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Risk–Return Linkages across India–GCC Equity Markets: Evidence from GARCH Framework.

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ABSTRACT

Purpose: The intensification of economic and financial uncertainty triggered by the pandemic, geopolitical conflicts, and trade frictions necessitates a comprehensive analysis of the risk-return relationship and volatility spillovers across emerging markets, particularly withinIndo-GCC stock markets.

Methodology: This study applies a combined GARCH framework to examine volatility dynamics using daily stock return data from 2011 to 2025, sourced from investing.com.

Findings: Empirical results showed a positive and significant risk–return relationship across all markets except Saudi Arabia and Bahrain. The EGARCH model reveals asymmetry in all markets except Bahrain, confirming a leverage effect dominated by negative shocks.

Implications: These findings enriched academic and professional understanding of cross-market volatility spillover dynamics in emerging markets. The evidence provided insights for investors on portfolio diversification, hedging, and risk management, while underscoring the need for stronger market stabilization policies and regulatory cooperation.

Originality: This study provided a novel perspective on financial markets by quantifying risk-return linkages and time-varying spillovers across emerging markets using GARCH....

Keywords: *Risk-Return, Volatility, India-GCC, Equity Markets, GARCH......*

Introduction

The increasing integration of the global economy has transformed the way financial markets operate and interact. Greater openness in trade, liberalization of financial systems, and rapid advances in technology have strengthened cross-border economic and financial linkages, allowing information, capital, and investment to move more freely across countries. As a result, stock markets have become more closely connected, enabling financial shocks in one market to spread quickly to others. This heightened level of integration has increased the possibility of volatility spillovers and systemic risk, while simultaneously reducing the effectiveness of international portfolio diversification (Kumar et al., 2026a; Zhang et al., 2021).Recent global events, including financial crises, the COVID-19 pandemic, geopolitical tensions, and disruptions in international trade, have highlighted the speed with which uncertainty can be transmitted across interconnected markets. Although these developments affect both advanced and emerging economies, the latter are generally more susceptible to external shocks because of their stronger dependence on international capital flows and global trade networks (Feng et al., 2023;Kaushal et al., 2026a). At the same time, emerging stock markets have expanded considerably in terms of size, liquidity, and investor participation, making them increasingly important in the global financial system. Their relatively higher growth potential and evolving market structures continue to attract international investors seeking enhanced returns and diversification opportunities. Consequently, understanding the nature and evolution of cross-market interconnectedness has become increasingly important for researchers, policymakers, and investors, as it provides valuable insights for risk management, portfolio allocation, and the formulation of policies aimed at maintaining financial stability (Kaushal et al., 2026b;Maharana et al., 2025)..

The motivation for focusing on the GCC region stems from the rapid development and increasing global relevance of its equity markets. Over the past few decades, structural economic reforms, financial market liberalization, and sustained periods of high oil prices have contributed to the expansion and integration of GCC financial markets, thereby attracting greater international investor participation (Alqahtani et al., 2019; Singh et al., 2025a; Singh et al., 2025). Established in 1981, the

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GCC comprises six hydrocarbon-dependent economies—Bahrain, Oman, Qatar, Saudi Arabia, the UAE, and Kuwait, formed to promote political and economic cooperation among member states. As major global producers and exporters of crude oil, the macro-financial performance of these countries remains closely linked to fluctuations in international oil prices, which substantially influence financial market dynamics within the region. India is included in this analysis due to its strong and multidimensional economic engagement with the GCC, as it relies heavily on the GCC region for energy supplies. Beyond energy trade, economic relations between India and the GCC encompass trade, investment, labour migration, and remittances. These economic interdependences create channels through which shocks may generate financial interactions and volatility spillovers between the financial markets of the two regions. India's *Look West Policy* (2005) further strengthened these economic and strategic relations. More recently, the *Vikshit Bharat @2047* vision has further emphasized the importance of strengthening economic engagement with the GCC to facilitate capital inflows, enhancing energy cooperation, promoting market diversification, and supporting financial stability. Simultaneously, India's financial market has witnessed substantial growth and become increasingly integrated with the global financial ecosystem over the past few decades (Khan, 2023; Singh et al., 2022). Despite these growing economic relations, empirical evidence on the risk-return relationship and volatility spillovers between India and GCC equity markets remains relatively unexplored (Alotaibi and Mishra, 2014; BenSaïda, 2019; Gupta, 2025; Hanif et al., 2025; Maharana et al., 2025;Singh et al., 2019; Singh et al., 2023(a); Singh et al., 2023(b); Singh et al., 2022(a); Singh et al., 2022(b); Singh et al., 2018*inter alia).*

The present study makes several contributionsto the extant literature on the risk-return relationship and volatility spillover across emerging and oil-dependent financial markets. First, it offers a methodological contribution by examining the risk–return relationship, volatility persistence, and leverage effects within a univariate GARCH-type models. The novelty of the study stems from this empirical strategy, which combines the strengths of GARCH-type model in modeling conditional volatility, thereby offering a more precise, robust, and comprehensive assessment of volatility transmission across stock markets.Second, the study enriches the empirical understanding of the risk-return relationship by applying the GARCH-in-Mean Model to examine whether higher levels of market risk are associated with higher expected returns across India-GCC stock markets. Third, the presence of leverage effects is captured through the application of the EGARCH model, allowing the analysisto identify asymmetric volatility responses and assessing whether negative shocks exert a stronger effect on volatility than positive shocks. Overall, by integrating risk–return analysis, and leverage-effect modelling the study offers a more nuanced understanding of financial linkages between India and GCC stock markets for investors and policymakers.

2 Literature Review: This section synthesizes the key studies in this domain into three strands, asoutlined below:

The first strand of the literature review synthesizes studies employing GARCH-type models to analyze volatility dynamics and resilience in Indian financial markets amid deepening global integration,aiming to discover the evolving complexities and strengthen risk management strategies. Within this framework, a substantial body of research investigates volatility linkages between India and developed markets (BenSaïda, 2019; Maharana et al., 2025; Samarakoon, 2011; Spulbar et al., 2020; Tabas et al., 2024; Thangamuthu et al., 2022; Singh et al., 2025; Singh et al., 2021; Singh R. K., 2013; Kumar, R.2012). Similarly, an expanding stream of empirical work has investigated volatility dynamics between India and other emerging market economies (Gupta, 2025; Kumar et al., 2026b; Mukherjee & Mishra, 2010; Sharma et al., 2021; Singh et al., 2024a; Singh et al., 2024b Syriopoulos et al., 2015; Tabajara et al., 2014). Collectively, these studies largely focus on volatility persistence, risk-return relationships, leverage effects, and shock transmission across advanced economies and mainstream regional emerging market groupings. Despite these valuable contributions, the prevailing literature remains geographically skewed, with limited attention to volatility interlinkages between India and GCC stock markets. This gap is significant given the strengthening economic and financial ties between India and GCC economies, highlighting the need for deeper analysis of volatility dynamics within a strategically important corridor of South–South financial integration.

