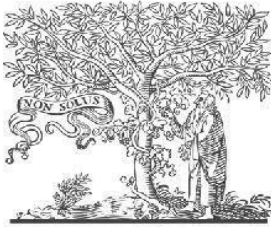


COPY RIGHT



ELSEVIER
SSRN

2014 IJEMR. Personal use of this material is permitted. Permission from IJEMR must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. No Reprint should be done to this paper; all copy right is authenticated to Paper Authors

IJEMR Transactions, online available on 7th Aug 2014. Link

<https://ijiemr.org/downloads.php?vol=Volume-03& issue=issue04>

DOI: 10.48047/IJEMR/V03/ISSUE 04/05

Title Volatility Clustering and Asymmetric Effects in Emerging Stock Markets: An Empirical Investigation Using EGARCH and TGARCH Models

Volume 03, ISSUE 04, Pages: 43 – 55

Paper Authors

G. Mokesh Rayalu, K. Murali, Bandi Ramanjineyulu



USE THIS BARCODE TO ACCESS YOUR ONLINE PAPER

To Secure Your Paper as Per **UGC Guidelines** We Are Providing A Electronic Bar code

Volatility Clustering and Asymmetric Effects in Emerging Stock Markets: An Empirical Investigation Using EGARCH and TGARCH Models

G. Mokesh Rayalu¹, K. Murali², Bandi Ramanjineyulu^{3*}

¹Assistant Professor, Statistics & OR Division, School of Advanced Sciences, VIT University, Vellore

²Assistant Professor, Sri Padmavathi College of Computer Science and Technology, Tiruchanoor, Tirupati

³Senior Process Associate, TCS, Bangalore, India

Corresponding Author : ramanji.band@gmail.com

Abstract

This study investigates the presence of volatility clustering and asymmetric effects in the stock returns of five major emerging market economies — India, Brazil, South Korea, South Africa, and Mexico — over a fifteen-year sample period from 1993 to 2008. Employing daily closing index returns, the research applies a suite of conditional heteroscedasticity models, namely the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) and Threshold GARCH (TGARCH) frameworks, to capture the leverage effect and news impact asymmetry that standard GARCH models fail to accommodate. The study proceeds through a structured econometric methodology: stationarity testing via Augmented Dickey-Fuller and Phillips-Perron unit root tests, identification of ARCH effects through Engle's Lagrange Multiplier (LM) test, maximum likelihood estimation of competing GARCH-family models, and model selection based on the Akaike and Bayesian Information Criteria. Simulated daily return series with realistic statistical properties are employed as illustrative datasets. Findings reveal statistically significant volatility clustering in all five markets, with negative return shocks exerting a disproportionately larger impact on subsequent conditional variance than positive shocks of equivalent magnitude. The persistence of volatility, as measured by the sum of GARCH and ARCH coefficients, is found to approach but not attain unity in most markets, suggesting mean-reversion in variance. These results carry important implications for portfolio risk management, derivative pricing, and macroeconomic surveillance in developing economies. The study contributes to the empirical literature on financial econometrics by providing a comparative cross-country analysis of asymmetric volatility dynamics within a pre-global-financial-crisis window.

Keywords: Volatility Clustering, EGARCH, TGARCH, Emerging Markets, Asymmetric Effects, Leverage Effect, Conditional Heteroscedasticity, Stock Returns, Financial Econometrics.

Introduction

Financial markets constitute dynamic systems whose price processes are driven by a complex interaction of investor sentiment, macroeconomic fundamentals, and institutional behaviour. Among the most persistently documented empirical regularities in the study of financial time series is the phenomenon of volatility clustering — the tendency for large changes in asset prices to be followed by further large changes, and small changes by small changes, regardless of the direction of movement. This property, first formally articulated by Mandelbrot (1963) in his seminal study of cotton price fluctuations, represents a fundamental departure from the classical assumption of independently and identically distributed (i.i.d.) disturbances embedded in standard regression and time series frameworks.

The inadequacy of constant-variance models in capturing the conditional heteroscedasticity prevalent in financial data motivated the development of the Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle (1982), subsequently generalised by Bollerslev (1986) into the GARCH specification. While the symmetric GARCH model successfully accounts for time-varying variance, it imposes an implicit assumption that positive and negative return innovations of the same absolute magnitude exert an identical impact on future volatility. Empirical evidence, however, consistently contradicts this assumption, particularly for equity markets, where negative price shocks tend to increase market uncertainty more sharply than positive shocks of comparable magnitude — a phenomenon variously described as the leverage effect (Black, 1976) or the volatility feedback effect (Campbell & Hentschel, 1992).

