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Research Article

Risk-Return Analysis of the Indian Power Sector Companies: A Simulation & DCC-GARCH based Comparative Study

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ABSTRACT

As global financial markets become increasingly complex and volatile, the need for advanced analytical tools to conduct risk-return assessments, optimize portfolios, and support strategic investment decisions has grown substantially. This review synthesizes recent academic research in financial analytics, focusing on modern approaches such as stochastic optimization, simulation-based modeling, advanced data visualization, and statistical frameworks like the DCC-GARCH model. Covering studies published between 2018 and 2025, the paper examines how evolving techniques contribute to more efficient portfolio management and risk assessment.

Traditional models like the Markowitz Efficient Frontier continue to provide foundational insights, while contemporary methods such as Monte Carlo simulations and machine learning algorithms offer improved forecasting accuracy and dynamic performance evaluation for diversified portfolios. Visualization techniques play a critical role in simplifying complex financial data; methods like star-coordinate plots, the Pareto Race approach, and multi-factor visualization systems such as Portfolio enhance investor comprehension and decision-making.The review also delves into sector-specific applications, particularly in the energy and power sectors, where tools like the DCC-GARCH model are applied to track price volatility and market interdependencies. Metrics including the Sharpe Ratio, Value at Risk (VaR), Beta coefficients, and Jensen's Alpha are used extensively to refine investment strategies and manage financial risk.

Moreover, the adaptability of these tools is highlighted in newer domains such as cryptocurrency portfolio optimization, showcasing their broad relevance. Overall, the literature underscores the value of computational finance in refining risk-return evaluations, guiding portfolio construction, and offering visual frameworks to navigate market uncertainty. This comprehensive overview serves as a resource for investors, financial practitioners, and policymakers seeking to make informed, data-driven decisions in today's dynamic economic landscape.

Keywords: Financial Analytics, Portfolio Optimization, Risk-Return Assessment, Stochastic Optimization, Monte Carlo Simulation, Machine Learning Algorithms, DCC-GARCH Model, Data Visualization, Cryptocurrency Portfolio, Value at Risk (VaR).

INTRODUCTION

In recent years, the global financial landscape has undergone rapid transformations driven by increased market complexity, geopolitical uncertainties, and heightened investor expectations. The interplay between technological advancement and economic volatility has intensified the demand for more sophisticated analytical frameworks to assess investment risks and returns. As a result, financial institutions, asset managers, and policy-makers are increasingly turning to advanced tools rooted in computational finance to guide portfolio management strategies, forecast market behavior, and respond dynamically to evolving economic indicators.

Traditional financial models, such as Harry Markowitz's mean-variance optimization and the Efficient Frontier framework, have long provided the theoretical foundation for modern portfolio theory. These models offer essential insights into diversification, asset allocation, and risk-return tradeoffs. However, in an era characterized by high-frequency trading, algorithmic decision-making, and real-time data flows, static and linear models often fall short in capturing the nuances of contemporary financial systems. Consequently, researchers and practitioners are integrating modern methodologies including stochastic optimization, machine learning, Monte Carlo simulations, and advanced econometric models to enhance predictive accuracy and decision-making robustness.

Among these innovations, stochastic optimization techniques have emerged as valuable tools for constructing portfolios under uncertainty. By accounting for randomness in input parameters such as asset returns, volatility, and correlation structures, these models enable more adaptive and resilient investment strategies. Similarly, simulation-based modeling, particularly through Monte Carlo methods, allows investors to evaluate a wide range of scenarios and outcomes, improving the robustness of portfolio forecasts. These approaches are especially pertinent in volatile or emerging markets, where historical data may be insufficient or non-representative. A significant advancement in financial analytics is the growing emphasis on data visualization, which serves as a bridge between complex quantitative analysis and intuitive decision-making. Traditional tables and two-dimensional plots are now being supplemented and often replaced by dynamic, multi-dimensional visual interfaces. Visualization techniques such as star-coordinate plots, the Pareto Race method, and multi-objective optimization viewers (e.g., sPortfolio) have become instrumental in allowing investors to comprehend high-dimensional data and explore tradeoffs among competing investment objectives. These systems enable more transparent, informed, and participatory investment processes, particularly in institutional settings where decision-making involves multiple stakeholders. Statistical modeling frameworks, such as the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, have also gained prominence in portfolio risk assessment. These models allow for time-varying correlations among financial assets and offer better insights into systemic risks and contagion effects during periods of financial stress. In contrast to static covariance matrices, the DCC-GARCH framework provides more nuanced understandings of market co-movements, especially in sectors prone to abrupt price fluctuations, such as energy, power, and commodities.

A parallel trend is the sector-specific application of advanced financial analytics. The energy and power industries, known for their susceptibility to geopolitical shifts, environmental regulations, and supply chain disruptions, have particularly benefited from sophisticated models like DCC-GARCH and other volatility tracking tools. These applications not only help identify interdependencies among energy assets but also support the development of hedging strategies and regulatory policies aimed at stabilizing markets. Performance metrics continue to play a crucial role in evaluating the effectiveness of portfolio strategies. Traditional indicators such as the Sharpe Ratio, Value at Risk (VaR), Beta coefficients, and Jensen’s Alpha remain central to risk assessment. These metrics provide a standardized way to compare investment options, assess downside risk, and determine whether a portfolio's return justifies the risk taken. However, their integration into newer modeling environments such as those powered by machine learning or simulation amplifies their utility, making them more adaptable to real-time decision-making environments.

