Predictive power of newfangled GARCH models in assessing stock price volatility of Indian textile companies

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ABSTRACT – REZUMAT

Predictive power of newfangled GARCH models in assessing stock price volatility of Indian textile companies

This research endeavours to contribute to the existing body of knowledge by assessing the predictive power of various GARCH models in the specific context of Indian textile companies listed on stock exchanges. The GARCH family encompasses several models, each designed to address specific aspects of volatility dynamics. By evaluating the performance of these models against historical stock price data, we aim to shed light on their efficacy in forecasting volatility patterns and enhancing risk management strategies for investors in the Indian textile sector by applying symmetric and asymmetric models, namely: FIGARCH, FIEGARCH, GJR-GACRH, EGARCH and GARCH (1.1). The object of the study includes quantitative analysis, estimation and forecasting of daily volatility with Normal, Students-t distributions and generalized error distribution constructs of various Indian textile market i.e. KPR Mill Limited (NLKPRM), The Trident Group (NLTRIE), Page industry limited (NLPAGE), Welspun India Limited (NLWLSP) and, Alok Industries Limited (NLALOK). The objective is to discern the impact of the global financial crisis on the linkages across these textile markets. The sample data spans a long period from April 2013 to May 2023 and includes the COVID-19 pandemic, the war between Russia and Ukraine, Current conflicts in the Middle East and climate risk.

Keywords: *textile industry in India, volatility, GARCH models, long memory, leverage effect, COVID-19 pandemic*

Puterea predictivă a modelelor GARCH de ultimă generație în evaluarea volatilității prețului acțiunilor companiilor textile din India

Acest studiu încearcă să contribuie la ansamblul de cunoștințe existente prin evaluarea puterii de predicție a diferitelor modele GARCH în contextul specific al societăților textile indiene cotate la bursă. Familia GARCH cuprinde mai multe modele, fiecare conceput pentru a aborda aspecte specifice ale dinamicii volatilității. Prin evaluarea performanței acestor modele în raport cu datele istorice privind prețurile acțiunilor, ne propunem să determinăm eficacitatea lor în prognozarea modelelor de volatilitate și îmbunătățirea strategiilor de gestionare a riscurilor pentru investitorii din sectorul textil din India, prin aplicarea modelelor simetrice și asimetrice, și anume: FIGARCH, FIEGARCH, GJR-GACRH, EGARCH și GARCH (1.1). Obiectul studiului include analiza cantitativă, estimarea și prognoza volatilității zilnice cu distribuții normale, Students-t și distribuții generalizate ale erorilor pe diferite piețe textile din India, și anume KPR Mill Limited (NLKPRM), The Trident Group (NLTRIE), Page industry limited (NLPAGE), Welspun India Limited (NLWLSP) și Alok Industries Limited (NLALOK). Obiectivul este de a discerne impactul crizei financiare globale asupra legăturilor dintre aceste piețe textile. Datele eșantionului se întind pe o perioadă lungă de timp, din aprilie 2013 până în mai 2023, și includ pandemia COVID-19, războiul dintre Rusia și Ucraina, conflictele actuale din Orientul Mijlociu și riscul climatic.

Cuvinte-cheie: *industria textilă din India, volatilitate, modele GARCH, memorie de lungă durată, efect de pârghie, pandemie COVID-19*

INTRODUCTION

In the dynamic environment of financial markets, the ability to accurately forecast and manage stock price volatility is crucial for investors, financial analysts, and policymakers alike [1–4]. Volatility, a measure of the degree of variation of a trading price series over time, plays a pivotal role in rational investment decisions and risk management strategies [5–9]. This research paper explores the realm of stock price volatility within the context of the Indian textile industry, employing advanced financial modelling techniques known as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models.

The textile industry in India, a cornerstone of the nation's economy, has witnessed substantial growth and transformation over the years [10–13]. As listed textile companies navigate through the complexities of global markets [14–17], understanding and effectively managing stock price volatility becomes imperative for sustaining competitiveness and ensuring financial stability. The GARCH family models, known for their efficacy in capturing time-varying volatility patterns, provide a robust framework for analysing and predicting the inherent uncertainty in stock prices [18–23]. This research endeavours to contribute to the existing body of knowledge by assessing the predictive power of various GARCH models in the specific context of Indian textile companies listed on stock exchanges. The GARCH family encompasses several models, each designed to address specific aspects of volatility dynamics [24–27] by evaluating the performance of these models against historical stock price data, we aim to shed light on their efficacy in forecasting volatility patterns and enhancing risk management strategies for investors in the Indian textile sector. The motivation behind this research stems from the critical need for accurate and reliable volatility forecasts in financial decision-making processes. Investors and financial institutions often rely on volatility estimates to make informed investment decisions, design optimal hedging strategies, and assess risk exposures. The unique characteristics of the Indian textile industry, influenced by both domestic and global factors, provide an intriguing backdrop for exploring the applicability and effectiveness of GARCH models in this particular economic context.

REVIEW OF LITERATURE

GARCH [28–30] family models are widely used in finance to forecast and analyse volatility in stock prices [31]. A study compared three GARCH models (Symmetric GARCH, GJR-GARCH, and E-GARCH) and found that the E-GARCH model was accepted for predicting and forecasting market volatility. These models take into account the uncertainty in stock returns, prices, and unexpected events [32]. They are important for risk management and portfolio optimization [31]. Another study compared seven GARCH-family models and found that the standard GARCH model provided the best one-step-ahead forecasts of daily conditional variance [33]. Different factors influence the performance of GARCH models, such as the sample window period, forecasting horizon, financial period, and underlying distribution of log returns [31]. The AR(1)-GARCH (1,1) model was found to be the best fit for estimating parameters, predicting share prices, and forecasting volatility [34]. Realized GARCH variants, such as log-linear RealGARCH, RealEGARCH, and GARCH@CARR, have been proposed for volatility forecasting.

A study comparing these variants found that the GARCH@CARR model outperformed the others in terms of forecasting efficiency [35].

