Volatility Analysis: An Empirical Investigation from South Asian Stock Markets Using the GARCH Model

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Abstract

This study examines the risk, return, and volatility of selected South Asian stock markets. It helps to measure the volatility patterns and compare the stability and risk characteristics of these markets. Major South Asian stock exchanges (PSX, BSE, and DSE). The main objective of this research is to use sophisticated GARCH models to assess volatility persistence over time and provide empirical support for regional diversification strategies within the SAARC block. This study uses secondary data collected from sources including Yahoo Finance, Investing.com, and the official websites of the PSX, BSE, DSE, and CSE. Closing prices used to compute returns in time series data. The data frequency is daily from January 2022 to April 2026. Key variables are risk, return, and volatility. The Univariate GARCH model is applied to the data. KSE has the highest average return of 0.12% with a risk of 1.2%, whereas it has the lowest risk per $ of average return (10.44), followed by the Bombay and Dhaka stock markets, respectively. The results show that ARCH and GARCH coefficients for all markets are significant at the 1% significance level. Mean reversion is computed as the sum of the ARCH and GARCH coefficients; a value closer to 1 indicates slower mean reversion (i.e., higher volatility). The Bombay Stock Exchange is the most volatile, followed by the Karachi and Dhaka stock exchanges. Half-life indicates the number of days it takes for markets to revert to their mean positions. Bombay, Karachi, and Dhaka markets take 40.58, 20.8, and 6.37 days, respectively, to revert to their mean positions. KSE offers better returns with moderate risk, which is the best option for investors.

Keywords: ***Risk, Return, Volatility, ARCH, GARCH, Stock Returns, South Asian stock markets***

JEL Classification: C22, G11, G32

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INTRODUCTION

Background of the study

The foundation of the contemporary financial system, global equity markets enable capital allocation and economic expansion. However, volatility, the pace at which an asset's price rises or falls for a range of returns, is a fundamental feature of these markets. Comprehending this volatility is essential for risk management and policy development, not just an academic endeavor. Due to its strong growth potential, the South Asian region, which includes economies such as Bangladesh, India, Sri Lanka, and Pakistan, has attracted attention from foreign investors. But the years 2018–2025 have been among the most volatile in recent memory. The regional indices (BSE, PSX, CSE, and DSE) have faced particular pressures, ranging from the financial liberalization and market reforms in India to the fiscal difficulties and currency devaluations in Pakistan and Sri Lanka. In a comparative study of SAARC nations, Ahmad et al. (2024) found that although the Indian market (BSE) frequently produces higher returns, it also exhibits longer "volatility memory" (persistence) than its neighbors'. This implies that although South Asian marketplaces are geographically close, they differ greatly in internal efficiency and news responsiveness.

Between 2018 and 2025, Pakistan's economy was marked by recurrent debt crises and persistent twin deficits. The nation experienced a serious balance-of-payments crisis beginning in 2018, which led to a $1 billion IMF bailout in 2019. After the epidemic, conditions worsened; by 2023–2024, Pakistan's inflation rate had risen to an all-time high of almost 35%. Massive currency devaluation and the elimination of energy subsidies in accordance with IMF directives were the main causes of this hyperinflationary environment. With a sizable share of the federal budget going toward interest payments, the debt-to-GDP ratio remained dangerously high. This resulted in extremely high volatility for the stock market (PSX). High interest rates aimed at reducing inflation caused capital to shift from stocks to fixed-income assets, while political and economic uncertainties made the market's "risk memory" more enduring.

Despite certain difficulties, India's economy continued to grow at the fastest rate among major economies. The Indian economy prioritized digital transformation and structural improvements between 2018 and 2025. Although India managed its debt better than its neighbors, inflation fluctuated and frequently exceeded the RBI's upper tolerance level of 6% due to disruptions in the food supply chain and global increases in crude oil prices. India used its "China Plus One" strategy in its 2024–2025 approach, drawing significant FDI (foreign direct investment). On the other hand, the Bombay Stock Exchange (BSE) showed persistently high volatility. According to Ahmad et al. (2024), the Indian market offers high returns but is extremely vulnerable to global shocks; compared with other SAARC countries, it takes longer (45 days) to return to its mean. This is mainly because of the country's close ties to international financial cycles. In the early years of this period (2018–2021), Bangladesh was praised as a "growth miracle" due to a strong garment export industry. But the post-pandemic period and the 2022 Russia-Ukraine conflict revealed weaknesses in its foreign reserves and energy sector. Bangladesh asked the IMF for help in managing its balance of payments in 2024–2025. Inflation reached double digits (9–10%) in 2024, having previously remained steady at 5–6%.

There was notable volatility clustering on the Dhaka Stock Exchange (DSE). It's interesting to note that, among SAARC nations, the DSE frequently exhibits the fastest mean reversion (about 10 days). This suggests that, despite being vulnerable to shocks, the DSE recovers quickly because it has a sizable base of retail investors and is less exposed to global institutional sell-offs than India. A comparative analysis of SAARC countries shows that India's BSE delivers higher returns but also exhibits greater volatility persistence, with a mean-reversion period of 45 days, compared to Pakistan and Bangladesh, highlighting varying levels of market efficiency across the region. By analyzing how quickly markets in Pakistan, India, and Sri Lanka recover, investors can better diversify their investments across these regions to reduce overall market risk. In developing South Asian countries, the Weak-form Efficiency of the Efficient Market Hypothesis is directly challenged by mean reversion and predictable volatility patterns (GARCH effects). A stock exchange's mean-reversion process is inconsistent; different industries, such as banking, oil and gas, and fertilizer, exhibit wildly disparate recovery rates due to industry-specific risks.

