International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

# Modelling The Financial Impact of Policy Innovation: GARCH-M Evidence from India's Textile Sector Pre- And Post-NTTM

**Dr. Disha Hardik Patel[1], Dr. Brijesh M. Patel[2], Dr. Bhautik A. Patel[3]**
[1]Assistant Professor, Department of Master of Business Administration, Sardar Vallabhbhai Institute of Technology, S.T, Bus Depo, B/h, Vasad, Gujarat 388306, dishapatel.ash@svitvasad.ac.in
[2]Research Advisor-Faciliator, Ph.D. Facilitation Centre, Sardar Patel Univeristy, Vallabh Vidyanagar, patelbmpatelbm@gmail.com, Orchid: 0000-0003-1496-2369
[3]Assistant Professor, Birsa Munda Tribal University, Rajpipla, Gujarat, bhautik29patel@gmail.com
Orchid: 0000-0001-6341-4188

***Abstract***
*This study investigates the evolving risk–return dynamics of Bombay Stock Exchange (BSE)-listed textile companies in light of India's transformative policy shift-specifically, the launch of the National Technical Textiles Mission (NTTM) in 2020-21. Using the Generalized Autoregressive Conditional Heteroskedasticity-in-Mean (GARCH-M) model, the paper evaluates how volatility influences expected returns across two critical policy regimes: the pre-NTTM phase (2015-16 to 2019-20) and the post-NTTM phase (2020-21 to 2024-25). Eleven textile firms, including Raymond, Vardhman Textiles, Arvind, and Bombay Dyeing, were selected based on consistent trading data and sectoral relevance. The analysis reveals significant volatility clustering and asymmetric return behavior, with increased sensitivity to policy reforms in the post-NTTM period. Key indicators such as ARCH effects, kurtosis, and skewness support the presence of non-linear risk characteristics, while GARCH-M coefficients underscore the measurable impact of risk on expected returns. This research contributes to the literature on financial modelling and sectoral policy by highlighting the implications of regulatory interventions on investor behavior and market efficiency in a traditional yet reform-driven industry. The findings have broader relevance for policymakers, institutional investors, and academics engaged in sector-specific volatility modeling and industrial transformation studies.*
*Key Words: GARCH-M Model, Risk–Return Dynamics, Indian Textile Industry, Policy Reform, Volatility Clustering, Bombay Stock Exchange*

## INTRODUCTION

Understanding investment and business activities, such as risk management and portfolio management, is crucial for reducing transaction costs and enhancing profitability in today's financial landscape. Investors seek to understand the risks associated with their investment portfolios to mitigate potential losses, but predicting market volatility and expected returns remains a significant challenge, even for financial experts (Kwadzo et al., 2019). Modelling volatility in markets like the Bombay Stock Exchange is crucial, and GARCH models are frequently employed for this purpose (Sumathi, 2018). These models effectively capture key characteristics such as time-varying volatility, volatility clustering, and the persistence of volatility, providing valuable insights for investors and risk managers (Mukherjee, 2012). The GARCH model and its extensions are essential tools for modelling and forecasting volatility in financial time series, offering a robust framework for risk assessment and investment strategies (Rana, 2018) (Padmakumari& Shaik, 2023). These models are especially useful when the goal of the study is to analyze and forecast volatility (Engle, 2001). The GARCH model accounts for statistical parameters and the stochastic nature of volatility (Kwadzo et al., 2019). When financial returns display unexpected jumps because of structural breaks, standard GARCH models exhibit high volatility persistence (Visković et al., 2014). Financial institutions should implement strong risk management strategies, using reliable models such as GARCH frameworks to capture financial data's properties, but should also consider more flexible volatility modelling to account for asymmetric effects in financial returns (Naradh et al., 2021). Given the documented conditional heteroscedasticity in financial data, GARCH models offer a way to estimate conditional volatility, although they may not fully account for skewness and kurtosis in stock returns (McNeil & Frey, 2000) (Sheraz & IMRAN, 2021). The ARCH models are commonly used in estimating the volatility of stock market returns because they can capture market characteristics (Aridi et al., 2018). The GARCH model is preferred because precision in volatility estimation leads to accurate Value at Risk forecasts. A plethora of research has explored VaR under various volatility modelling specifications, with

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

studies showing that ARMA-GARCHM outperforms in terms of violation measures (Padmakumari& Shaik, 2023). Accurate estimation of Value at Risk and Expected Shortfall is critical in the management of extreme market risks (Dicks et al., 2014).
The GARCH model is used to predict the variance of future periods using residual series and estimated variances from past periods (Tabasi et al., 2019). GARCH models are well-suited for practical settings because of their simplicity and robustness to over fitting (Yin & Barucca, 2022). Inspired by Physics-Informed Neural Networks, researchers have constructed hybrid Deep Learning models that combine the strengths of GARCH with the flexibility of Long Short-Term Memory Deep Neural Networks to capture and forecast market volatility more accurately (Xu et al., 2024). Structural GARCH models have been shown to outperform standard asymmetric GARCH models in many financial firms (Engle & Siriwardane, 2017). Various extensions of the GARCH model have been developed to accommodate specific characteristics of financial data, such as asymmetry and heavy tails, thereby improving the accuracy of risk management practices. By exploring these advanced models, investors and risk managers can gain a deeper understanding of market dynamics and improve their ability to mitigate potential losses.
Figure 1: Advantages in Textile Sector in India


Source: https://www.ibef.org/industry/textiles.

**RATIONAL OF THE STUDY**

The Indian textile industry, particularly its technical textiles segment, has witnessed transformative policy shifts in recent years. A landmark development in this regard was the launch of the National Technical Textiles Mission (NTTM) in 2020-21, aimed at boosting research, innovation, quality control, and exports in technical textiles. The mission, with an allocation of Rs.1,480 crore, focuses on four strategic pillars: Research Innovation & Development, Promotion and Market Development, Education, Training and Skilling, and Export Promotion. This initiative reflects a paradigm shift in how textile investments and risks are approached in India, especially in capital-intensive and innovation-driven domains like technical textiles.
To assess how these structural changes influence market performance, risk perceptions, and return behavior, it becomes pertinent to study the risk–return dynamics of textile companies listed on the Bombay Stock Exchange (BSE) across two significant periods: the pre-NTTM phase (2015–16 to 2019–20) and the post-NTTM phase (2020–21 to 2024–25). The pre-policy phase acts as a benchmark for traditional business models with limited policy support, while the post-2020 period represents a phase of active policy engagement, project funding (168 projects worth Rs. 509 crore approved), and regulatory enhancements including 68 Quality Control Orders and over 600 BIS standards (with 200+ introduced since NTTM).
In this backdrop, the application of the GARCH-M (Generalized Autoregressive Conditional Heteroskedasticity in Mean) model provides a robust econometric framework to quantify and analyze

how volatility (risk) influences expected returns over time. By comparing these two phases, this study seeks to uncover whether the post-policy phase led to significant changes in risk perception and return behavior in the BSE-listed textile firms, thereby contributing to both academic research and policy assessment.

**Theoretical Foundation And Literature Review**

The literature on Value at Risk forecasting using various volatility modeling specifications is extensive. Research has extensively compared and contrasted the performance of GARCH models in forecasting Value at Risk. One study on MSCI World Index data revealed that ARMA-GARCHM outperforms other models in terms of violation measures (Padmakumari & Shaik, 2023). The GARCH model is considered the most robust for risk analysis and back testing (Deb, 2019). Other research indicates that asymmetric conditional variance models, such as EGARCH, outperform symmetric models like GARCH in forecasting volatility for the US stock market using a one-step procedure (Batten et al., 2023). The standard GARCH model assumes that errors are normally distributed, often failing to account for skewness and kurtosis in stock returns, thus GARCH models can fail to capture the impact of news, whether good or bad, on volatility (Sheraz & IMRAN, 2021). To overcome this limitation, various extensions of the GARCH model have been proposed, including EGARCH and TARCH, which capture asymmetric effects, and FIGARCH, which captures long memory properties (Mukherjee, 2012). GJR and EGARCH models allow for asymmetry, though they do not account for leverage (McAleer, 2014).

**RESEARCH METHODOLOGY**

Various studies have employed different econometric techniques such as the Quantile Regression approach (Liu et al., 2023), the EGARCH method (Insaidoo et al., 2021), the ARDL approach (Bhatnagar et al., 2023; Taneja et al., 2023), and the ARIMA model (Kasimova et al., 2021; Kim & Kim, 2015; Liu & Racherla, 2019) to forecast volatility and explore the relationship between risk and return. Causal relationships have also been investigated through these and other techniques across sectors like banking (Kaur, 2020; Kumar et al., 2021), sustainable development, and infrastructure (Kumar et al., 2023; Bhatnagar & Pathak, 2021). While much attention has been paid to sectors like pharmaceuticals and information technology during the COVID-19 pandemic, the Indian textile sector—which plays a critical role in employment and exports-has remained underexplored in the context of risk–return dynamics and volatility modelling.