Stock price volatilities are assessed using GARCH models by analysing historical data and estimating parameters based on closing prices, as well as other information such as daily minimum and maximum prices [36]. These models help in understanding the behaviour of stock returns and the risk associated with them [37]. Different types of GARCH models are used to assess stock price volatility. Some commonly used models include Symmetric GARCH, GJR-GARCH, E-GARCH, and TGARCH [38]. The choice of model depends on factors such as the sample window period, forecasting horizon, financial period, and underlying distribution of log returns [31].

Assessing stock price volatility is significant for Indian textile companies as it helps investors and market participants make informed investment decisions [39–41]. Volatility provides opportunities for risk-seeking investors to earn unexpected profits, but it also raises concerns for risk-averse investors.

Understanding and predicting volatility can help companies manage their risk exposure and optimize their financial strategies [32, 42].

GARCH family models are used to assess stock price volatility in Indian textile companies. These models help in understanding and predicting volatility, which is significant for investors and companies in managing risk and making informed decisions. Different types of GARCH models are used based on various factors, and they take into account the uncertainty and unexpected events in stock returns and prices.

Research gap

Despite the extensive use of GARCH models in financial research, a noticeable research gap exists in the context of Indian textile companies. No studies have specifically investigated the predictive power of GARCH models in assessing stock price volatility within this industry. Given the unique dynamics of the Indian textile sector, characterized by diverse factors such as raw material fluctuations, global market dependencies, and policy influences, there is a dearth of comprehensive analyses. This research aims to fill this gap by providing an in-depth examination of the applicability and effectiveness of GARCH models in forecasting stock price volatility for Indian textile companies, contributing valuable insights to both academic literature and financial practitioners.

Need of the study

This research aspires to contribute valuable insights to both academic and practitioner communities by exploring the predictive power of GARCH family models in assessing stock price volatility within the unique context of the Indian textile industry. As financial markets continue to evolve, the ability to navigate and mitigate risks associated with stock price fluctuations remains paramount, making this investigation particularly timely and relevant. The findings from this study can empower investors, financial institutions, and policymakers to make informed decisions regarding investments in Indian textile companies. By assessing the predictive capabilities of GARCH models, the research contributes to enhancing market efficiency, enabling more transparent and rational decision-making. Investors can benefit from improved risk assessments, adjusting their portfolios to navigate the dynamic landscape of stock price movements. Furthermore, the study's outcomes may have broader implications for economic stability, influencing regulatory measures and strategies to promote financial health. This research not only advances academic knowledge in the field but also has practical applications that extend to investor education, industry competitiveness, and the overall economic growth of society at large.

Limitations of the study

- External Factors and Market Shocks: GARCH models primarily focus on endogenous factors to explain volatility, neglecting important exogenous variables and unforeseen events that can significantly impact stock prices. External factors such as macroeconomic changes, geopolitical events, or sudden market shocks may not be adequately captured by the GARCH model. Consequently, the model's predictive power may be limited in situations where these external factors play a crucial role in driving volatility.
- Parameter Sensitivity and Model Calibration: GARCH models involve the estimation of various parameters, and the results can be sensitive to the chosen model specifications and calibration techniques. Different researchers might use different parameter values, leading to divergent conclusions. Sensitivity to parameter choices can undermine the robustness of the findings and make it challenging to generalize the results across different studies or periods.

RESEARCH METHODOLOGY

India is one of the most successful countries in the textile industry, along with China. In today's competitive world, the textile manufacturing industry in India has made a global splash in garment manufacturing using advanced technology. India's top textile companies have been working to create a competitive product range and increase the number of innovative clients. Companies are constantly working to improve product quality and stay in the global market. The textile industry is one of the most important industries in the history of India. The textile industry is a field which has a strange connection between agriculture and industry. The cultivation of cotton, the cultivation of silk – the outcome of which depends largely on the textile industry. India is currently emerging as one of the brightest places in the world economy for textile companies. This country is currently the most attractive investment destination in the world. This research paper examines changes in volatility parameters as well as the movement behaviour of selected Indian textile industries market (i.e. KPR Mill Limited (NLKPRM), The Trident Group (NLTRIE), Page industry limited (NLPAGE), Welspun India Limited (NLWLSP) and Alok Industries Limited (NLALOK). They were selected based on their market capitalization as listed on the money control website, accessed on September 2023. For this purpose, we collected the daily opening price, closing price, high price, and low price of the various textile industries (figure 1 and table 1).

Steps of analysing the data

Step-1: Variables Description and Data Sources
Step-2: Calculation of Log Returns
Step-3: Unit Root Test
Step-4: Visualization of Volatility Clustering
Step-5: ARCH effect Diagnosis.
Step-6: Different GARCH Model formulation.
Step-7: Selection of Suitable GARCH Model using the statistics like LLH, AIC and SIC.

This paper's primary goal is to examine the method for estimating the influence of long-term volatility on the Analysis of Volatility of selected sample using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) class models; GARCH (1, 1) model, EGARCH model, GJR-GARCH, PGARCH, FIGARCH and FIEGARCH model to estimate the presence of leverage effect. Traditional heteroskedastic models either specify the conditional variance as in Bollerslev [28] or describe the conditional standard deviation directly as in Taylor [43]. ADF and PP test statistics) have been used to determine whether the data is stationary to apply various

Table 1

DESCRIPTION AND SOURCE OF DATA RELATED TO INDIAN TEXTILE INDUSTRIES

Name of the company	Source of data collection	Observations
KPR Mill Limited (LKPRM)	https://finance.yahoo.com	2610
The Trident Group (NLTRIE)	https://finance.yahoo.com	2610
Page industry limited (NLPAGE)	https://finance.yahoo.com	2610
Welspun India Limited (NLWLSP)	https://finance.yahoo.com	2610
Alok Industries Limited (NLALOK)	https://finance.yahoo.com	2610

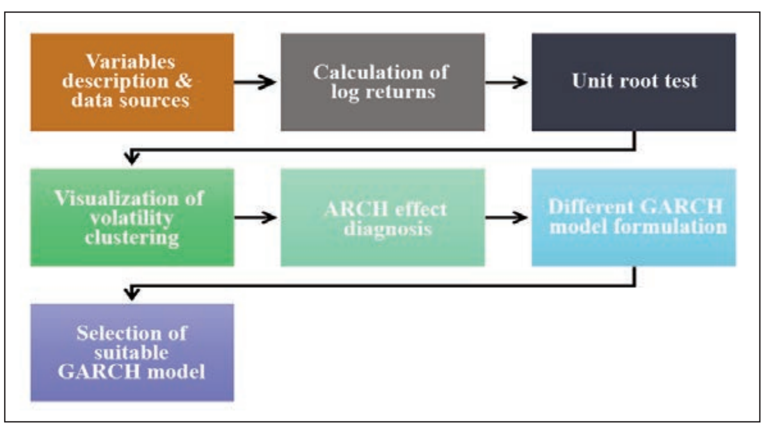

Fig. 1. Flow chart depicting the process of analysing the data

GARCH family models. To choose the most appropriate asymmetric volatility model for stock markets, numerous criteria have been used to examine the results of the models after they had been created using different distributions. E-Views 12 has been applied to the creation of models for certain stock indexes.

