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Predicting Portfolios Using Fuzzy Logic And Optimization Techniques: A Case Study Of BSE-IT Listed Companies

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Stock price trends were considered in this study, the companies in the BSE-IT index, with a view to optimizing portfolio allocation based on risk tolerance. The GARCH model has been applied here to allow an investigation into the volatility of the stock returns and to set up different clusters using K-Means clustering that group together companies owning the same attributes related to volatility for strategic classification. Data collection and processing occur between April 1, 2014, and March 31, 2024, for reasons of reliability and relevance. Descriptive statistics report on the variance of stock performance across companies; different risk-return profiles are thus exposed. The GARCH model measures each stock's long-term variance, along with sensitivity to past shocks, and overall volatility persistence, making this an excellent inventory for risk assessment. K-Means clustering groups companies based on similar volatility patterns, thereby informing portfolio construction. Findings present how clustering with econometric modeling may assist in the production of optimal portfolios that depend on specified risk capacities, thus efficiently managing and implementing an IT investment strategy.

Keywords: BSE-IT, stock price prediction, portfolio optimization, GARCH model, K-Means clustering.

Introduction

In the past decades, machine learning techniques, fuzzy logic, and advanced statistical models have transformed financial analysis significantly, providing adaptive, accurate tools for forecasting stock market trends. A striking model is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. It has been the most important in handling the volatility inherent in financial data and can capture the dynamic, time-varying nature of stock prices. GARCH models are specifically used to forecast in those sectors in which high volatility and fluctuations occur. Therefore, GARCH models are effective in industries like technology, where abrupt fluctuations heavily affect investment returns.

This paper integrates the machine learning and fuzzy logic approach with statistical techniques such as GARCH(1,1) and K-Means clustering algorithms to predict key BSE-IT sector companies' stock price movement. The environment of Indian IT as an industry represents the field of high growth coupled with innovativeness in this space. Such fields present their complexity while being fascinating and complex for investors. Such complexity forms the center of research using selected companies listed on BSE, the stock price data for them having started between April 1, 2014, and ended on March 31, 2024. This dataset is used to inform a portfolio optimization model: the approach here is through risk-sensitive portfolios explicitly tailored towards the level of different investor risk capacities.

Portfolios are optimized through core stock identification, using machine learning to classify the risk profiles and return. Stocks are then clustered through K-means, and portfolios can also be aligned according to risk level. After the clustering, a risk-capacity-based portfolio selection algorithm evaluates the generated portfolio against predefined risk thresholds. This level of risk control incorporated in the model will enable the investor to choose an optimized portfolio that aligns with his or her risk preferences while accounting for expected returns.

It will be the first study in which GARCH is combined with machine learning for the stock classification and portfolio optimization to adjust volatility, with an offer of a full-fledged approach to financial forecasting in the BSE-IT sector. It provides insights and tools helpful to investors for making proper decisions within a complex, high-volatility market environment and makes a meaningful contribution to financial modeling and portfolio optimization.

Objectives:

- Apply machine learning and GARCH modeling techniques to analyze the volatility of the stock prices in the BSE-IT sector.
- Classify BSE-IT stocks into clusters based on risk-return profile using K-Means clustering.
- Design and development of a portfolio optimization model based on the investor's risk capacity

Problem Statement

The very volatile and dynamic nature of the information technology sector in India provides a unique challenge to investors in terms of investment decision-making in the BSE-IT stock sector. Traditional investment models are weak enough to grasp the proper dynamics of stock price movements due to the widespread changes, higher risk factors, and a significant influence on global market trends. However, investors are not all the same regarding risk appetite; therefore, portfolio options must be customized to meet their expectations about returns and risks.

To overcome these problems, the study combines the GARCH model, machine learning techniques, and portfolio optimization methods toward developing an adaptive framework to predict stock prices for listed companies in BSE-IT and develop risk-adjusted investment portfolios. The present study contributes to developing insights to help investors navigate sector-level volatility and make more effective investment decisions.

Organization of study Chapter 1 : Background information to the research, Objectives, and problem statement. Chapter 2: Literature review; Chapter 3: Methodology such as machine learning, GARCH and fuzzy logic models that will be used. Chapter 4: Data analysis and results Chapter 5: Discussion of findings with conclusions, implications, and recommendations.