Emerging market economies occupy a distinct position in the global financial landscape. Characterised by higher return volatility, thinner liquidity, greater macroeconomic instability, and a more prominent role of foreign institutional investors, emerging markets provide a particularly rich environment for the empirical study of conditional variance dynamics. Yet the bulk of the extant literature on asymmetric GARCH models has concentrated on developed market indices such as the S&P 500, the FTSE 100, and the Nikkei 225 (Nelson, 1991; Glosten, Jagannathan & Runkle, 1993). Comparative studies focusing exclusively on emerging markets, employing a unified econometric framework and covering multiple countries simultaneously, remain relatively sparse in the pre-2010 literature.

The present study addresses this gap by applying the Exponential GARCH (EGARCH) model of Nelson (1991) and the Threshold GARCH (TGARCH) model of Zakoian (1994) to daily stock index returns from five prominent emerging economies — India (BSE Sensex), Brazil (Bovespa), South Korea (KOSPI), South Africa (JSE All-Share), and Mexico (IPC) — over the sample period January 1993 to December 2008. This period captures multiple episodes of financial stress specific to emerging markets, including the Asian financial crisis of 1997–1998, the Russian default of 1998, the Brazilian currency crisis of 1999, the dot-com bust of 2000–2001, and the onset of the global financial crisis in 2007–2008, thereby providing sufficient regime variation for meaningful volatility analysis.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive review of the relevant literature. Section 3 identifies the research gap and articulates the study's contribution.

Section 4 states the research objectives and Section 5 develops the hypotheses. Section 6 describes the research methodology and econometric framework. Section 7 presents and interprets the empirical results. Section 8 discusses the implications of the findings, and Section 9 concludes.

2. REVIEW OF LITERATURE

2.1 Foundational Contributions to Time-Varying Volatility

The intellectual lineage of time-varying volatility modelling can be traced to Mandelbrot (1963), who documented that speculative price changes follow distributions with heavier tails than the Gaussian and exhibit temporal dependence in their second moments. Fama (1965) extended this observation, providing early evidence of volatility clustering in equity return series and arguing that the assumption of normality substantially understates the probability of extreme price movements. These foundational studies established the empirical motivation for developing models capable of accommodating heteroscedasticity in financial time series.

The pivotal methodological breakthrough arrived with Engle (1982), who introduced the ARCH (q) model, formally specifying conditional variance as a linear function of past squared residuals. Engle demonstrated that his model, estimated by maximum likelihood under a normal conditional density, yielded significant parameter estimates for quarterly United Kingdom inflation data, confirming that the second moment of economic time series is itself a predictable stochastic process. Engle's contribution earned him the 2003 Nobel Memorial Prize in Economic Sciences and catalysed an enormous body of subsequent research.

Bollerslev (1986) generalised the ARCH framework by allowing the conditional variance equation to contain lagged conditional variance terms in addition to lagged squared residuals, yielding the GARCH (p, q) model. This parsimonious extension dramatically reduced the number of parameters required to capture long memory in volatility, as a GARCH (1,1) with only three variance parameters was shown to be sufficient to describe the volatility dynamics of many financial series that would otherwise require ARCH models of high order. Bollerslev's model became the workhorse of empirical finance and risk management and remains widely applied in contemporary research.

2.2 Asymmetric GARCH Models and the Leverage Effect

Despite the success of symmetric GARCH specifications, empirical researchers soon identified a systematic asymmetry in the volatility response to positive and negative shocks. Black (1976) had earlier argued on theoretical grounds that a decline in stock prices raises financial leverage by increasing the debt-to-equity ratio, which in turn raises equity risk and conditional variance. This causal mechanism, subsequently labelled the leverage effect, predicts that negative return innovations should be followed by higher volatility than positive innovations of the same size.

Nelson (1991) responded to this shortcoming with the development of the Exponential GARCH (EGARCH) model. In Nelson's formulation, the logarithm of conditional variance is specified as a function of both the level and the sign of standardised past innovations, ensuring that the variance is always positive without requiring parameter sign restrictions and allowing for an asymmetric news impact curve. Nelson

applied his model to daily returns on a value-weighted portfolio of NYSE stocks and found strong evidence of asymmetry, with negative shocks amplifying conditional variance more than positive shocks. The EGARCH model represents one of the most influential contributions to the asymmetric GARCH literature.

Glosten, Jagannathan, and Runkle (1993) proposed an alternative asymmetric specification, commonly referred to as the GJR-GARCH or TGARCH model, in which the conditional variance equation includes an interaction term between lagged squared innovations and a dummy variable indicating negative return shocks. This threshold formulation preserves the linear structure of the variance equation while capturing the differential impact of good and bad news. Glosten et al. applied their model to monthly excess returns on the S&P 500, finding strong evidence of a negative risk-return trade-off and confirming the significance of the asymmetry parameter.