ANALYSIS, RESULTS AND DISCUSSION

There are various models in the GARCH Family. A brief of each kind of GARCH model is mentioned below.

EGARCH model

"The log of the variance distinguishes the EGARCH model from the GARCH variance structure" [44]. The EGARCH model is represented by equation 1.

$$\log(\sigma_t^2) = \omega + \sum_{j-i}^{p} \beta\, i \log(\sigma_{t-i}^2) + \\ + \sum_{j-1}^{q} \alpha\, i \langle \frac{\varepsilon\, i-t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - yi\, \frac{\varepsilon\, i-t}{\sigma\, i-t} \rangle \quad (1)$$

GJR-GARCH

The model proposed by Glosten et al. [45] is a variation of the GARCH model that considers the asymmetry of returns. It is denoted by GJR-GARCH and defined by equation 2:

$$\sigma_t = \omega + \alpha\iota\, [\varepsilon_{t=1} \geq 0]\,\varepsilon_{t=1} + \gamma\iota\, [\varepsilon_{t=1} < 0]\,\varepsilon_{t=1}\beta\,\alpha_{t-1} \quad (2)$$

The impulse of unfavourable shocks $(\alpha + \gamma)$ is greater than the impulse of favourable shocks (α), indicating asymmetry.

PGARCH models

The variance in a PGARCH model (general) is written as:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} (\alpha_i\, |y_{t-i}| - y_i\, y_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^{\delta} \quad (3)$$

This is an essential prerequisite for the positive variance. In the financial data series, higher values of the α_i coefficient show a greater volatility response to market shocks, whereas larger coefficients of the β_j coefficient shows the presence of market shocks [46, 47].

FEGARCH

FEGARCH, or Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroscedasticity, is a statistical model used in financial econometrics and time series analysis to model and forecast volatility in financial data. It is an extension of the more commonly known GARCH model [48].

Mathematically, the FEGARCH (p, d, and q) model can be represented as follows:

$$r_t = \sigma_y\, \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \Sigma_{i=1} \alpha_i (|\varepsilon_{t-1}| - \gamma |\varepsilon_{t-1}|)\, \Sigma_{j=1} \beta_j\, \sigma_{t-j}^2 + \\ + \Sigma_{k=1} \theta_k (|\epsilon_{t-k}| - \gamma |\epsilon_{t-k}|) \quad (4)$$

FIEGARCH model

The FIEGARCH model was proposed by Bollerslev and Mikkelsen [28, 49]. In its simplest form, the FIEGARCH model is given by:

$$\gamma_t = \sigma_y\, \varepsilon_t\, (1 - \varphi L)(1 - L)^d \log \sigma_t^2 = \omega + g(\varepsilon_t - 1) \quad (5)$$

where $g(\varepsilon_t) = \alpha\left(|\varepsilon_t| - \sqrt{\frac{2}{\pi}}\right) + \gamma\varepsilon_t$ and ε_t is the Gaussian white noise with variance 1. The parameter y measures the leverage effect, as before d in the long memory parameter.

Empirical results and findings

We begin with a descriptive statistics study to understand the value of investor return in chosen textile market indexes from April 2013 to March 2023. Table 2 summarizes the profitability statistics of five textile industries' prices. When compared to another sample, the mean return of NLKPRM (0.001522) is greater than other samples, followed by NLPAGE (0.000931) and NLTRIE (0.000468). The standard deviation of NLTRIE (0.054654) and NLWLSP (0.053083) was higher as compared to other samples, followed by NLALOK (0.035647). This means that while textile industries deliver bigger returns, their volatility (risk) is also higher. The skewness of NLTRIE and NLWLSP is negative, and all industries' prices are leptokurtic since the kurtosis value is greater than three. The presence of leptokurtic influence on the series returns is shown by the aberrant pattern of kurtosis.

All the selected samples of Indian textile industries contain a significant number of normal volatility rates and quantifiable anomalous scales. Investors, academics, and researchers should pay close attention to the post-financial crisis scale and positive return ratios. It indicates unambiguously how seriously investors take long-term investing.

Log returns for financial data series, such as the NLPAGE, NLKPRM, NLTRIE, NLWLSP, and NLALOK have been determined for the eight asymmetric GARCH Models, GARCH (1, 1), EGARCH, GJR-GARCH, PGARCH, FIGARCH and FIEGARCH. The unit root test, or the Augmented Dickey-Fuller Test, was used to assess the stationarity of the sample data of Indian textile industries, which contains the test equations Intercept, Trend, and Intercept, and None. The sample data were discovered to be stationary since the probability values are significant at <0.01 (lower part of table 2). In the following table 3, the group unit root test of all selected samples from Indian textile industries has been highlighted. The group's sample data were also discovered to be stationary since the probability values are significant at <0.01 (table 3).