2 Literature review

To provide the foundation for this study, the literature review finds three areas of subject interest related to forecasting stock prices, managing volatility, and even optimizing portfolios in this BSE-IT industry: application of machine learning in finance, GARCH estimation of volatility, and risk-based clustering and selection in portfolio optimization. Relevant literature is synthesized below in service of each theme and related citations for facilitating knowledge development within a domain.

Because of their efficiency in dealing with complex patterns in financial data, machine learning techniques have widely been applied to predict stock prices. For instance, (Fama, 1970) proposed the Efficient Market Hypothesis (EMH)-the hypothetical assumption that the prices of stocks reflect all information available at any given time. However, recent machine learning studies challenge this by showing that stock prices can be forecasted to some extent by sophisticated algorithms that capture nonlinearities in financial data (Latha et al., 2022; Sun, Guo, Karimi, et al., 2015; Sun, Guo, Reza Karimi, et al., 2015).

(Giaremis et al., 2024) discussed whether deep learning models could effectively replace these traditional models, including recurrent neural networks (RNNs) and long short-term memory (LSTM), that have been used in the last few years to learn sequential data. As such, the application of such deep learning models has proven effective in stock price predictability, suggesting that they have managed to capture dependency and patterns in terms of time.

Combine statistics models with GARCH as a basis to improve the accuracy in forecasting stock prices. (Hu et al., 2020) have developed hybrid models that combine GARCH and LSTM with different groups of volatility clusters in solving the complex temporal variations and increasing precision in the prediction of volatile sectors such as IT.

(Bollerslev, 1986; Engle, 1982) pioneered volatility estimation when they introduced the ARCH and GARCH models. These are now the standard model for conditional volatility of financial time series because they capture volatility clustering and persistence in time, which characterizes financial data.

Studies like (Kakade et al., 2022; Kim et al., 2021; Song et al., 2021) applied GARCH models on stock markets, finding that these models could well capture changing volatility in returns for stocks, which is so very crucial in sectors like IT, as the volatility parameter is extreme owing to factors in the external market.

For instance, varieties of the GARCH model, such as EGARCH and TGARCH, have in fact been used to bet better capture asymmetric volatility where negative shocks substantially differ from their positive counterparts in inducing volatility (Liu & Hung, 2010; Menvouta et al., 2023; Zhang et al., 2023). Improvements for that type of sector, such as technology, wherein negative news or global uncertainties directly impact volatility disproportionately.

(Michaud, 1989) developed the framework of Modern Portfolio Theory, which emphasizes that the optimization of return per unit of risk or more precisely put as risk-adjusted return optimization. This theory sets the premise for portfolio optimization in the creation of an optimal balance between return and risk based upon investor preference.

With the development in algorithms related to clustering, researchers used various techniques, such as K-means clustering, for classifying the risks/returns involved in stocks to introduce optimally designed portfolios to the investors. (Chandrinos & Lagaros, 2018; Esparcia & López, 2024; Habbab & Kampouridis, 2022) worked on portfolio optimization using K-means and proved that the portfolios developed may be better aligned with the investors' risk capacity through clustering based on the risk dimension.

Fuzzy logic has been progressively used to deal with financial decisions including ambiguous markets. (Chourmouziadis & Chatzoglou, 2016; Mansour et al., 2019), introduced fuzzy logic into portfolio optimization. The study was further extended by (Yin et al., 2022), proving that fuzzy logic has assisted in managing uncertainty in choosing stocks, especially in a volatile market, including IT.

GARCH-based portfolio optimization- the context of studies in that sense, studies include GARCH models in the optimization of the portfolio where time-varying volatility is considered. This encompasses, for example, studies in which (Dridi & Boughrara, 2023; Yuan et al., 2022) showed how the use of GARCH models to estimate dynamic volatility improves the quality of the risk estimates with respect to more robust portfolio optimization strategies for volatile sectors.

Combining clustering techniques like K-Means and fuzzy logic were also used. (Chen & Chen, 2015; Vullam et al., 2023) applied the combination of K-means, with the aid of a fuzzy set to arrive at investor-specific portfolios. This too marks the direction of the present study, optimizing portfolios with respect to various risk capacities.

Further research also reveals that methodology of the machine coupled with the optimization of traditional helps in producing more refined strategies for the portfolio. (Carapuço et al., 2018; Sawhney et al., 2021) combined reinforcement learning and machine learning in relation to adapting portfolios to changes in market conditions, mainly applicable in volatile sectors such as BSE-IT.