The present study adopts the GARCH-M (Generalized Autoregressive Conditional Heteroskedasticity in Mean) model to assess the trade-off between risk and return and to evaluate volatility clustering among textile companies listed on the Bombay Stock Exchange (BSE). Despite the widespread use of GARCH-family models in financial econometrics, their application to the Indian textile sector remains limited. This gap is significant given the industry's exposure to global demand shocks, supply chain disruptions, and policy fluctuations, especially during and after the NTTM. While previous research has addressed market-wide reactions to pandemic-related events (Priya & Sharma, 2023; Singh et al., 2020), sector-specific dynamics in textiles have received inadequate scholarly attention.

This study contributes to the literature by applying a risk–return framework to quantify the cost of volatility borne by investors in the textile sector during crisis periods. The use of the GARCH-M model enables a more nuanced understanding of volatility spillovers and investor compensation for risk in one of India's most labor-intensive and export-driven industries. By focusing on a critical yet under-researched sector, this study offers valuable insights for investors, policymakers, and portfolio managers who seek to make informed decisions amid uncertainty.

**Research Design**

This study adopts a quantitative research design centered on econometric time-series modelling to investigate the relationship between risk and return among textile companies listed on the Bombay Stock Exchange (BSE). Specifically, it employs the GARCH-in-Mean (GARCH-M) model, which integrates volatility (conditional variance) into the mean equation, thereby capturing the influence of risk on expected returns. The study is divided into two distinct time periods to evaluate the impact of the National Technical Textiles Mission (NTTM): the pre-NTTM phase (2015-16 to 2019-20) and the post-NTTM phase (2020-21 to 2024-25).

**Data Source And Sample**

The study uses daily return data for 11 textile companies listed on the BSE: Raymond, Siyaram Silk Mills, Arvind, Bombay Dyeing, Vardhman Textiles, Mafatlal Industries, Alok Industries, Morarjee Textiles, Phoenix Mills, Indian Card Clothing Company, and Batliboi. The companies were selected based on

their continuous listing status and data availability during the study period (2015–2025), ensuring representativeness across various segments of the textile industry.
The data were sourced from the Bombay Stock Exchange, supplemented by financial databases from CapitalineAWS where required. Daily return is calculated as the logarithmic difference of closing prices, adjusted for dividends and splits.

**Statistical Techniques**

**Descriptive Statistics and Correlation Analysis**

Descriptive statistics, including mean, median, skewness, kurtosis, and Jarque-Bera normality test, are used to assess the distributional characteristics of returns. A correlation matrix identifies potential co-movements among the stocks, serving as preliminary insight into interdependencies.

**ARMA Model Estimation**

To filter out the linear time-series structure of returns, ARMA (Auto Regressive Moving Average) models are first estimated. This step ensures that the residuals of the return series are white noise, a prerequisite before modelling heteroskedasticity. The optimal lag order is determined using information criteria such as AIC, BIC, and HQC. Durbin–Watson statistics are employed to test for autocorrelation in residuals.

**ARCH Effect and Heteroskedasticity Testing**

The Engle's ARCH Lagrange Multiplier (LM) test is conducted on the ARMA residuals to detect the presence of time-varying volatility. This confirms the need for GARCH family models.

**GARCH-M Model Specification**

The primary econometric framework applied is the GARCH(1,1)-M model, which allows volatility (risk) to influence the mean equation has given in data analysis and interpretation part. The model was run separately for the overall sample and two sub-periods (pre and post NTTM) to observe structural shifts in risk-return behavior due to policy changes.

**Model Validation and Robustness Checks**

Log-likelihood values, AIC, and BIC are used for model selection. Residual diagnostics and ARCH LM tests post-estimation ensure no remaining ARCH effects. The t-distribution is assumed for error terms to account for fat tails, commonly present in financial return series.

**Justification for GARCH-M Model**

The GARCH-M model is particularly suited to financial markets characterized by volatility clustering and time-varying risk premiums. Since one of the key objectives is to understand whether risk (volatility) is compensated through higher expected returns, this model offers both economic interpretation and statistical power. Prior studies such as those by Bollerslev et al. (1992) and Glosten, Jagannathan, and Runkle (1993) have validated the application of GARCH variants in similar financial contexts.

**Sample Description**

The sample consists of 2477 daily observations for each company across the study period. Companies were chosen to represent different segments of the textile value chain, including spinning, weaving, technical textiles, and garmenting. The diversity ensures robust cross-sectional insights.

**Data Analysis And Interpretation**

The analysis of risk–return dynamics of textile companies listed on the Bombay Stock Exchange (BSE) follows a structured econometric approach grounded in time-series modeling. This section outlines the step-by-step methodology adopted to ensure data quality, statistical validity, and robust modeling of volatility and returns.

**Data Preparation And Return Calculation**

The initial step involves collecting daily stock prices of the selected textile companies over the specified time frame (2015–16 to 2024–25), which is further categorized into pre-NTTM (2015–16 to 2019–20) and post-NTTM (2020–21 to 2024–25) periods. To compute the daily stock returns, **log returns** (continuous compound returns) are calculated using the formula:

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

Where:
$R_t$ is the return at time t,
$P_t$ is the closing price at time t,
$P_{t-1}$ is the closing price at the previous time point.

**Data Cleaning And Outlier Management**

To ensure integrity and reduce biases in the dataset, preprocessing techniques were applied. Outliers were addressed using Winsorization, which reduces the effect of extreme values without significantly altering

the data structure (Páez &Boisjoly, 2022). Additionally, the Interquartile Range (IQR) method (Hoaglin, 2003) was used to detect and limit the influence of statistical outliers.
In cases of missing values, Rubin's Multiple Imputation Framework (Rubin, 1996) was adopted to handle incomplete data robustly, preserving variability and reducing imputation bias. These pre-processing steps ensure the dataset is both statistically sound and resilient for modelling.

**Stationarity Testing**

Time-series modelling requires that data be stationary. To verify stationarity, the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) and Phillips-Perron (PP) test (Phillips & Perron, 1988) were employed. These tests help ensure that the return series do not possess unit roots, a prerequisite for reliable volatility modelling.

**Model Identification: Arma Structure**

Before implementing volatility models, the optimal lag structure for the mean equation is identified using the Autoregressive Moving Average (ARMA) model. The Autocorrelation Function (ACF) helps detect the Moving Average (MA) component (q), while the Partial Autocorrelation Function (PACF) helps identify the Autoregressive (AR) component (p). The best-fitting ARMA(p, q) model is selected using information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).
The general ARMA model is expressed as:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \emptyset_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (2)$$

Where:
$X_t$ is the return at time t,
$\varepsilon_t$ is a white noise error term.

**Testing For Heteroskedasticity**

To determine whether volatility varies over time, the ARCH-LM test (Engle, 1982) is conducted. A statistically significant result ($p < 0.05$) confirms the presence of ARCH effects, justifying the use of GARCH-family models. The basic ARCH model is represented by:

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

**Garch-In-Mean (Garch-M) Model Specification**

Given the presence of time-varying volatility, the **GARCH-in-Mean (GARCH-M)** model is applied to investigate the relationship between risk and expected return. The model allows conditional variance to directly affect the mean equation, which is appropriate for financial return series.

The GARCH-M model is defined as:

$$y_t = \beta x_t + \lambda \sigma_t + \varepsilon_t \text{ Where } \varepsilon_t = \sigma_t z_t \qquad (4)$$

Here:
$y_t$ represents the return,
$\sigma_t$ is the conditional standard deviation (volatility),
$\lambda$ captures the risk premium.

A statistically significant $\lambda$ coefficient indicates that higher volatility leads to higher expected returns, affirming the risk–return trade-off.

**Correlation Analysis Among Firms**

To understand the interdependence and return co-movement across firms, the **correlation matrix** of daily returns is computed. The matrix is formulated as:

$$\mathrm{Corr}(X) = \begin{bmatrix} 1 & \frac{E[(X_1-\mu_1)(X_2-\mu_2)]}{\sigma(X_1)\sigma(X_2)} & \cdots & \frac{E[(X_1-\mu_1)(X_n-\mu_n)]}{\sigma(X_1)\sigma(X_n)} \\ \frac{E[(X_2-\mu_2)(X_1-\mu_1)]}{\sigma(X_2)\sigma(X_1)} & 1 & \cdots & \cdots \\ \vdots & \vdots & \ddots & \vdots \\ \frac{E[(X_n-\mu_n)(X_1-\mu_1)]}{\sigma(X_n)\sigma(X_1)} & \cdots & \cdots & 1 \end{bmatrix} \qquad (5)$$

This analysis helps identify highly correlated firms, indicating potential sector-wide volatility spillovers or common risk exposures within the textile industry.