The Johansen cointegration test is a statistical method used in econometrics to assess whether there is a long-run relationship, or cointegration, between two or more time series variables. This test is particularly useful when dealing with non-stationary time series data, where the variables may have trends and exhibit stochastic behaviour. Results indicated

Table 2

DESCRIPTIVE STATISTICS					
Variables	**NLPAGE**	**NLKPRM**	**NLTRIE**	**NLWLSP**	**NLALOK**
$\bar{x}$	0.000931	0.001522	0.000468	$-1.51 \cdot 10^{-5}$	0.000104
σ	0.0197	0.023645	0.054654	0.0530 83	0.035647
x~	–0.00027	0.000000	–0.000977	–0.00093	0.000000
Skew	0.343168	0.372254	–27.99227	–30.39278	0.918334
β2	6.528163	8.784051	1181.382	1303.335	7.054886
Max.	0.145081	0.134037	0.182322	0.164303	0.257189
Min.	–0.108278	–0.195999	–2.288696	–2.278659	–0.150481
Jarque-Bera	1404.402	3697.121	1.51E+08	$1.84 \cdot 10^{8}$	2154.105
Sum Sq. Dev.	1.012113	1.458104	7.790358	7.348835	3.314042
Numbers	2609	2609	2609	2609	2609
Probability	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
ADF test	–48.57012 (< 0.01)	–48.94204 (< 0.01)	–48.81558 (< 0.01)	–49.82232 (< 0.01)	–27.84377 (< 0.01)
PP test	–48.51221 (< 0.01)	–49.02635 (< 0.01)	–48.79528 (< 0.01)	–49.82361 (< 0.01)	–41.35911 (< 0.01)

Notes: The table presents the main statistics (the max (Max.) and minimum (Max.), the mean ($\bar{x}$), standard deviation (σ), skewness (Skew.), and kurtosis (Kurt.)) for the selected textile industries prices considering the value of log returns. Sample period: April 2013 – March 2023. Number of observations: 2610 for each sample.

Table 3

GROUP UNIT ROOT TEST				
Group unit root test: Summary				
Series: NLPAGE, NLKPRM, NLTRIE, NLWLSP, NLALOK				
Automatic lag length selection based on SIC: 0 to 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	–134.714	< 0.0001	5	13039
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	–112.696	< 0.0001	5	13039
ADF – Fisher Chi-square	285.148	< 0.0001	5	13039
PP – Fisher Chi-square	123.293	< 0.0001	5	13040

Notes: ** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

that the all the selected index are cointegrated as we can see that the value of the trace statistics and max-Eigen statistics is greater than the value of the 0.06 critical value.

The following sections are built on evaluating the relevant hypotheses needed to create the various GARCH family models. Figure 1 shows graphs with the log returns of the selected Indian textile industries market displayed to show the presence of volatility clustering (figures 2 and 3). Movement style of the Stationary Series for NLPAGE, NLKPRM, NLTRIE, NLWLSP, and NLALOK. Figure 2 shows graphs with the log returns of the selected indexes of the top five countries' stock markets displayed to show the presence of volatility clustering.

The property of figure 2 indicates there are different clusters in this diagram because we can see that in the Line graphs in figure 2, sometimes volatility is high and sometimes volatility is less. In figure 3, we represent the comparative volatility sketches of all selected indices.

After examining the log return graphs of selected financial data series in figures 2 and 3, it is clear that the data exhibits volatility clustering. These significant changes during 2008 and 2020 are a blatant sign that the pandemic is having a leveraging impact on market values, and asymmetric GARCH models would be suitable for simulating the volatility of the stock prices of a chosen index.

Implementation of GARCH Models for Alok Industries Limited of India

Alok Industries Limited is an Indian textile company that operates in various segments of the textile industry.

Table 4

JOHNSON COINTEGRATION TEST AND CORRELATION MATRIX						
Series: NLPAGE NLKPRM NLTRIE NLWLSP NLALOK						
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Max-Eigen Statistics**	**0.05 Critical value**	**Prob.****
None *	0.191857	2284.355	69.81889	554.6933	33.87687	0.0000
At most 1 *	0.171755	1729.662	47.85613	490.7147	27.58434	0.0000
At most 2 *	0.166832	1238.947	29.79707	475.2809	21.13162	0.0000
At most 3 *	0.162685	763.6662	15.49471	462.3529	14.26460	0.0000
At most 4 *	0.109268	301.3134	3.841465	301.3134	3.841465	0.0000
Correlation	**NLPAGE**	**NLKPRM**	**NLTRIE**	**NLWLSP**	**NLALOK**	-
NLPAGE	1	-	-	-	-	-
NLKPRM	0.1647	1	-	-	-	-
NLTRIE	0.0598	0.1502	1	-	-	-
NLWLSP	0.0919	0.1308	0.0778	1	-	-
NLALOK	0.0889	0.1742	0.1358	0.0977	1	-