Techniques like genetic algorithms (GAs) and particle swarm optimization (PSO) have been used on the improved portfolio selection models proposed by (Tawarish & Satyanarayana, 2019) These methods include constraints including the investor's aversion to risk and sector volatility, which are in close alignment with the objective of the current study, that is, optimizing BSE-IT portfolios.

In sector-specific studies, (Keren et al., 2008; Pagnottoni & Spelta, 2024) consider the IT sector separately as it possesses different characteristics of risk and return, which further indicates that sector-based optimization led to relatively more practical portfolios in the eyes of investors due to the volatile nature of sectors and their inherent tendency to cluster.

The research by (Bouras et al., 2019) introduced the risk-capacity models, a combination of the level of risk an investor can stomach and the market conditions to enable dynamic adjustment on the portfolio. This has proved to be very helpful in companies that enjoy highly growing businesses, such as IT, whose trends change fast, hence necessitating a robust portfolio management strategy.

This literature thus shows promising results of machine learning and GARCH models in dealing with stock market volatility and price prediction problems, especially concerning the BSE-IT sector. Adding portfolio optimization techniques such as clustering, fuzzy logic, and heuristic algorithms helps develop risk-adjusted portfolios sensitive to market dynamics and the investor's risk capacity. These results are then used in designing a GARCH-improved, machine-learning-based optimized portfolio approach in the BSE-IT sector, built with well-established financial theories and high-powered modeling.

Research gap:

The major research gaps addressed by this study are the lower application of machine learning and GARCH models to sector-specific volatility and portfolio optimization in the BSE-IT sector. Though machine learning models are highly applied in predicting stock prices, their combination with GARCH for volatility modeling in the Indian IT industry is rare. In addition, portfolio optimization tends to neglect investor-specific risk capacity. Considering the volatility of IT stocks, it is quite an important factor. Most of the studies lack an approach that combines GARCH for volatility estimation with machine learning and K-means clustering for a more customized selection of portfolios. Moreover, the sector-focused portfolio models use less fuzzy logic in terms of managing uncertainty. This study fills in these gaps by proposing a hybrid approach that integrates machine learning, GARCH, and fuzzy logic within a risk-based, investor-centered portfolio optimization framework that can be uniquely designed and shaped to meet the distinctive features and dynamics of BSE-IT companies.

3 Proposed Methodology

In the methodology proposed in this research work, it analyzes the BSE-IT stock price data, following which optimized investment portfolios are developed using both machine learning and econometric models. In the first step, stock price data is collected from April 2014 to March 2024 and also pre-processed. For controlling heteroskedasticity in the data, a GARCH (1,1) model was used, giving residual errors and key parameters such as α, β, and γ. These are volatility and price-based stocks classified by a K-Means clustering algorithm.

The resultant portfolios are then evaluated against the risk capacity prescribed by the investor. Having an iteration for each portfolio, the researchers will choose portfolios which fall below or beyond the threshold set for the risk, and those that would be considered optimal investments. Combining historical trends in price with machine learning under a system based on Python, it augments the portfolio selection processes and risk assessments.

Algorithm 1 Collect_portfolio Algorithm

Require: *risk_capacity*
Ensure: Optimized portfolio dataset
Collect stock daily prices
Pre-process the data
Check for heteroskedasticity:
if heteroskedasticity exists **then**
    Apply GARCH(1,1): $GARCH = (\alpha \times SLR + \beta \times LV + \gamma \times LRV)$
    Collect residual errors, α, β, γ values
end if
Classify stocks using K-Means algorithm
Generate portfolios $portfolio_1$ to $portfolio_n$
for each $portfolio_i$ in portfolios **do**
    if $risk\_capacity < risk(portfolio_i)$ **then**
        Select $portfolio_i$
    end if
end for
return dataset

Algorithm-1 illustrates the portfolio optimization for stock prices, which predicts such prices in the context of a risk management approach, incorporating econometric models and machine learning.

It begins by gathering historical daily prices of some companies listed under BSE-IT. These data must be prepared so that all the noise present is removed before further processing. After preparation, the algorithm checks for heteroskedasticity, which mainly occurs in financial time series wherein variance is not constant. Since heteroskedasticity is found, the applied model would be GARCH (1,1) because volatility clustering indicates such data. The estimated values of the three variables are alpha (α), beta (β), and gamma (γ). These indicate short-term impact, long-term persistence, and mean reversion, respectively. Other residuals and the estimated three parameters are documented in the findings. Next, the stocks were classified through the K-Means clustering algorithm, where the stocks were classified into clusters of stocks having similar attributes. The classification based on the K-Means clustering algorithm supported the categorization of stocks with diverse risk-return characteristics for the generation of portfolio combinations.