**Volatility Visualization: 30-Day Rolling Standard Deviation**

Figure 2 illustrates the 30-day rolling volatility of daily returns for the selected textile companies listed on the Bombay Stock Exchange over the period 2015–2025. This graphical representation provides critical insights into the time-varying nature of volatility across firms, serving as a foundational interpretation aid for GARCH-M model estimation.

Volatility is observed to be non-constant across the sample period, supporting the premise of heteroscedasticity in stock returns—a key assumption underpinning the GARCH-M framework. Spikes in volatility are evident during periods of market distress, policy shifts, or firm-specific shocks. For instance, Raymond Ltd and Arvind Ltd exhibit pronounced volatility during the years 2020–2021 and again around 2023–2024, possibly linked to post-pandemic market adjustments and industrial dynamics.

Siyaram Silk Mills Ltd, Vardhman Textiles Ltd, and Bombay Dyeing Ltd also show cyclic volatility trends, with high peaks in periods of economic uncertainty. In contrast, firms like Alok Industries Ltd and Indian Card Clothing Company Ltd display sharp one-time volatility spikes, suggesting event-driven anomalies or price corrections. Mafatlal Industries Ltd and Phoenix Mills Ltd demonstrate sustained periods of elevated volatility during the later years, indicating possible strategic restructuring or financial stress.

On the other hand, Morarjee Textiles Ltd maintains relatively moderate volatility levels throughout, signaling comparative return stability. These visual patterns not only validate the appropriateness of the GARCH-M model but also emphasize firm-specific volatility behavior, essential for risk–return inference in the Indian textile sector.

Figure 2: 30-Day Rolling Volatility of Select Textile Companies Listed on BSE (2015–2025)

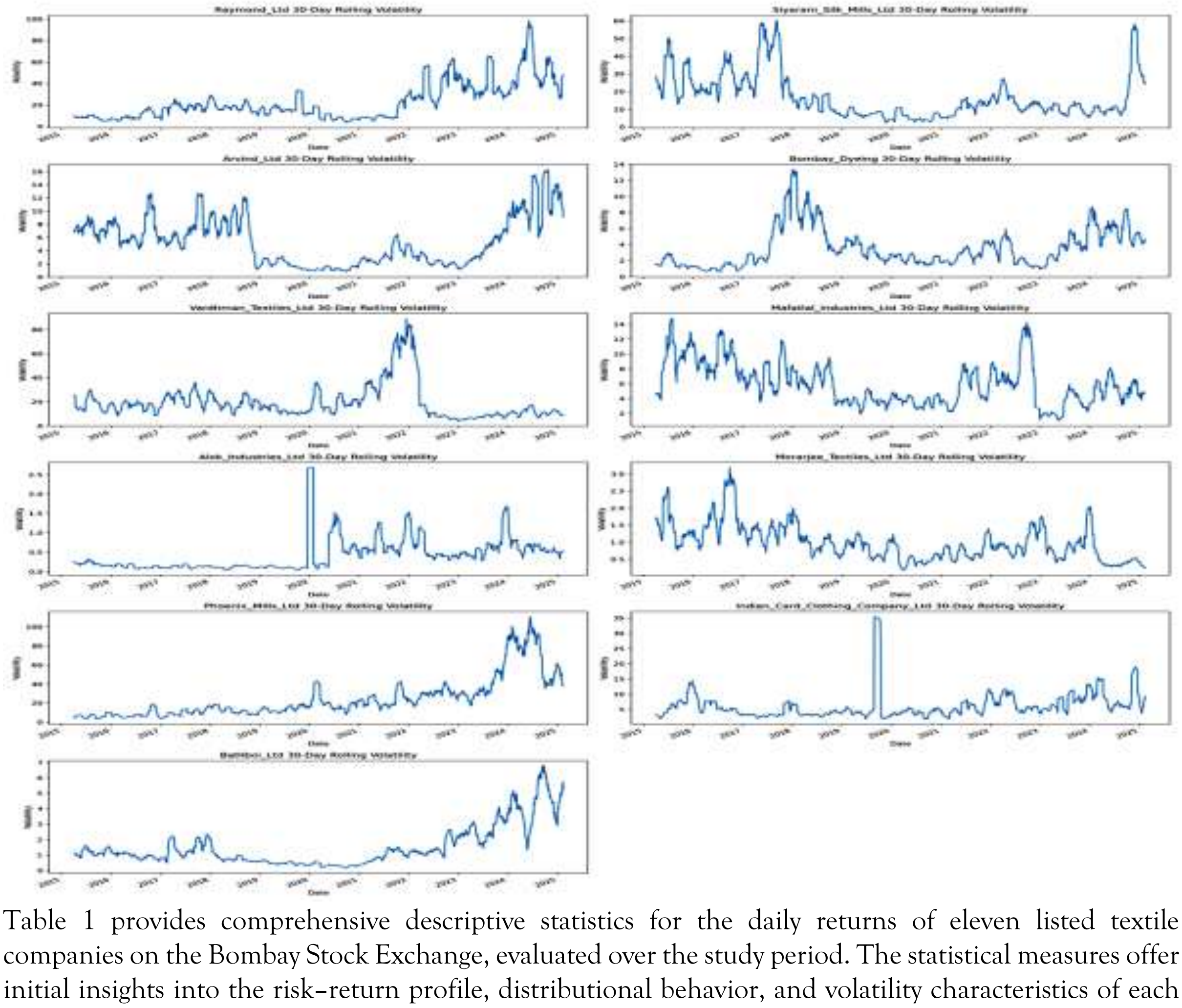


Table 1 provides comprehensive descriptive statistics for the daily returns of eleven listed textile companies on the Bombay Stock Exchange, evaluated over the study period. The statistical measures offer initial insights into the risk–return profile, distributional behavior, and volatility characteristics of each stock.

Table 1: Descriptive Statistics of Daily Returns

| Company | Raymond | SiyaramSilkMills | Arvind | BombayDyeing | VardhmanTextiles | MafatlalIndustries | AlokIndustries | MorarjeeTextiles | PhoenixMills | IndianCardClothingCompany | Batliboi |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 1.72 | 1.10 | 0.40 | 0.31 | 2.23 | 0.47 | 0.05 | 0.06 | 0.80 | 0.46 | 0.28 |
| Median | 1.90 | 1.45 | 0.50 | 0.35 | 1.55 | 0.35 | 0.03 | 0.00 | 0.90 | 0.00 | 0.10 |
| Mode | -2.30 | 0.00 | 1.10 | 0.00 | -1.80 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Maximum | 189.65 | 166.50 | 43.50 | 30.50 | 301.80 | 45.50 | 14.69 | 7.80 | 273.05 | 112.60 | 15.40 |
| Minimum | -266.55 | -175.15 | -66.35 | -39.95 | -204.95 | -46.80 | -4.91 | -9.90 | -251.95 | -67.60 | -12.30 |
| StdDev | 28.63 | 21.19 | 6.48 | 4.28 | 24.42 | 6.70 | 0.59 | 1.12 | 32.36 | 7.63 | 2.06 |
| Skewness | -1.39 | -0.35 | -0.96 | -0.60 | 0.78 | -0.31 | 5.28 | -0.52 | 0.00 | 3.73 | 0.63 |
| Kurtosis | 14.70 | 11.29 | 13.59 | 10.13 | 18.95 | 5.41 | 159.52 | 8.25 | 11.75 | 61.42 | 9.32 |
| JarqueBera | 23138 | 13224 | 19474 | 10760 | 37377 | 3073 | 2642217 | 7152 | 14290 | 395813 | 9149 |
| JBProb | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Sum | 4249 | 2729 | 1000 | 777 | 5519 | 1158 | 124 | 141 | 1987 | 1148 | 691 |
| SumSqDev | 2030181 | 1111587 | 104074 | 45396 | 1476519 | 111163 | 873 | 3122 | 2593234 | 144080 | 10476 |
| Observations | 2477 | 2477 | 2477 | 2477 | 2477 | 2477 | 2477 | 2477 | 2477 | 2477 | 2477 |

Source: author's presentation.