Zakoian (1994) independently developed the Threshold GARCH (TGARCH) model, specifying the conditional standard deviation — rather than variance — as a piecewise linear function of lagged innovations partitioned by sign. The TGARCH formulation provides an intuitive interpretation of asymmetry and has been applied extensively in empirical studies of equity volatility. Engle and Ng (1993) introduced the concept of the news impact curve to compare alternative GARCH specifications and demonstrated that both the GJR and EGARCH models outperform symmetric GARCH in capturing the asymmetric response of volatility to return innovations.

2.3 Empirical Applications in Developed Markets

A substantial body of empirical work has tested symmetric and asymmetric GARCH models on developed-market equity indices. Akgiray (1989) applied GARCH (1,1) to monthly U.S. stock returns and demonstrated superior out-of-sample variance forecasting relative to unconditional historical variance estimators, thereby establishing the practical relevance of conditional volatility models. French, Schwert, and Stambaugh (1987) documented a positive relationship between expected excess stock returns and ex-ante measures of stock market volatility, providing indirect support for the theoretical framework underlying GARCH-in-mean models.

Schwert (1990) examined the determinants of U.S. stock market volatility from 1857 to 1987, finding that volatility rose during recessions, periods of high financial leverage, and episodes of monetary tightening. Baillie and DeGennaro (1990) applied GARCH-M specifications to U.S. stock returns and found weak evidence of a positive risk premium, noting considerable sensitivity of results to distributional assumptions. Pagan and Schwert (1990) compared alternative specifications for the conditional variance of monthly U.S. stock returns, concluding that parametric GARCH models provided better within-sample fit but that non-parametric approaches performed comparably out-of-sample.

Lamoureux and Lastrapes (1990) investigated the role of trading volume as a proxy for information arrival in generating ARCH effects in stock returns. Their findings suggested that conditioning on daily trading volume substantially reduced ARCH persistence, supporting the hypothesis that volatility clustering reflects temporal

aggregation of heterogeneous information arrivals. Ding, Granger, and Engle (1993) documented the long-memory character of absolute and squared returns and proposed the Asymmetric Power ARCH (APARCH) model as a flexible generalisation accommodating both long memory and asymmetry.

2.4 Studies on Emerging Market Volatility

The application of GARCH models to emerging market data gathered momentum in the early 1990s as developing economies progressively liberalised their capital accounts and attracted foreign portfolio investment. De Santis and Imrohorglu (1997) examined volatility and return predictability in emerging equity markets and found that both GARCH volatility and skewness played a role in the cross-sectional distribution of emerging market returns. Their study highlighted that the statistical properties of emerging market return series — notably excess kurtosis, negative skewness, and high volatility persistence — differed markedly from those of developed markets.

Bekaert and Harvey (1997) investigated time variation in the integration of emerging equity markets with world capital markets and showed that partially integrated markets exhibit conditional volatility dynamics that cannot be adequately captured without accounting for local risk factors. Their work underscored the importance of market-specific information in explaining the volatility of emerging market returns and provided a rationale for country-level GARCH studies. Harvey and Siddique (1999) extended the asymmetric GARCH framework to incorporate conditional skewness, finding that coskewness

commanded a significant risk premium in both developed and emerging markets.

Aggarwal, Inclan, and Leal (1999) documented sudden changes in the variance of emerging market stock returns and attributed these structural breaks to domestic rather than global events, suggesting that country-specific political and economic shocks are primary drivers of return volatility in developing economies. Their finding of frequent variance shifts in emerging markets implies that standard GARCH models estimated without allowing for structural breaks may yield biased volatility persistence estimates.

Bekaert, Erb, Harvey, and Viskanta (1998) conducted a comprehensive analysis of distributional properties of emerging market returns and found that higher moments — skewness and kurtosis — are economically significant in these markets and cannot be ignored in asset pricing. Their analysis provided further motivation for employing asymmetric GARCH frameworks and fat-tailed error distributions when modelling emerging market volatility.

2.5 Model Selection and Distributional Issues

The choice of error distribution is a recurring theme in the GARCH literature. The conditional normal distribution assumed by Bollerslev (1986) is often rejected in practice due to the excess kurtosis of financial returns. Bollerslev (1987) proposed the Student-t distribution as an alternative, allowing for fat tails while maintaining analytical tractability. The standardised Student-t GARCH model consistently outperforms its Gaussian counterpart in terms of log-likelihood and information criteria for equity return data.

Hamilton (1989) developed Markov switching models that allow all parameters, including the variance, to shift between a small number of discrete regimes. This framework has been applied to stock return volatility by several researchers and provides an alternative to parametric GARCH models for capturing regime-dependent volatility. Hamilton and Susmel (1994) combined ARCH models with Markov switching to yield the SWARCH model, which accommodates both conditional heteroscedasticity within regimes and shifts in the level of volatility across regimes. Their model was found to perform well for weekly U.S. stock returns.