The second strand synthesizes research on GCC equity markets within the GARCH-type modeling framework to understand volatility dynamics and their evolving patterns.Early evidence by Nekhili and Mohammad (2010) revealed strong volatility spillover effects across GCC equity markets, with pronounced spillover effects from individual GCC markets to the Saudi market. Alotaibi and Mishra (2014) employed an EGARCH model using weekly data to examine volatility spillovers across GCC stock markets and confirmed Saudi Arabia's dominant role in regional spillovers, exerting positive volatility effects on most GCC markets, except Bahrain, where the effect was negative. Extending this analysis, Arin et al. (2019) reported evidence of volatility spillovers from Saudi Arabia to Qatar, Abu Dhabi, and Dubai, highlighted that spillovers from the larger markets increased following the 2014 oil crisis. Similarly, Hung (2021) reported the financial interconnectedness of GCC stock markets (2009-2019) and identified that the UAE, Saudi Arabia, and Kuwait as major transmitters of risk within the region. Subsequent studies expanded the scope to sectoral and cross-market dynamics. Kapar et al. (2023) assessed sectoral return and volatility spillovers within GCC countries (2007-2021) and observed that in most sectors, Saudi Arabia's influence in spillovers declined over time relative to the UAE and Qatar. Matar (2023) investigated the interrelationship between GCC and Amman stock market employing weekly data (2009-2020) and a DCC-GARCH model. The evidence confirmed that Saudi Arabia is the most connected to Amman, followed by Bahrain, Qatar, and the UAE, while Kuwait and Oman are the least connected. Alqahtani et al. (2019) examined the co-movements of GCC stock market returns with global oil price uncertainty from 2007 to 2008 using weekly data. Employing ARMA-DCC-EGARCH and time-varying Student-*t* copula models, the study found that GCC markets are negatively affected by oil market uncertainty, however, the magnitude and intensity of this impact vary across markets. Sadraoui and Mili (2025) investigated the impact of oil prices on the fiscal policy of GCC countries (2000-2024), indicated that government spending and fiscal balances are highly sensitive to oil price and volatility shocks, with countries exhibiting heterogeneous responses. Beyond intra-GCC linkages, some studies explore broader regional and cross-asset interconnectedness. Shahateet et al. (2019) examined the linkage within fifteen Arab financial markets and indicated weak linkages among sampled markets except for the GCC markets. Danila (2023) investigated the co-movement and volatility spillover between foreign exchange and stock markets between ASEAN and GCC countries (2015-2020) and reported the bidirectional spillovers in Malaysia; unidirectional spillovers in Indonesia, Singapore, Thailand, and Bahrain; while insignificant spillover effects in the Philippines, Saudi Arabia, and the UAE markets. Collectively, the literature demonstrates strong and evolving financial interconnectedness within GCC markets, shifting leadership in regional spillover dynamics, particularly involving Saudi Arabia and the UAE.

The preceding literature review suggests that most research on conditional volatility and volatility spillovers have focused on inter- and intra-regional linkages within established economic blocs or on relationships between developed and emerging markets. However, direct financial linkages between India and GCC stock markets remain largely unexplored within a empirical framework. This study seeks to address this empirical gap.

3. Research Approach

The study employs a empirical strategy to investigate risk–return relationships and volatility spillovers between India and GCC equity markets. This design generates comprehensive and policy-relevant evidence to support portfolio diversification and risk management decisions. GARCH-in-Mean (Bollerslev, 1986) and EGARCH (Nelson, 1991) models are employed to estimate short- and long-run volatility components, volatility persistence, the risk–return relationship, and the leverage effect. Similar models have been employed in earlier studies by Alotaibi and Mishra (2014), Sharma et al. (2021), Singh et al. (2024a), Tabas et al. (2024), and Gupta (2025) to examine these dimensions of conditional volatility.

3.1 Objectives of this Study: The objectives of the current research framework are constructed as follows:

1.To study Risk-Return Relationship across India-GCC stock markets.

2. To examinevolatility persistence and the presence of leverage effects across India and GCC stock markets using GARCH models.

The proposed study empirically examines daily closing prices of India and GCC stock markets covering the period from April 1, 2011, to March 31, 2025, extracted from Investing.com. The 14-year sample period captures both post-Global Financial Crisis (2007-08) recovery and several episodes of global disruptions, including Brexit, the COVID-19 pandemic, the Russia-Ukraine War, geopolitical tensions, and trade–tariff conflicts. This extended period facilitates a comprehensive assessment of volatility spillovers across both stable and crisis periods, reinforcing the robustness and generalizability of the findings for emerging markets. The focus on India-GCC stock markets is economically justified, given their growing integration within the global supply chain and increasing economic interdependence. These linkages align with India's long-term development strategy, *Vikshit Bharat @2047*. The study incorporates leading benchmark indices representing each market: Bahrain (BAX), Oman (MSM 30), Qatar (QSI), Saudi Arabia (TASI), the United Arab Emirates (FTSE ADX), Kuwait (BKP), and India (BSE), serving as proxies for national equity market performance. Methodologically, the study contributes by jointly examining risk–return dynamics, leverage effects, and leverage effect. To address the objective, GARCH-type specifications are estimated using EView 12 to estimate volatility persistence, the risk–return dynamics, and leverage effects. To ensure data consistency and avoid estimation bias from non-synchronous trading days, only common trading days across all markets are retained, resulting in a fully balanced panel of daily observations. Daily closing prices are transformed into logarithmic returns using the standard log-difference transformation:

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

where r_t = Returns; p_t = Daily closing prices at current period: p_{t-1}=Closing prices of the previous day.

3.2 Model Specification: In alignment with the study's objectives, two separate models have been employed -- a conditional volatility model and a time-varying spillover model. Their design and specification are presented below:

3.2.1 Modeling Volatility using GARCH Models: GARCH-type models are employed to examine volatility persistence, the risk–return relationship, and the leverage effect, assuming the Gaussian distribution of error terms.

3.2.2 Model Specification

The symmetric and asymmetric models utilized in the present study are illustrated as follows:

ARCH Model: The Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982), is used to estimate time-varying volatility dynamics. The model is defined as follows:

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

Where σ_t^2 is conditional volatility, α_0 is the mean, q denotes the number of the previous 􀜧t2terms, andε_{t-i}^2 is white noise representing the residuals of the time series,$\sum_{i=1}^{q} \alpha_i < 1$stating that the process of covariance is stationary.

GARCH Model: The GARCH model is asymmetric model, developed by Bollerslev (1986). It extends the ARCH model by incorporating both past squared residuals and past conditional variances and is defined as follow:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i\, \sigma_{t-i}^2 \qquad (2)$$

Where, $\alpha_0 =$ constant term; α_1= ARCH term and short-run persistence; β_i = GARCH term and long-run persistence; $\varepsilon_{t-i}^2 =$ the first leg of the squared return; σ_{t-i}^2= is trailing variance; σ_t^2 = conditional variance. The conditional variance is the function of volatility from past period and the square of the previous residual. Thus, GARCH (1,1) model can be expressed as below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (3)$$

Where, α_0 = constant term; ε_{t-1}^2= volatility of the last period (the ARCH term); σ_{t-1}^2 = last period's forecast variance (the GARCH term); σ_t^2 = is a prediction variance based on the information of the previous period; α_1 = reaction parameter (GARCH error coefficient); β_1 = persistence parameter (GARCH lag coefficient). A large value of α_1 suggests that volatility responds strongly to market shocks, while a high value of β_1 indicates greater volatility, implying shocks will take a long time to die out.

GARCH-in-Mean Model: The GARCH-M model is a symmetric model, developed by Bollerslev et al. (1986), as an extension of the GARCH model. It incorporates conditional variance into the mean equation to capture the risk-return linkages. The model is expressed through mean and variance equations:

Mean Equation: $r_t = \mu_t + \lambda\sigma_t^2 + \varepsilon_t$ (4)

Variance Equation: $\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (5)

Where λ represents the risk premium parameter, a positive and significant coefficient, indicating that investors are compensated for assuming the greater risk.

EGARCH Model: The EGARCH model, introduced by Nelson (1991), is an asymmetric specification which illustrates that negative news exert a greater effect on conditional volatility rather than positive shocks. The specifications of EGARCH (1,1) is presented below:

$$log(\sigma_t^2) = \alpha_0 + \beta_i\, ln(\sigma_{t-i}^2) + \alpha_i \left[\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right] - \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \qquad (6)$$

The coefficient γ_i denotes the leverage effect.The general specification of the EGARCH (p, q) model is expressed as follows:

$$log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \beta_i \, log(\sigma_{t-i}^2) + \sum_{i=1}^{q} \alpha_i \left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] - \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \qquad (7)$$

Where p denotes the number of previousσ^2 terms and q denotes the number of previous ε^2 terms, γ_i = the leverage effect coefficient, $\gamma_i = 0$ shows the symmetric effect, $\gamma_i < 0$ shows the impact of bad news, $\gamma_i > 0$ shows the impact of good news, α_i = the impact of good news on volatility; $\alpha_i + \gamma_i$. = the impact of bad news on volatility.

TGARCH Model: The Threshold GARCH model was introduced by Glosten et al. (1993) to measure the leverage effects. The TGARCH (1,1) model can be presented as below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-i}^2 + \gamma d_{t-i} \, \varepsilon_{t-i}^2 + + \beta_i \sigma_{t-i}^2 \qquad (8)$$

A TGARCH model with general specification, TGARCH (p, q) is expressed as follow:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \alpha_1 \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 I_{t-i} \qquad (9)$$

Where, γ_i shows asymmetries, $\gamma_i < 0$ shows the impact of bad news, $\gamma_i > 0$ shows the impact of good news, α_i = the impact of good news on volatility; $\alpha_i + \gamma_i$. = the impact of bad news on volatility.