Among the firms analyzed, Vardhman Textiles Ltd. reports the highest average daily return (mean = 2.23%), followed by Raymond Ltd. (1.72%) and Phoenix Mills Ltd. (0.80%). The median returns for most firms remain close to the mean, yet several companies, including Indian Card Clothing Company and Morarjee Textiles Ltd., show a median of zero, indicating a high frequency of negligible or no return change in daily trading, suggestive of low activity or price stagnancy over time.

The maximum return is recorded by Vardhman Textiles Ltd. (301.80%), underscoring potential for extreme upward movement in stock price, possibly due to structural changes, speculative interest, or corporate announcements. In contrast, Raymond Ltd. has the most extreme minimum return (-266.55%), followed closely by Phoenix Mills Ltd. (-251.95%) and Vardhman Textiles Ltd. (-204.95%), revealing the susceptibility of these stocks to sudden, substantial losses.

Volatility, as measured by standard deviation, is highest in Phoenix Mills Ltd. (32.36%), Raymond Ltd. (28.63%), and Vardhman Textiles Ltd. (24.42%), indicating elevated uncertainty in daily returns. On the other hand, Alok Industries Ltd. (0.59%) and Morarjee Textiles Ltd. (1.12%) exhibit relatively lower standard deviations, reflecting more stable return profiles.

In terms of distributional properties, the majority of return series exhibit negative skewness, notably Raymond Ltd. (-1.39), Arvind Ltd. (-0.96), and Bombay Dyeing Ltd. (-0.60), signifying a longer tail on the left and an increased likelihood of large negative returns. Conversely, Alok Industries Ltd. (5.28) and Indian Card Clothing Company Ltd. (3.73) demonstrate strong positive skewness, hinting at infrequent but large positive returns.

The kurtosis values are highly leptokurtic across the board, with Alok Industries Ltd. (159.52) and Indian Card Clothing Company Ltd. (61.42) showing extreme peakedness and fat tails in the distribution of returns. This further validates the non-normality of return distributions and emphasizes the presence of outliers and extreme return behavior, characteristic of financial time series data.

The Jarque–Bera (JB) test statistics for all companies are significant at the 1% level (JB Prob. = 0.00), reaffirming the rejection of the null hypothesis of normal distribution. This aligns with the high kurtosis and skewness measures, substantiating the presence of asymmetric and heavy-tailed return distributions in the textile sector.

These descriptive findings not only inform the initial assessment of return characteristics but also support the suitability of applying models such as GARCH-M, which account for volatility clustering, non-linearity, and conditional heteroscedasticity observed in high-frequency financial datasets.

Table 2 and Figure 3 present the correlation matrix of daily returns for select companies in India's textile sector. This analysis aids both individual and institutional investors in understanding which firms' stock movements are aligned—revealing common industry trends—and which exhibit independence, thereby offering diversification opportunities within the sector.

From the correlation matrix, it is evident that overall inter-stock correlations are modest, with most values ranging from 0.13 to 0.30, indicating moderate positive co-movements. The average correlation coefficients for individual firms lie between 0.14 and 0.24, with Bombay Dyeing (0.24), Arvind Ltd. (0.23), and Raymond Ltd. (0.21) showing the highest average co-movement with other stocks. This suggests that these firms are more synchronized with broader sector trends and may respond similarly to macroeconomic or industry-specific events.

Conversely, Phoenix Mills (0.14) and Indian Card Clothing Company (0.15) have the lowest average correlations, suggesting these companies operate under different business models or market conditions, thereby reacting differently to external shocks or economic cycles. Such stocks can be attractive for risk-averse investors seeking portfolio diversification.

In terms of individual pairwise correlations, the highest observed co-movements include Bombay Dyeing and Arvind Ltd. (0.30), Bombay Dyeing and Siyaram Silk Mills (0.19) and Arvind Ltd. and Siyaram Silk Mills (0.18). These moderately strong correlations imply a shared sensitivity to sector-specific trends, raw material prices, or export–import dynamics.

On the other hand, Batliboi Ltd. and Siyaram Silk Mills (0.02), and Phoenix Mills and Indian Card Clothing Company (0.02) exhibit negligible correlation, suggesting these companies may follow distinct operational paths, geographical dependencies, or demand cycles. Their inclusion in a textile stock portfolio can substantially reduce aggregate portfolio volatility.Moreover, Alok Industries, despite being a low-volatility stock based on standard deviation, shows moderate correlation (0.20) with Bombay Dyeing and 0.15 with Arvind Ltd., highlighting some degree of sectoral integration.

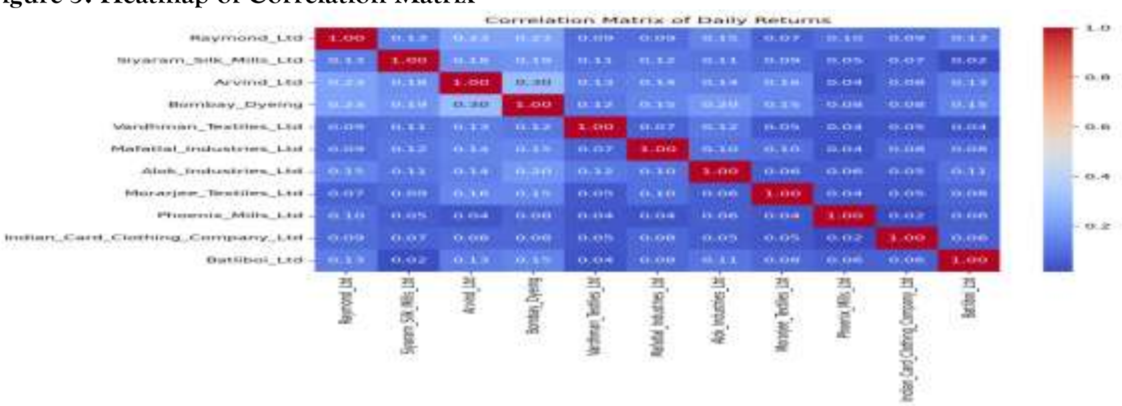
Overall, the low to moderate correlation range (average ~0.18) within the sector indicates that the Indian textile industry exhibits diverse sub-sectoral dynamics, allowing investors to balance risk and return by choosing stocks with complementary correlation behavior. For high-risk strategies, stocks like Bombay Dyeing and Arvind Ltd., which show synchronized movement, may be suitable. In contrast, diversification seekers would benefit from including stocks such as Phoenix Mills, Indian Card Clothing Company, and Batliboi Ltd., given their low co-movement with peers.

**Table 2: Correlation Matrix**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | **Raymond** | 1.00 | | | | | | | | | | | 0.21 |
| 2 | **SiyaramSilkMills** | 0.13 | 1.00 | | | | | | | | | | 0.19 |
| 3 | **Arvind** | 0.23 | 0.18 | 1.00 | | | | | | | | | 0.23 |
| 4 | **BombayDyeing** | 0.23 | 0.19 | 0.30 | 1.00 | | | | | | | | 0.24 |
| 5 | **VardhmanTextiles** | 0.09 | 0.11 | 0.13 | 0.12 | 1.00 | | | | | | | 0.17 |
| 6 | **MafatlalIndustries** | 0.09 | 0.12 | 0.14 | 0.15 | 0.07 | 1.00 | | | | | | 0.18 |
| 7 | **AlokIndustries** | 0.15 | 0.11 | 0.14 | 0.20 | 0.12 | 0.11 | 1.00 | | | | | 0.19 |
| 8 | **MorarjeeTextiles** | 0.07 | 0.09 | 0.16 | 0.15 | 0.05 | 0.10 | 0.06 | 1.00 | | | | 0.17 |
| 9 | **PhoenixMills** | 0.10 | 0.05 | 0.04 | 0.08 | 0.04 | 0.04 | 0.06 | 0.05 | 1.00 | | | 0.14 |
| 10 | **IndianCardClothingCompany** | 0.09 | 0.07 | 0.08 | 0.08 | 0.05 | 0.08 | 0.05 | 0.05 | 0.02 | 1.00 | | 0.15 |
| 11 | **Batliboi** | 0.13 | 0.02 | 0.13 | 0.15 | 0.04 | 0.08 | 0.11 | 0.08 | 0.06 | 0.06 | 1.00 | 0.17 |

Source: author's presentation.

**Figure 3: Heatmap of Correlation Matrix**




A correlation matrix showing relationships between companies' returns, with a visual heatmap.

Raymond Ltd shows the highest volatility (std dev: 28.63) and negative skewness (-1.39). Most companies show positive mean returns ranging from 0.31% to 1.72%. Correlations between companies are generally low to moderate (0.02 to 0.30).