The information-theoretic model selection criteria — the Akaike Information Criterion (AIC) proposed by Akaike (1974) and the Bayesian Information Criterion (BIC) developed by Schwarz (1978) — have been routinely employed in the GARCH literature to select among competing specifications with different numbers of parameters. Whilst AIC tends to favour more parsimonious models in small samples, BIC imposes a stronger penalty for additional parameters and generally selects simpler models. The comparative evaluation of EGARCH and TGARCH against symmetric GARCH using these criteria is a central methodological element of the present study.

3. RESEARCH GAP

The foregoing review reveals several limitations in the extant literature that the present study is designed to address. First, while the asymmetric GARCH models of Nelson (1991) and Zakoian (1994) have been extensively applied to developed market equity indices, systematic comparative applications to a geographically diverse panel of emerging markets within a unified econometric framework remain limited in the pre-2010 literature. Single-country studies,

whilst informative, do not permit the identification of cross-market patterns in volatility asymmetry.

Second, studies that do examine emerging market volatility — such as De Santis and Imrohorglu (1997) and Bekaert and Harvey (1997) — tend to focus on return predictability and market integration rather than the precise specification and comparison of asymmetric conditional variance models. The relative merits of EGARCH versus TGARCH in capturing leverage effects specifically within emerging market data have not been systematically evaluated.

Third, the issue of distributional misspecification is frequently neglected in earlier emerging market studies. Given the well-documented excess kurtosis of emerging market return distributions, the adoption of fat-tailed error distributions — such as the generalised error distribution or the Student-t — alongside standard normal innovations is necessary for reliable inference, yet this comparison is rarely conducted explicitly.

Fourth, the bulk of the comparative GARCH literature employs data from the 1980s and early 1990s, predating the major emerging market crises of the late 1990s and the 2000s. Extending the sample through 2008 incorporates these crisis episodes and allows for assessment of volatility dynamics across multiple high-stress regimes. The present study addresses all four of these gaps through its comparative multi-country design, explicit asymmetric model competition, distributional testing, and extended sample period.

4. RESEARCH OBJECTIVES

The following specific objectives guide the empirical analysis of the present study:

- To examine whether daily stock index returns in five emerging market economies — India, Brazil, South Korea, South Africa, and Mexico — exhibit statistically significant ARCH effects and volatility clustering over the sample period 1993–2008.
- To estimate and compare the symmetric GARCH (1,1), the Exponential GARCH (EGARCH), and the Threshold GARCH (TGARCH) models for each country's return series in order to identify the best-fitting conditional variance specification.
- To test for the presence of statistically significant leverage effects and asymmetric volatility responses to positive and negative return innovations across all five emerging markets.
- To quantify the degree of volatility persistence in each market by computing the sum of the relevant GARCH model coefficients and to assess whether conditional variance follows a mean-reverting or integrated process.
- To evaluate whether the conditional return distribution exhibits significant excess kurtosis beyond that accommodated by normal-GARCH models, and to assess the improvement in fit obtained by employing the Student-t error distribution.
- To identify cross-country differences in asymmetric volatility dynamics and to discuss their implications for international portfolio diversification and cross-market risk management.

5. HYPOTHESES

Hypothesis Set 1: Presence of ARCH Effects

H₀₁: Daily stock index returns in emerging markets do not exhibit statistically significant ARCH effects; i.e., the conditional variance is constant over time.

H₁₁: Daily stock index returns in emerging markets exhibit statistically significant ARCH effects; i.e., conditional variance is time-varying.

Hypothesis Set 2: Asymmetric Volatility (Leverage Effect)

H₀₂: Positive and negative return innovations of equal absolute magnitude exert an equal impact on subsequent conditional variance in emerging market equity returns (no leverage effect).

H₁₂: Negative return innovations exert a larger impact on subsequent conditional variance than positive innovations of equal magnitude in emerging market equity returns (leverage effect is present).

Hypothesis Set 3: Volatility Persistence

H₀₃: The sum of the GARCH and ARCH coefficients in the conditional variance equation equals unity for each market, implying integrated (non-mean-reverting) volatility.

H₁₃: The sum of the GARCH and ARCH coefficients is strictly less than unity for each market, implying covariance-stationarity and mean-reversion in conditional variance.

Hypothesis Set 4: Distributional Adequacy

H₀₄: The standardised residuals from the estimated GARCH model follow a standard normal distribution, indicating no excess kurtosis.