Then, combining different stocks from various clusters generates a wide range of portfolios. The algorithm iterates through each portfolio. It then compares the portfolio's risk level with a predefined capacity threshold. Only the portfolios that qualify under the risk criteria will be selected, aligning the final portfolio with the user's tolerance towards risk. In the last step, the algorithm outputs a dataset of chosen portfolios that fulfill the risk criteria. This dataset is optimized for investment and portfolio analysis in terms of a good balance between return potentials and acceptable levels of risks based on well-balanced combinations of econometrics and machine learning techniques.

4 Implementation and results

This study involves gathering BSE-IT stock data, processing and analysis that optimizes a portfolio with specific risk levels and predictive models. This approach uses advanced predictive analytics employed by the GARCH model and machine learning techniques with K-Means clustering for better handling of volatility while optimizing asset allocation in a given risk tolerance. Such results illustrate how the model captures market volatility and, therefore, gives optimized portfolios in accordance with the specific risk capacity of investors.

Table 1: Descriptive statistics for BSE-IT listed and selected companies

Company	count	mean	min	25%	50%	75%	max	std
TCS	120	2146.84	1013.11	1227.06	1947.98	3158.56	4095.10	945.59
Infosys	120	909.57	362.55	530.99	716.06	1374.74	1906.85	456.31
HCL	120	694.93	344.25	430.12	524.33	975.81	1663.85	336.60
Wipro	120	307.21	171.75	210.13	241.40	400.05	715.35	132.45
TEML	120	756.92	354.91	492.06	660.10	1018.23	1734.73	321.40
OFSS	120	3571.26	2032.45	3162.94	3475.55	3817.26	8766.05	818.67
PERS	120	953.67	235.55	316.53	368.91	1669.20	4320.52	997.78
MBFL	120	1257.54	359.88	533.79	961.60	1962.69	3396.45	855.61
COFO	120	2062.41	348.90	484.84	1300.38	3812.58	6561.40	1841.40
TTEX	120	2690.71	252.91	786.86	963.79	5643.66	9015.10	2883.46
CYIE	120	704.09	199.10	477.70	557.76	811.82	2292.40	399.11
SOFT	120	180.15	17.98	59.60	117.32	262.62	811.30	173.20
BIRS	120	205.23	58.17	84.47	119.51	286.59	848.50	172.63
ZENT	120	242.56	72.01	170.83	211.23	274.03	610.55	122.69
TNSL	120	364.42	5.36	33.41	49.98	752.95	1888.45	480.70
APSL	120	151.73	19.90	59.07	85.87	128.14	1111.22	222.31
MAST	120	934.64	57.94	183.74	440.85	1706.99	3318.85	967.56
BLAC	120	79.47	10.42	18.41	24.46	140.95	316.56	83.86
RSYS	120	133.88	26.70	48.56	70.00	215.19	548.70	130.42
MOSC	120	35.11	1.98	11.18	28.00	53.88	103.65	27.84
CIGN	120	455.67	194.01	324.68	409.81	488.71	1266.50	202.62

DATC	120	173.56	40.66	72.27	103.05	284.14	723.90	162.97
NSEL	120	438.54	151.00	245.66	350.25	522.53	1582.35	299.81
VAKR	120	64.86	14.21	27.30	42.18	74.08	373.77	65.50
SKCT	120	640.86	157.01	351.76	595.44	882.25	1641.40	348.64
ACCY	120	1114.07	635.15	921.74	1037.85	1348.94	1833.60	260.47
63MO	120	143.19	46.90	80.10	104.93	175.96	490.80	91.64
NELC	120	304.92	42.30	93.78	206.93	532.23	989.40	262.38
AXIT	120	181.53	27.80	72.26	138.38	248.79	799.10	147.87
EXPL	120	767.21	145.90	471.64	600.88	1137.64	1725.25	402.57
DLIL	120	137.59	28.32	92.48	118.40	164.97	323.54	67.06
DSSL	120	130.79	2.97	15.68	31.90	148.73	1023.65	208.82
RMCS	120	388.64	72.20	253.60	361.13	476.31	954.50	185.49
KELL	120	52.32	4.22	32.62	53.74	69.90	112.90	26.79
SUBX	120	18.40	3.07	8.42	11.00	29.27	62.20	14.59
CONP	120	343.26	42.00	235.98	299.98	411.18	1004.90	188.57
XCHA	120	60.81	17.10	44.66	56.55	75.90	135.37	24.11
OTEC	120	156.23	37.40	62.29	75.23	232.59	624.70	149.86
TIIN	120	48.48	13.20	34.15	42.65	57.97	109.40	21.04
CRES	120	11.48	0.19	1.22	2.84	21.98	54.29	15.69