The analysis of Fama's (1970) Efficient Market Hypothesis (EMH) is a crucial component of this research. Weak-form efficiency states that it is difficult to forecast future price movements since present stock prices should reflect all historical trading data. This idea is called into question by the existence of GARCH effects and "fat-tails" (leptokurtosis) in Asian markets, as noted by Ahmad et al. (2016). The random walk theory is often considered broken when markets exhibit "volatility clustering," and past trends can, in fact, reveal future risk levels. Asian stock markets often show 'fat tails' (leptokurtic behavior), which means that large price jumps either crashes or surges happen more often than standard normal distribution models would predict.

A "natural experiment" for market stability was the worldwide COVID-19 pandemic. The pandemic caused structural changes in South Asian indices, according to research by Ahmad et al. (2024) across the pre-, during-, and post-pandemic phases. The post-pandemic recovery (2023–2025) has demonstrated that markets have not fully returned to their pre-2020 stability benchmarks and that the persistence of shocks during this period reached previously unheard-of levels. The "leverage effect" in these markets, in which negative news causes greater instability than positive news of equal magnitude, was exacerbated during this period by aggressive interest-rate hikes and global inflationary pressures.

The post-pandemic recovery phase differed greatly from the pre-2020 period due to a structural shift brought about by the pandemic, in which the "memory" of market shocks became more persistent. In an effort to fight inflation, interest rates were raised aggressively worldwide between 2018 and 2025. This has greatly enhanced the "leverage effect," which causes bad news to cause more volatility than positive news. The Speed of Mean Reversion is a crucial indicator of market resiliency. This is the time it takes for a market index to return to its long-term average after a major shock. In their analysis of Pakistani indices (KSE, LSE, and ISE), Palwasha et al. (2018) found that regional exchanges process information at varying rates even within a single nation. Additionally, Vveinhardt et al. (2016) and Akhtar & Khan (2016) expanded this analysis to the sectoral level, demonstrating that certain industries, such as banking or energy, may stabilize more quickly than others. To build a diversified portfolio that reduces systemic risk, an investor adhering to Modern Portfolio Theory (Markowitz, 1952) must understand the disparate recovery rates in Bangladesh, Sri Lanka, India, and Pakistan.

Regional liquidity and trading volume directly affect how quickly an exchange stabilizes following a price shock, according to an analysis of mean-reversion speed across the KSE, LSE, and ISE. There is a clear dearth of comprehensive, multi-country comparisons incorporating the most recent data up to 2025, even though earlier research has examined individual crises or specific nations. By using a univariate GARCH approach to the PSX, BSE, CSE, and DSE, the current study seeks to close this gap. This study offers a new perspective on how these markets have changed in response to domestic financial crises, international pandemics, and shifts in monetary policy, examining the years 2018–2025. Over the past ten years, the Colombo Stock Exchange (CSE) has experienced structural breaches in its volatility patterns due to its notable vulnerability to local political unrest and debt crises.

Scope of the study

Using historical data, the study examines the risk, return, and volatility of selected South Asian stock markets. The Univariate GARCH model is applied to measure volatility patterns and compare the stability and risk characteristics of these markets. Major South Asian stock exchanges (PSX, BSE, and DSE). By employing family models, the research focuses on measuring volatility persistence and the risk-return tradeoff using daily index data.

Objectives of the study

The main objectives of this research are:

- To use a stochastic GARCH model to gauge volatility in the markets under consideration.
- To compare the speed of mean-reversion among the markets under consideration.

Statement of the problem

The main issue with South Asian markets is the high level of "volatility persistence." In contrast to developed markets, where shocks fade rapidly, a single negative event in (stock) markets like PSX and BSE causes a long-lasting ripple effect that keeps the market unstable for weeks. A serious "leverage effect" affects emerging economies, causing investors to overreact to negative news (such as inflation or debt) while underreacting to positive news. Risk models that presume symmetrical market reactions are challenged by this. Sovereign credit risk is a constant source of "noise" in the stock market, particularly in debt-ridden countries like Pakistan. The way a nation's default status permanently modifies the volatility DNA of its equities index is not explained by current research. The 2020 pandemic produced a fundamental rupture in global variance equations. Most existing financial research is outdated since it does not account for the 'new normal' of high-inflation regimes and interest rate hikes predicted between 2023 and 2025.

Although mean reversion is a well-known concept, investors are unable to distinguish between a short-term market decline and a long-term bearish trend due to a critical absence of empirical data on the "Speed of Adjustment" for South Asian indexes. The conventional link between stock returns and economic growth has been broken by aggressive monetary tightening (high interest rates) to fight inflation, leaving portfolio managers in the SAARC area without a trustworthy hedge. The Efficient Market Hypothesis is directly violated by volatility clustering on South Asian exchanges. This results in an unfair environment in which individual investors suffer unpredictable losses while "informed" traders can exploit prior patterns.

Research questions

- Is the ARCH effect significant?
- Is the GARCH effect significant?
- Does the data exhibit mean reversion?

Research gap

Since typical GARCH models cannot account for the differential impact of positive and negative stock returns, future research should focus on asymmetric GARCH models (like EGARCH) to capture the leverage effect in South Asian markets. Comparative data on how the risk-return relationship changed across South Asian borders during and after global systemic stock market crises are lacking, particularly for GARCH-in-Mean models. In the context of regional financial integration, cross-market volatility transmission (spillover) among India, Pakistan, and Bangladesh remains under-researched despite well-documented volatility in individual markets. There is a research gap in the use of FIGARCH models to examine the "Long Memory" property of returns in South Asian frontier markets, despite most studies assuming volatility decays quickly.