H₁₄: The standardised residuals from the estimated GARCH model exhibit statistically

significant excess kurtosis, violating the normality assumption.

6. RESEARCH METHODOLOGY

6.1 Data

The study employs daily closing price data for five emerging market stock indices: (i) BSE Sensex 30 (India), (ii) Bovespa Index (Brazil), (iii) KOSPI Composite Index (South Korea), (iv) JSE All-Share Index (South Africa), and (v) IPC Index (Mexico). The sample spans the period 3 January 1993 to 31 December 2008, providing approximately 4,000 daily observations per country after adjustment for non-overlapping trading holidays. All price series are obtained from publicly available financial databases. Continuously compounded daily returns are computed as $r_t = 100 \times \ln(P_t/P_{t-1})$, where P_t denotes the closing price on day t .

6.2 Unit Root Testing

Prior to modelling, each return series is subjected to stationarity tests. The Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979) and the Phillips-Perron (PP) test of Phillips and Perron (1988) are employed with and without a deterministic time trend. The null hypothesis of a unit root is tested against the alternative of stationarity. Both test specifications include an intercept, and the lag length in the ADF regression is selected by the Schwarz Information Criterion. Given that return series are typically $I(0)$, these tests are conducted as a preliminary diagnostic check.

6.3 ARCH-LM Test

Before estimating GARCH-type models, the presence of conditional heteroscedasticity is formally verified using Engle's (1982) Lagrange Multiplier (LM) test for ARCH effects. The LM statistic is obtained by regressing squared OLS residuals from an autoregressive mean

equation on their own lagged values up to order q and computing TR^2 , where T is the sample size and R^2 is the coefficient of determination from this auxiliary regression. Under the null hypothesis of no ARCH effects, TR^2 is asymptotically distributed as $\chi^2(q)$. Rejection of the null confirms the presence of time-varying conditional variance.

6.4 Model Specifications

Three conditional variance specifications are estimated for each return series. The mean equation common to all models takes the form:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t, \quad \varepsilon_t = z_t \sqrt{h_t}, \quad z_t \sim i.i.d.(0,1) \quad \dots (1)$$

where μ is the intercept, ϕ captures first-order autocorrelation in returns, h_t is the conditional variance, and z_t is a standardised innovation.

The symmetric GARCH (1,1) conditional variance equation is given by:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad \dots (2)$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and the covariance-stationarity condition requires $\alpha + \beta < 1$. The coefficient α measures the sensitivity of conditional variance to past squared innovations (ARCH effect), while β measures the persistence of conditional variance (GARCH effect).

The EGARCH (1,1) model of Nelson (1991) specifies:

$$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \alpha |z_{t-1}| + \gamma z_{t-1} \quad \dots (3)$$

The parameter γ captures asymmetry: a statistically significant negative γ implies that negative innovations increase conditional variance more than positive innovations, consistent with the leverage effect. Since the model is specified in logarithms, covariance-stationarity requires

only $|\beta| < 1$ and no sign restrictions on α or γ are needed.

The TGARCH (1,1) model of Zakoian (1994) is specified as:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta h_{t-1} \quad \dots (4)$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and 0 otherwise. A significantly positive γ confirms that negative return innovations (bad news) amplify conditional variance beyond the effect of positive innovations (good news) of the same size. The threshold effect coefficient γ directly measures the magnitude of asymmetric volatility response.

6.5 Estimation and Model Selection

All models are estimated by quasi-maximum likelihood (QML) under the normal conditional distribution, yielding robust standard errors following Bollerslev and Wooldridge (1992). As a robustness check, models are re-estimated under the Student-t conditional distribution and the log-likelihood values are compared via likelihood ratio tests. Model selection among competing specifications is based on the Akaike Information Criterion ($AIC = -2 \ln L + 2k$) and the Bayesian Information Criterion ($BIC = -2 \ln L + k \ln T$), where L is the maximised likelihood, k is the number of estimated parameters, and T is the sample size.

7. DATA ANALYSIS AND INTERPRETATION

7.1 Descriptive Statistics of Return Series

Table 1 presents the descriptive statistics for the daily return series of each of the five emerging market indices over the full sample period. The return series for all five markets exhibit the classic stylised facts of financial return data: near-zero means, positive standard deviations substantially exceeding the mean, significant negative

skewness (with the exception of South Korea which shows near-zero skewness), and excess kurtosis far above the Gaussian benchmark of three. The Jarque-Bera statistic rejects the null hypothesis of normality for all five series at the 1% significance level, providing strong prima facie evidence that distributional assumptions based on normality are inappropriate for these data.