One of the most dynamic areas in contemporary financial research is the application of these advanced tools to emerging asset classes, such as cryptocurrencies. The inherently volatile and unregulated nature of crypto markets presents unique challenges that traditional financial models are often ill-equipped to handle. In this context, machine learning algorithms, adaptive optimization models, and real-time analytics have been employed to optimize crypto portfolios, analyze transaction networks, and forecast price movements. The adaptability of financial analytics tools across both conventional and emerging markets underscores their broad applicability and relevance in today’s investment landscape. The review presented in this paper synthesizes key academic contributions between 2018 and 2025, aiming to provide a comprehensive understanding of the evolving toolkit available to financial analysts and portfolio managers. It highlights how new techniques not only improve computational efficiency and forecasting precision but also enhance the interpretability and transparency of investment decisions. From traditional theories to cutting-edge technologies, the body of literature reflects a growing consensus that combining quantitative rigor with user-friendly visualization tools is essential for navigating the complexity of modern markets. In sum, the convergence of statistical modeling, simulation techniques, and interactive visualization has marked a paradigm shift in financial analytics. This integrated approach empowers investors with greater clarity, flexibility, and responsiveness in portfolio construction and risk management. As financial systems continue to evolve, so too must the analytical frameworks used to understand them positioning computational finance as a cornerstone of strategic decision-making in the 21st century

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LITERATURE REVIEW

- **Risk-Return Ratios in Portfolio Analytics**

Kamran, 2024, in their study conducted a risk-return analysis utilizing data from 10 companies for the selected duration of 2018-2022. It helped the investors design portfolio construction and optimization strategies using financial analytics like variance and standard deviation to make their investment decision-making skills better.

In a book chapter named *Risk Assessment in Investment Portfolio* (2024), stochastic optimization and simulation technique was used to assess the risk-return trade-off of the securities to maximize investor's returns. It also employed various ratios and metrics like Value at Risk (VAR), Sharpe ratio, standard deviation, beta, etc. Lakshmi et al. 2023, conducted a portfolio analysis & assessed the risk-return analysis of the selected stocks. It also utilized Markowitz Model for the construction of an efficient frontier combining those securities that maximizes their return while minimizing the risk. Rajyaguru (2023), in his study analysed risk-return profiles of a portfolio consisting of 60% stocks and 40% liquid assets like cash & cash equivalents. It accessed data from 5 countries of the years 2000 to 2020. Chandavar et al. 2022, conducted a risk-return analysis on stock data taken from 30 companies. It assessed the trade-off between stocks of these companies. For the purpose of the analysis, Sharpe and Treynor Ratio, Jensen's alpha & other measures were used to construct optimum portfolio strategies.

- **Visualization Techniques in Financial Analytics**

Al Ganideh (2022), in a book chapter discussed various visualization techniques for determining the correlation between portfolio construction & its optimization. It helps the investors in effective decision-making regarding portfolio analytics & management. L. -E. Huang et al. (2022), in his study proposed a system that helps build visualizations & also analyses the portfolio performance of various stocks. This helped investors' decision-making regarding stock selection easier. The study utilized various trend ratios. Talukder & Deb (2021), studied the techniques of financial analytics & then proposed a visualization method that involved star-coordinate plots which were effective in displaying the various trade-off solutions.

It also involved the 'Pareto Race' technique to counter exploratory data & generate their analytics. Yue et al. (2020), used a multi-factor model named sPortfolio that was found to be effective in visualizing various levels of Portfolio Analytics, i.e., the Single Portfolio level, the Multiple Portfolio level & the Risk Factor level. It also presented three case studies to demonstrate their application. Simon & Turkay (2018), in their study discussed various ways to visualize dynamics related to portfolio construction & optimization. Methods like proximity swarm, multi-dimensional scaling, etc. were used for the purpose of visualization.

- **Monte Carlo Simulation in Portfolio Optimization**

Norozpour (2025) in his research, studied the mathematical optimization of the simulation parameters that are used to assess various investment options by predicting the stock prices related to the concerned option. Python codes were used for the purpose of the study. The study resulted in proving the effectiveness of Monte Carlo simulations in the prediction of the stock prices & consideration of all the factors while making investment decision-making. Andreeva et al. (2024), in their study utilized this simulation method in portfolio construction & optimization of cryptocurrencies, specifically the ones with higher market capitalization. The findings revealed that this simulation-based approach is effective in forecasting investment related decisions in the cryptocurrency market & the optimal portfolio constructed reduces the risk that has been generated on the part of the investors. Hu (2024), used machine learning & Monte Carlo Simulation as a means for portfolio optimization which involved generation of all the possible outcomes for the assessment of investment strategies. The study utilized historical data for the assessment & optimization of concerned portfolios. At the end of the study, it was observed that strategies regarding optimization like the ones that involve Sharpe Ratios were able to trade-off between risk & return. Li (2023), utilized Monte Carlo Simulation for portfolio optimization & construction of the Efficient Frontier. It also helped in drawing out weights for Maximum Sharpe Ratios as well as Minimum Variance Ratios for the assessment of portfolio performance. Timmerman (2022), investigated & assessed US-based Equity Instruments based on the Modern Portfolio Theory & utilized the Simulation Model for identifying optimal portfolios & maximize returns on those portfolios while minimizing the risk i.e., the risk-return trade-off.

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Research Article

- **Dynamic Condition Correlation (DCC-GARCH) Model to assess correlation & volatility**

Adailah et al. (2024), in their study that took place in Jordan employed the DCC-GARCH model to assess the impact of global energy price volatility on oil derivatives. The purpose of the study was also to provide risk mitigation strategies to combat the issue of price volatility within the energy sector. Findings revealed that there exists an impact of global oil prices on local oil derivative prices which in turn increases the consumer price index. Chaudhry (2024), used this model for detecting dynamic relations between selected green indices listed on the Indian Stock Exchange. The data used for this study was taken from the duration February 2018 to August 2023 and this model helped in analysing the dynamic spillover effects. It was observed at the end of the study that there is a positive impact regarding spillovers on the Indian Stock Market and also a cross-market volatility effect. Kim et al. (2022), employed this model to analyse the movements between volatility, financial factors and industrial electricity demand leading towards findings that revealed extreme tail dependence between the concerned factors. Gargallo et al. (2021), studied the co-movements between & within the energy sector that involves analysing volatility spillovers & correlations of the prices of fossil fuels. Vector Autoregressive-DCC-GARCH model was exactly used in the study which resulted in findings that revealed that there is a significant rise in the investments made in the clean energy domain & also volatility spillovers have been consistent among fossil fuels, allowances made in the European Union within the sector & energy stocks. Bauwens et al. (2011), employed this model within the power sector to assess multivariate modelling of electricity futures. It was found at the end of the study that there is a difference in the dynamics of correlation study when it came to long-term & short-term futures.