Table 1 provides the descriptive statistics of some selected companies listed on the BSE-IT index, which would be invaluable for providing information about their stock performance. The mean stock price of OFSS is very high at 3571.26, with good market valuation, while the lowest average is recorded for SUBX at 18.40, reflecting less interest in the market. Minimum and maximum prices indicated great variation, and TCS had a range from 1013.11 to 4095.10, thus representing a high price fluctuation. Regarding the volatility, the greatest standard deviation is that of COFO at 1841.40 that indicates high price fluctuation, and KELL has minimum standard deviation at 26.79, so the prices are stable in nature. The 25th percentile and 75th percentile for TCS stand at 1227.06 and 3158.56 respectively. It indicates a great spread of usual prices whereas the 25th percentile for Wipro stands at 210.13 and 400.05 indicating less variability. TTEX and COFO have a right-skewed distribution, implying that a few high-value stocks inflate the mean. The rest of the firms like SUBX and BLAC are much more consistent in price distributions. These statistics vary risk and return for the BSE-IT companies and would guide investment strategies to decide which firm would give better growth or stability.

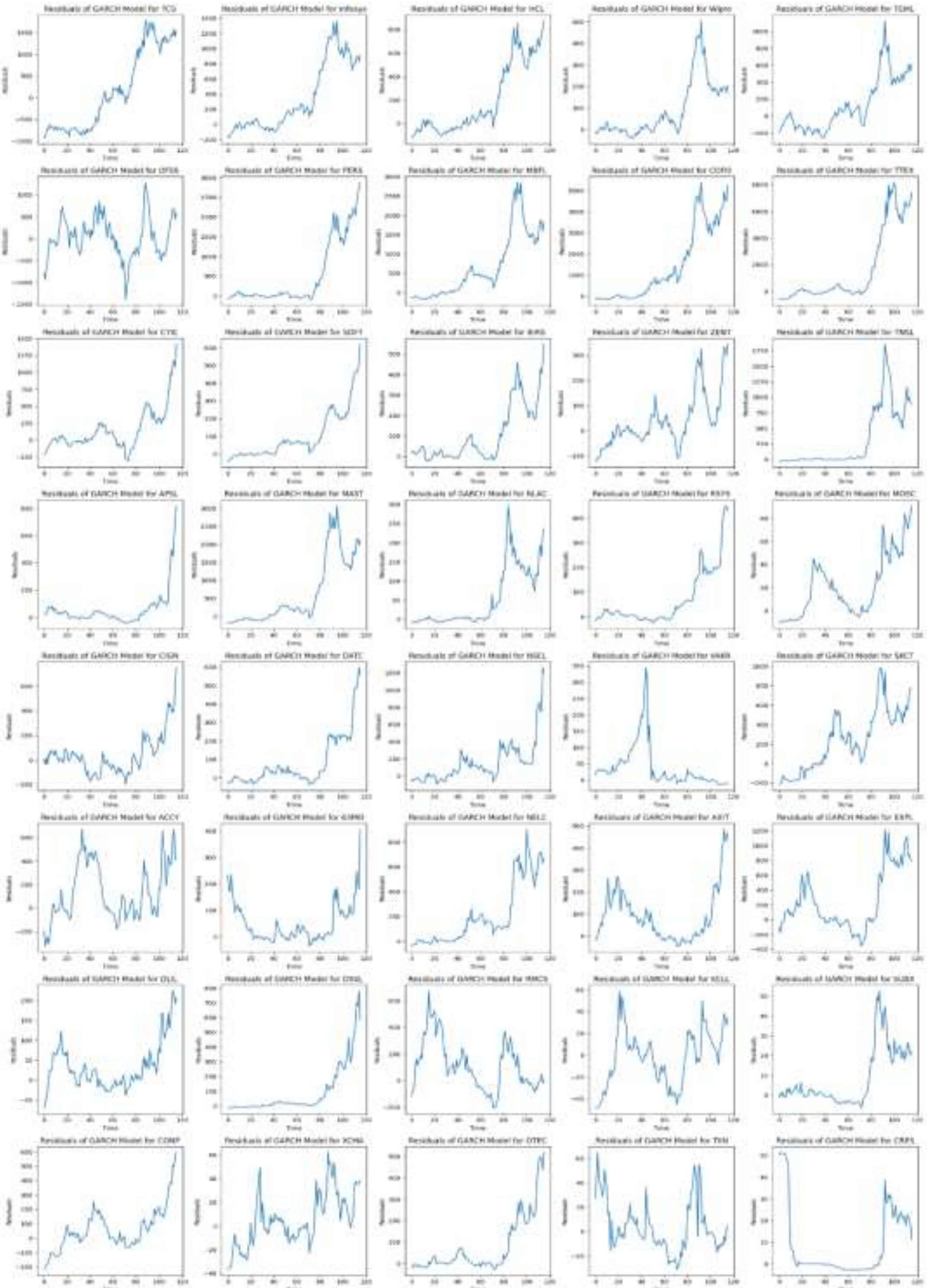

Figure 1: residual graph for each software company

Figure 1 shows the results of residual graphs. The GARCH model provides information regarding the volatility dynamics in the return of the stock of various companies. Omega (ω) is an estimate of the long-run average variance. COFO with omega 67,250.10 and