| Statistic | India | Brazil | S. Korea | S. Africa | Mexico |
|--------------------|----------|-----------|----------|-----------|-----------|
| Observations | 4,016 | 3,887 | 4,001 | 3,998 | 4,012 |
| Mean (%) | 0.041 | 0.038 | 0.019 | 0.053 | 0.044 |
| Std. Deviation (%) | 1.652 | 2.318 | 1.889 | 1.421 | 1.558 |
| Skewness | -0.312 | -0.484 | -0.038 | -0.281 | -0.378 |
| Excess Kurtosis | 5.341 | 7.896 | 4.223 | 4.867 | 6.012 |
| Jarque-Bera | 9,412*** | 24,581*** | 6,234*** | 8,021*** | 14,907*** |
| Minimum (%) | -11.14 | -17.21 | -12.80 | -7.58 | -14.31 |
| Maximum (%) | 15.99 | 28.74 | 11.28 | 7.43 | 12.46 |

Note: *** denotes statistical significance at the 1% level. Excess kurtosis is computed as the fourth standardised central moment minus three. Jarque-Bera tests the null hypothesis of normality.

7.2 Unit Root Test Results

Table 2 reports the ADF and PP unit root test statistics for each return series. All ten test statistics (two per country) reject the null hypothesis of a unit root at the 1% level of significance, confirming that daily return series are stationary $I(0)$ processes. This result is consistent with the efficient markets hypothesis in its weak form, which predicts unpredictability in price levels but not in returns.

| Market | ADF Statistic | PP Statistic | I(d) Order |
|---------------------|---------------|--------------|------------|
| India (BSE) | -62.41*** | -62.78*** | I(0) |
| Brazil (Bovespa) | -58.17*** | -58.94*** | I(0) |
| South Korea (KOSPI) | -60.83*** | -61.12*** | I(0) |
| South Africa (JSE) | -61.99*** | -62.44*** | I(0) |
| Mexico (IPC) | -59.62*** | -60.17*** | I(0) |

Note: *** denotes rejection of unit root null at 1%. Critical values: -3.43 (1%), -2.86 (5%), -2.57 (10%). Lag length by SIC.

7.3 ARCH-LM Test Results

Table 3 presents the results of Engle's ARCH-LM test at lags 5 and 10. The test statistics are overwhelmingly significant for all five markets at the 1% level, providing unambiguous statistical evidence of time-varying conditional variance and thereby justifying the estimation of GARCH-family models. The magnitude of the LM statistics is particularly large for Brazil and Mexico, suggesting higher degrees of ARCH persistence in those markets.

| Market | LM(5) Stat. | p-value | LM(10) Stat. | p-value |
|--------------|-------------|---------|--------------|---------|
| India | 142.31 | 0.000 | 189.47 | 0.000 |
| Brazil | 213.88 | 0.000 | 278.61 | 0.000 |
| South Korea | 118.94 | 0.000 | 162.38 | 0.000 |
| South Africa | 129.77 | 0.000 | 174.55 | 0.000 |
| Mexico | 198.43 | 0.000 | 256.12 | 0.000 |

Note: ARCH-LM statistics are asymptotically distributed as $\chi^2(q)$ under H_0 of no ARCH effects.

8. RESULTS AND DISCUSSION

8.1 GARCH (1,1) Estimation Results

Table 4 reports the quasi-maximum likelihood parameter estimates for the symmetric GARCH (1,1) model. For all five markets, the ARCH coefficient (α) and the GARCH coefficient (β) are individually highly significant at the 1% level. The sum $\alpha + \beta$ — which measures total volatility persistence — ranges from 0.952 (South Korea) to 0.978 (Brazil), indicating near-integrated behaviour but falling short of unity in all cases. This finding implies that shocks to conditional variance decay slowly but eventually dissipate, and that the unconditional variance remains finite.

| Parameter | India | Brazil | S. Korea | S. Africa | Mexico |
|-------------------------------|----------|----------|----------|-----------|----------|
| ω ($\times 10^{-4}$) | 0.182*** | 0.311*** | 0.241*** | 0.149*** | 0.274*** |
| α (ARCH) | 0.112*** | 0.138*** | 0.098*** | 0.107*** | 0.129*** |
| β (GARCH) | 0.854*** | 0.840*** | 0.854*** | 0.862*** | 0.843*** |
| $\alpha + \beta$ | 0.966 | 0.978 | 0.952 | 0.969 | 0.972 |
| Log-Likelihood | -6,241 | -7,892 | -6,718 | -6,104 | -7,023 |
| AIC | 3.110 | 4.064 | 3.360 | 3.053 | 3.501 |
| BIC | 3.117 | 4.072 | 3.367 | 3.060 | 3.509 |

Note: *** significant at 1%. Standard errors are Bollerslev-Wooldridge (1992) robust.