RESEARCH OBJECTIVES

The following objectives have been devised after carefully considering the relevant literature:

1. To evaluate and compare the key risk-oriented ratios of the four leading power sector companies selected for the purpose of the study.
2. To study the interrelationships between the stocks of these four companies.
3. To use advanced model like Monte Carlo Simulation for the purpose of portfolio optimization of the concerned stocks.
4. To also study the dynamic correlation structure of individual stocks using DCC-GARCH model.

RESEARCH METHODOLOGY

Data Collection

For the purpose of this study, daily stock price data was collected from the National Stock Exchange (NSE Finance, 2025) or Yahoo Finance. The data was properly screened afterwards and the opening as well as closing date were also taken into consideration.

Ratio Analysis

The following table presents the Ratio Analysis of four leading power sector companies using various risk-adjusted metrics based on performance:

Table 1: Ratio Analysis

Stock	Sharpe Ratio	Sortino Ratio (Rf=6.4%)	Calmar Ratio	Treynor Ratio	Omega Ratio
Tata Power	0.0545	0.0546	0.0701	0.0027	1.206
NTPC	0.0419	0.0423	0.0804	0.0023	1.166
ONGC	0.0213	0.0209	0.0938	0.0009	1.100
Reliance	0.0119	0.0121	0.0881	0.0002	1.079

Source: Author's Computation via R programming

AFTER THE TABULAR ANALYSIS, THESE WERE THE OBSERVATIONS THAT FOLLOWED

I. **Sharpe Ratio:** The Sharpe ratio is indeed the ratio of the excess realized or expected return of an investment versus a benchmark portfolio or a risk-free rate (numerator) to its return standard deviation over the same

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Research Article

period of time (denominator) (Anelli, 2023). The package used by R studio to calculate this ratio was *Performance Analytics* in this study. Atmaca (2022) used the following formula to calculate this ratio which as described is basically the division of residual return by risk of portfolio.

$$SharpeRatio(RVAPp) = \frac{rp - rf}{\sigma p}$$

After the analysis of all the four companies, it was observed that Tata Power was the best performer with the ratio of 0.0545 whereas Reliance was the worst (0.0119). Despite its popularity, the Sharpe ratio suffers from a methodological problem: because of the presence of random denominators in its definition and the difficulty in determining the sample size needed to achieve asymptotic normality, the Sharpe measure does not easily allow for evaluation of its own sampling distribution (Vinod & Morey, 1999). This is the rationale behind considering several other ratios in this study as seen in table 1.

II. Sortino Ratio: The Sortino ratio is a variation of the Sharpe ratio, the most universal measure of return to risk. The Sortino ratio was created in recognition of the realizations that large positive performance deviations should not be penalized in the same way as large negative performance deviations and that failing to earn the mean return is not how most investors define risk (Kidd, 2012). The numerator of the Sortino ratio is the expected return of the risky portfolio minus a defined threshold, T, and the denominator is the root of the expected squared return deviations below T. Unfortunately, where T differs from the risk-free rate, the Sortino ratio of a portfolio is affected by the risk-free vs. risky assets mix and this effect increases with the deviation of T from the riskless rate. Thus, in the case where T differs from the risk-free rate, a portfolio's Sortino ratio is sensitive to its equity level and the optimal composition of the equity components of the portfolio cannot be separated from its optimal mix between the risky and the risk-free component (Kroll, Marchioni, & Ben-Horin, 2024). The following formula was taken into consideration for the purpose of the study (Sortino & Price, 1994):

$$[\textbf{Sortino Ratio} = \frac{R_a - \textbf{MAR}}{\delta_{\textbf{MAR}}}]$$

If we consider the 5 years' data utilized for the study, Tata Power is considered the most efficient performer with the Sortino Ratio of **0.0546** and the least performer is Reliance Industries with the Sortino Ratio of **0.0121.**

This indicates that while considering the downside risk, Tata Power provides the most return per unit of the risk considered for the study.

Assumption of the risk-free rate: To incorporate a risk-free rate for the determination of Sortino ratio, the yield of a government bond is considered i.e., the yield of a free instrument as a proxy for the risk-free rate. For the purpose of this study, India 5-Year Bond Yield was taken into account which utilized as per NSE database. The monthly data was taken from the investing.com website where the lowest yield for this bond was of 4.828%, the change percent, 2.208 leading towards an average that will be used as the proxy i.e., 6.408%.

III. Calmar Ratio: The Calmar ratio (CR) was introduced by Young (1991) and it is the ratio of (CAR) to (MDD). It computes risk-adjusted returns of funds and stocks (Ghouse, Ejaz, Bhatti, & Aslam, 2022). Dombrowski, Drobetz, and Momtaz (2023) defines it as the risk based on the largest losses investors could potentially suffer. It is similar to the other ratios, but it uses max drawdown in the denominator as opposed to standard deviation (Xiao, Lin, Wu, & Sun, 2025) which measures risk as the largest return losses of CFi during the sample period; MDDi, l is CFi's largest decline (Dombrowski et al., 2023). It is calculated using the following mathematical equation (Xiao et al., 2025):

$$CR = \frac{r_i - r_f}{\textbf{MDD}}$$

After the analysis of the 5 years' data in R programming, it was found that ONGC was the best performer with a ratio of 0.0938 & Tata Power, the worst performer with the ratio of 0.0701. It hinted towards the stability shown by companies like ONGC in the long-run followed by the Reliance Industries.

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Research Article

IV. **Treynor Ratio**: Treynor Ratio is the other important and well-known performance indicator in financial literature. Treynor is called as reward to volatility and it is again one parameter measurement method. It includes residual return and beta (β) constant (Karan, 2004). β is a constant as seen below, it is calculated with the help of an index or benchmark portfolio. Treynor Ratio is calculated by division of residual return by beta of portfolio (Atmaca, 2022), presented as follows:

$$\beta = \frac{\mathbf{Cov}(i, m)}{\sigma_m^2}$$

$$\textbf{Treynor Ratio}(RVOL_p) = \frac{(r_p - r_f)}{\beta}$$

After the analysis of the power sector stocks, it was observed that Tata Power with the Treynor Ratio of 0.0027 utilized the return accumulated on excess of the risk-free rate per unit of systematic risk, i.e., Beta whereas companies like Reliance Industries, with the Treynor Ratio of 0.0002, has the worst performance.