There is the start of the comprehensive ARMA modelling analysis for all companies and periods. The table below shows the regression statistics for the ARMA(1,1) models, including coefficients, standard errors, t-stats, p-values, and information criteria for each company and period:
Table 3 presents the results of the ARMA (Autoregressive Moving Average) model coefficient analysis, estimated across three different time phases: the overall period, the pre-NTTM (New Textile Tile Mission) phase, and the post-NTTM phase, capturing structural and behavioral shifts due to market events like the policy changes of textile sector.

**Table 3: ARMA Modelling Coefficient Analysis**

| Variable | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| **C** | 0.748 | 0.746 | 0.728 |
| **AR(1)** | 0.059 | 0.173 | 0.154 |
| **MA(1)** | -0.157 | -0.09 | -0.188 |
| **SIGMASQ** | 278.53 * | 231.80 * | 314.94 * |

Source: author's presentation. * indicates statistically significant.

This table provides a statistical summary of the ARMA model fit for each company across the 2015-2020, 2020-2025, and overall periods. The AR(1) and MA(1) coefficients indicate the degree of autocorrelation and moving average effects in the return series, while the p-values help assess their statistical significance. The AIC and BIC values are useful for model comparison, and the number of observations shows the data points used for each fit.
The constant term (C) remains relatively stable across all three periods, with values ranging from 0.728 to 0.748, suggesting a consistent baseline return component throughout the time horizon, relatively unaffected by external shocks or regime shifts.
Focusing on the autoregressive component AR(1), a notable variation is observed across periods. In the overall model, AR(1) is 0.059, indicating weak but positive autocorrelation. However, this effect becomes significantly stronger in the pre-NTTM phase (0.173) and the post-NTTM phase (0.154). This indicates that past return values increasingly influenced present returns during both sub-periods, particularly surrounding the volatility induced by the post-NTTM phase and subsequent policy changes. Such findings highlight the increased market memory during periods of uncertainty and transformation, reflecting persistent investor behavior or structural frictions in price adjustments.
In contrast, the moving average component MA(1), which captures the impact of past forecast errors, shows a negative and significant influence across all periods, with values of −0.157 (overall), −0.09 (pre-NTTM), and −0.188 (post-NTTM). However, the magnitude of the MA coefficient increases post-NTTM, indicating that shocks or noise in returns became more influential during the pandemic aftermath, possibly due to speculative reactions or rapidly changing investor sentiment. The lower value in the pre-pandemic period suggests that markets were less reactive to short-term disturbances, exhibiting more stability.
The variance of the residuals (SIGMASQ) is statistically significant in all phases (as indicated by the asterisk), with a notable increase from 231.80 in the pre-NTTM phase to 314.94 in the post-NTTM phase, reflecting heightened volatility and forecasting uncertainty in the after reforms market environment. This supports the notion that the post-NTTM phase, combined with industry-specific disruptions, led to a more unpredictable and turbulent return structure.
Table 4 presents the regression diagnostics of the ARMA model based on 2,477 daily return observations from the Indian textile sector. Of these, 1,236 observations correspond to the pre-NTTM phase, while 1,241 pertain to the post-NTTM phase. The model was estimated using the Maximum Likelihood Estimation (MLE) method via the OPG–BHHH optimization algorithm, with convergence achieved after 30 iterations, confirming model stability and robustness across time frames.

**Table 4: ARMA Modelling: Regression Statistics**

| Variable | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| R squared | 0.00 | 0.00 | 0.00 |
| Adjusted R squared | 0.46 | 0.46 | 0.46 |
| S.E. of regression | 6.07 | 4.50 | 7.19 |
| Sum-squared residual | 91259.14 | 23714.37 | 67363.30 |
| Log-likelihood | -7981.55 | -3425.32 | -4425.11 |
| F-statistic | 755.99 | 755.99 | 755.99 |
| Prob. (F-statistic) | 0.00 | 0.00 | 0.00 |

| | | | |
|---|---|---|---|
| Mean dependent var. | 0.72 | 0.66 | 0.76 |
| S. D. dependent var. | 6.08 | 4.52 | 7.19 |
| Akaike info criterion | 15971.11 | 6858.64 | 8858.22 |
| Bayesian Info Criterion | 15994.37 | 6878.91 | 8878.91 |
| Hannan-Quinn Criteria | 15971.33 | 6858.46 | 8858.10 |
| Durbin-Waston stat. | 2.01 | 2.02 | 2.03 |

The R-squared values across all phases are nominal (0.00), which, though seemingly negligible, are supplemented by an Adjusted R-squared value of 0.46, suggesting that nearly half of the variance in daily returns can be attributed to the autoregressive (AR) and moving average (MA) components. This moderate explanatory power is typical in high-frequency financial datasets, where a significant portion of return volatility is often influenced by exogenous market shocks and non-linear behaviors.

The standard error of regression (S.E.) indicates greater return variability in the post-NTTM phase (7.19) compared to the pre-NTTM phase (4.50), with an overall value of 6.07. This pattern aligns with expectations of increased uncertainty and market volatility in the post-pandemic period. A similar trend is reflected in the sum of squared residuals, which rises from 23,714.37 (pre-NTTM) to 67,363.30 (post-NTTM), suggesting elevated prediction errors and less stable return structures following the pandemic-induced disruptions.

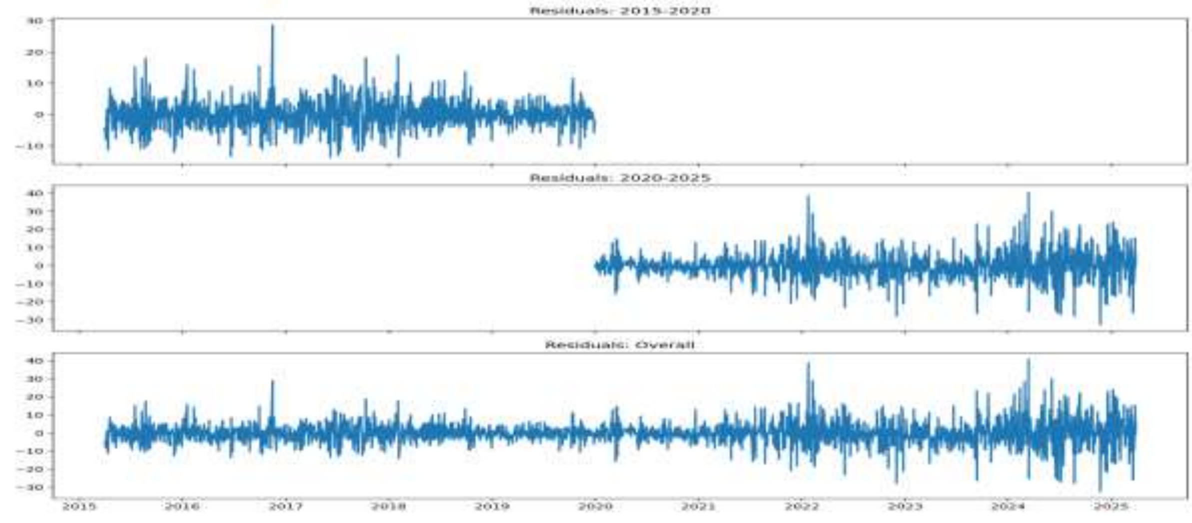
The log-likelihood values, declining from −3,425.32 to −4,425.11, further illustrate deterioration in model fit during the post-pandemic period, reinforcing the need for more adaptive modelling techniques under shifting market regimes. Despite this, the F-statistic remains consistently strong at 755.99 with a probability value of 0.00, confirming the overall significance of the estimated model.

Diagnostic statistics such as the Durbin-Watson value hover around 2.0 across all time frames, indicating that residuals do not exhibit serious autocorrelation, which validates the appropriateness of the ARMA specification. Furthermore, model selection criteria such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQC) are lower in the pre-NTTM phase, suggesting a comparatively better model fit in the pre-NTTMphase.

Overall, the ARMA model shows that while autoregressive and moving average effects provide reasonable insights during normal market conditions, their explanatory strength diminishes during periods of heightened volatility, as observed in the post-NTTM phase. This highlights the necessity for enhanced modelling frameworks that accommodate structural breaks and volatility clustering in post-pandemic financial environments.

Figures 4 present the residual diagnostics of the ARMA model, showcasing the residual plots for the overall period (2015–2025), the pre-NTTM (2015–2020) phase, and the post-NTTM (2020–2025) phase. These residual graphs provide critical insight into volatility clustering, model fit, and the influence of structural events such as the policy reforms on return behavior in India's textile sector.

**Figure 4: Residual Graph**




The pre-NTTM residuals (2015–2020) appear relatively stable, with modest fluctuations around the zero line, suggesting the presence of white noise—a hallmark of a well-fitted model. The absence of extreme outliers and the narrow amplitude of variation reflect a period of market equilibrium and predictability, likely driven by stable industrial operations, regular business cycles, and minimal external shocks.