News Impact Curve: The present study employed the news impact curve (Engle and Ng 1993) to visually depict the influence of positive and negative news on the fluctuation of stock returns. The graph's horizontal axis depicts a range of values, where the negative parameter implies unpleasant news, and the positive parameter signifies pleasant news. The vertical axis of the graph reflects the degree of volatility in returns. A news impact curve has been constructed for all BRICS countries by using linear and non-linear models.

Volatility Spillover:The transmission of variations or shocks in one country's stock market indices to another country is termed the volatility spillover effect (Dedi et al. 2016; Ke et al. 2010). Volatility spillover can take two forms: bidirectional, in which shocks in the stock indices of both nations affect each other's stock returns, and unidirectional, in which shocks in one market affect the other market but not vice versa. This study uses the EGARCH model to capture spillover effects, as it is identified as the best-fitting model in most cases. The following equations describe the specification of the extended EGARCH model:

Mean Equation of Return Spillover

$$R_t = c + \omega R_{t-1} + \gamma R_{t-1\,(stock\ indices)} + \varepsilon_t$$

Variance Equation of Volatility Spillover

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \sigma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_1 \left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \delta \text{ (Volatility residuals of stock indices)}$$

In the mean equation, $R_t$represents the stock price returns: *c*—intercept, *ω*—stock price coefficient, which measures the effect of the previous day's return on the next day's return, and γ—measures the return spillover from one market to another market.

In the variance equation, $\alpha_0$denotes the constant level of volatility: $\alpha_1 h_{t-1}$ is the function of volatility: $\sigma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ captures the asymmetric effect of volatility: $\beta 1 \varepsilon t{-}1 ht{-}1$ denotes the response of volatility to a change in the news, and the coefficient δ denotes the volatility spillover from one market to another market. In contrast, 'volatility residuals of stock indices' (RSI) represents the volatility residuals for each stock market index and is used as a proxy for volatility spillover (Ahmed et al., 2021; Jebran et al., 2017).

4. Preliminary Analysis

Figure 2 illustrates time series plots of daily logarithmic returns for GCC-India stock market indices, demonstrating volatility clustering: periods of high volatility are followed by periods of high volatility, and periods of low volatility are succeeded by periods of low volatility.

Figure 2: Plots of Volatility Clustering in India- GCC Stock Markets

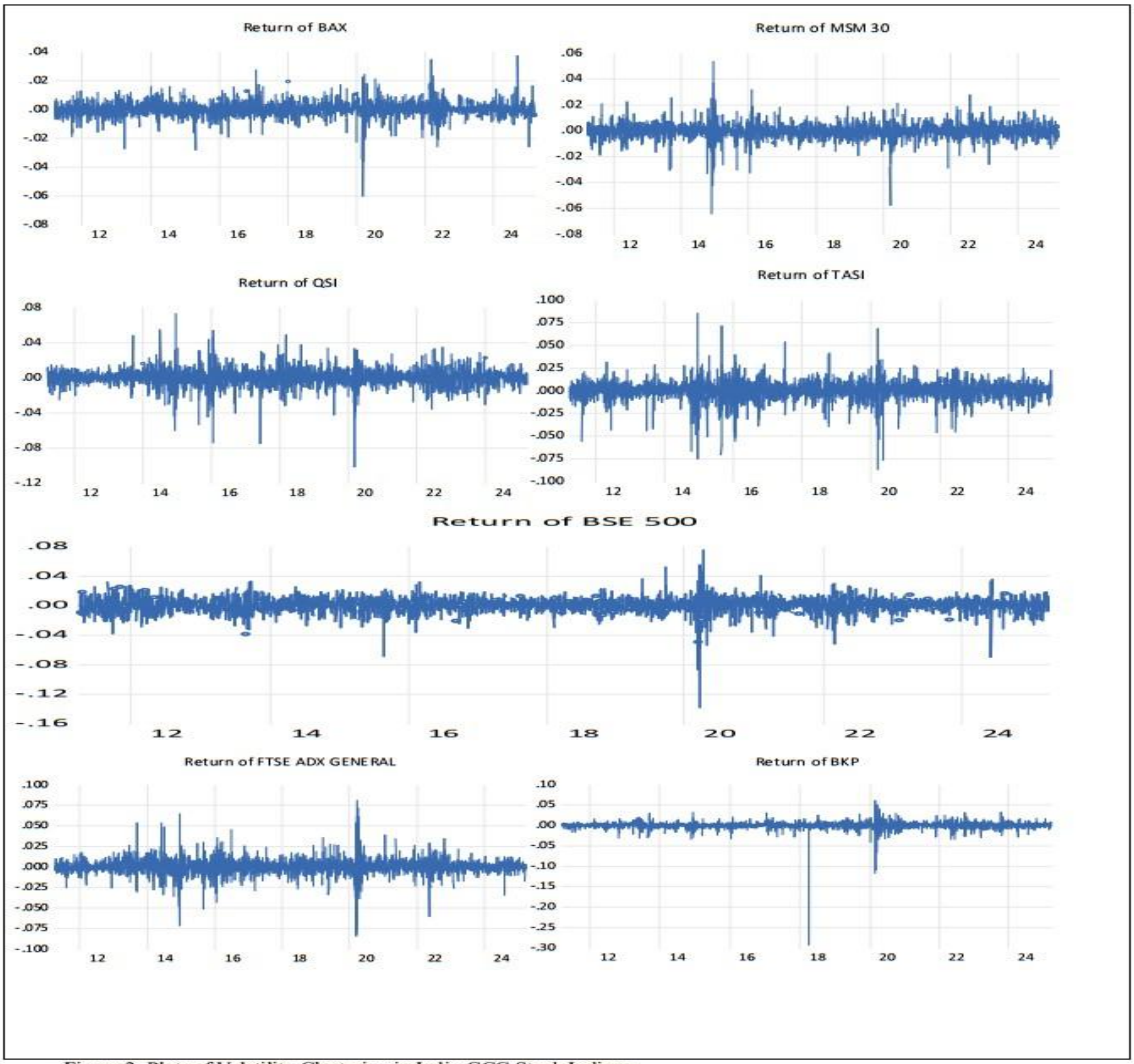

Figure 2: Plots of Volatility Clustering in India-GCC Stock Indices.

Table II presents descriptive statistics and diagnostic tests for the India-GCC stock markets. The minimum returns are negative across all markets, indicating losses; the Kuwait stock market (0.293565) recorded the largest decline, followed by India, Qatar, Saudi Arabia, UAE, Oman, and Bahrain. In contrast, the maximum return values indicate the highest positive returns (gains), with Saudi Arabia's market reporting the highest gains, followed by the UAE, India, Qatar, Kuwait, Oman, and Bahrain. The average (mean) stock returns are positive across all markets except Oman, indicating better performance across the region. The Indian stock market experiences the highest mean return (0.000434), followed by the UAE, Saudi Arabia, Kuwait, Bahrain, and Qatar. In contrast, Oman's negative average value (-0.000101) indicates a slight downward trend. The standard deviation estimates confirm that India (0.010268) is the most volatile market, followed by Saudi Arabia, UAE, Kuwait, Qatar, Oman, and Bahrain. The negative skewness coefficients for all stock markets imply that deviations are on the higher side of the mean, and return distributions are right-skewed. Furthermore, kurtosis coefficients are positive and exceed three across all markets, confirming leptokurtic distributions with fat tails. Kuwait reported an exceptionally high kurtosis, indicating periods of intense volatility or market turbulence.

Diagnostic tests are applied to assess the justification for applying the GARCH framework. The ADF and PP estimates are significant at the 1% level for all markets, rejecting the null hypotheses of a unit root, confirming the stationarity of the return series. The J-B test statistics are also significant at 1% level, indicating non-normal return distributions with fat tails and asymmetry. The ARCH-LM test estimates are significant for all markets except Kuwait, confirming the presence of ARCH effects. Therefore, these findings validate the application of GARCH models across allmarkets except the Kuwait stock market, where the ARCH effect is not statistically significant. Figure 3 shows a heat-map of the correlation matrix across India-GCC market, indicating low (30–45), weak (15–30), and poor (0–15)correlations among the sampled equity markets.