If we talk about the usefulness of this ratio, Treynor' asset weights are different from those of the other ratios, which contributes to its unique performance & higher volatility. It also appears that Treynor can predict a somewhat unique portfolio of securities, in which a loss could quickly be recouped (Surtee & Alagidede, 2023).

V. **Omega Ratio:** Omega is a natural feature of the returns distribution. It takes into consideration the level of return against which a given outcome will be viewed as a gain or loss. It also provides additional information in situations where the returns are normally distributed (Keating & Shadwick, 2002). Basically, this ratio assesses the performance of securities against a benchmark, on one side, and it accounts for the asymmetry in returns distributions by separately considering upside and downside deviations, on the other side (Guastaroba et al., 2014).

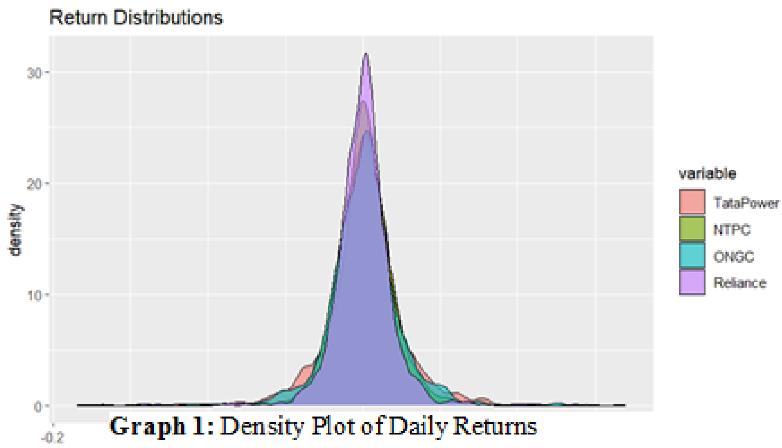
Shadwick and Keating (2002b), numerically expressed this ratio as:

$$\Omega(L) = \frac{\int_L^b [1 - F(x)]\, dx}{\int_a^L F(x)\, dx}$$

As per the analysis made in the R programming regarding this ratio, it was observed that Tata Power had the highest gain/loss ratio which was 1.206 whereas Reliance had the least, i.e., 1.079, indicating that for every loss suffered, Tata Power made the highest gain, considering the downside risk.

VISUALIZATION TECHNIQUES

Density plot of daily returns:



Graph 1: Density Plot of Daily Returns

Source: Visualization generated via R Programming

Journal of Information Systems Engineering and Management
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Research Article

The density plot of daily returns represents the log returns of the four leading Power Sector Companies, i.e., Tata Power, NTPC, ONGC & Reliance Industries where the x-axis represents the log returns & y-axis represents the density. Log returns are the changes that occur in the stock prices consistently whereas the y-axis reflects the times when variability in those returns occur. The peaks or the curves that have occurred during the analysis as depicted by the following figure, represents the four sample companies. The red curve represents Tata Power, green represents the NTPC, blue represents the ONGC whereas the Reliance Industries is indicated or represented by purple.

The interpretation of this analysis revolves around few factors, which are kurtosis, nature of distributions and inter-firm comparison. (Pearson, 1905) introduced kurtosis as a measure of how flat the top of a symmetric distribution is when compared to a normal distribution of the same variance. The graph 1 exhibits some high peaks indicating towards leptokurtosis which is denoted by properties of having higher peaks and fatter tails. The presence of leptokurtosis is typical in studies of financial returns. In other words, the empirical data reveal greater peakedness than in the normal distribution, or to put it another way, the empirical distribution has fatter tails than the Gaussian model (López Martín, García García, & García Pérez, 2012). This indicates that instead of having stability in terms of their returns, these companies are having either extreme positive or extreme negative returns. If we look at the nature of distributions, it can be interpreted that all the four distributions exhibit similar characteristics of forming a cluster near 0%. It indicates that the extreme positive or negative returns indicated by kurtosis are balanced and the returns are usually smaller and no abnormal behavior is accounted in the market during the concerned period. The last factor that needs to be taken into consideration is the comparison between the selected companies. It is evident from the graph that the companies are moreover similar in nature but there can be very minute differences if carefully assessed. These differences are briefly explained in the following points:

I. Reliance (purple) has the tallest peak and also the narrowest which indicates that its daily returns are mostly concentrated around 0% and has a lower volatility of **0.297** which has been assessed in the later parts of this study.

II. Tata Power (red) and ONGC (blue) are having distributions which are more scattered or flattered in comparison to Reliance Industries which implies that they have a higher volatility and are more likely to have more possibilities of higher returns.

III. NTPC (green) shows behaviors in somewhat middle of what we have previously observed. It has a moderate peak and flatter tails.

These observations are critical in creating and implementing portfolio diversification & management strategies.

After the analysis of density plot, let's understand the cumulative returns which has been shown by these four companies in the selected duration of 5 years.