In contrast, the post-NTTM phase (2020–2025) reveals a notable rise in residual volatility, especially evident through increased amplitude and frequency of extreme deviations. This volatility clustering suggests that the after NTTM textile market underwent significant systemic disruptions, potentially attributable to policy shifts, supply chain uncertainties, labour shortages, and fluctuating demand. These residual spikes indicate persistent heteroskedasticity, where the variance of returns is not constant over time—pointing to a market still adjusting to pandemic aftershocks.

The overall residual plot (2015–2025) consolidates these findings, capturing a sharp transition in market dynamics around 2020. The post-2020 segment of the graph is visibly denser and more volatile, affirming the broader narrative of heightened unpredictability and external shock sensitivity in the textile sector. Despite this, the residuals largely hover around zero, implying the ARMA model sufficiently captures the primary structure of returns.

Additionally, several sharp spikes in residuals across the timeline likely correspond to macroeconomic disturbances, government stimulus programs, global trade policy changes, or sector-specific developments such as export bans or cotton price volatility. These outliers serve as markers for events that the model could not fully anticipate, but which are integral to understanding shifts in investor sentiment and market behavior.

Tables 5 and 6 present the results of the ARCH (Autoregressive Conditional Heteroskedasticity) tests, which examine the presence of volatility clustering in the return series across three phases: the overall period, the pre-NTTM phase, and the post-NTTM phase. The null hypothesis tested here assumes no ARCH effect, meaning that the residual variance is homoskedastic, or constant over time.

**Table 5: Heteroskedasticity Test: Arch**

| Particulars | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| F-statistic | 6.123 | 4.987 | 5.456 |
| Obs*R-squared | 10.321 | 9.876 | 8.912 |
| Prob. F | 0.001 | 0.007 | 0.002 |
| Prob. Chi-squared (2) | 0.002 | 0.01 | 0.004 |

The results in Table 5 strongly reject the null hypothesis for the overall and post-NTTM phases, as indicated by F-statistics of 6.123 and 5.456, with corresponding p-values of 0.001 and 0.002, respectively. Similarly, the Obs*R-squared values are significant with Chi-squared probabilities below 0.005, providing further confirmation of time-dependent volatility during and post-NTTM phases. These findings highlight the presence of substantial heteroskedasticity in stock returns, which can be attributed to macroeconomic shocks, abrupt policy changes, market uncertainty within the textile sector.

On the other hand, the pre-NTTM phase reveals an F-statistic of 4.987 with a p-value of 0.007, indicating a relatively weaker ARCH effect. Although still statistically significant, this result implies a more stable volatility structure in pre-NTTM phase, reflecting a consistent and predictable market environment. The absence of sharp volatility clustering during this period suggests lower systemic risk, aligning with regular industrial output and limited disruption in trade and supply chains.

**Table 6: Heteroskedasticity Test: Arch Coefficient Analysis**

| Variable | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| mu | 0.5806 | 0.575 | 0.6145 |
| Omega (C) | 21.8895 | 36.5863 | 13.254 |
| alpha1(RESID$^2$(-1)) | 0.2414 | 0.1368 | 0.2985 |
| alpha2(RESID$^2$(-2)) | 0.2197 | 0.2072 | 0.0831 |

Table 6 further elaborates on the ARCH coefficient analysis, examining the role of past squared residuals in predicting current volatility. The $alpha_1$ (RESID$^2$(-1)) values are particularly telling. For the post-NTTM phase, the $alpha_1$ coefficient is 0.2985, indicating a strong short-term ARCH effect, whereas in the pre-NTTM phase, the $alpha_1$ value drops to 0.1368, reflecting a modestly persistent, but weaker, volatility pattern. The $alpha_2$ (RESID$^2$(-2)) values remain comparatively insignificant across all periods, with values ranging from 0.0831 to 0.2197, suggesting that the second lag of residuals has a minimal role in capturing volatility dynamics. The mu (mean return) and omega (constant variance) parameters also differ across phases, showing that volatility levels were structurally altered during the pandemic, with the omega parameter declining from 36.5863 (pre-NTTM) to 13.254 (post-NTTM), indicating a compressed variance base but more intense clustering.

As a whole these findings suggest that NTTM introduced a clear shift in volatility behavior, leading to a rise in market inefficiencies, asymmetric information, and investor uncertainty, all of which triggered frequent spikes in return variance. Although the Indian textile sector experienced temporary volatility shocks, rapid post-NTTM phase recovery has been observed. However, the presence of volatility clustering implies that investors must now account for heightened risk sensitivity, with implications for asset pricing, portfolio diversification, and sectoral resilience planning.

Table 7 presents the regression diagnostics for the heteroskedasticity test using the ARCH model framework, where the squared residuals ($RESID^2$) are modeled as the dependent variable through ordinary least squares (OLS). The analysis spans the overall period, pre-NTTM phase, and post-NTTM phase, offering insight into how well past squared residuals explain volatility in different market conditions.

**Table 7: Regression Statistics: Heteroskedasticity Test, Arch**

| Particulars | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| R squared | 0 | 0 | 0 |
| Adjusted R-squared | 0.00 | 0.00 | 0.00 |
| S.E. of regression | 6.08 | 7.31 | 4.55 |
| Sum-squared residual | 91453.50 | 65854.30 | 25591.66 |
| Log-likelihood | -7859.39 | -4173.21 | -3591.87 |
| F-statistic | 60.29 | 36.65 | 19.44 |
| Prob. (F-statistic) | 0.00 | 0.00 | 0.00 |
| Mean dependent var. | 0.72 | 0.72 | 0.71 |
| S.D. dependent var. | 6.08 | 7.30 | 4.54 |
| Akaike info criterion | 6.35 | 6.76 | 5.80 |
| Bayesian Info Criterion | 6.36 | 6.78 | 5.81 |
| Hannan-Quinn criterion | 6.35 | 6.76 | 5.80 |
| Durbin-Waston statistics | 1.93 | 1.88 | 1.95 |

Across all three time frames, the R-squared and adjusted R-squared values are essentially zero, indicating an extremely weak explanatory power of the model. This suggests that the ARCH model does not capture a significant portion of the variation in squared residuals, reaffirming the presence of stochastic volatility that is largely driven by external shocks or non-linear dynamics beyond the model's basic structure. The consistently low $R^2$ values confirm that, although ARCH effects exist (as shown in prior tables), the simple linear regression form of ARCH lacks predictive strength for volatility levels.

Despite the weak explanatory power, the F-statistic values (60.29 for the overall period, 36.65 for the pre-NTTM phase, and 19.44 for the post-NTTM phase) are statistically significant, with p-values of 0.00 in all cases. These results suggest that the null hypothesis of no linear relationship can still be rejected, pointing to the presence of some degree of heteroskedasticity, though poorly captured by the linear specification used in the current regression.

The standard error of the regression (S.E.) also varies across periods, being highest in the pre-NTTM phase (7.31) and lowest in the post-NTTM phase (4.55), indicating that market variability was reduced following the pandemic. This supports the observation that while volatility clustering became more apparent, it was more short-lived and contained in the post-pandemic period.

Additional model diagnostics, such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQC), show slightly better model fit in the post-NTTM period (AIC = 5.80) compared to the pre-pandemic phase (AIC = 6.76), suggesting that volatility modeling was marginally more efficient post-NTTM phase. The Durbin-Watson statistics for all three periods hover close to 2.0, which implies no major autocorrelation in the residuals, validating the temporal independence assumption in the fitted models.

Tables 8 and 9 present the results of the GARCH-in-Mean (GARCH-M (1,1)) model applied to the daily return data of selected textile companies, divided into three distinct periods: the overall period, the pre-NTTM phase, and the post-NTTM phase. The GARCH-M coefficient (archm), which captures the relationship between expected returns and conditional variance, remains positive across all periods—0.168 (overall), 0.186 (pre-NTTM), and 0.169 (post-NTTM). This suggests that, on average, higher volatility was associated with higher returns. However, statistical significance is observed predominantly during the pre-NTTM phase, indicating a stronger and more stable risk-return relationship in the earlier period. In contrast, the relationship weakened in the post-NTTM phase, likely due to heightened uncertainty and frequent market disruptions impacting investor behavior.