Table II: Descriptive Statistics and Diagnostic Test of India-GCC Stock Market

Indices	BAX	MSM 30	QSI	TASI	FTSE ADX	BKP	BSE 500
Min	-0.060013	-0.064129	-0.102077	-0.086846	-0.084063	-0.293565	-0.137891
Max	0.036958	0.053696	0.073095	0.085475	0.080762	0.061446	0.074933
Mean	9.28×10^{-5}	-0.000101	5.44×10^{-5}	0.000171	0.000366	9.40×10^{-5}	0.000434
Std. Dev	0.004858	0.005744	0.009266	0.010133	0.009306	0.0093	0.010268
Skew	-0.752865	-0.873296	-0.636074	-0.967943	-0.289616	-10.73109	-1.287535
Kurt	16.79183	18.70401	14.37137	14.36011	17.66203	309.881	18.30864
ADF Test	-28.61395 *	-44.18587 *	-30.43460 *	-52.17484 *	-55.83794 *	-51.61692 *	-56.86031 *
PP Test	-54.84298 *	-44.65854 *	-52.54141 *	-52.24378 *	-56.03463 *	-52.03686 *	-57.00129 *
J-B Test	27581.03 *	35795.94 *	19044.33 *	19350.04 *	31372.55 *	13,611,895.00 *	34802.33 *
ARCH-LM Test	4.319901 *	18.02014 *	10.32966 *	9.215459 *	33.75151 *	0.014045	37.15905 *

Source: E-views-12, output, author's calculation. *, represents p-value< 1%, **, represents p-value< 5%, and ***, represents p-value<10% respectively.

5. Empirical Results and Discussion

Table III presentestimates from the ARCH model, highlighting the relationship between past shocks (lagged squared residuals) and current volatility. The results indicate that the mean return (μ) is positive and statistically significant for both the UAE and India, reflecting relatively higher returns in these markets, while the negative and significant coefficients for Saudi Arabia suggest slight downward trends in its mean returns. Bahrain and Qatar experienced positive but insignificant mean returns, whereas Oman reported a negative and insignificant average return. The variance constants (c) are positive and statistically significant across all markets, confirming that the conditional volatility is well-defined. Among the markets, the UAE shows the highest ARCH coefficient (α = 0.539069), indicating strong volatility persistence and that past shocks have a lasting effect on current volatility. In contrast, India (α = 0.253769) and Bahrain (α = 0.299067) display the lowest ARCH coefficients, suggesting relatively lower volatility persistence. Additionally, Oman, Qatar, and Saudi Arabia exhibit moderate short-term volatility. Overall, the findings suggest that volatility clustering, a common phenomenon in financial time series, is present across all India–GCC stock markets, with varying degrees of volatility persistence and baseline risk. The UAE market demonstrates that past shocks have a more sustained impact on current volatility, whereas the Indian market tends to return to its mean volatility more quickly.

Table III: Estimates of the ARCH (1) Model for India-GCC Stock Market

Indices	Mean Equation Constant (μ)	Variance Equation Constant (c)	ARCH Term (α)
BAX	9.76×10^{-5}	1.67×10^{-5} *	0.299067 *
MSM 30	-9.24×10^{-5}	1.95×10^{-5} *	0.376957 *
QSI	0.000144	5.79×10^{-5} *	0.341985 *
TASI	-0.000248 ***	6.64×10^{-5} *	0.344216 *
FTSE ADX	0.000471 *	4.54×10^{-5} *	0.539069 *
BSE 500	0.000480 *	7.56×10^{-5} *	0.253769 *

Source: E-views-12, output, author's calculation. *, represents p-value< 1%, **, represents p-value< 5%, and ***, represents p-value<10% respectively.

The following equations present the derivation of the variance equation from the ARCH model, capturing volatility dynamics in the India–GCC stock markets:

BAX $\sigma^2 = 1.67 \times 10^{-5} + 0.299067\varepsilon_{t-1}^2$

MSM 30 $\sigma^2 = 1.95 \times 10^{-5} + 0.376957\varepsilon_{t-1}^2$

QSI $\sigma^2 = 5.79 \times 10^{-5} + 0.341985\varepsilon_{t-1}^2$

TASI $\sigma^2 = 6.64 \times 10^{-5} + 0.344216\varepsilon_{t-1}^2$

FTSE ADX $\sigma^2 = 4.54 \times 10^{-5} + 0.539069\varepsilon_{t-1}^2$

BSE 500 $\sigma^2 = 7.56 \times 10^{-5} + 0.253769\varepsilon_{t-1}^2$

Figure 3 presents the news impact curves for the India–GCC stock markets. The analysis indicates that these curves display a symmetrical response of market volatility to both positive and negative news. Thus, symmetry implies that favorable and unfavorable news exert an equal influence on volatility across all the sampled markets.

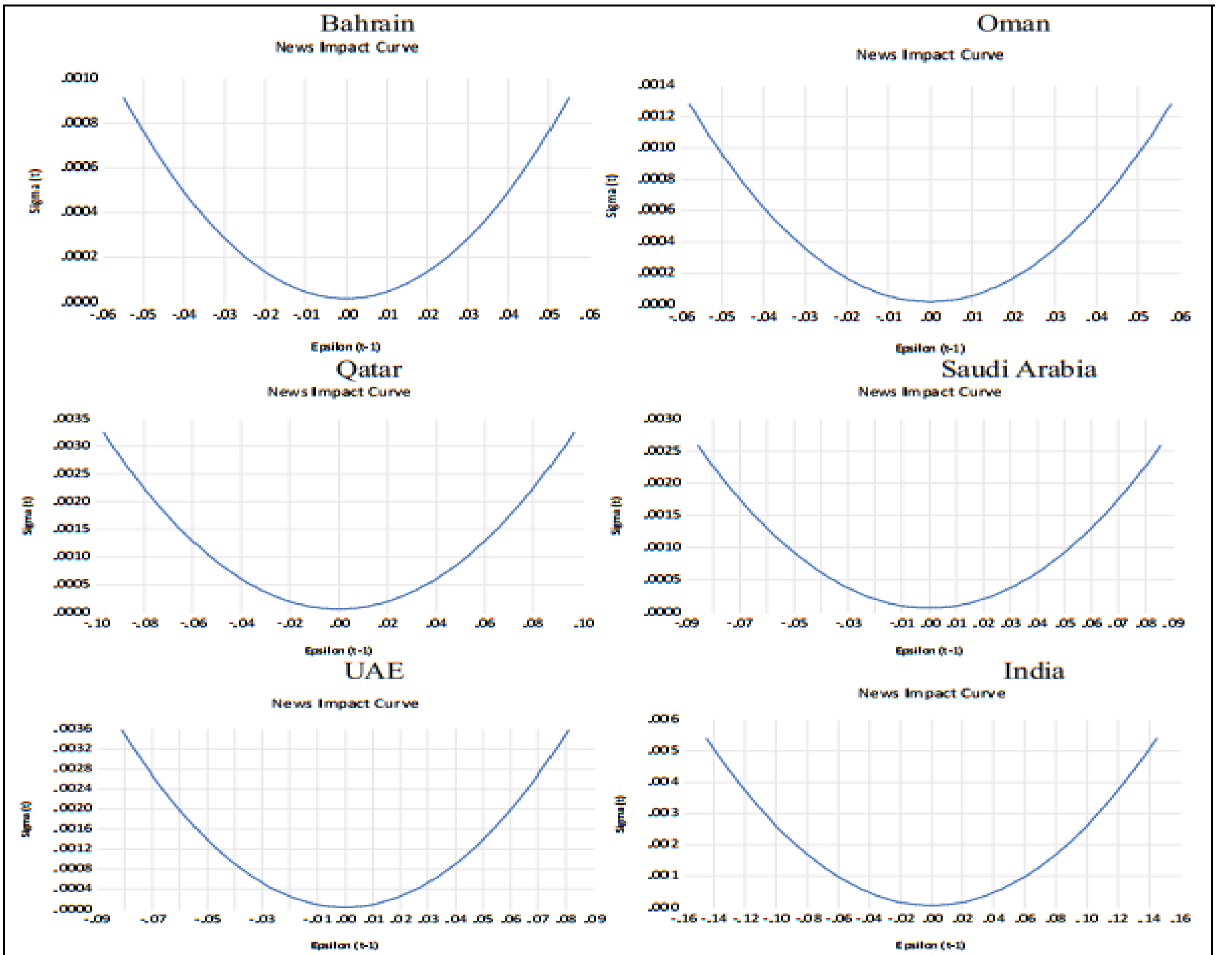

Figure 3: News Impact Curves (ARCH Model)