TTEX with omega 164,900.23 depict higher levels of volatility persistence. This would mean there would be higher fluctuations in the stock returns of such companies over time. In contrast, the omega for Wipro has been calculated to be 167.71, depicting lesser variability in returns. The alpha (α) parameter measures sensitivity in conditional variance to the past period's squared return. It is 1 for companies like HCL and Wipro, meaning high dependence on past shocks. Lower values for alpha indicate lesser sensitivity toward historical shocks; an example is CIGN with 0.59. Persistence in volatility from previous periods would be represented by the parameter beta, β. Those companies like HCL and TEML have values pretty close to 0: the effect of past volatilities decays within really short periods. The coefficients like COFO and TTEX hold values pretty close to 1, meaning past volatility affects for a relatively more extended period. Model fit statistics like Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which show that the less the value, the stronger the model, therefore one can see the strength of fits of Wipro with AIC = 1304.50 and then with SKCT with AIC = 1664.48. Again, Log-likelihood function (LLF) also indicates some good fits at those places where the LLF will be at higher values like -971.91 of COFO. In general, the GARCH model points to the fact that while some companies do have significant long-term volatility, the others can have lower risk profiles with a great dependence on past returns and rapid decay in the impact of past volatility, thereby giving a more accurate view of the behavior of their markets.