Cumulative Returns (2020-2025): The cumulative returns chart shown in the figure below indicates the performance of four major companies, i.e., Tata Power, NTPC, ONGC & Reliance showcasing the trends and patterns observed over the selected 5 years. The y-axis denotes the cumulative returns whereas the x-axis denotes the trading sessions or the number of days on which the stocks were traded throughout these five years. **The following observations were made after charting the returns of above-mentioned companies:**

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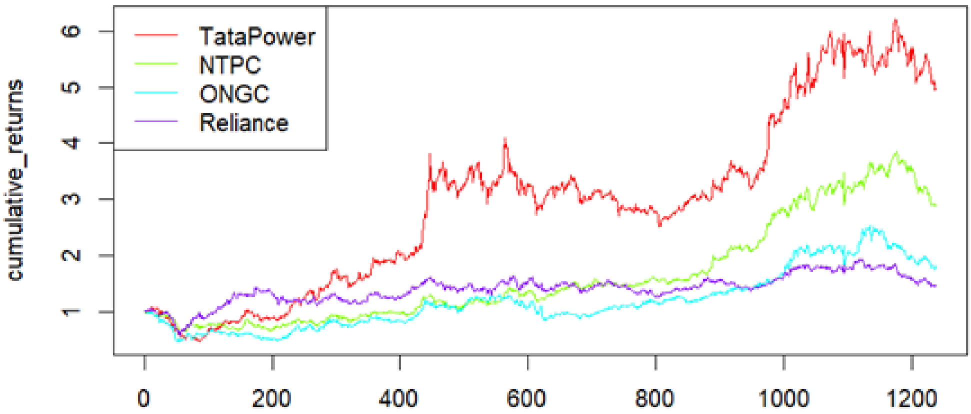
https://www.jisem-journal.com/

Research Article



Graph 2: Cumulative Returns

Source: Visualization generated via R Programming

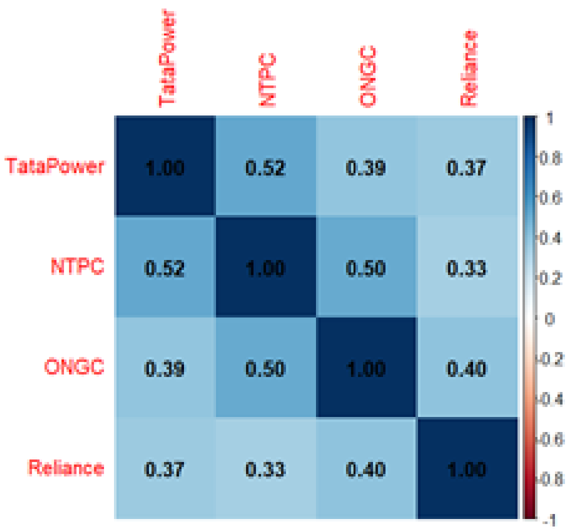
i. Tata Power has outperformed the other three companies as denoted by the red line in the chart. Its growth can be clearly seen through the multiple peaks it has achieved, one during the 410th session, another one approximately at the 600th and the highest peak nearly at the 1100th. Graph 2 indicates that Tata Power has implemented some of the best strategies in the aftermath of the pandemic.

ii. NTPC, which has been denoted by the green line has peaked in the later stages on the cumulative returns chart indicating that post pandemic, it has aligned its strategies with the dimensions and domains of sustainability by employing such technologies that reduces the carbon emissions produced in the power plants of such companies.

iii. ONGC and Reliance have shown a similar trend exhibiting lesser returns in comparison to the other companies. It can be attributed to the traditional methods of operations in such companies.

It has been clearly depicted through this chart that the companies that have adapted according to the needs of the environment have flourished whereas the less adaptive companies have shown stable but minimum growth. This chart becomes an essential factor in determining long-term investment decisions by the concerned investors.

CORRELATION OF STOCK RETURNS



The correlation heatmap shown in the figure alongside presents the relationships among the stocks of four major power sector companies, i.e., Tata Power, NTPC, ONGC and the Reliance Industries. The correlation coefficient is a statistical measure often used in studies to show an association between variables or look at the agreement between two methods (Janse et al., 2021). As we are certainly aware that the correlation coefficients range from -1 to +1 indicating whether the selected stocks in this case move in a similar, i.e., positive manner or in the opposite, i.e., in a negative manner. These degrees of correlation are arranged in the following manner as cited by Haldun Akoglu (2018) in his study as seen in table 2.

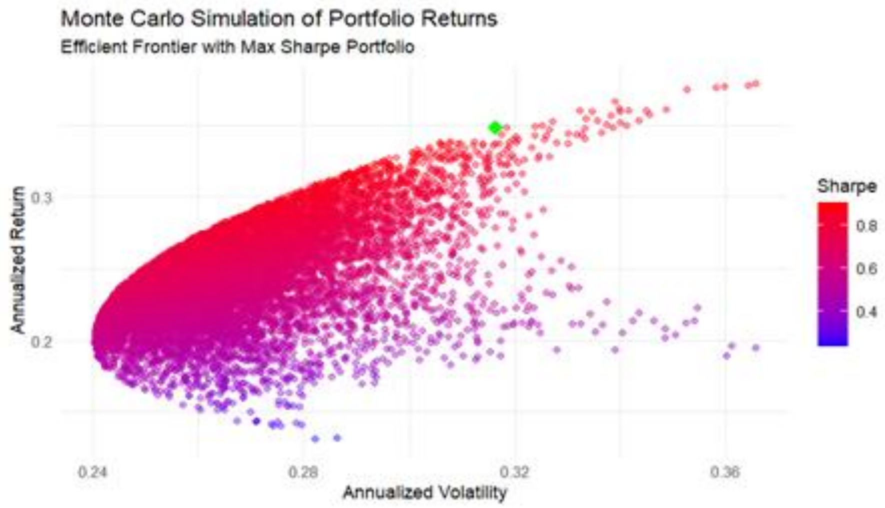
Interpretation of the correlation coefficient (Dancey & Reidy, 2007): +1, -1 indicates perfect positive/negative correlation. Strong positive/negative correlation is indicated by **+0.7 to +0.99** and **-0.7 to -0.99**. Moderate positive/negative correlation is indicated by **+0.4 to +0.69** and **-0.4 to -0.69** whereas weak positive/negative correlation is indicated by **+0.1 to +0.39** and **-0.1 to -0.39**. Finally, **0** denotes zero correlation.

During the correlation analysis of the companies, Tata Power was considered the proxy & a perfect positive correlation was observed diagonally as we look at the matrix. It also helps us to understand the dynamics between the other 3 companies and the proxy company & also an inter-connection between them. The strongest correlation can be observed between NTPC & Tata Power which is **0.52**. This moderate positive correlation between these two companies has been due to the similarities that has risen from their strategic & operational framework. Their plans and policies have been synchronized and visible in somewhat similar stock patterns & behaviours. ONGC has a weak positive correlation of **0.39** with Tata Power, moderate positive correlation of **0.50** with NTPC & **0.40** with Reliance indicating that correlation starts declining as soon as we move towards a renewable energy stock from a traditional energy stock. Reliance Industries exhibits a weaker correlation with all the other companies making Reliance a very unique stock as compared to others. This could benefit the other companies in terms of diversification as Reliance becomes that company which can survive in such market conditions where other might fail.