Table IV presents the GARCH (1,1) estimates for the India–GCC stock markets and provides important insights into volatility dynamics and information transmission. The α and β coefficients are positive and statistically significant at the 1% level across all markets, confirming that both recent (α) and lagged (β) shocks play a vital role in shaping conditional volatility. The consistently larger magnitude of β relative to α indicates that volatility is predominantly driven by past shocks, underscoring strong persistence and gradual information diffusion in price formation. The β coefficient is highest for India (0.854591), reflecting pronounced sensitivity to lagged information and slower adjustment to new information, whereas Bahrain (0.705507) records the lowest β, indicating comparatively weaker dependence on historical shocks. The UAE, with the highest α (0.191837), exhibits stronger responsiveness to recent information, suggesting more efficient price discovery and faster adjustment to new developments, likely supported by higher liquidity, greater institutional participation, and stronger global integration; in contrast, India's lower α (0.106491) points to delayed information incorporation. The persistence parameters (α + β) are close to unity for Qatar (0.978024), Saudi Arabia (0.971611), India (0.961082), and the UAE (0.957626), indicating pronounced volatility persistence and slow mean reversion, consistent with near-integrated volatility processes. Conversely, Oman (0.901748) and Bahrain (0.852906) exhibit relatively lower persistence, suggesting faster mean reversion and more rapid adjustment toward equilibrium. Furthermore, the news impact curves (Figure 4) reveal a symmetric volatility response, implying that positive and negative shocks exert similar effects across markets under the standard GARCH framework. Collectively, these findings highlight substantial cross-market heterogeneity in volatility persistence, information processing, and market efficiency.

Table IV: Estimates of the GARCH Model for India-GCC Stock Market.

Indices	Mean Equation Constant (μ)	Variance Equation Constant (c)	ARCH Term (α)	GARCH Term (β)	Persistence (α + β)
BAX	7.17×10^{-5}	3.36×10^{-6} *	0.147399 *	0.705507*	0.852906
MSM 30	-5.31×10^{-5}	2.82×10^{-6} *	0.176105 *	0.725643 *	0.901748
QSI	0.000288 **	2.84×10^{-6} *	0.148998 *	0.829026 *	0.978024
TASI	0.000516 *	3.85×10^{-6} *	0.164150 *	0.807461 *	0.971611
FTSE ADX	0.000419 *	4.03×10^{-6} *	0.191837 *	0.765789 *	0.957626
BSE 500	0.000638 *	3.96×10^{-6} *	0.106491 *	0.854591 *	0.961082

Source: E-views-12, output, author's calculation. *, represents p-value< 1%, **, represents p-value< 5%, and ***, represents p-value<10% respectively.

The variance equations derived from the GARCH model for the India–GCC stock markets are specified as under:

BAX $\sigma_t^2 = 3.36 \times 10^{-6} + 0.147399\varepsilon_{t-1}^2 + 0.705507\sigma_{t-1}^2$

MSM 30 $\sigma_t^2 = 2.82 \times 10^{-6} + 0.176105\varepsilon_{t-1}^2 + 0.725643\sigma_{t-1}^2$

QSI $\sigma_t^2 = 2.84 \times 10^{-6} + 0.148998\varepsilon_{t-1}^2 + 0.829026\sigma_{t-1}^2$

TASI$\sigma_t^2 = 3.85 \times 10^{-6} + 0.164150\varepsilon_{t-1}^2 + 0.807461\sigma_{t-1}^2$

FTSE ADX $\sigma_t^2 = 4.03 \times 10^{-6} + 0.191837\varepsilon_{t-1}^2 + 0.765789\sigma_{t-1}^2$

BSE 500 $\sigma_t^2 = 3.96 \times 10^{-6} + 0.106491\varepsilon_{t-1}^2 + 0.854591\sigma_{t-1}^2$

Figure 4 presents the news impact curves for the GARCH conditional on the India–GCC stock indices. The findings report that both good and bad news exert similar influence on volatility across all markets.

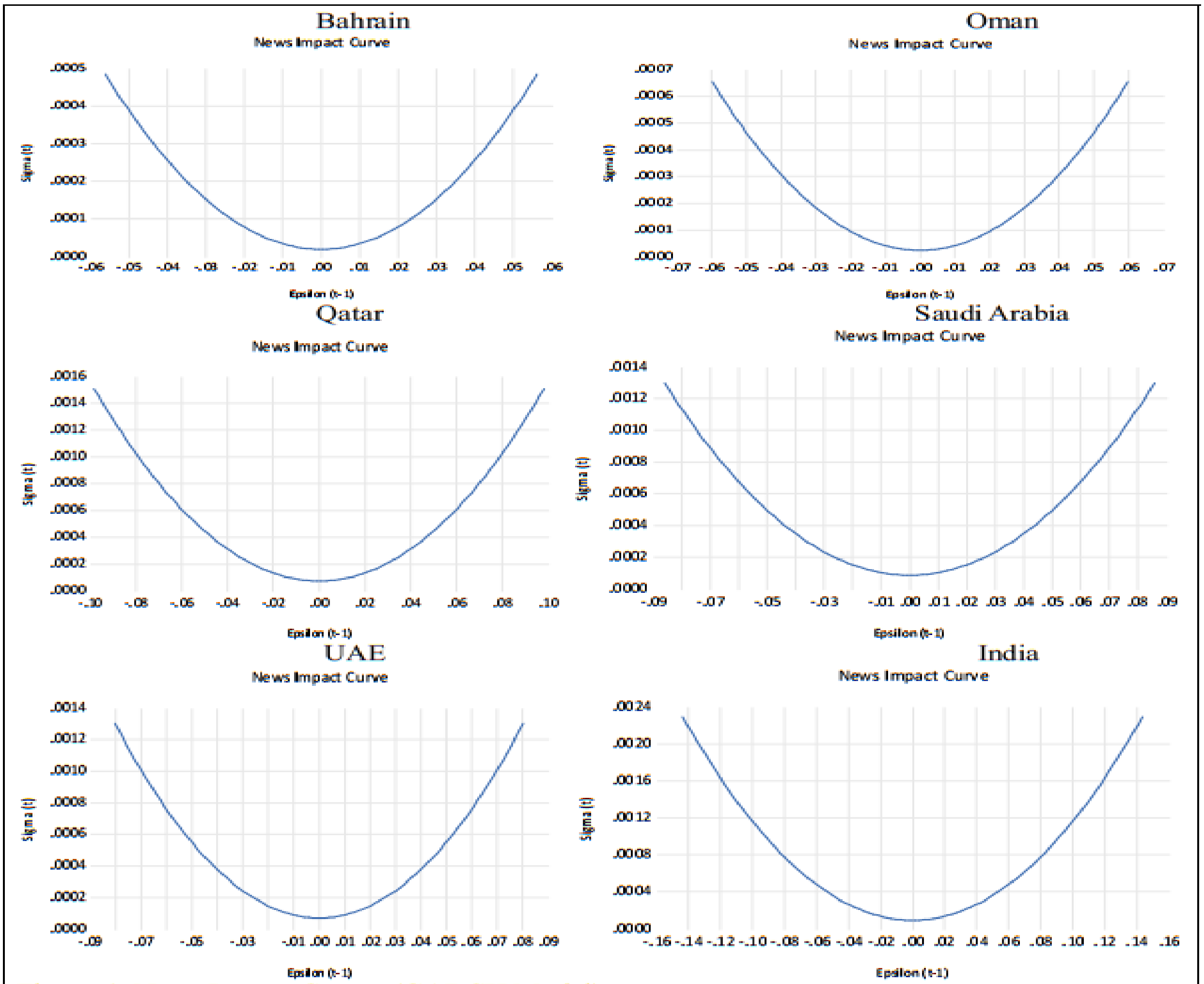

Figure 4: News Impact Curves (GARCH Model)