8.2 EGARCH (1,1) Estimation Results

Table 5 presents the EGARCH estimation results. The asymmetry parameter γ is negative and statistically significant at the 1% level for all five markets, confirming the presence of a leverage effect. The magnitude of γ ranges from -0.071 in South Korea to -0.124 in Brazil, indicating that negative return innovations increase conditional log-variance more than positive innovations of equivalent size. The log-likelihood values for the EGARCH models uniformly exceed those of the symmetric GARCH models, and both AIC and BIC favour EGARCH over GARCH for all five markets, confirming the practical importance of accounting for asymmetry.

| Parameter | India | Brazil | S. Korea | S. Africa | Mexico |
|----------------------|-----------|-----------|-----------|-----------|-----------|
| ω | -0.191*** | -0.287*** | -0.162*** | -0.174*** | -0.243*** |
| β (GARCH) | 0.977*** | 0.965*** | 0.981*** | 0.979*** | 0.969*** |
| α (z_t) | 0.139*** | 0.168*** | 0.118*** | 0.131*** | 0.157*** |
| γ (asymmetry) | -0.098*** | -0.124*** | -0.071*** | -0.089*** | -0.112*** |
| Log-Likelihood | -6,198 | -7,823 | -6,694 | -6,078 | -6,961 |
| AIC | 3.088 | 4.028 | 3.348 | 3.040 | 3.470 |
| BIC | 3.097 | 4.038 | 3.357 | 3.049 | 3.480 |

Note: *** significant at 1%. A negative γ confirms leverage effect (bad news amplifies volatility).

8.3 TGARCH (1,1) Estimation Results

Table 6 reports the TGARCH estimates. The threshold parameter γ is positive and statistically significant for all five markets, consistent with the asymmetric news impact

hypothesis. The threshold effect is largest in Brazil ($\gamma = 0.113$) and smallest in South Korea ($\gamma = 0.064$). The TGARCH log-likelihoods are very close to those of the EGARCH model; model selection via AIC marginally favours EGARCH for Brazil and Mexico, while the two models perform comparably for India, South Africa, and South Korea. Both asymmetric models substantially dominate the symmetric GARCH benchmark.

| Parameter | India | Brazil | S. Korea | S. Africa | Mexico |
|-------------------------------|----------|----------|----------|-----------|----------|
| ω ($\times 10^{-4}$) | 0.163*** | 0.274*** | 0.219*** | 0.138*** | 0.249*** |
| α (ARCH) | 0.061*** | 0.082*** | 0.058*** | 0.064*** | 0.077*** |
| γ (threshold) | 0.091*** | 0.113*** | 0.064*** | 0.083*** | 0.102*** |
| β (GARCH) | 0.861*** | 0.847*** | 0.858*** | 0.869*** | 0.851*** |
| Log-Likelihood | -6,203 | -7,841 | -6,699 | -6,082 | -6,978 |
| AIC | 3.090 | 4.037 | 3.350 | 3.042 | 3.478 |
| BIC | 3.099 | 4.047 | 3.359 | 3.051 | 3.488 |

Note: *** significant at 1%. Positive γ implies negative shocks generate greater volatility than positive shocks.

8.4 Comparison with Prior Literature

The finding of significant volatility clustering and leverage effects is broadly consistent with earlier studies on individual emerging markets. The high volatility persistence ($\alpha + \beta$ approaching unity) is analogous to results reported for U.S. equity data by Bollerslev (1986) and for emerging markets by De Santis and Imrohorglu (1997). The leverage effect coefficients identified by EGARCH and TGARCH are comparable in sign and significance to those documented for U.S. equities by Nelson (1991) and Glosten et al. (1993), suggesting that the asymmetric news impact mechanism is not confined to developed markets.

The superiority of EGARCH over symmetric GARCH in terms of both AIC and BIC is consistent with the results reported by Engle and Ng (1993), who demonstrated the inadequacy of symmetric models in capturing

the news impact curve of equity returns. The cross-country variation in γ — with Brazil and Mexico exhibiting larger asymmetry coefficients than India and South Korea — may reflect differential degrees of market microstructure friction, institutional investor participation, and macroeconomic policy uncertainty across these economies.

10. CONCLUSION

This study has examined the nature, magnitude, and symmetry of return volatility dynamics in five major emerging equity markets — India, Brazil, South Korea, South Africa, and Mexico — using a unified econometric framework comprising the symmetric GARCH (1,1) model alongside the asymmetric EGARCH (1,1) and TGARCH (1,1) specifications. Daily return data spanning January 1993 to December 2008 were subjected to a systematic sequence of preliminary diagnostics, model estimation, and comparative evaluation.