Overall, the correlation heatmap presents the investors' an opportunity to invest in a variety of stocks with reduced systematic risk leading to portfolio avenues offering better returns.

PORTFOLIO OPTIMIZATION

Efficient Frontier (Monte Carlo Simulation):



Graph 3: Evaluation and Assessment the optimal risk return.

Monte Carlo Simulation is an established method for evaluating the effects of uncertain ties and used as a tool to quantify risks (Maggauer & Fina, 2025).

It has been used in this study as shown in the Figure to evaluate & assess the optimal risk-return tradeoff concerning the four major companies of the Power Sector, i.e., Tata Power, NTPC, ONGC & Reliance Industries. The dataset was taken from Yahoo Finance, as mentioned earlier & of 5 years as seen in graph 3.

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Research Article

Table 3: Annual sharp ratio of the risk and return of the stocks.

Companies	Annualized Volatility	Annualized Returns
Tata Power	0.393	0.404
NTPC	0.295	0.261
ONGC	0.387	0.195
Reliance Industries	0.297	0.120

The Simulation was basically used not only to provide an optimal portfolio as shown in the Table 1 but also to create an efficient frontier that is helpful in maximizing the Sharpe Ratio as shown in the following table 3:

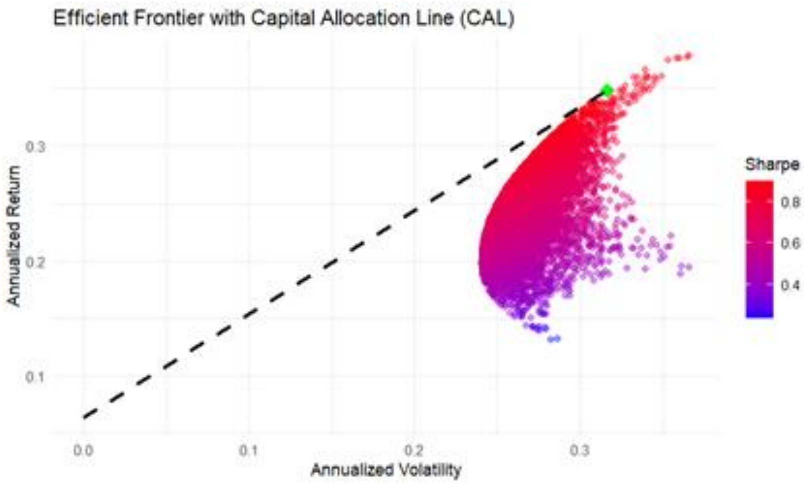
As we know that Sharpe Ratio provides a wholesome picture of the risk & return, it eventually becomes an essential indicator of these simulations. The simulation was also able to generate multiple possibilities regarding the combination of these stocks & weights were also assigned to them. To design the optimum portfolio for these stocks, the following weights were assigned along with the highest Sharpe Ratio which was 0.899 to be precise:

Tata Power was allocated **62.47%** of the portfolio whereas NTPC was allocated **35.35%**, ONGC **1.38%** & **0.84%** was allocated to Reliance Industries. The annualized return & volatility yielded by this combination of stocks were **34.83%** & **31.63%** respectively. If we assume the individual data points for the study & their comparison, the following information is revealed as indicated in the Table 3:

i. Tata Power has outperformed the other three companies by displaying annualized return of **40.4%** and volatility of **39.3%**. NTPC followed a similar trail by exhibiting annualized returns of **26.1%** and a lower volatility of **29.5%**.

ii. ONGC showed the possibility of modest returns of **19.5%** and volatility of **38.7%** whereas Reliance Industries displayed a minimal annualized return of **12%** and volatility of **29.7%**.

These findings suggest that although there are chances of higher risk, if found a suitable combination of securities, it can provide the investors, an opportunity to maximize their returns.



Graph 4: Representation of the risk-return profile of a portfolio on a line.

The Capital Allocation Line is the graphical representation of the risk-return profile of a portfolio on a line. It helps the investor identify the most fruitful combination of securities that increases their return but not the risk. The Sharpe Ratio of 0.899 generated using the simulation points out the most desirous portfolio or the combination of securities.

This analysis helps not only in visualization of multiple securities but also the possibilities of attaining more and more return on minimal risky ventures. The investors who are interested in seeking such opportunities can

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certainly use this simulation technique to strengthen their decision-making potential when it comes to investing in power sector companies as shown in graph 4.

DYNAMIC CONDITIONAL CORRELATION (DCC-GARCH)

The family of Generalized AutoRegressive Conditional Heteroscedastic (GARCH) models has been developed for financial time series analysis (Bauwens et al., 2006; Engle, 2004). Among the multi variate GARCH models, the dynamic conditional correlation (DCC) GARCH model gained substantial attention for estimating time varying correlations (Engle, 2002; Tse and Tsui, 2002).

This model allows obtaining time-varying dynamic conditional correlation coefficients between variables and provides more detailed information in the analysis of time-dependent co-movements compared to the unconditional correlation analysis. The DCC-GARCH model is considered a powerful model because it explains the time-varying volatility spillovers between commodity assets as well as providing information about the volatility of the assets (Yıldırım, Esen, & Ertuğrul, 2022).