Table V reports the GARCH-in-Mean (GARCH-M) results, providing key insights into the risk-return relationship across India-GCC stock markets. The presence of positive and statistically significant risk coefficients ($\lambda > 0$) for Oman (9.755088), India (7.475766), Qatar (6.552354), and the UAE (5.198153) provides strong support for the theoretical risk–return paradigm, indicating that investors in these markets are rewarded for bearing higher risk. In contrast, although Saudi Arabia exhibits a positive λ coefficient (3.152101), its statistical insignificance suggests that the risk–return relationship is weak or unstable, possibly reflecting market-specific factors such as government intervention, market concentration, or the dominance of institutional investors. Bahrain, however, displays a negative and insignificant λ coefficient (−1.924737), indicating the absence of a meaningful risk–return trade-off and suggesting potential market inefficiencies, structural constraints, and risk-averse investor behavior. The news impact curves, presented in Figure 5, derived from the GARCH-M model, demonstrate a symmetric response of volatility to good and bad news, indicating the absence of leverage effects. Overall, these results reveal substantial heterogeneity in risk pricing across India–GCC markets, reflecting differences in financial development, market efficiency, liquidity, and integration with the global financial landscape, with key implications for asset allocation, diversification, and risk management strategies.

Table V: Estimates of the GARCH-M Model for India-GCC Stock Market

Indices	Mean Equation Constant (μ)	Risk Premium (λ)	Variance Equation Constant (c)	ARCH Term (α)	GARCH Term (β)	Persistence (α + β)
BAX	0.000108	-1.924737	3.36×10^{-6} *	0.147342 *	0.705573 *	0.852915
MSM 30	-0.000257 **	9.755088 ***	2.48×10^{-6} *	0.177302 *	0.723722 *	0.901024
QSI	-7.45×10^{-5}	6.552354 **	2.96×10^{-6} *	0.150817 *	0.825547 *	0.976364
TASI	0.000324 ***	3.152101	3.88×10^{-6} *	0.164260 *	0.806982 *	0.971242
FTSE ADX	0.000171	5.198153 **	4.01×10^{-6} *	0.191860 *	0.766031 *	0.957891
BSE 500	8.83×10^{-5}	7.475766 **	4.20×10^{-6} *	0.110277 *	0.848399 *	0.958676

Source: E-views-12, output, author's calculation. *, represents p-value < 1%, **, represents p-value < 5%, and ***, represents p-value < 10% respectively.

BAX $\sigma_t^2 = 3.36 \times 10^{-6} + 0.147342\varepsilon_{t-1}^2 + 0.705573\sigma_{t-1}^2$

MSM 30 $\sigma_t^2 = 2.48\text{ V} \times 10^{-6} + 0.177302\varepsilon_{t-1}^2 + 0.723722\sigma_{t-1}^2$

QSI $\sigma_t^2 = 2.96 \times 10^{-6} + 0.150817\varepsilon_{t-1}^2 + 0.825547\sigma_{t-1}^2$

TASI $\sigma_t^2 = 3.88 \times 10^{-6} + 0.164260\varepsilon_{t-1}^2 + 0.806982\sigma_{t-1}^2$

FTSE ADX $\sigma_t^2 = 4.01 \times 10^{-6} + 0.191860\varepsilon_{t-1}^2 + 0.766031\sigma_{t-1}^2$

BSE 500 $\sigma_t^2 = 4.20 \times 10^{-6} + 0.110277\varepsilon_{t-1}^2 + 0.848399\sigma_{t-1}^2$

Figure 5: News Impact Curves (GARCH-M Model)

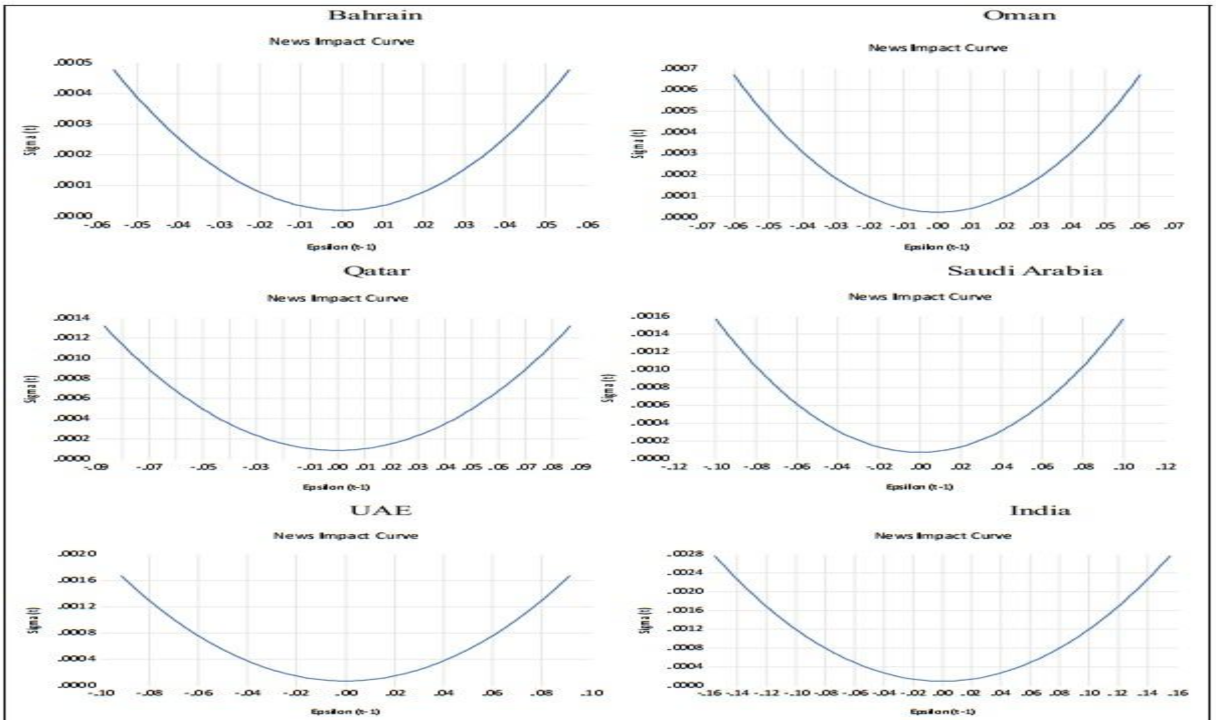

Figure 5: News Impact Curves (GARCH-M Model)

Table VIillustrates the estimates of the exponential GARCH model for the India-GCC stock markets, offering deeper insights into volatility dynamics, persistence, and asymmetry. A key strength of the EGARCH specification lies in its ability to capture asymmetry in volatility responses. The negative and statistically significant asymmetry coefficients (ϒ) for most markets—Oman (−0.062412), Qatar (−0.101756), Saudi Arabia (−0.128767), the UAE (−0.069038), and India (−0.106683)—provide strong evidence of leverage effects, indicating that negative shocks (bad news) exert a greater impact on volatility than positive shocks (good news) of similar magnitude. This asymmetry reflects behavioral and structural factors, including investor overreaction to adverse information, increased uncertainty during downturns, and the amplification of risk through financial leverage. Bahrain, however, exhibits an insignificant asymmetry coefficient (−0.013530), suggesting a symmetric volatility response and weaker sensitivity to the positive and negative news, possibly due to lower market depth or limited speculative activity. Overall, these findings underscore the dominant role of downside risk in shaping volatility dynamics across most India–GCC markets, with important implications for risk management, derivative pricing, hedging strategies, and the design of regulatory policies aimed at strengthening market resilience to adverse shocks.