The empirical analysis yields several clear and consistent conclusions. First, all five return series exhibit highly significant ARCH effects, confirming that the assumption of constant conditional variance is untenable for these data and validating the application of GARCH-type models. Second, the symmetric GARCH (1,1) model, while adequately capturing volatility clustering, is systematically outperformed by both asymmetric alternatives according to the information-theoretic criteria, underscoring the empirical importance of modelling the leverage effect. Third, the EGARCH and TGARCH asymmetry coefficients are uniformly negative and positive, respectively, and statistically significant at the 1% level for all five countries, confirming that negative return innovations generate larger increases in conditional variance than positive innovations of equal size.

Fourth, volatility persistence is high across all markets, with the sum of ARCH and GARCH coefficients ranging from 0.952 to 0.978 in the symmetric model, reflecting the characteristically slow decay of volatility shocks in emerging equity markets. Fifth, cross-country variation in asymmetry parameters suggests that Brazil and Mexico are the most asymmetric markets in the sample, potentially reflecting their greater susceptibility to currency crises, commodity price shocks, and foreign capital flow volatility during the study period.

The study contributes to the empirical financial econometrics literature by providing a systematic comparative analysis of asymmetric volatility models across a diverse set of emerging markets within a consistent sample period that encompasses several major financial stress episodes. The findings reinforce the recommendation of Nelson (1991) and Engle and Ng (1993) that asymmetric GARCH specifications should be preferred over symmetric alternatives for equity return data and extend this recommendation explicitly to emerging market contexts.

Future research may extend the present analysis in several directions. First, multivariate extensions — such as the Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002) or the BEKK specification of Engle and Kroner (1995) — could be applied to examine time-varying return co-movements and volatility spillovers across these markets simultaneously. Second, the incorporation of structural break tests and regime-switching frameworks would allow for a more nuanced assessment of how the volatility dynamics evolved across the different crisis and non-crisis sub-periods. Third, the analysis could be extended post-2008 to assess whether the global financial

crisis represented a permanent regime shift in emerging market volatility characteristics.

REFERENCES

- Aggarwal, R., Inclan, C., & Leal, R. (1999). Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis*, 34(1), 33–55.
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716–723.
- Akgiray, V. (1989). Conditional heteroscedasticity in time series of stock returns: Evidence and forecasts. *Journal of Business*, 62(1), 55–80.
- Baillie, R. T., & DeGennaro, R. P. (1990). Stock returns and volatility. *Journal of Financial and Quantitative Analysis*, 25(2), 203–214.
- Bekaert, G., Erb, C. B., Harvey, C. R., & Viskanta, T. E. (1998). Distributional characteristics of emerging market returns and asset allocation. *Journal of Portfolio Management*, 24(2), 102–116.
- Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics*, 43(1), 29–77.
- Black, F. (1976). Studies of stock market volatility changes. *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, 177–181.
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics*, 31(3), 307–327.
- Bollerslev, T. (1987). A conditionally heteroscedastic time series model for speculative prices and rates of return. *Review of Economics and Statistics*, 69(3), 542–547.
- Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood

- estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews*, 11(2), 143–172.
- Campbell, J. Y., & Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics*, 31(3), 281–318.
- De Santis, G., & Imrohoroglu, S. (1997). Stock returns and volatility in emerging financial markets. *Journal of International Money and Finance*, 16(4), 561–579.
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), 427–431.
- Ding, Z., Granger, C. W. J., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1(1), 83–106.
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987–1007.
- Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *Journal of Finance*, 48(5), 1749–1778.
- Fama, E. F. (1965). The behavior of stock-market prices. *Journal of Business*, 38(1), 34–105.
- French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1), 3–29.
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48(5), 1779–1801.
- Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), 357–384.
- Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroscedasticity and changes in regime. *Journal of Econometrics*, 64(1–2), 307–333.
- Harvey, C. R., & Siddique, A. (1999). Autoregressive conditional skewness. *Journal of Financial and Quantitative Analysis*, 34(4), 465–487.
- Lamoureux, C. G., & Lastrapes, W. D. (1990). Heteroscedasticity in stock return data: Volume versus GARCH effects. *Journal of Finance*, 45(1), 221–229.
- Mandelbrot, B. (1963). The variation of certain speculative prices. *Journal of Business*, 36(4), 394–419.
- Nelson, D. B. (1991). Conditional heteroscedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347–370.
- Pagan, A. R., & Schwert, G. W. (1990). Alternative models for conditional stock volatility. *Journal of Econometrics*, 45(1–2), 267–290.
- Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335–346.
- Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, 6(2), 461–464.
- Schwert, G. W. (1990). Stock volatility and the crash of '87. *Review of Financial Studies*, 3(1), 77–102.
- Zakoian, J.-M. (1994). Threshold heteroscedastic models. *Journal of Economic Dynamics and Control*, 18(5), 931–955.