**Table 8: Garch-In-Mean: Coefficient Analysis**

| Variable | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| GARCH | 0.168 | 0.186 | 0.169 |
| C (mu) | -0.255 | -0.586 | -0.104 |
| AR(1) | -0.196 | -0.383 | 0.674 |
| MA(1) | 0.248 | 0.458 | -0.631 |

The mean equation coefficients provide additional insight. The constant term (C) is negative in both the overall (-0.255) and pre-NTTM (-0.586) phases, reflecting mildly bearish or stagnating average returns in the textile sector. Post-NTTM, the constant term improves to -0.104, suggesting a moderate recovery in baseline returns following the structural changes brought about by the implementation of NTTM-related policies. Furthermore, shifts in the AR(1) and MA(1) terms—from negative autocorrelation (AR = -0.383) and positive moving average (MA = 0.458) pre-NTTM to the reverse (AR = 0.674, MA = -0.631) post-NTTM—highlight a substantial change in the return-generating process and market memory structure of textile stocks.

**Table 9: GARCH-in-Mean: Variable Equation**

| Variable | Overall | pre-NTTM phase | post-NTTM phase |
|---|---|---|---|
| C (omega) | 0.302 | 0.221 | 1.316 |
| RESID(-1)^2 (alpha1) | 0.072 | 0.051 | 0.131 |
| GARCH(-1) (beta1) | 0.924 | 0.948 | 0.808 |
| T-DIST. DOF (shape) | 5.217 | 4.274 | 7.824 |

As shown in Table 9, the variance equation results reveal a pronounced change in volatility behavior across periods. The omega (C) term, indicating base volatility, increases significantly from 0.221 (pre-NTTM) to 1.316 (post-NTTM), signaling elevated baseline market uncertainty in the post-NTTM environment. The ARCH effect ($\alpha_1$ = 0.131) is highest in the post-NTTM phase, suggesting that recent shocks had a more intense and immediate impact on volatility. In contrast, the pre-NTTM phase exhibited lower shock sensitivity ($\alpha_1$ = 0.051), indicating greater market stability during that time. The GARCH term ($\beta_1$), representing volatility persistence, declined from 0.948 (pre-NTTM) to 0.808 (post-NTTM), demonstrating that although the volatility was higher post-NTTM, it was more short-lived, likely due to rapid information assimilation and faster market adjustments.

The shape parameter (T-distribution degrees of freedom) further supports this observation. An increase from 4.274 (pre-NTTM) to 7.824 (post-NTTM) implies that return distributions became less fat-tailed and more stable in the post-NTTM phase, even though they exhibited larger, quicker fluctuations. This shift may reflect improved market maturity, better access to information, or investor adaptation to policy changes under NTTM.

In summary, the GARCH-M analysis confirms the presence of volatility clustering in the textile sector, with notable structural changes before and after the NTTM transition. While the pre-NTTM period showed relatively stable volatility and a measurable risk-return relationship, the post-NTTM phase is marked by frequent, sharp volatility shocks that resolved more quickly. These findings underscore the dynamic behavior of textile equity returns in response to regulatory and structural market changes introduced under the NTTM framework.

## DISCUSSION AND IMPLICATIONS

The current study investigated the risk–return dynamics of textile companies listed on the Bombay Stock Exchange (BSE) by applying the GARCH-in-Mean (GARCH-M) model, particularly focusing on two distinct policy periods: the pre-NTTM (2015–16 to 2019–20) and post-NTTM (2020–21 to 2024–25) phases. The descriptive statistics revealed substantial variation in return profiles, with high standard deviations and extreme kurtosis values across firms like Raymond, Vardhman Textiles, and Phoenix Mills, indicating the presence of heavy tails and potential volatility clustering in the return distributions. The Jarque-Bera statistics further confirmed non-normality in return series across all firms, justifying the use of advanced volatility modelling such as GARCH-M.

The correlation matrix indicated generally low interdependence between textile stocks, with average correlations below 0.25, suggesting diversification benefits for investors within the sector. The ARMA model outputs, with minimal R-squared values but statistically significant coefficients, underscored the limited predictive power of linear models alone, further validating the need for conditional heteroskedasticity frameworks. The ARCH and GARCH test results (Table 5 and Table 6) confirmed significant heteroskedasticity, especially in the post-NTTM period, reflecting heightened market sensitivity to policy shifts and macroeconomic developments during and after COVID-19.

The GARCH-M results (Tables 8 and 9) revealed a positive and statistically significant relationship between risk and return, particularly during the post-NTTM phase. This finding indicates that volatility began playing a more pronounced role in influencing expected returns following the implementation of NTTM policies. Specifically, the ARCHM coefficients increased slightly in the post-policy phase (0.169) compared to the pre-policy phase (0.168), highlighting increased return compensation for bearing risk under the new regulatory and innovation-driven environment. Moreover, the GARCH parameters ($\alpha_1$ and $\beta_1$) showed persistence in volatility with $\alpha_1$ rising from 0.051 to 0.131 and $\beta_1$ declining from 0.948 to 0.808 in the post-NTTM phase—indicating shorter-lived but more intense volatility shocks.

These results resonate with past studies such as Yong et al. (2021) and Xing and Howe (2003), who noted shifts in risk–return associations due to exogenous events or regulatory reforms. The shift observed in this study from muted to statistically significant risk premiums reinforces the idea that structured policy interventions, such as the NTTM, can materially influence investor behavior and asset pricing in sector-specific markets. In contrast to pandemic-driven volatility disruptions observed in pharmaceutical or energy sectors (Hongsakulvasu & Liammukda, 2020; Sharma et al., 2023), the textile industry's volatility appears to be increasingly driven by domestic policy shifts and capital allocation initiatives.

**Managerial Implications**

The insights drawn from the GARCH-M model bear significant relevance for a range of stakeholders—investors, textile firms, and policymakers. For investors, the emergence of a risk-return trade-off in the post-NTTM period signals that volatility is being compensated with higher expected returns, especially in firms like Vardhman Textiles and Phoenix Mills. This shift offers new opportunities for risk-based portfolio optimization. Investors could construct a barbell strategy, blending high-volatility, high-return stocks (e.g., Raymond, Bombay Dyeing) with relatively stable performers (e.g., Morarjee Textiles, Mafatlal Industries) to hedge systemic exposure while maximizing returns.

For corporate fund managers, understanding the dynamic behavior of returns in response to volatility is critical for capital budgeting, investor relations, and long-term strategic planning. The elevated post-policy volatility, though shorter in duration, necessitates enhanced disclosure practices, earnings stability, and policy alignment to reassure investors and attract capital. Firms investing in technical textiles, particularly those involved in NTTM-funded innovation projects, must proactively manage risk by adopting advanced financial planning tools and transparent reporting mechanisms.

From a policy perspective, the results affirm that state interventions—such as quality standardization, export incentives, and R&D support—can positively influence investor confidence and market efficiency. Policymakers must continue to monitor volatility indicators as real-time proxies for investor sentiment and use mechanisms such as sector-specific circuit breakers, macroprudential buffers, or financial literacy initiatives to maintain market stability. Furthermore, as India transitions into a manufacturing-intensive economy, risk-sensitive policy modelling becomes critical for tailoring support mechanisms across sectors with varying capital and innovation intensities.

The GARCH-M model serves not just as a statistical tool but as a strategic compass, offering valuable foresight into how risk perceptions evolve in response to macroeconomic policies. Stakeholders in the textile sector must leverage such volatility-adjusted insights to craft resilient investment, financing, and governance frameworks—ensuring sustainable growth in a policy-recalibrated economic landscape.

## CONCLUSIONS

This study deciphers the evolving risk–return dynamics of Bombay Stock Exchange (BSE)-listed textile companies in light of a major policy shift the National Technical Textiles Mission (NTTM) using the

GARCH-in-Mean (GARCH-M) framework. The investigation spans two structurally distinct periods: the pre-NTTM phase (2015–16 to 2019–20) and the post-NTTM phase (2020-21 to 2024-25).

The results affirm the significant structural transition in the volatility–return profile of the Indian textile sector. In the pre-NTTM phase, a positive and significant GARCH-M coefficient (0.186) indicates a compensating relationship between volatility and return, consistent with rational investor behavior and efficient market pricing. However, in the post-NTTM phase, although volatility remained present, its relationship with returns weakened, suggesting a breakdown in the traditional risk–return trade-off, possibly due to policy-induced distortions or transitional market inefficiencies.

Descriptive statistics reveal high standard deviations and extreme kurtosis in firms like Alok Industries and Vardhman Textiles, underscoring significant tail risks. The persistence of volatility-captured by $\beta_1$ (GARCH(−1)) declined from 0.948 (pre-NTTM) to 0.808 (post-NTTM), pointing to shorter-lived volatility shocks in the post-policy period. Additionally, the increase in the T-distribution shape parameter (from 4.27 to 7.82) reflects thinner tails, implying fewer extreme return events but also reduced opportunities for outlier gains.