Although South Asian stock markets, such as those in Bangladesh and Pakistan, are sometimes regarded as inefficient, little research has used GARCH models to examine how quickly these markets assimilate new information into stock prices compared with the Indian market. The volatility spillover, the transfer of risk between SAARC countries, is rarely investigated in a comparative framework using multivariate GARCH models, despite the fact that individual market volatility is studied. Most research focuses solely on volatility or returns. Investigating the "Risk-Return Tradeoff" to determine whether investors are genuinely receiving higher returns for taking greater risks in volatile South Asian markets is severely lacking. To close this gap, a comparison analysis is required.

LITERATURE REVIEW

Review of the Literature

This study provides comprehensive data on the behavior of South Asian stock markets. The GARCH (1,1) model was applied, and the results indicate that volatility significantly influences market returns. The results demonstrate the stochastic trend and correlation of South Asian stock markets (Almarashi et al, 2018). The results emphasize favorable conditions for portfolio managers to develop diversification strategies in South Asian equity markets, revealing a comparatively low degree of volatility transmission and a stronger influence of spillovers within markets than across them. According to empirical research, emerging markets such as those in Pakistan, India, and Sri Lanka are more resilient to volatility than industrialized economies. According to the study, GARCH models are best suited for displaying both symmetric and asymmetric volatility across indices. The results from FIGARCH and GARCH (1,1) indicate that shocks to NSE returns persist for a considerable time. Furthermore, volatility forecasting is critical for South Asian analysts, as negative news has a stronger effect on stock volatility than positive news (leverage effect). The analysis reveals heteroskedasticity and a strong link between South Asian stock markets. The KSE 100 had the lowest volatility coefficient (2.078) among the Asian giants, according to the GARCH (1,1) model. However, all markets exhibit significant ARCH and GARCH effects, indicating that past shocks have a considerable impact on current volatility. The pace of mean reversion in GARCH (1,1) estimation is determined by the sum of the ARCH (alpha) and GARCH (beta) coefficients. A market that is less efficient and where risk lasts longer is indicated by a higher half-life. In South Asian markets, where the sum of the ARCH and GARCH coefficients (\alpha + \beta) is close to 1, the analysis validates the persistence of high volatility. This suggests that volatility shocks have a very long half-life, meaning the market takes a long time to recover from a crisis. (Ahmad et al., 2016; Bhowmik et al., 2022).

Marketplaces in different cities behave differently, even within Pakistan. After a crisis, risk is "stuck" in the major Karachi index (KSE-100) for longer than in the Islamabad market, which recovers swiftly (Palwasha et al 2018). Because standard risk models assume a normal distribution, they frequently underestimate market danger. However, empirical evidence from emerging economies indicates that stock returns exhibit skewness and heavy tails, necessitating the adoption of GARCH-family models to capture volatility clustering. The choice of volatility model significantly affects the efficacy of Value-at-Risk (VaR) projections. To give investors realistic risk assessments, asymmetric news impacts, where negative news raises volatility more than positive news, must be taken into consideration in emerging economies. Stock markets show heterogeneity even within the same geographic area. A one-size-fits-all paradigm is insufficient for regional market analysis, according to research showing that different indices (such as the JCI and the KLSE) respond differently to stocks. Diagnostic tests such as the Augmented Dickey-Fuller (ADF) test for stationarity and the Ljung-Box test for autocorrelation in return series are crucial for ensuring data integrity in volatility models. Khan et al. (2023) claim that the COVID-19 pandemic was a major external shock that led financial markets to experience unprecedented levels of uncertainty and instability. According to their findings, stock markets undergo structural changes during such crises, resulting in increased volatility that conventional static models cannot fully account for.

Khan et al. (2024) show that GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models are better instruments for predicting time-varying volatility in their study of market dynamics. These models offer a more practical framework for risk assessment in emerging economies because they are particularly effective at capturing "volatility clustering," a phenomenon in which high-volatility events are followed by comparable volatility. One important finding of Khan et al. (2023) is the existence of asymmetric volatility, in which the market reacts far more strongly to negative news (bad news) than to positive news of the same magnitude. When estimating potential losses and portfolio risk, investors in South Asian markets must account for this leverage effect.

The study by Khan et al. (2023) emphasizes the importance of policymakers understanding the persistence of volatility during global health or economic crises. According to their data, risk management techniques need to be dynamic and regularly updated to maintain financial stability, as volatility tends to cluster during a crisis. The study verifies that financial return series show high kurtosis and heavy tails during turbulent times. The study uses GARCH models that account for these statistical anomalies, which is justified because assuming a normal distribution in risk modeling during a pandemic underestimates the likelihood of a "black swan" event. A key indicator of market risk is volatility.

The foundation of contemporary financial management, according to Gaffar et al. (2024), lies in the ability to precisely measure returns and volatility, as these directly affect the choices made by institutional and individual investors. The study further argues that the GARCH (1,1) approach is particularly effective for assessing the persistence of shocks in a time series, despite the availability of several econometric techniques. This model is an essential tool for analyzing high-frequency data from emerging stock exchanges because it can update volatility estimates based on the most recent market data. Thorough pre-modeling tests are necessary to guarantee the integrity of a comparison study. According to this study, the Augmented Dickey-Fuller (ADF) test confirms that the absence of a unit root is a necessary condition for avoiding erroneous results in volatility forecasting.

Theories

The Autoregressive Conditional Heteroscedasticity (ARCH) model, which offers a systematic approach to modeling time-varying volatility, was first presented in Engle (1982). The Generalized ARCH (GARCH) paradigm, which remains the gold standard for examining the "memory" of stock markets, was developed by Bollerslev (1986). Changes in commodity prices frequently cause volatility on a global scale. Ahmad (2018), for example, showed that crude oil returns show notable volatility clustering, which frequently affects equities markets, especially in emerging economies that rely heavily on oil.