Table VI: Estimates of the EGARCH Model for India-GCC Stock Market

Indices	Mean Equation Constant (μ)	Variance Equation Constant (ω)	ARCH Term (α)	GARCH Term (β)	Asymmetry (ϒ)	Persistence (α + β)
BAX	-1.52×10^{-5}	-1.687878 *	0.294625 *	0.862795 *	-0.013530	1.157420
MSM 30	-9.74×10^{-5}	-1.176070 *	0.304646 *	0.910476 *	-0.062412 *	1.215122
QSI	3.41×10^{-5}	-0.553766 *	0.213867 *	0.958873 *	-0.101756 *	1.172740
TASI	0.000197	-0.657849 *	0.230065 *	0.949063 *	-0.128767 *	1.179128
FTSE ADX	0.000232 **	-0.713982 *	0.286157 *	0.948321 *	-0.069038 *	1.234478
BSE 500	0.000275 **	-0.576171 *	0.168946 *	0.952289 *	-0.106683 *	1.121235

Source: E-views-12, output, author's calculation. *, represents p-value< 1%, **, represents p-value< 5%, and ***, represents p-value<10% respectively.

BAX $\ln(\sigma_t^2) = -1.687878 + 0.862795\ln(\sigma_{t-1}^2) + 0.294625\left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] + (-0.013530)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$

MSM $\ln(\sigma_t^2) = -1.176070 + 0.910476\ln(\sigma_{t-1}^2) + 0.304646\left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] + (-0.062412)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$

QSI $\ln(\sigma_t^2) = -0.553766 + 0.958873\ln(\sigma_{t-1}^2) + 0.213867\left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] + (-0.101756)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$

TASI $\ln(\sigma_t^2) = -0.657849 + 0.949063\ln(\sigma_{t-1}^2) + 0.230065\left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] + (-0.128767)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$

FTSE ADX $\ln(\sigma_t^2) = -0.713982 + 0.948321\ln(\sigma_{t-1}^2) + 0.286157\left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] + (-0.069038)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$

BSE 500 $\ln(\sigma_t^2) = -0.576171 + 0.952289\ln(\sigma_{t-1}^2) + 0.168946\left[\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right] + (-0.106683)\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$

Figure 6: News Impact Curves (EGARCH)

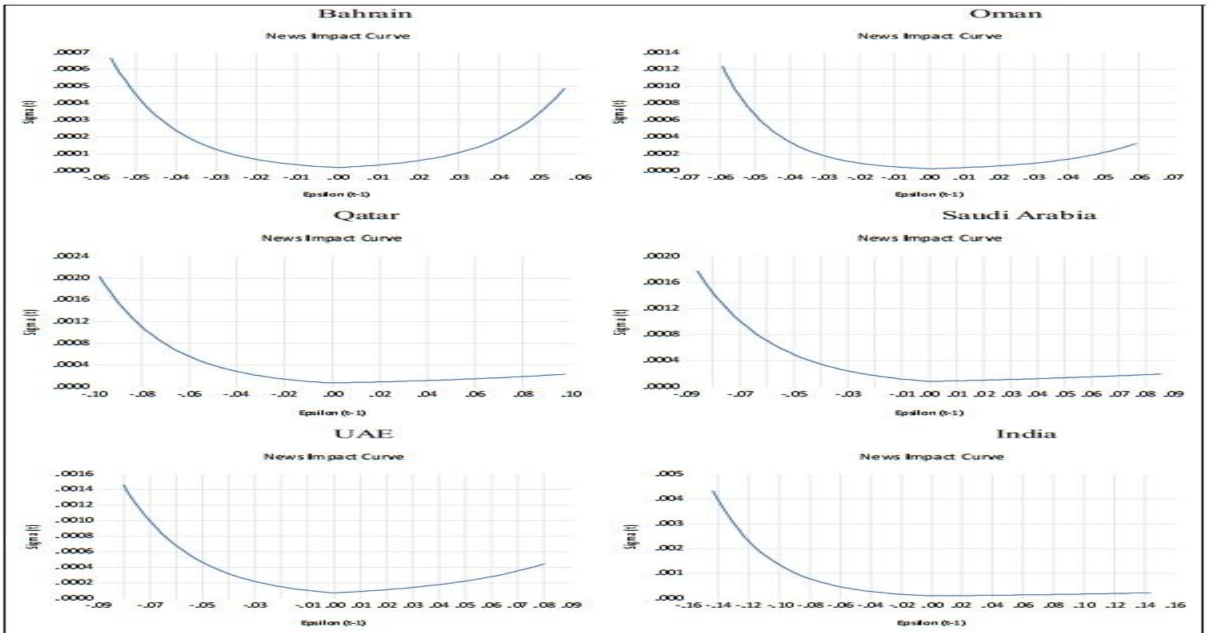

Figure 6: News Impact Curves (EGARCH Model)

The TGARCH model provides an additional asymmetric volatility framework to further validate asymmetric volatility behavior in the India-GCC stock markets. Table VI reports the estimated volatility parameters for each market. The leverage effects, denoted by Gamma (ϒ), are positive and significant for all indices except Bahrain, implying symmetric volatility behavior in which negative shocks intensify volatility more than positive ones. Although Bahrain's market shows the impact of negative news in both asymmetric models, the absence of statistical significance weakens the reliability of the conclusions. The news impact curves presented in Figure 7 confirm strong leverage effects in India, the UAE, Qatar, and Saudi Arabia, where negative shocks intensify volatility than positive shocks. Oman exhibits a largely symmetric curve, suggesting a weak leverage effect, although negative shocks still slightly increases volatility. Conversely, Bahrain's curve appears U-shaped, with no significant asymmetry, confirming the absence of a notable leverage effect

Table VII: Estimates of the TGARCH Model for India-GCC Stock Market

Indices	Mean Equation Constant (μ)	Variance Equation Constant (c)	ARCH Term (α)	GARCH Term (β)	Asymmetry (ϒ)	Persistence (α + β + ϒ/2)
BAX	6.55×10^{-5}	3.41×10^{-6} *	0.139703 *	0.702911 *	0.017117	0.851173
MSM 30	-0.000119	2.67×10^{-6} *	0.104983 *	0.745358 *	0.108444 *	0.904563
QSI	3.63×10^{-5}	2.95×10^{-6} *	0.055729 *	0.840020 *	0.150629 *	0.971064
TASI	0.000254 ***	3.78×10^{-6} *	0.026480 *	0.826638 *	0.220855 *	0.963546
FTSE ADX	0.000290 **	3.81×10^{-6} *	0.090653 *	0.793005 *	0.142355 *	0.954836
BSE 500	0.000355 **	5.09×10^{-6} *	0.030842 *	0.836033 *	0.155174 *	0.944462

Source: E-views-12, output, author's calculation. *, represents p-value< 1%, **, represents p-value< 5%, and ***, represents p-value<10% respectively.

BAX $u_t^2 = 3.41 \times 10^{-6} + 0.139703u_{t-1}^2 + 0.702911\sigma_{t-1}^2 + 0.017117u_{t-1}^2 I_{t-1}$

MSM 30 $u_t^2 = 2.67 \times 10^{-6} + 0.104983u_{t-1}^2 + 0.745358\sigma_{t-1}^2 + 0.108444u_{t-1}^2 I_{t-1}$

QSI $u_t^2 = 2.95 \times 10^{-6} + 0.055729u_{t-1}^2 + 0.840020\sigma_{t-1}^2 + 0.150629u_{t-1}^2 I_{t-1}$

TASI $u_t^2 = 3.78 \times 10^{-6} + 0.026480u_{t-1}^2 + 0.826638\sigma_{t-1}^2 + 0.220855u_{t-1}^2 I_{t-1}$

FTSE ADX $u_t^2 = 3.81 \times 10^{-6} + 0.090653u_{t-1}^2 + 0.793005\sigma_{t-1}^2 + 0.142355u_{t-1}^2 I_{t-1}$

BSE 500 $u_t^2 = 5.09 \times 10^{-6} + 0.030842u_{t-1}^2 + 0.836033\sigma_{t-1}^2 + 0.155174u_{t-1}^2 I_{t-1}$

Figure 7: News Impact Curve (TGARCH Model)