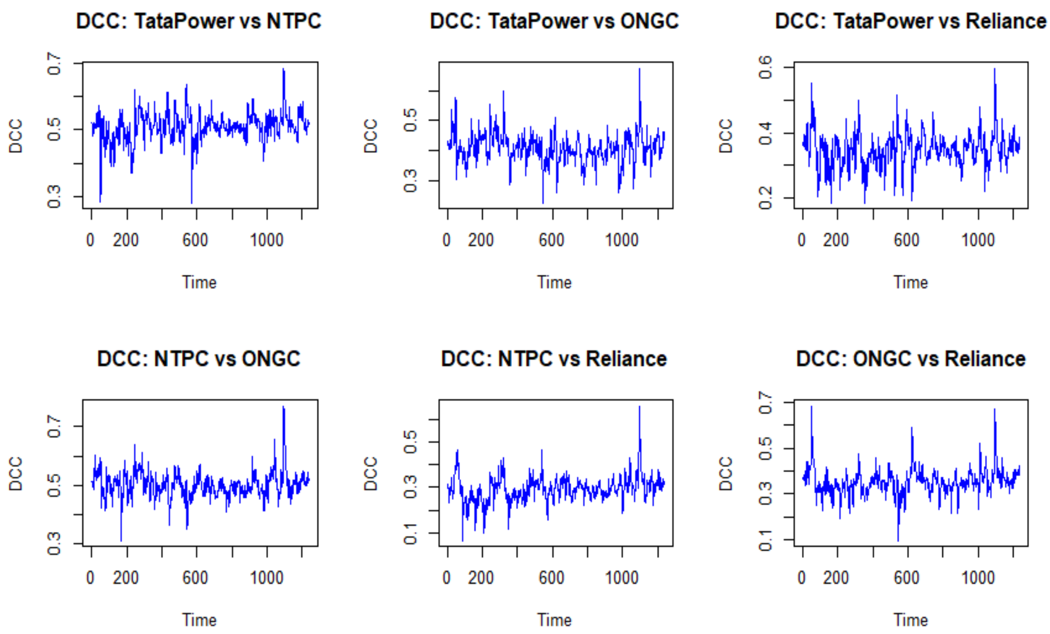

Figure 1: DCC-GARCH Model

Source: Author's computation via R Programming

As it can be observed in several cases that the DCC-GARCH model has been effective in providing insights regarding correlations of and between the selected stocks. In this study, the selected stocks are Tata Power, NTPC, ONGC and Reliance and after applying this model with the help of R programming where the selected codes where rugarch (for the purpose of the study of univariate data) & rmgarch (for the purpose of the study of multivariate data, as applied in this study), the following observations have been generated:

Note: These observations have been portrayed in the above Figure 3.

i. Tata Power & NTPC, both have become a major hub dealing in the Power Sector with the help of green technologies in the recent years, showing stable and high dynamic conditional correlation, i.e., between 0.3 and 0.7 which suggests that they have been moving in the similar direction generating similar reactions from their investors.

ii. The relationships of Tata Power with ONGC and Reliance have been shown between 0.2 to 0.6 and between 0.1 to 0.5 indicating towards a positive but volatile correlation supported by macroeconomic agents or external factors as these companies are not completely but partially aligned with each other.

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iii. The traditional stocks like ONGC and Reliance have shown correlations within values that ranges from 0.1 to 0.7. These variances have possibly occurred due to shocks and waves happening in the market as well as the impact that Reliance has on it as a business model that supports diversification in the form of operations carried by them over the years.

This dynamic structure shown by the DCC-GARCH model point out the interplay between these stocks specifically the connection between Tata Power and NTPC, both being the companies occupying a larger share of the market when it comes to the Power Sector. Whereas the structure posed by ONGC and Reliance has shown inconsistencies and variations which has arrived possibly due to differences owing to policies creation and adoption and also due to their traditional moves and motives. The relationship between NTPC and reliance offers investors, an opportunity to mint money through diversified as well as balanced portfolio providing more and more return with less systematic risk.

It seems like all the energy firms despite listed on exchanges as green or brown stocks or both are moving together in a similar direction but in reality, due to their innate structural differences, they are offering diversification as well as hedging benefits providing the investors, means to counter or reduce systematic risk as denoted by beta & shown in the section of the Ratio Analysis. The spike patterns shown in the DCC graph have been attributed due to the Covid-19 pandemic which presents the transition regarding pre & post Covid. This transition has been effectively captured by DCC-GARCH model which also proves the significance of this model in assessing real-time data. These interpretations also point out towards the need of having adaptive portfolio strategies as the market isn't static & is constantly affected by extraneous factors.

Overall, the DCC-GARCH model reveals a complex but understandable side of the stock market dynamics. It also presents an inter-firm similarities & differences and derives insight from the multi-variate analysis which was conducted using a 5-year market data (collected from Yahoo Finance database) employing & merging individual points & then plotting it onto a graph. It also reveals that some stocks follow a similar trail due to their similarities while others run parallel to each other & also display a higher level of independence.

This was the complete interpretation of the analysis.

FINDINGS & DISCUSSION

The evolution of financial analytics over the past decade has significantly transformed the methodologies and tools available for investment analysis and portfolio management. This discussion explores the implications of emerging techniques particularly stochastic optimization, simulation modeling, data visualization, and econometric frameworks within both traditional and modern financial contexts. By integrating these advancements, financial practitioners can better navigate the intricate dynamics of global markets, make data-driven decisions, and respond proactively to uncertainties. One of the most prominent themes in recent literature is the shift from static financial models toward dynamic, scenario-based approaches. While traditional tools such as the Markowitz Efficient Frontier continue to provide critical theoretical insights into risk-return optimization, their assumptions of normal distribution and linearity are often incompatible with today's turbulent market behavior. In response, stochastic optimization models have gained traction due to their ability to incorporate randomness, adapt to shifting input variables, and produce a more realistic set of portfolio outcomes. By modeling uncertainty directly, these approaches are particularly suited for volatile environments and allow for a higher degree of robustness in strategic asset allocation. Closely tied to stochastic modeling is the use of simulation techniques, especially Monte Carlo simulation, which has become a cornerstone in financial forecasting. Monte Carlo methods enable analysts to simulate thousands of potential outcomes for a portfolio under varying conditions of asset return, volatility, and correlation. This capacity for probabilistic modeling enhances stress-testing and scenario analysis, thereby allowing investors to better assess downside risk and tail events. The flexibility of simulation techniques makes them highly applicable not only to equity portfolios but also to derivatives pricing, fixed-income investments, and structured products.