Financial time series data frequently show periods of significant volatility interspersed with periods of relative calm. This time-varying variance can be systematically modeled with the ARCH model, which is crucial for understanding risk in contemporary equity markets.

A more adaptable lag structure is enabled by the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model, which captures the long-memory characteristics of volatility typical of returns in international stock markets.

An important external factor for emerging markets is the global price of commodities, especially crude oil. Oil price volatility clustering frequently precedes stock market volatility in South Asian countries that buy oil.

Hypotheses

H1: The daily South Asian Stock Returns (PSX, BSE, and DSE) exhibit a significant ARCH effect.

H2: The daily South Asian Stock Returns (PSX, BSE, and DSE) observe a significant GARCH effect.

H3: The daily South Asian Stock Returns (PSX, BSE, and DSE) exhibit mean-reversion.

METHODOLOGY

This study uses a quantitative research design. It analyzes daily stock prices using time series data. It analyzes volatility strength and compares volatility across the major South Asian stock markets. This study focuses on the major emerging South Asian markets, including Pakistan, India, and Bangladesh, and performs a volatility test on these.

This research aims to: analyze and compare South Asian stock market returns; measure and compare volatility across South Asian markets; and analyze the mean-reversion process. This study uses secondary data. The data includes daily closing prices of major South Asian stocks: PSX-100 Index (Pakistan Stock Exchange), BSE-SENSEX (Bombay Stock Exchange), and DSE Board Index (Dhaka Stock Exchange).

The daily data is obtained from Jan, 2022 to Apr, 2026 and collected from the sources Yahoo Finance, Investing.com, and the official websites of PSX, BSE, and DSE. Closing prices used to compute returns. The variables of the study are the risk, return, and volatility. This study employs a deductive methodology in which theoretical assumptions are tested against actual data using statistical and mathematical methods. Which is based on positivism, ensures that research is repeatable and value-neutral by treating social and financial realities as objective and quantifiable. Researchers can derive universal principles by quantifying complex phenomena such as conditional variance and volatility clustering using models such as ARCH and GARCH. In the end, this exacting paradigm converts unprocessed observations into meaningful, broadly applicable information, offering a precise foundation for prediction and data-driven decision-making.

Descriptive Models

The first analysis of stock behavior and the trend of each stock market is displayed graphically over time. Each stock market's log returns must be modeled, followed by correlations (r), standard deviations (σ), and CV, which stands for coefficient of variation. When two stock market results are interdependent, correlation is utilized. The formal descriptive method of mean, standard deviation, and coefficient of variation has been used for measuring and ranking purposes following a preliminary study. It's also crucial to remember that the standard deviation measures the dispersion around the mean for a given set of stock market data over a given time period. In particular, this spread is referred to as volatility, and CV is a relative indicator of volatility. Bartlett's test, an inferential analysis used to test the null hypothesis of equal variances across all data sets, was also part of the descriptive analysis and was used to validate the alternative hypothesis, which asserts that at least one pair of variances differs from the remaining pairs. The study calculates the Mean, Standard Deviation (risk), Skewness, and Kurtosis to understand the data's behavior. This helps assess the average return, the level of risk, and whether returns exhibit extreme values (fat tails). The log return is used to calculate stock prices for each stock market. Stock price data is converted to log returns to facilitate analysis. The following is an expression for the mathematical formula for log returns:

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

The Augmented Dickey-Fuller (ADF) unit root test is used to test whether the data is stationary (stable over time). If the data is non-stationary, we remove non-stationarity by taking first differences [I(1)], thereby obtaining stationarity.

Econometric Models

Engle (1982) introduced the ARCH process as a technique for quantifying fluctuations in conditional variance across various time intervals. In the ARCH model, the conditional variance is modeled as a linear function of past squared errors with a given lag. The sequential correlation in volatilities is modeled by allowing the conditional variance of error terms in the ARCH(p) model, which changes based on the previous value of the squared error: In the equation above, is the information set that is shown at the first lag of the time period. The ARCH models provide an analytical framework, and the ARCH family includes time-series models for quantifying volatility. ARCH models are useful in many ways, but they also have some problems and limitations. The number of lags (q) has been determined using the likelihood ratio test, and the squared residuals have been incorporated into the model. The squared error and its associated number of lags, which are useful for capturing dependence in the conditional variance, may be excessively large, potentially resulting in a larger conditional variance in the model and thereby lacking parsimony. To circumvent this perplexing issue, Engle (1982) ingeniously established an arbitrary, linearly declining lag length for an ARCH model. The conditional variance equation holds other factors constant and includes more parameters. Some of these parameters may have negative estimated values. So, the non-negativity constraint may not be necessary. (Ahmad et al., 2016).

The GARCH model was created to address these same limitations. This model has built-in artificial limits that let it handle non-negative conditions. Boleslaw (1986) was the only person to develop the GARCH model. The model has two distributed lags that are used to explain variance. The first is used to capture frequency effects, and the second to capture variance in lagged values themselves. The GARCH (1, 1) model predicts the variance in a data set by adding the long-run variance to the expected variance from the previous period. This is then adjusted to account for the size of the shock observed in the previous period. In the GARCH model, the estimates for financial returns, including the sum of the coefficients on lagged squared returns and the trailing conditional variance, are excessively close to 1. This shows that shocks to the conditional variance persist for a long time and that memory is fairly long, even though it is smaller than 1 and still returns to the mean. In simpler terms, even though volatility takes a lot of time, in the end, it reverts to its initial state, or the average degree of volatility. This indicates that the long-term forecast is unaffected by the information now available. (Ahmad et al. 2016). As a result, we focus on summarizing the primary methods, with special attention to how each model specification and inferential technique generates volatility projections. The long-term average variance holds only when a + b < 1 and a > 0, b > 0, and ω > 0; then 1 – α –β applies (Vveinhardt et al., 2016). The GARCH(1,1) model is used to measure and analyze time-varying volatility (risk) in stock returns. This model is used for time-varying volatility. It consists of:

$$\text{Mean Equation: } R_t = \mu + \beta R_{t-1} + \varepsilon_t$$

$$\text{Variance Equation: } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varepsilon_t$$