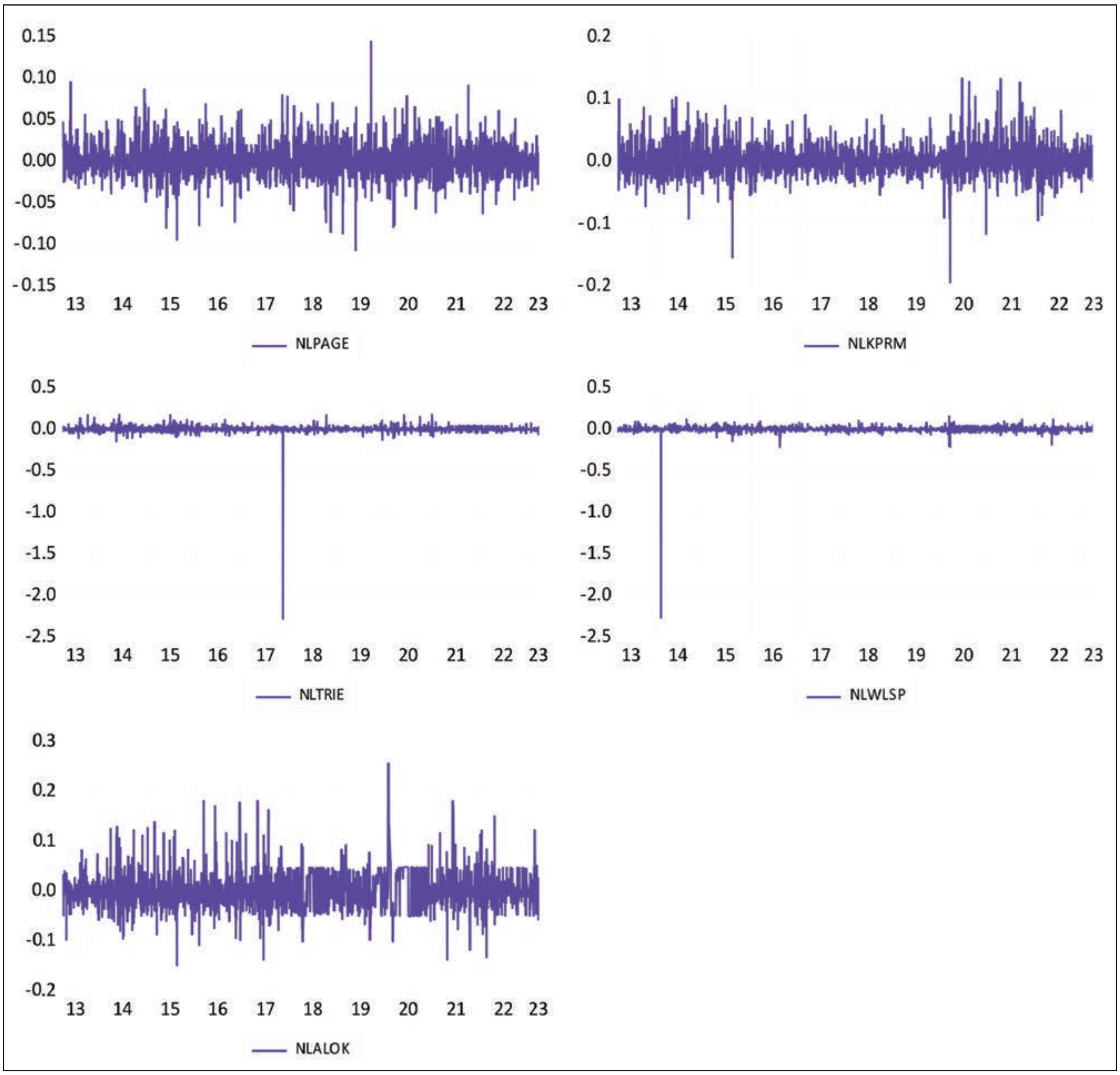

Fig. 2. Movement pattern of selected variables of Indian textile industries

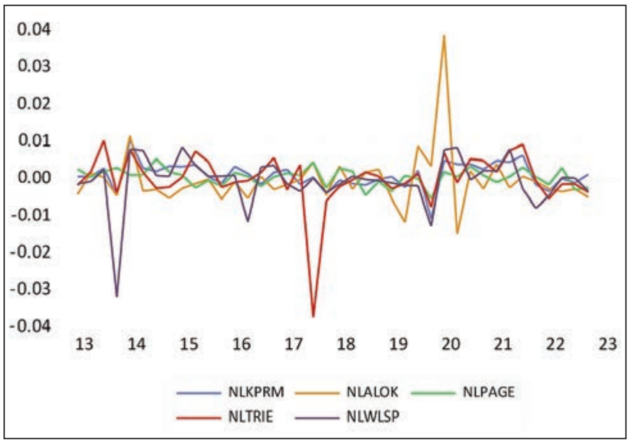

Fig. 3. Comparative volatility sketches of Indian textile industries

It is engaged in the manufacturing of a wide range of textile products, including cotton yarn, synthetic yarn, fabric, and garments. The company's products cater to both domestic and international markets. The company serves a diverse customer base, supplying textiles and garments to various sectors, including apparel brands, retailers, and institutional buyers. Alok Industries has a significant focus on exports and is known for its global reach. The company exports its products to several countries around the world. Alok Industries has a significant focus on exports and is known for its global reach. The company exports its products to several countries around the world.

All of the asymmetric GARCH models reflect the asymmetric volatility effect for Alok Industries Limited of India (table 5). The study discovered that the PGARCH under Student-t distribution is the best to explain asymmetric volatility of selected textile stocks returns, as the Adjusted R2 and Log likelihood values are high with significant coefficient and Arch effect. As a result, the PGARCH model is thought to be the best one. The table below lists the outcomes of the chosen PGARCH Model for Alok Industries Limited of India.

Table 5

CHOOSING AN APPROPRIATE GARCH MODEL: ALOK INDUSTRIES LIMITED OF INDIA			
GARCH models	**LLH**	**AIC**	**SIC**
ARCH	5365.980	–4.111181	–4.099934
GARCH (11)	5388.013	–4.127311	–4.113815
GJR-GARCH	5388.039	–4.126564	–4.110818
EGARCH	5396.816	–4.133294	–4.117549
PGARCH	**5409.652**	**–4.142371**	**–4.124377**
FIGARCH	5396.333	–4.132924	–4.117178
FIEGARCH	5207.914	–3.987664	–3.969669

Alok Industries Limited of India is represented in the above table as the output of the PGARCH (1, 1, 1) model using students' distribution constructed as a best model. The constant (mu) in the primary equation is significant because their probabilities are less than 0.05. As their probability values are all less than 0.05, every coefficient in the variance equation is considered significant. Focus should be placed on the fact that the coefficient of the asymmetric term Alpha /ARCH) is negative, or –0.016212. This suggests that there is a leverage effect on the Alok industries' price volatility, and it also indicates that negative news has a greater impact on this volatility.

Implementation of GARCH Models for KPR Mill Limited of India

KPR Mill Limited is an Indian company operating in the textile industry. It is one of the largest vertically integrated textile manufacturers in India and is involved in various segments of the textile value chain, including yarn, fabric, and garments. KPR Mill is known for its vertical integration, which means it is involved in multiple stages of the textile value chain,

Table 6

RESULTS OF VARIOUS GARCH MODELS: ALOK INDUSTRIES LIMITED OF INDIA							
GARCH models	**Constant (mu)**	**Unconditional variance (ω)**	**Alpha (ARCH)**	**Beta (GARCH)**	$\alpha+\beta$	γ	
ARCH	–0.002615	**0.250341**	0.640816	-	-	-	
GARCH (11)	–0.002258*	0.246620*	0.504361*	0.325076*	0.82	-	
TGARCH	–0.002284*	0.246161*	0.497540*	0.325606*	**0.81**	**0.018754 (0.8660)**	
EGARCH	–0.002219*	0.262543*	0.555596*	0.710309*	1.26	–0.013929 (0.7084)	
PGARCH	**–0.002964***	**0.211929***	**0.326823***	**0.486898***	**0.80**	**–0.016212 (0.8284)**	
		OMEGA	ALPHA	BETA	THETA1	THETA2	D
FIGARCH	–0.002379*	0.231829*	0.568524*	0.361573 (0.0035)			0.263816 (0.0201)
FIEGARCH	–0.000538	0.000000	0.0009*	0.0480*	0.0000	0.1586	0.0000

