,1) model is a useful and powerful tool to analyze the volatility of the financial markets in Asian equity markets in general. The study has implications for investors, portfolio managers, financial analysts, and policymakers as it enhances risk assessment and portfolio management in the volatile market conditions. The framework could be expanded in future studies by adopting other asymmetric volatility models like EGARCH, TGARCH, or multivariate GARCH to gain deeper insights into the study of volatility spillovers and cross-market interdependence.

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