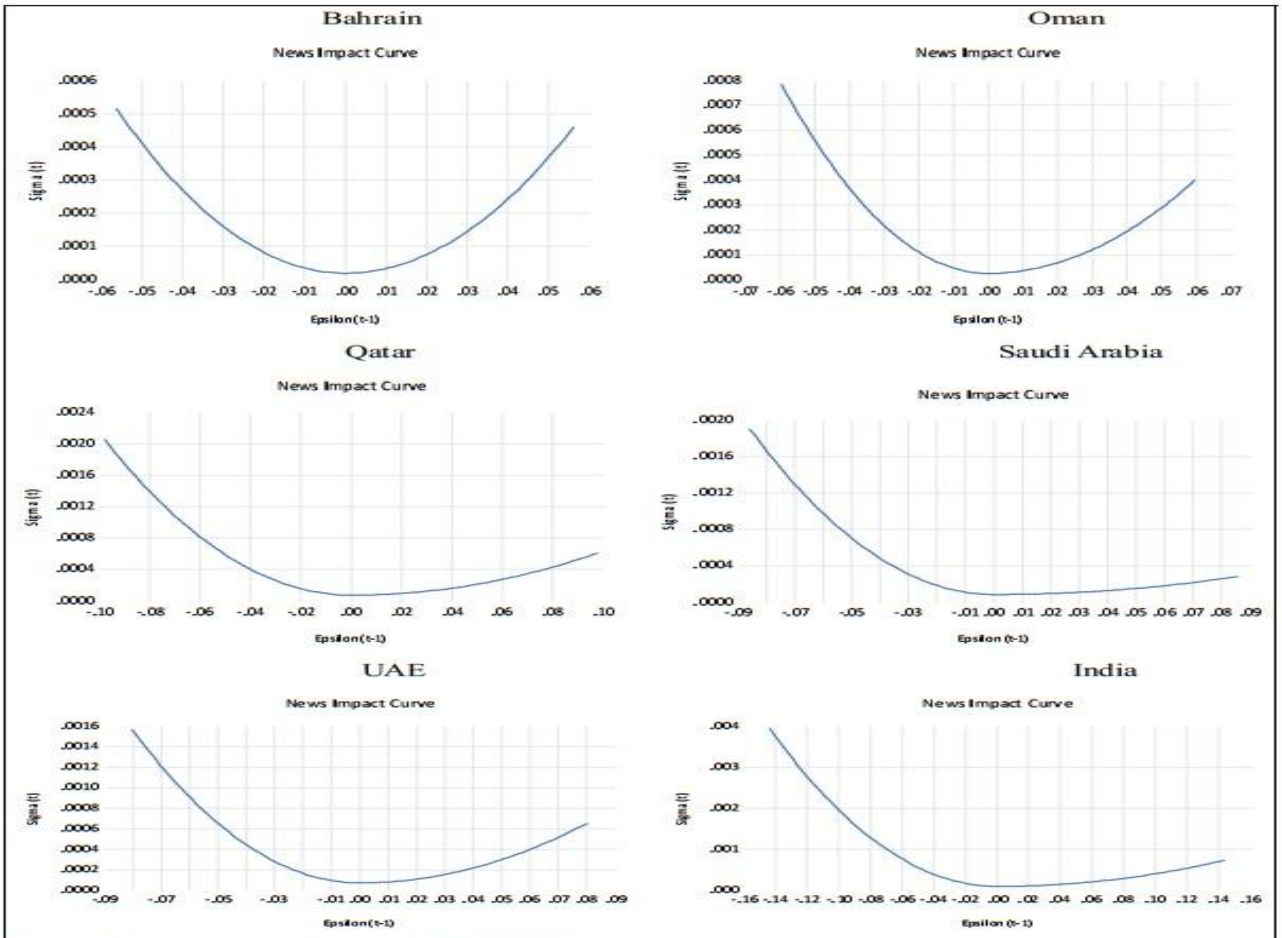

Figure 7: News Impact Curves (TGARCH Model)

Table VIII shows the results for various GARCH-type models — ARCH, GARCH, GARCH-M, EGARCH, and TGARCH — estimated for the India-GCC stock market indices. According to econometric standards, the best-fitting model is the one with the highest Log-Likelihood (LL) and the lowest Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) values (Engle, 1982; Bollerslev, 1986). The analysis indicates that the EGARCH model fits Bahrain, Qatar, Saudi Arabia, the UAE, and India best. However, some minor deviations are observed: for Bahrain, the SIC value favors the GARCH model, while for Qatar, the AIC slightly favors the GARCH model. In Oman, the TGARCH model outperforms all others, suggesting that threshold effects and asymmetry significantly influence market dynamics. Overall, the analysis suggests that the EGARCH model best describes India-GCC markets, indicating that negative shocks have a stronger, more persistent impact on volatility than positive shocks, consistent with the leverage effect observed in financial markets.

Table VIII: Evaluation of GARCH-Type Models to Identify the Best-Fitted Framework

PARTICULAR	ARCH	GARCH	GARCH-M	TGARCH	EGARCH
Bahrain					
LL	13639.06	13737.62	13737.65	13737.85	13740.65
AIC	-7.931975	-7.988728	-7.988164	-7.988279	-7.989907
SIC	-7.924828	-7.979794	-7.977444	-7.977558	-7.979186
Oman					
LL	13264.40	13492.57	13494.15	13503.30	13485.87
AIC	-7.709534	-7.841612	-7.841947	-7.847270	-7.837136
SIC	-7.702391	-7.832682	-7.831232	-7.836555	-7.826421
Qatar					
LL	11612.68	11866.01	11869.37	11909.06	11917.75
AIC	-6.652540	-6.979143	-6.798493	-6.821237	-6.826217
SIC	-6.645483	-6.788321	-6.787906	-6.810650	-6.815630
Saudi Arabia					
LL	11388.62	11706.34	11707.42	11767.15	11779.80
AIC	-6.512943	-6.694130	-6.694179	-6.728349	-6.735581
SIC	-6.505895	-6.685321	-6.683608	-6.717778	-6.725010
UAE					
LL	11836.49	12157.78	12160.19	12179.16	12189.34
AIC	-6.769158	-6.952390	-6.953197	-6.964051	-6.969871
SIC	-6.762111	-6.943581	-6.942626	-6.953480	-6.959300
India					
LL	11159.36	11369.35	11372.96	11408.54	11412.27
AIC	-6.438880	-6.559508	-6.561014	-6.581554	-6.583706
SIC	-6.431780	-6.550633	-6.550364	-6.570904	-6.573056

Source: E-views 12, output, author's calculation. LL-log likelihood; AIC-Akaike information criterion; and SIC-Schwardz information criterion.

6. Conclusion and Implications

This study examines the risk-return relationships and volatility spillover dynamics across India-GCC equity markets (2011-2025), using GARCH models. Results from all linear and non-linear GARCH models indicate that both α *and* βcoefficients arepositive and significant across all markets, indicating that large shocks tend to follow large shocks and small shocks tend to follow small shocks, consistent with financial market behaviour. Volatility persistence ($\alpha + \beta$) estimates are close to unity in most markets, suggesting prolonged volatility episodes driven by oil price fluctuations, geopolitical risks, and macroeconomic factors, accompanied by a slow mean-reversion process. The estimated risk premium (λ) is positive and significant for Oman, Qatar, India, and the UAE, suggesting that investors are rewarded for taking additional risk. Conversely, the insignificant positive value for Saudi Arabia and the insignificant negative value for Bahrain indicate the absence of a clear risk–return trade-off, pointing to possible market inefficiencies and more risk-averse investor behaviour. The asymmetry coefficients (γ) are significant across all markets except Bahrain, confirming the presence of a leverage effect, wherein bad news generates volatility than positive news under the EGARCH framework, highlighting market sensitivities to downside risk.

This study offers valuable insights for academics, investors, and policymakers. For scholars, it contributes to the financial markets literature by applying a combined GARCH framework to analyze conditional volatility dynamics in emerging markets, enriching research on cross-regional integration and market efficiency. For investors, the results act as an effective early-warning tool, highlighting the importance of cautious risk management, hedging strategies, and portfolio diversification during times of increased market stress. From a policy standpoint, higher downside risk underscores the need for strong market stabilization measures, improved cross-border regulatory coordination, enhanced information-sharing mechanisms, higher trade-investment cooperation, and improved information sharing, and robust early-warning system. Therefore, the evidence highlights the structural vulnerabilities and emphasizes theimportance of resilient policy frameworks and informed investment strategies in promoting a stable financial market ecosystem.

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