Note: * means p value is < 0.05.

from spinning yarn to producing fabrics and ready-made garments. This integration allows the company to have better control over the quality and efficiency of its products. KPR Mill has its headquarters in Coimbatore, Tamil Nadu, India. The company's product range includes a wide variety of yarns, fabrics, and ready-made garments, catering to both domestic and international markets. KPR Mill is known for its high-quality products and has earned a reputation as a reliable supplier in the textile industry. Additionally, the company places a strong emphasis on sustainability and eco-friendly practices. It has implemented various measures to reduce its environmental impact and promote responsible manufacturing. The empirical results show that our approach is statistically superior to other models and represents a valuable methodology that can be used by risk managers, investors, and policymakers to assess the effects of the pandemic on spillover effects in energy markets.

Table 7

CHOOSING AN APPROPRIATE GARCH MODEL: KPR MILL LIMITED OF INDIA			
GARCH models	**LLH**	**AIC**	**SIC**
ARCH	6110.482	–4.682885	–4.673888
GARCH (11)	6189.956	–4.743064	–4.731818
GJR-GARCH	6190.988	–4.743089	–4.729592
EGARCH	6200.343	–4.750263	–4.736767
PGARCH	6198.873	–4.748369	–4.732623
FIGARCH	6202.560	–4.751963	–4.738467
FIEGARCH	**6206.828**	**–4.753702**	**–4.735707**

The aforementioned table shows that in all six GARCH family models with normal, student t's distribution and Generalized error construct, it was determined that FIEGARCH with student's distribution parameter has the lowest AIC (–4.753702) and SIC (–4.735) when compared to the other models when the AIC and SIC of all the aforementioned other models are compared. Aside from that, the FIEGARCH model has the highest Log Likelihood (6206.828). As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen FIEGARCH Model for the KPR Mill Limited of India.

KPR Mill Limited of India is represented in the following table as the output of the FIEGARCH model using the student's distribution parameter. Focus should be placed on the fact that the coefficient of the asymmetric term is negative, or –0.028 (table 8), and statistically significant. This suggests that there is a leverage effect on the KPRM stock price volatility, and it also suggests that negative news has a greater impact on this volatility. According to the FIEGARCH estimation results in table 8, for the KPR Mill Limited of India, the estimated coefficient is significant. Results also revealed that the value of Beta is negative, showing that negative shocks are associated with more volatility than positive shocks.

Implementation of GARCH Models for Page industry limited of India

Page Industries is a value-driven, fully integrated manufacturing, marketing, distribution and Retail Company dedicated to building world-class brands. Page Industries Limited is a well-known Indian company that operates in the textile industry. It is primarily engaged in the manufacturing, distribution, and marketing of innerwear, loungewear, and other related products. The company is known for being the exclusive licensee of Jockey International Inc. USA for the manufacturing, distribution, and marketing of Jockey brand products in India, Sri Lanka, Bangladesh, Nepal, and the UAE. Page Industries Limited was founded in 1995 and has its headquarters in Bengaluru, Karnataka, India. Over the years, the company has achieved significant growth and

Table 8

RESULTS OF APPROPRIATE GARCH MODEL: KPR MILL LIMITED OF INDIA							
GARCH models	**Constant (mu)**	**Unconditional variance (ω)**	**Alpha (ARCH)**	**Beta (GARCH)**	**α+β**	**γ**	
ARCH	0.00129*	0.076004*	0.18248*	NA	NA	NA	
GARCH	0.00125*	0.044533*	0.06921*	0.90035*	0.96	-	
GJR-GARCH	0.001179 (<0.05)	0.045962 (0.0228)	0.062383 (<0.05)	0.898848 (<0.05)	0.95	0.020899 (0.0260)	
EGARCH	0.001098 (0.0091)	0.043727 (0.0277)	0.178673 (<0.05)	0.956912 (<0.05)	1.12	–0.00708 (0.3737)	
PGARCH	0.001103 (0.0088)	0.041319 (0.0327)	0.092630 (<0.05)	0.893657 (<0.05)	0.98	0.036183 (0.4750)	
		OMEGA	**ALPHA**	**BETA**	**THETA1**	**THETA2**	**D**
FIGARCH	0.001181 (0.0044)	0.041013 (0.0601)	0.329594 (<0.05)	0.461237 (<0.05)	NA	NA	0.234017
FIEGARCH	0.001161 (0.0047)	–6.623230 (<0.05)	0.836007 (0.0013)	–0.31422 (0.2032)	–0. 0.247 (<0.05)	–0.02848 (0.0185)	0.079849 (0.5061)

Note: * means p value is < 0.05.

Table 9

CHOOSING AN APPROPRIATE MODEL: PAGE INDUSTRY LIMITED OF INDIA			
GARCH models	**LLH**	**AIC**	**SIC**
ARCH	6582.605	–5.044942	–5.035945
GARCH (11)	6610.454	–5.065532	–5.054285
TGARCH	6611.678	–5.065704	–5.052208
EGARCH	6617.956	–5.070518	–5.057022
PGARCH	6616.332	–5.068506	–5.052761
FIGARCH	6614.146	–5.067596	–5.054100
FIEGARCH	**6622.369**	**–5.072368**	**–5.054374**

market presence, establishing itself as a leading player in the innerwear segment in the Indian market. The aforementioned table shows that in all six GARCH family models with normal, student t's distribution and Generalized error construct, it was determined that FIEGARCH with student's distribution parameter has the lowest AIC (–5.072) and SIC (–5.054) when compared to the other models when the AIC and SIC of all the aforementioned other models are compared. Aside from that, the FIEGARCH model has the highest Log Likelihood (6222.37). As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen FIEGARCH Model for the KPR Mill Limited of India.