Mean Reversion (Half-Life)

It shows how quickly a stock price returns to its average after moving up or down. After confirming that the returns exhibit mean reversion with the ARCH and GARCH models, as previously mentioned, the next step is to calculate the speed of mean reversion using the half-life approach. The time it takes for returns to shift half the distance between the long-term average values of the PSX, BSE-SENSEX, DSE, and CSE indices can be determined using the half-life approach. To ascertain which stock markets exhibit faster mean reversion than others, these markets can be compared using numerical measures of mean-reversion speed. The following is the half-life model:

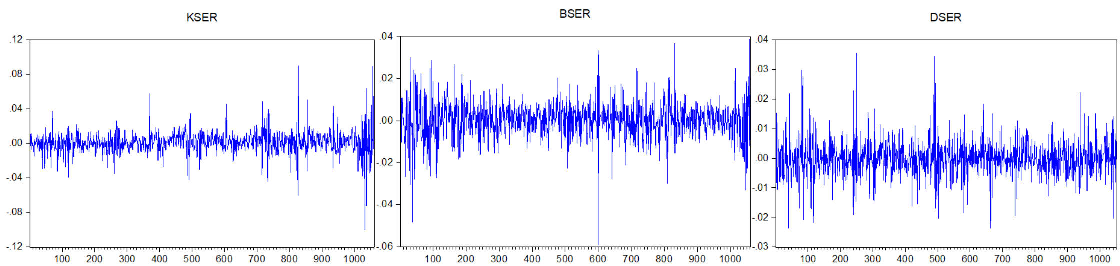
$$HL = \frac{\log(0.5)}{\log \lambda}$$

where λ is the sum of the GARCH and ARCH parameters in the GARCH model. (Palwasha et al., 2017).

Package and Tools

MS Excel is used for data organization and log return calculations, whereas EViews has been used for descriptive analysis and econometric estimation, such as ADF tests and GARCH modeling.

RESULTS AND FINDINGS



Graphical Analysis

The graphs indicate that all market returns are stationary, as the mean and variance remain constant over time. Moreover, no trend is observed.

Unit Root Test

ADF Test			
		t-Statistic	Prob.*
KSE 100 Returns	-31.85408	0.0000	
BSE 30 Returns	-33.46835	0.0000	
DSE 30 Returns	-37.89295	0.0000	
	1% level		-3.436307
Test critical values:	5% level		-2.864059
	10% level		-2.568162

*MacKinnon (1996) one-sided p-values.

A formal investigation of stationarity is carried out with the Augmented Dickey-Fuller (ADF) test, which shows that all ADF t-Statistics are more negative than the MacKinnon critical values.

Moreover, their P-values indicate that all are significant at the 1% level, with p-values < 0.01.

Descriptive Analysis

Descriptive			
	KSER	**BSER**	**DSER**
Mean	0.001232	0.000247	2.74E-05
Std. Dev.	0.012864	0.008828	0.006063
Maximum	0.090256	0.038726	0.035588
Minimum	-0.10063	-0.05912	-0.02362
Skewness	-0.04806	-0.38035	0.473395
Kurtosis	13.72779	7.026701	7.414299
CV	10.44156	35.74089	221.2774
Rank	3rd	2nd	1st
Jarque-Bera	5083.351	740.991	891.7319
Probability	0	0	0
Observations	1060	1059	1050

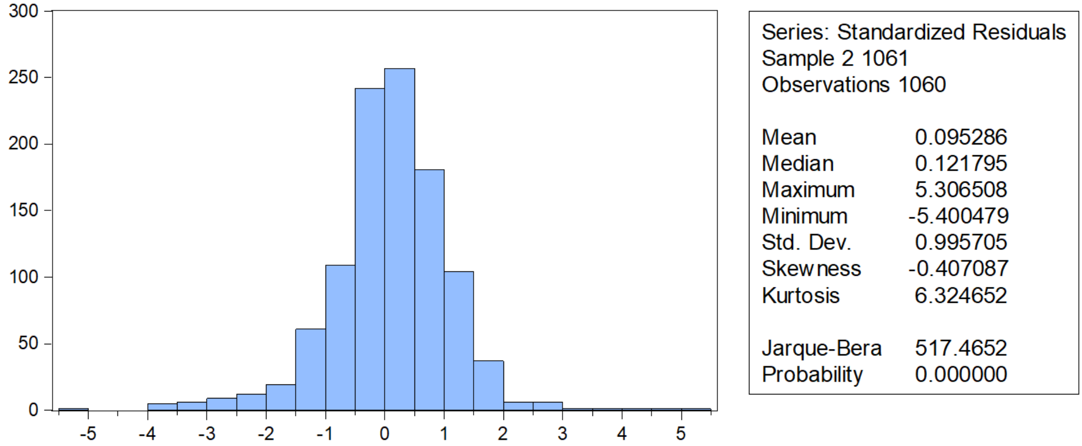
KSE has the highest average return of 0.12% and a risk of 1.2%. whereas it has the lowest risk per $ of average return (10.44), followed by the Bombay and Dhaka stock markets. Moreover, Skewness should be 0, and Kurtosis should be 3. In the above table, it is not a normal distribution. Jarque-Bera is the combined statistic of skewness and kurtosis. The Jarque-Bera normality test shows a P-value of 0, indicating that the null hypothesis is rejected.