A complementary development is the increasing reliance on machine learning (ML) algorithms in both forecasting and optimization tasks. ML techniques such as support vector machines, neural networks, and random forests have demonstrated significant improvements in predicting asset returns, detecting market anomalies, and automating

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trading strategies. Unlike traditional econometric models, which require a priori assumptions about relationships between variables, machine learning models can uncover complex, nonlinear patterns from large datasets. Their integration with other financial analytics tools provides a hybrid approach that balances theory-driven and data-driven insights. Advanced data visualization represents another major breakthrough in financial analytics. As the volume and dimensionality of financial data continue to expand, conventional visualization tools often fall short in providing clarity. Modern visualization platforms such as star-coordinate plots, Pareto Race systems, and interactive dashboards like sPortfolio offer intuitive, multi-dimensional views of data. These tools not only assist in interpreting complex trade-offs in portfolio optimization but also enhance stakeholder communication, particularly in institutional settings where investment decisions involve collaboration across teams. Visualization thus serves as a vital link between quantitative analysis and strategic planning.

Among the most rigorous statistical frameworks employed in modern finance is the DCC-GARCH model, which has been widely adopted for analyzing time-varying volatility and dynamic correlations between assets. The model's strength lies in its ability to update estimates in real time, providing a more accurate depiction of market interdependencies. This capability is especially relevant in the energy and power sectors, where geopolitical events, policy changes, and supply chain disruptions can lead to rapid shifts in asset behavior. By capturing these intertemporal relationships, DCC-GARCH models facilitate more precise hedging strategies, volatility forecasting, and capital allocation decisions. In practice, these tools are supported by an array of performance metrics that remain fundamental to risk management. The Sharpe Ratio, Beta, Jensen's Alpha, and Value at Risk (VaR) continue to serve as standardized benchmarks for evaluating the efficiency and risk-adjusted returns of portfolios. However, their role has expanded as they are now embedded within more sophisticated, often machine-assisted, optimization frameworks. These metrics not only provide historical performance evaluation but also serve as constraints or objectives within optimization algorithms, guiding strategy development in real time.

The versatility of financial analytics frameworks is further demonstrated by their application to emerging asset classes, most notably cryptocurrencies. Given the decentralized, volatile, and often speculative nature of digital assets, traditional risk modeling techniques struggle to provide reliable insights. In contrast, adaptive models enhanced by machine learning and real-time data feeds have proven more effective in capturing the unique behaviors of crypto markets. Portfolio optimization in this domain benefits from tools that account for liquidity risk, sentiment analysis, and blockchain-specific metrics, offering a blueprint for expanding financial analytics into previously underserved areas.

Overall, the convergence of these advanced tools suggests a new paradigm in financial decision-making—one that is proactive, flexible, and integrative. Rather than relying solely on historical data or static models, contemporary financial analytics emphasize responsiveness to real-time information, the fusion of qualitative and quantitative analysis, and the enhancement of user engagement through interactive platforms. This integrated approach not only improves the accuracy and efficiency of investment decisions but also democratizes access to sophisticated analytics by making them more interpretable and actionable. Moreover, as regulatory environments tighten and investor expectations evolve, the role of transparent, data-driven financial tools becomes even more critical. Stakeholders including fund managers, analysts, and policymakers must increasingly justify their decisions based on empirical evidence, robust simulations, and forward-looking risk assessments. Financial analytics, therefore, is no longer a supplementary function but a core strategic capability. In conclusion, the body of research reviewed in this paper illustrates how the fusion of traditional financial theory with modern computational techniques is reshaping the landscape of investment analysis. Tools such as stochastic optimization, Monte Carlo simulations, and the DCC-GARCH model, when combined with effective visualization and machine learning capabilities, empower financial professionals to make more informed, responsive, and resilient decisions. As the financial world continues to evolve, the continued integration of these tools into everyday practice will be key to navigating uncertainty and achieving sustainable investment outcomes.

CONCLUSION

The growing complexity and volatility of global financial markets have necessitated a fundamental shift in how investment analysis and portfolio management are conducted. This review highlights the transformative role of advanced financial analytics, showcasing how a convergence of modern methodologies including stochastic optimization, Monte Carlo simulations, machine learning algorithms, and advanced visualization tools has redefined traditional investment frameworks. These innovations not only address the limitations of static models but also offer adaptive, data-driven approaches capable of responding to real-time market dynamics.Stochastic optimization models have proven particularly effective in managing uncertainty, enabling more robust portfolio construction by accounting for variability in inputs such as asset returns and volatilities. In parallel, simulation-based approaches, most notably Monte Carlo methods, have become indispensable in stress-testing portfolios and evaluating potential future scenarios. These techniques offer investors deeper insights into risk exposure and help ensure greater resilience against market shocks.

Machine learning has further enhanced financial decision-making by uncovering complex patterns in large and unstructured datasets. Its integration into forecasting and optimization processes supports dynamic investment strategies that can evolve alongside changing economic conditions. Likewise, the rise of multi-dimensional visualization tools has improved the interpretability of complex financial data, bridging the gap between quantitative analysis and strategic execution. Tools like sPortfolio and star-coordinate plots allow stakeholders to visually explore risk-return trade-offs, making investment decision-making more transparent and inclusive.

Econometric models such as the DCC-GARCH framework provide additional depth to risk assessment by capturing time-varying correlations and volatility clustering, especially within sensitive sectors like energy and power. Moreover, the integration of performance metrics such as Sharpe Ratio, VaR, Beta, and Jensen's Alpha into modern computational environments further refines investment evaluation and strategy alignment. Importantly, the adaptability of these tools extends to emerging markets and asset classes, particularly in the realm of cryptocurrencies, where conventional models often fail. The combination of machine learning, real-time analytics, and blockchain-specific insights positions financial analytics as a forward-looking discipline capable of meeting the demands of evolving financial ecosystems. In summary, the fusion of classical financial theory with cutting-edge computational techniques marks a paradigm shift toward more resilient, informed, and proactive investment strategies. As global markets continue to evolve, the strategic implementation of these advanced analytical tools will be essential for navigating uncertainty and sustaining long-term financial performance.

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