Results of the various GARCH models for Page industry limited of India is represented in the above table 10 as the output of the FIEGARCH model using student's distribution parameter considered as the best models. Focus should be placed on the fact that the coefficient of the theta 2 term is negative, or –00.105 (table 10), and statistically significant. This suggests that there is a leverage effect on the page industries' stock price volatility, and it also suggests that negative news has a greater impact on this volatility. According to the FIEGARCH estimation results in table 10, for the textile stock index, i.e. Page industry limited of India, the estimated coefficient is also significant. Results also revealed that the value of Alpha, beta and theta 1 is also significant.

Implementation of GARCH Models for the Trident Group

The Trident Group is an Indian business conglomerate with diversified interests across various industries. It is primarily known for its presence in the textile and paper sectors. Apart from textiles and paper, the Trident Group has diversified its operations into other sectors, such as energy, chemicals, and agriculture. The Trident Group has a widespread international presence, with its products being exported to numerous countries across the world. The company has implemented various sustainability initiatives to

Table 11

CHOOSING AN APPROPRIATE GARCH MODEL: THE TRIDENT GROUP			
GARCH models	**LLH**	**AIC**	**SIC**
ARCH	4786.024	–3.667196	–3.658199
GARCH	5716.618	–4.379309	–4.365812
GJR-GARCH	5636.794	–4.317326	–4.301581
EGARCH	5694.356	–4.361469	–4.345724
PGARCH	**5728.262**	**–4.386704**	**–4.368709**
FIGARCH	3550.589	–2.718243	–2.704747
FIEGARCH	3552.489	–2.727436	–2.724754

Table 10

RESULTS OF VARIOUS GARCH MODELS: PAGE INDUSTRY LIMITED OF INDIA							
GARCH models	**Constant (mu)**	**Unconditional variance (ω)**	**Alpha (ARCH)**	**Beta (GARCH)**	**α+β**	**γ**	
ARCH	0.000892 (0.0123)	0.066533 (0.0017)	0.197670 (<0.05)	NA	NA	NA	
GARCH (11)	0.000191 (0.0071)	0.061848 (0.0047)	0.142541 (<0.05)	0.646401 (<0.05)	0.79	NA	
GJR-GARCH	0.000908 (0.0161)	0.061564 (0.0047)	0.122183 (<0.05)	0.633587 (<0.05)	0.75	0.052228 (0.0047)	
EGARCH	0.000853 (0.0137)	0.073356 (0.0008)	0.302104 (<0.05)	0.770460 (<0.05)	1.07	–0.01698 (0.2956)	
PGARCH	0.000831 (0.0168)	0.073937 (0.0006)	0.167971 (<0.05)	0.622654 (<0.05)	0.79	0.062461 (0.2704)	
		OMEGA	**ALPHA**	**BETA**	**THETA1**	**THETA2**	**D**
FIGARCH	0.001006 (0.0073)	0.064620 (0.0040)	0.720028 (<0.05)	0.658809 (<0.05)	NA	NA	0.105013
FIEGARCH	0.000849 (0.0141)	–7.64267 (<0.05)	0.629240 (<0.05)	0.081839 (<0.05)	0.281126 (<0.05)	–0.010463 (<0.05)	–0.77940

Source: Author's calculation.

Table 12

RESULTS OF VARIOUS GARCH MODELS: TRIDENTS GROUPS							
GARCH models	**Constant (mu)**	**Unconditional variance (ω)**	**Alpha (ARCH)**	**Beta (GARCH)**	**α+β**	**γ**	
ARCH	–0.00194 (<0.05)	0.000521 (<0.05)	2.346774 (<0.05)	NA	NA	NA	
GARCH	–0.00125 (0.0036)	0.090502 (<0.05)	0.555549 (<0.05)	0.321263 (<0.05)	0.88	NA	
GJR-GARCH	–0.00128 (0.0002)	0.000324 (<0.05)	0.592112 (<0.05)	0.302868 (<0.05)	0.89	–0.00922 (0.9519)	
EGARCH	–0.00092 (0.0439)	0.099669 (<0.05)	0.488416 (<0.05)	0.637322 (<0.05)	1.080	0.119755	
PGARCH	–0.00157	0.017504 (0.0471)	0.359679 (<0.05)	0.478377 (<0.05)	0.82	–0.05290 (0.4527)	
		OMEGA	**ALPHA**	**BETA**	**THETA1**	**THETA2**	**D**
FIGARCH	–0.00870 (0.0041)	0.002695 (<0.05)	0.492288 (<0.05)	0.546367 (<0.05)	NA	NA	1.076363
FIEGARCH	–0.00077 (0.0911)	–7.165940 (<0.05)	–0.92831 (<0.05)	0.849409 (<0.05)	0.444586 (<0.05)	0.199228 (<0.05)	0.131969

Table 13

CHOOSING AN APPROPRIATE GARCH MODEL: WELSPUN INDIA LIMITED			
GARCH models	**LLH**	**AIC**	**SIC**
ARCH	5864.066	–4.493149	–4.481902
GARCH	5877.234	–4.502480	–4.488984
GJR-GARCH	5877.345	–4.501798	–4.486053
EGARCH	5857.100	–4.486273	–4.470528
PGARCH	5889.753	–4.510547	–4.492552
FIGARCH	3711.462	–2.841612	–2.828115
FIEGARCH	5861.556	–4.488156	–4.467912

reduce its environmental impact and promote responsible business practices. It has undertaken measures for resource conservation and waste management.

All of the asymmetric GARCH models reflect the asymmetric volatility effect for the Trident Group returns. The study discovered that the power GARCH is the best to explain asymmetric volatility of Trident groups stocks return (table 11), and of Welspun India Limited (table 13) as the Adjusted R2 and Log likelihood values are high. As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen PGARCH Model for the Tridents groups (table 12) and for the Welspun India Limited in table 14.