GARCH Model

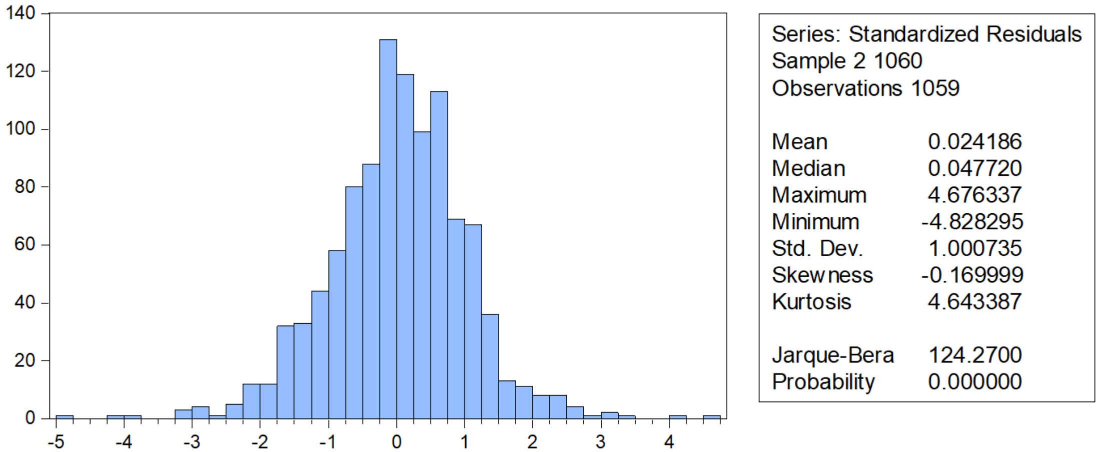
GARCH Model			
	KSER	**BSER**	**DSER**
ARCH	0.1820***	0.0926***	0.0906***
GARCH	0.7836***	0.8900***	0.7883***
Mean Reversion	0.9656	0.9826	0.8788
Half-Life	20.80	40.58	6.37
***1% sig level			
**5% sig level			
*10% sig level			

The results show that ARCH and GARCH coefficients for all markets are significant at the 1% significance level. Mean reversion is computed as the sum of the ARCH and GARCH coefficients; a value closer to 1 indicates slower mean reversion (i.e., higher volatility). The Bombay Stock Exchange is the most volatile, followed by the Karachi Stock Exchange and the Dhaka Stock Exchange. Half-life indicates the number of days it takes for markets to revert to

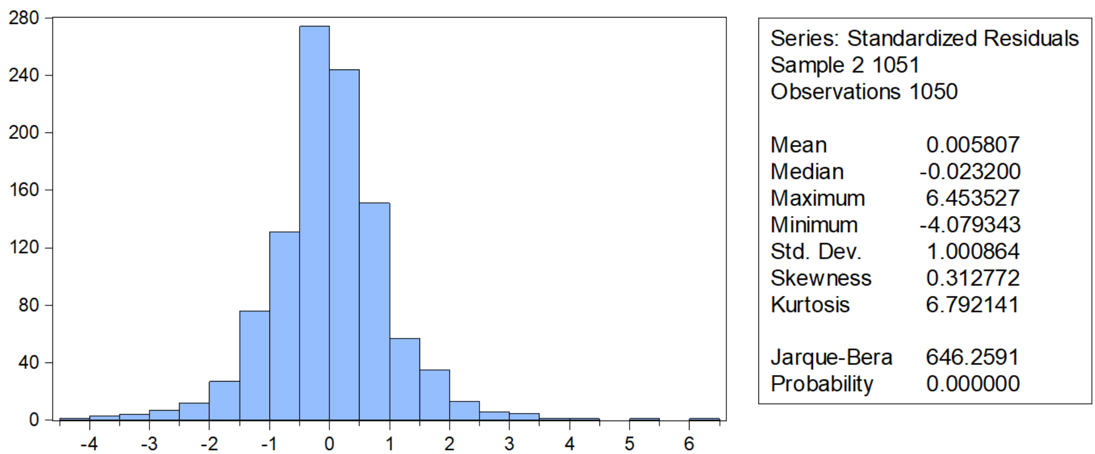
Residual Diagnostics – KSER



Residual Diagnostics BSER



Residual Diagnostics DSE30



their mean positions. Bombay, Karachi, and Dhaka markets take 40.58, 20.8, and 6.37 days, respectively, to revert to their mean positions.

Discussion

This study provides empirical evidence on the return, risk, and volatility dynamics of three major South Asian stock markets by applying the GARCH framework to daily data from January 2022 to April 2026. The findings reveal notable differences in the performance and volatility persistence of the Karachi Stock Exchange (KSE), Bombay Stock Exchange (BSE), and Dhaka Stock Exchange (DSE), offering useful insights for investors, portfolio managers, and policymakers interested in regional capital markets.

The results indicate that the Karachi Stock Exchange generates the highest average daily return among the selected markets while maintaining a moderate level of risk. More importantly, KSE records the lowest risk per dollar of average return (10.44), suggesting superior risk-adjusted performance compared with the Bombay and Dhaka stock exchanges. This finding supports the argument that higher returns do not necessarily imply disproportionately higher risk when market fundamentals and investor confidence remain relatively stable. Similar conclusions have been reported by Ahmad et al. (2016), Ahmad et al. (2023), and Khan et al. (2024), who found that Pakistan's stock market frequently outperforms other South Asian markets in terms of return potential despite operating within an emerging market environment. Likewise, Ahmad et al. (2024) and Topcu and Gulal (2020) also documented that the Pakistani equity market offers comparatively attractive investment opportunities within the SAARC region.