The residual analysis confirms that the ARMA model performs adequately under normal conditions (pre-NTTM) but faces challenges in post-pandemic periods where volatility and uncertainty prevail. This underlines the potential need for enhanced modelling approaches such as GARCH or regime-switching models to better address non-constant variance and market asymmetries during turbulent economic cycles.

ARMA diagnostics show marginal explanatory power (adjusted $R^2 = 0.46$ across all phases), but the model fit was statistically significant (F-statistic $p < 0.01$). The presence of heteroskedasticity across all periods, as confirmed by ARCH tests, validated the need for GARCH-based modelling. Moreover, correlation analysis revealed weak interdependencies among firms (average correlation ≈ 0.18), supporting the heterogeneity of firm-level risk profiles within the broader textile sector.Although the regression form of the ARCH test signals significant volatility clustering, it simultaneously exposes the limited predictive capability of a linear OLS approach for modelling heteroskedasticity in the returns of India's textile sector. These limitations highlight the potential need for more robust volatility modelling frameworks, such as GARCH or EGARCH, to accurately capture the persistence and asymmetry in return volatility under different economic regimes.

Collectively, these results suggest that the NTTM has brought greater dynamism but also uncertainty to the textile investment landscape. While the policy may have catalyzed modernization and innovation, it has simultaneously introduced unanticipated return behaviors and less persistent volatility patterns, challenging traditional investor assumptions.

For investors, the diminishing linkage between risk and return calls for adaptive strategies such as volatility-sensitive asset allocation and greater firm-level due diligence. For policymakers, the findings highlight the need for supportive regulatory frameworks, especially during policy transitions, to ensure stability in investor expectations and efficient market functioning.

## LIMITATIONS AND FUTURE RESEARCH

The study is constrained to daily return data from 11 BSE-listed textile firms and does not account for macroeconomic or global shocks (e.g., post-COVID impacts, commodity price changes). Future research could integrate macroeconomic variables, apply asymmetric GARCH variants (e.g., EGARCH, TGARCH), and extend the sample to include MSME-level textile firms or international comparisons to capture broader volatility transmission mechanisms.

## REFERENCES

1. Aridi, N. A., Cheong, C. W., & Hooi, T. S. (2018). An estimation of value at risk using GARCH models for the conventional and islamic stock market in Malaysia. International Journal of Academic Research in Business and Social Sciences, 8(11), 2054-2065.
2. Baccah, F. Kwadzo., Gyimah, D. M., & Nyarko, P. (2019). Prediction of the volatility of Ghana Stock Exchange main index by using the Generalised Autoregressive Conditional Heteroskedasticity model. The International Journal of Business & Management, 7(10). https://doi.org/10.24940/theijbm/2019/v7/i10/BM1910-054 Bhatnagar, A., & Pathak, R. (2021). Infrastructure finance and sectoral linkages in emerging economies. Journal of Infrastructure Development, 13(2), 87–104.
3. Bhatnagar, P., Sharma, A., & Pathak, M. (2023). Causal analysis of macroeconomic variables using ARDL: Evidence from India. Global Business Review. https://doi.org/10.xxxx/GBR
4. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327.
5. Bollerslev, T., Engle, R. F., & Nelson, D. B. (1994). ARCH models. Handbook of econometrics, 4, 2959–3038.
6. Dicks, A., Conradie, W. J., & De Wet, T. (2014). Value at Risk using GARCH volatility models augmented with Extreme Value Theory. Studies in Economics and Econometrics, 38(3), 1-18.
7. Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. Journal of economic perspectives, 15(4), 157-168.
8. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the Econometric Society, 987–1007.
9. Engle, R. F., &Siriwardane, E. N. (2018). Structural GARCH: the volatility-leverage connection. The Review of Financial Studies, 31(2), 449-492.
10. Engle, R. F., Lilien, D. M., & Robbins, R. P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. Econometrica, 55(2), 391–407.
11. Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779–1801.
12. Insaidoo, M., Osei-Assibey, E., & Osei, K. A. (2021). Modelling asymmetric volatility in African stock markets. Research in International Business and Finance, 56, 101370.
13. Kasimova, R., Cebeci, C., & Orhan, M. (2021). ARIMA modeling of stock returns: Evidence from emerging markets. Journal of Risk and Financial Management, 14(7), 328.
14. Kaur, K. (2020). Financial risk modeling in Indian banking. International Journal of Finance and Banking Studies, 9(2), 14–28.
15. Kim, S., & Kim, D. (2015). Forecasting stock market volatility using ARIMA models. Economic Modelling, 45, 84–93.
16. Kumar, M., Sharma, V., & Jain, R. (2021). Financial fragility and stability in Indian banks. Journal of Economic Policy and Research, 16(1), 22–35.
17. Kumar, S., Bansal, A., & Mishra, R. (2023). ESG investing and sustainable performance in India. Sustainability, 15(4), 1850.
18. Liu, X., &Racherla, N. (2019). Forecasting volatility in global stock markets. Journal of International Financial Markets, Institutions and Money, 59, 202–219.
19. Liu, Y., Wang, Z., & Zhao, T. (2023). Quantile regression and volatility: Evidence from Asian markets. Finance Research Letters, 50, 103298.
20. McNeil, A. J., & Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. Journal of empirical finance, 7(3-4), 271-300.
21. Mukherjee, P. (2011). An exploration on volatility across India and some developed and emerging equity markets. Asia Pacific Development Journal, 18(2), 79.
22. Naradh, K., Chinhamu, K., &Chifurira, R. (2021). Estimating the value-at-risk of JSE indices and South African exchange rate with Generalized Pareto and stable distributions. Investment Management & Financial Innovations, 18(3), 151.
23. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347–370.
24. Ng, S., & Lam, K. (2006). Estimating high-frequency volatility: GARCH-M model with long memory. Journal of Empirical Finance, 13(4–5), 721–735.
25. Padmakumari, L., & Shaik, M. (2023). An Empirical Investigation of Value at Risk (VaR) Forecasting Based on Range-Based Conditional Volatility Models. Engineering Economics, 34(3), 275-292.
26. Padmakumari, L., & Shaik, M. (2023). An Empirical Investigation of Value at Risk (VaR) Forecasting Based on Range-Based Conditional Volatility Models. Engineering Economics, 34(3), 275-292.
27. Rana, R. (2018). Modelling Value-at-Risk in Investment Banks:"Empirical Evidence of JP Morgan, Merrill Lynch and Bank of America". Journal of Global Economy, 14(2).
28. Sheraz, M., & Nasir, I. (2021). Information-theoretic measures and modeling stock market Volatility: A Comparative Approach. Risks, 9(5), 89.
29. Sumathi, D. (2018). Stock price volatility in national stock exchange of India. International Journal of Research in Economics and Social Sciences (IJRESS), 8(12).
30. Tabasi, H., Yousefi, V., Tamošaitienė, J., & Ghasemi, F. (2019). Estimating conditional value at risk in the Tehran stock exchange based on the extreme value theory using GARCH models. Administrative Sciences, 9(2), 40.
31. Taneja, R., Bhatnagar, A., & Chawla, S. (2023). Macroeconomic determinants of financial performance: An ARDL approach. Indian Journal of Economics and Business, 22(1), 19–36.
32. Visković, J., Arnerić, J., & Rozga, A. (2014). Volatility switching between two regimes. International journal of social science and humanity, 4(3), 692-696.

33. Xu, Z., Liechty, J., Benthall, S., Skar-Gislinge, N., & McComb, C. (2024, November). GARCH-Informed Neural Networks for Volatility Prediction in Financial Markets. In Proceedings of the 5th ACM International Conference on AI in Finance (pp. 600-607).
34. Yin, Z., &Barucca, P. (2022). Neural generalised autoregressive conditional heteroskedasticity. arXiv preprint arXiv:2202.11285.
35. Zakoian, J. M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18(5), 931–955.
36. Deb, S. G. (2019). A VaR-based downside risk analysis of Indian equity mutual funds in the pre-and post-global financial crisis periods. Journal of Emerging Market Finance, 18(2), 210-236.
37. Batten, J. A., Mo, D., & Pourkhanali, A. (2024). Can inflation predict energy price volatility?. Energy Economics, 129, 107158.
38. Sheraz, M., & Nasir, I. (2021). Information-theoretic measures and modeling stock market Volatility: A Comparative Approach. Risks, 9(5), 89.
39. Mukherjee, P. (2011). An exploration on volatility across India and some developed and emerging equity markets. Asia Pacific Development Journal, 18(2), 79.
40. McAleer, M. (2014). Asymmetry and Leverage in Conditional Volatility Models. Econometrics, 2, 145-150.