Table 14

RESULTS OF VARIOUS GARCH MODELS: WELSPUN INDIA LIMITED							
GARCH models	**Constant (mu)**	**Unconditional variance (ω)**	**Alpha (ARCH)**	**Beta (GARCH)**	**α+β**	**γ**	
ARCH	–0.00078 0.0660	**0.094603**	0.442317	NA	**NA**	**NA**	
GARCH	–0.00075 (0.0719)	0.338497 (<0.05)	0.457337 (<0.05)	0.333126 (<0.05)	0.78	NA	
GJR-GARCH	–0.00079 (0.0614)	0.325641 (<0.05)	0.453510 (<0.05)	0.341256 (<0.05)	0.79	0.038946 (0.6476)	
EGARCH	–0.00056 (0.1957)	–1.106721 (<0.05)	0.176080 (<0.05)	0.860271 (<0.05)	1.03	0.101091	
PGARCH	–0.00083 (0.0455)	0.009075 (<0.05)	0.158672 (<0.05)	0.661826 (<0.05)	0.81	0.040122 (0.6255)	
		OMEGA	**ALPHA**	**BETA**	**THETA1**	**THETA2**	**D**
FIGARCH	–0.01017 (<0.05)	0.001820 (<0.05)	0.253912 (0.2458)	0.024251 (0.8477)	NA	NA	0.570301
FIEGARCH	–0.00069 (0.1121)	–7.20603 (<0.05)	0.998189 (<0.05)	–0.91018 (<0.05)	0.264719 (<0.05)	0.145994 (<0.05)	–0.40431

Implementation of GARCH Models for Welspun India Limited

Welspun India Limited is one of the leading textile companies based in India. It is primarily engaged in the manufacturing of various textile products, including home textiles, terry towels, bedsheets, rugs, and bathrobes. The company is known for its quality products and has a strong presence in both the domestic and international markets. It is a globally recognized brand and exports its textile products to countries all over the world. It has a strong customer base and distribution network in several countries. Welspun India is primarily known for its textiles business, the company has diversified its operations into other areas as well, including renewable energy and infrastructure. It also invests in research and development to introduce new products and technologies that meet the evolving demands of the market.

Trident group's stocks return and that of Welspun India Limited are represented in the above table (tables 12 and 14 respectively) as the output of the PGARCH (1, 1, 1) model using students' distribution Construct. The outcomes come in two sections. Results revealed that the constant (C) and unconditional variance in the primary equation are significant because their probabilities are less than 0.05 in both stock returns. In the case of stock returns of the tridents groups on India, the coefficient of the asymmetric term (y) is negative, or –0.05290 (table 12). This suggests that there is a leverage effect on the stock price volatility, and it also suggests that negative news has a greater impact on this volatility. While outcomes of the PARCH models for the Welspun India Limited, the value of y is positive. This suggests that there is a leverage effect on the stock price volatility. It indicates that the series have strong volatility presence and have a strong impact on listed textile stocks.

CONCLUSION

The empirical data and findings indicate that the chosen Indian textile industry displays different degrees of profitability and volatility. The descriptive statistics presented in table 2 provide a comprehensive overview of the mean returns, standard deviations, skewness, kurtosis, and other relevant measures for five textile industries – NLPAGE, NLKPRM, NLTRIE, NLWLSP, and NLALO – over the period from April 2013 to March 2023. The mean return of NLKPRM is notably higher than other samples, followed by NLPAGE and NLTRIE. However, this higher return is associated with increased volatility, as evidenced by the higher standard deviations of NLTRIE and NLWLSP. The negative skewness of NLTRIE and NLWLSP indicates a distribution with a longer left tail, suggesting occasional extreme negative returns. Moreover, the leptokurtic nature of all industry prices, as indicated by kurtosis values greater than three, highlights the presence of heavy tails and potential outliers in the return distributions. This finding is supported by the Jarque-Bera test results, which reject normality assumptions for all textile industry prices. The stationarity of the log returns is confirmed through unit root tests, providing a foundation for subsequent analyses. The Johansen cointegration test further indicates a long-run relationship among the selected index series, emphasizing the interconnectedness of the textile market variables. The volatility clustering observed in log return graphs (figure 2) and the comparative volatility sketches (figure 3) further support the need for sophisticated modelling techniques to capture the dynamic nature of stock price volatility, particularly during significant events such as the 2008 financial crisis and the COVID-19 pandemic. The implementation of various GARCH models for Alok Industries Limited, KPR Mill Limited, Page Industries Limited, Trident Group, and Welspun India Limited reveals the significance of asymmetric volatility effects in these companies' stock returns. The PGARCH model is identified as the most suitable for simulating volatility in Alok Industries Limited, while the FIEGARCH model is preferred for KPR Mill Limited, Page Industries Limited, Trident Group, and Welspun India Limited. The results of these models emphasize the importance of considering asymmetric effects, especially negative news impacting stock price volatility. For instance, in the case of Alok Industries Limited, the negative coefficient of the asymmetric term (Alpha/ARCH) suggests a leverage effect, indicating that negative news has a more pronounced impact on volatility. In conclusion, the findings of this research underscore the necessity of employing advanced modelling techniques, particularly asymmetric GARCH models, to effectively capture and predict stock price volatility in the Indian textile industry. The insights provided can be valuable for investors, researchers, and policymakers seeking a deeper understanding of the dynamics and risks associated with investing in these companies.

Again, utilizing Normal and Student-t density functions, along with various GARCH family models, including FIGARCH, FIEGARCH, GJR-GARCH, and EGARCH, the study revealed asymmetric behaviour in the conditional volatility of the selected stocks. Notably, the Exponential model with Student-t distribution exhibited superior performance in capturing asymmetric volatility effects across all six index classes. The presence of leverage effects (asymmetry) in financial series was substantiated by significant results from multiple GARCH family models, suggesting that negative shocks (volatility) tend to persist for an extended duration. In literature, there were previously conducted several research studies that examined the stock market behaviour using GARCH family models [50–53]. The findings underscore the importance of volatility projections in risk management, security valuation, portfolio diversification, and monetary policymaking. However, it is acknowledged that the study's scope was limited to the textile industry, and future research could enhance its comprehensiveness by including diverse financial assets such as Gold, Crude oils, Agriculture commodities, and investment funds.

Methodologically, extending the analysis to incorporate additional forecasting models, like CGARCH, COGARCH, Copula GARCH, EVT-GARCH, F-ARCH, FIAPARCH, DCC models, and GRS-GARCH, could further contribute to a nuanced understanding of daily volatility in investment funds. Additionally, exploring the impact of various risk indices, such as geopolitical risk and climate risk, on the textile industry would be a valuable avenue for future research investigations.

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