The estimated GARCH models further confirm the presence of significant ARCH and GARCH effects across all three markets, indicating that volatility clustering is a common characteristic of South Asian equity markets. This behavior is consistent with financial market theory, in which periods of high volatility are generally followed by additional periods of elevated volatility. Similar evidence has been reported by Palwasha et al (2018), Ghaffar et al. (2024), Khan et al. (2024), and Bui Quang et al. (2018), all of whom demonstrated the effectiveness of GARCH-type models in capturing volatility persistence in financial markets. The significance of both ARCH and GARCH parameters also supports the existence of time-varying conditional variance, reinforcing the suitability of the GARCH framework for modeling stock market volatility.

An important finding of this study is that the Bombay Stock Exchange exhibits the highest volatility persistence, followed by the Karachi and Dhaka stock markets. The higher sum of the ARCH and GARCH coefficients for the BSE suggests that shocks persist in the market for a longer period before gradually dissipating. The estimated half-life values reinforce this conclusion, with BSE requiring approximately 40.58 days to revert to its long-run equilibrium, compared with 20.8 days for KSE and only 6.37 days for DSE. These findings imply that although the Indian market is relatively mature and liquid, it is also more sensitive to prolonged information shocks and macroeconomic uncertainty. Comparable evidence on volatility persistence and long-memory characteristics has been documented by Ahmad et al (2016), Palwasha et al. (2018), Duppati et al. (2017), and Tang et al. (2022), who emphasized that slower mean reversion increases the duration of market uncertainty and affects investors' risk perception.

The comparatively moderate mean reversion observed in KSE indicates a balanced market structure where shocks dissipate at a reasonable pace without creating excessive instability. This finding aligns with Ahmad et al (2024), who reported that although Pakistan experienced elevated volatility during the COVID-19 period, the market gradually regained stability in the post-pandemic phase. Similarly, Ahmad et al. (2024) found that South Asian markets differ considerably in their resilience to external shocks, reflecting differences in market depth, institutional quality, and investor behavior. Recent studies by Augustin et al. (2022) further suggest that macroeconomic uncertainty, sovereign risk, and inflationary pressures remain important drivers of volatility in emerging equity markets.

From an investment perspective, these findings reinforce the importance of regional portfolio diversification. The observed differences in returns and volatility indicate that investors can improve portfolio efficiency by strategically allocating investments across South Asian markets in line with their individual risk preferences. This interpretation is consistent with Khan et al. (2024), Ahmad et al. (2024), Kou et al. (2025), Rahman (2025), Rehman et al (2023), and Almeida and Gonçalves (2023), who highlighted that imperfect market integration and heterogeneous volatility dynamics create opportunities for diversification and risk reduction. Moreover, the documented persistence of volatility suggests that investors should incorporate dynamic risk-management techniques rather than relying solely on static portfolio allocation strategies. Overall, the study confirms that while all three markets exhibit conditional heteroscedasticity, the Karachi Stock Exchange offers the most favorable balance between return and risk, making it an attractive investment destination within the South Asian region.

CONCLUSION, LIMITATIONS, AND RECOMMENDATIONS

Conclusion

The findings of this study provide valuable insights into the risk-return dynamics and volatility behavior of major South Asian stock markets. Among the selected markets, the Karachi Stock Exchange (KSE) exhibits the most favorable investment profile, offering the highest average daily return while maintaining a moderate level of risk. Moreover, its lowest risk-per-dollar of average return (10.44) indicates superior risk-adjusted performance compared with the Bombay and Dhaka stock exchanges. Although the Bombay Stock Exchange exhibits the highest level of volatility persistence, the KSE shows a balanced volatility pattern with a mean reversion period of approximately 20.8 days, suggesting that market shocks dissipate at a moderate pace. These findings suggest that the KSE offers an attractive combination of return potential and manageable volatility, making it a comparatively suitable investment destination in the South Asian region. Overall, the study provides empirical evidence to help investors and policymakers understand regional market behavior and make informed decisions about portfolio diversification.

Limitations

This study has certain limitations that should be considered when interpreting the findings. First, the analysis is based on daily data from January 2022 to April 2026, and incorporating a longer historical period could provide a more comprehensive understanding of long-term volatility dynamics and market behavior. Second, the study employs a standard GARCH framework without explicitly accounting for structural breaks caused by major economic or financial events. Future research could identify and estimate breakpoints associated with significant shocks, such as the COVID-19 pandemic or major geopolitical and policy changes, to better capture shifts in market volatility and improve the robustness of empirical findings.

Recommendations

The findings of this study offer several important implications for policymakers, stock market regulators, and investors in South Asia. First, regulators should continue strengthening market transparency, disclosure standards, and corporate governance practices to enhance investor confidence and reduce unnecessary market uncertainty. Second, given the relatively strong risk-adjusted performance of the Karachi Stock Exchange (KSE), policymakers should introduce measures to attract both domestic and foreign institutional investors by ensuring regulatory stability, improving market infrastructure, and adopting investment-friendly policies.

Furthermore, regional financial authorities should encourage greater cooperation among South Asian stock exchanges by promoting cross-border investment frameworks, information sharing, and harmonized market regulations. Such initiatives can improve market integration and provide investors with better diversification opportunities within the region. Since the Bombay Stock Exchange exhibits relatively higher volatility persistence, regulators should strengthen market surveillance systems and implement timely risk-management mechanisms to mitigate excessive market fluctuations. Finally, investor education programs should be expanded to improve awareness of portfolio diversification, risk management, and long-term investment strategies. These measures can contribute to more efficient, resilient, and sustainable capital markets across South Asia while supporting informed investment decisions.