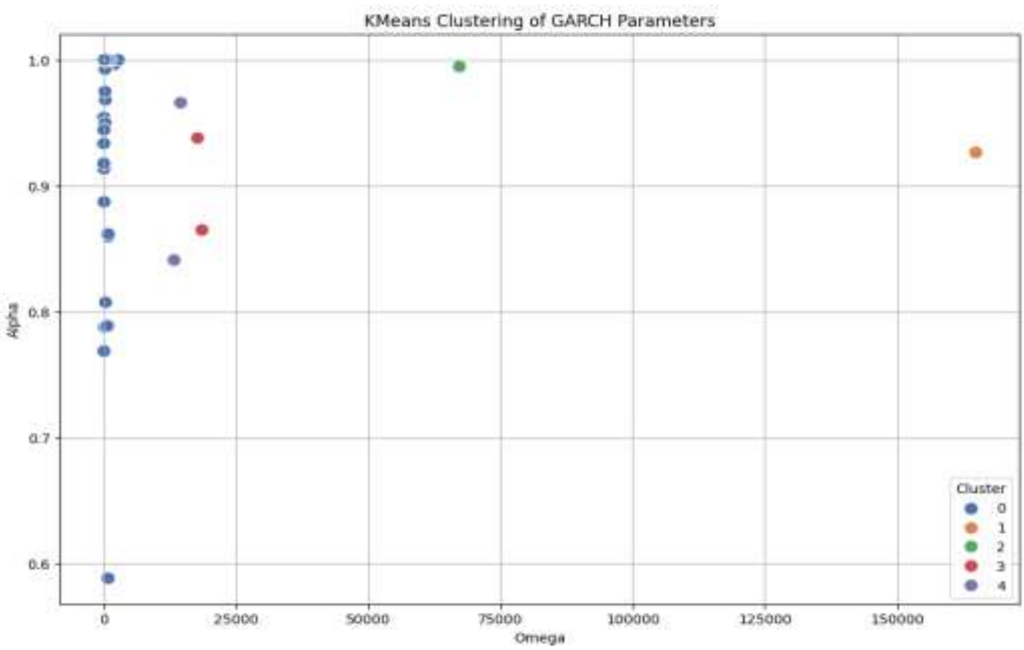

Figure 2: KMeans clustering of GARCH result on BSE-IT companies

The output comes from running KMeans clustering on different companies' GARCH parameters (Omega, Alpha, and Beta).

The company column lists the names of the companies analyzed, and Omega shows the long-term average variance in the GARCH model. This means the higher the value, the greater the baseline volatility. Alpha represents the current volatility response to past squared returns; close to 1 shows that an asset reacts sensitively to market shocks. Beta measures the persistence of volatility over time; values close to 0 indicate temporary volatility, while those close to 1 indicate lasting volatility.

The Cluster column includes the cluster to which every company was assigned after KMeans clustering. In this case, the firms bearing the same cluster number would inherit the same properties by dint of GARCH parameters. To illustrate, TCS finds itself in Cluster 3, which implies a value Omega- that is, 17733.85- as holding large baseline volatility, which is relatively different from other firms. Infosys has a low Omega of 873.27 and falls in Cluster 0. The persistence of the firm's response to shocks is also moderate. COFO has an extremely high baseline volatility of 67250.10 and has a strong responsiveness of Alpha = 0.995. It falls in Cluster 2. TTEX has a very high Omega of 164900.23 with low persistence and falls in Cluster 1. Such agglomeration is beneficial so that firms can be understood and categorized based on their volatility features, which might become pretty helpful in handling the risk, investment strategy, and comparison of a firm's performances.

5 Findings and Conclusion

This research paper gives an integrated overview of the dynamics of the stock price of the BSE-IT sector and portfolio optimization, motivated by historical data regarding stock and advanced modeling via econometric methods. Significant findings in that direction arise from utilizing the GARCH model for volatility evaluation and K-Means clustering, which are applied to classify companies based on similar volatility features. Major observations are:

Descriptive Statistics presents the varying degrees of volatility and average stock prices among the companies. High mean stock prices, such as those of OFSS, suggest a high market valuation, while those with less meaningful means, such as SUBX, indicate lesser market interest. This range enables investors to choose between growth and stable stocks according to investor preference.

GARCH models valuable information for the volatility profile of each company, long-run variance (Omega), past shock response (Alpha), and persistence (Beta). For example, COFO and TTEX reveal higher degrees of volatility persistence, and their fluctuation trend over time appears to be more significant. Firms like Wipro indicate very negligible variation. This information is helpful for the short-and long-term risk profiles for BSE-IT firms.

K-means clustering was used in this study. It classifies firms with similar volatility characteristics by grouping companies based on GARCH parameters. This leads to the valuable strategic grouping for investment analysis. For example, high-baseline volatility TCS falls into a cluster different from Infosys at moderate volatility. Such clustering allows a more structured approach to selecting stocks according to investor risk tolerance and expected returns.

As the model captures the different volatility levels across the clusters, it can build portfolios based on a given risk tolerance. An investor with a low risk-bearing capacity will like more portfolios in the lower volatilities of the clusters. In contrast, a risk-tolerant investor will opt for clusters in higher volatilities.

Conclusion:

This study demonstrates how the integration of econometric modeling with clustering techniques of machine learning works effectively for analyzing the performance of stocks and optimization in the portfolio. The GARCH model excels in capturing market volatility, and K-Means clustering helps group stocks by the characteristics of volatility, providing a nuanced view of portfolio decisions. By aligning portfolios with investors' risk capacity, this study provides a practical approach to managing risk and optimizing returns in the BSE-IT sector. This approach, emphasizing volatility and clustering, may be extended to other industries, making the tool versatile for financial analysis and formulating investment strategies.

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