REFERENCES

Ahmad, N., Ahmed, R.R., Streimikiene, D., Streimikis, J. and Raza Ul Mustafa, A. (2024). Stock Returns and Volatility: Comparative Investigation from SAARC Countries. Acta Monstanistica Slovaca, 29(2), 343- 352. DOI: https://doi.org/10.46544/AMS.v29i2.09

Ahmad, N., Ahmed, R.R., Vveinhardt, J., & Streimikiene, D. (2016). Empirical analysis of stock returns and volatility: evidence from Asian stock markets. Technological and Economic Development of Economy, 22(6), 808-829. https://doi.org/10.3846/20294913.2016.1213204

Ahmad, N., Nazeer, R., & Kaddour, A. (2023). Pre, During and Post Covid-19 Stock Returns and Volatility Comparison: Empirical Investigation from Pakistan. International Journal of Experiential Learning & Case Studies, 8(2), 144-167. https://doi.org/10.22555/ijelcs.v8i2.1042

Akhtar, S., & Khan, N.U. (2016). Modeling volatility on the Karachi Stock Exchange, Pakistan. Journal of Asia Business Studies, 10(3), 253-275. DOI: https://doi.org/10.1108/JABS-05-2015-0060.

Almarashi, A.M., Abbasi, U., Hanif, S., Alzahrani, M.R., & Khan, K. (2018). Modeling Volatility in Stock Prices Using ARCH/GARCH. Sci. Int. (Lahore), 30(1), 89-94. https://www.researchgate.net/publication/325603538_Modelling_Volatility_in_stock_prices_using_ARCHGARCH_technique

Almeida, J., & Gonçalves, T. C. (2023). Portfolio Diversification, Hedge and Safe-Haven Properties in Cryptocurrency Investments and Financial Economics: A Systematic Literature Review. Journal of Risk and Financial Management, 16(1), 3. https://doi.org/10.3390/jrfm16010003

Augustin, P., Sokolovski, V., Subrahmanyam, M.G., & Tomio, D. (2022). How sovereign is sovereign credit risk? Global prices, local quantities. Journal of Monetary Economics, 131(2022), 92-111. https://doi.org/10.1016/j.jmoneco.2022.07.005

Bhowmik, R., Debnath, G.C., Debnath, N.C., Wang, S. (2022). Emerging stock market reactions to shocks during various crisis periods. PLoS ONE 17(9), e0272450. https://doi.org/10.1371/journal.pone.0272450

Bui Quang, P., Klein, T., Nguyen, N. H., & Walther, T. (2018). Value-at-Risk for South-East Asian Stock Markets: Stochastic Volatility vs. GARCH. Journal of Risk and Financial Management, 11(18), 1-19. https://doi.org/10.3390/jrfm11020018

Duppati, G., Kumar, A.S., Scrimgeour, F., & Li, L. (2017). Long memory volatility in Asian stock markets. Pacific Accounting Review, 29(3), 423–442. doi: https://doi.org/10.1108/PAR-02-2016-0009

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486

Ghaffar, A., Ahmad, N., & Siddique, M. (2024). Gauging Returns and Volatility of Crude Oil using GARCH Approach. International Journal of Experiential Learning & Case Studies, 9(1), 33-58. https://doi.org/10.22555/ijelcs.v9i1.1155

Khan, M., Kayani, U. N., Khan, M., Mughal, K. S., & Haseeb, M. (2023). COVID-19 Pandemic & Financial Market Volatility; Evidence from GARCH Models. Journal of Risk and Financial Management, 16(50), 1-20. https://doi.org/10.3390/jrfm16010050

Khan, M.N., Fifield, S.G.M., & Power, D.M. (2024). The impact of the COVID 19 pandemic on stock market volatility: evidence from a selection of developed and emerging stock markets. SN Bus Econ, 4(6), article 63. https://link.springer.com/article/10.1007/s43546-024-00659-w

Markowitz, H. (1952). Portfolio Selection. The Journal of Finance, 7(1), 77–91. https://doi.org/10.2307/2975974

Palwasha, R. I., Ahmed, R. R., Nawaz, A., & Vveinhardt, J. (2018). Speed of mean reversion: an empirical analysis of KSE, LSE and ISE indices. Technological and Economic Development of Economy, 24(4), 1435-1452. Link:(https://www.researchgate.net/publication/327023344_SPEED_OF_MEAN_REVERSION_AN_EMPIRICAL_ANALYSIS_OF_KSE_LSE_AND_ISE_INDICES)

Rahman, M. L. (2025). Return predictability in South Asian stock markets (Version 1). Open Research Newcastle. https://hdl.handle.net/1959.13/1322117

Rehman, M. U., Khursheed, Z., & Ali, M. K. (2023). Time-frequency Volatility Spillovers of Conventional Stock Markets: Evidence from Developed, Emerging, and Frontier Markets. Journal of Finance and Accounting Research, 5(1), 1-29. https://doi.org/10.32350/jfar.51.01

Tang, C., Liu, X., & Zhou, D. (2022). Financial market resilience and financial development: A global perspective. Journal of International Financial Markets, Institutions and Money, 80(2022), 101650. https://doi.org/10.1016/j.intfin.2022.101650

Topcu, M., & Gulal, O. S. (2020). The impact of COVID-19 on emerging stock markets. Finance research letters, 36, 101691. https://doi.org/10.1016/j.frl.2020.101691

Vveinhardt, J., Streimikiene, D., Ahmed, R.R., Ahmad, N., & Rehman, A. (2016). Mean reversion: an investigation from Karachi stock exchange sectors. Technological and Economic Development of Economy, 22(4), 493-511. https://doi.org/10.3846/20294913.2016.1181685