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THE INFLUENCE OF GREENHOUSE GAS EMISSIONS AND RESOURCE EFFICIENCY ON STOCK PRICE VOLATILITY: EVIDENCE FROM NIFTY 100 FIRMS

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ABSTRACT
This research explores the influence of greenhouse gas emissions and resource efficiency on stock market volatility among firms in the Nifty 100 index. By employing a least squares regression model on cross-sectional data from 2023-24, the study aims to understand how environmental performance affects firm-level volatility. The findings reveal a significant inverse relationship between both greenhouse gas emissions and resource efficiency with volatility, suggesting that firms with better environmental practices exhibit reduced stock price fluctuations. These results emphasize the critical role of sustainability in enhancing market stability and reducing financial risks. The research provides important insights for investors, corporate managers, and policymakers, underscoring the need for integrating environmental responsibility into financial decision-making to promote long-term market resilience.

KEYWORDS: *Volatility, GHG emissions, Resource efficiency, Nifty 100*

I. INTRODUCTION

Volatility is a crucial concept in financial markets, significantly impacting investment decisions, risk management, and overall market dynamics (Rohilla, 2023). It plays a vital role in areas like portfolio management and asset pricing, and is also important for meeting regulatory requirements (Opschoor, 2009). A comprehensive understanding of volatility is essential for making informed decisions in the financial sector, as it exhibits clustering behavior and is key to effective risk management and asset allocation (Vagif & Rustamov, 2024). A closer look at the Nifty 100 index—comprising firms that account for over 70% of India's market capitalization—reveals that individual firms exhibit varying levels of volatility, with some demonstrating greater stability than others (Kumar & Gupta, 2009). This index not only reflects the performance of its constituent firms but also serves as an important indicator of the overall health of the Indian economy (Chinnaiah.P.M, 2020; Majumdar & Saha, 2018). In recent years, corporate sustainability has shifted from being a peripheral concern to a core focus within business strategy and academic research (Diermeier & Dowell, 2015). This growing emphasis on environmental sustainability is driven by global challenges, changing expectations from stakeholders, and the necessity for responsible business practices (Mishra, 2023). As companies recognize the importance of integrating environmental, social, and governance (ESG) principles into their operations, they are better positioned to tackle pressing issues and ensure long-term success (Mishra, 2023). The rise in interest towards corporate environmental responsibility has been gradual but significant, especially since the 1980s (Ulhøi et al., 1996). Corporate Social Responsibility (CSR) plays a pivotal role in facilitating environmental sustainability initiatives, helping companies balance profit motives with societal obligations (Pathania & Rastogi, 2024). Understanding the links between resource efficiency, emissions, and volatility is vital for stakeholders aiming to maximize benefits and minimize risks in energy markets (M. Doğan et al., 2023). Moreover, this exploration can contribute to achieving macroeconomic stability through a "just transition" that supports both economic growth and environmental sustainability (Murat Can Genç et al., 2021). Additionally, examining how resource efficiency and emissions relate to volatility can enhance the competitive advantage of firms that possess dynamic capabilities, especially in highly volatile environments (Lei-Yu Wu et al., 2010).

II. LITERATURE REVIEW

Traditional drivers of firm volatility include market conditions and economic factors. Market volatility significantly affects firm volatility across most sectors, with larger firms showing stronger commonality (Narayan et al., 2014). Economic factors such as uncertainty about price levels, interest rates, risk premiums, and profit-torevenue ratios explain a substantial portion of market volatility (Binder & Merges, 2000). The impact of news-related volatility varies across firm characteristics and industries, highlighting the importance of firm-specific information in driving stock price movements. Environmental factors significantly influence stock market volatility. Climate conditions, natural disasters, and carbon dioxide emissions demonstrate a significant relationship with stock price fluctuations (Chaudhuri et al., 2022). Environmental disclosure practices, including energy policy, impact of biodiversity, and firm size, have been found to have significant effects on stock market return volatility in Nigeria (Obida et al., 2019). Additionally, economic factors such as uncertainty about the price level, riskless interest rate, equity risk premium, and the ratio of expected profits to revenues explain a substantial portion of stock market volatility (Binder & Merges, 2000). Sustainability reporting has positive short-term and long-term impacts on stock market valuation (Du S. et al., 2017). These studies collectively highlight the importance of environmental and economic factors in determining stock market stability and volatility, emphasizing the need for consistent environmental disclosure standards and consideration of these factors in financial decision-making. Improved environmental management systems and performance result in reductions in firms' beta, which contributes to stock volatility (G. Halkos et al., 2007). Non-financial environmental, social, and governance (ESG) sustainability performance factors are positively associated with idiosyncratic volatility, especially when economic performance is weaker. (A. C. Ng et al., 2020). Recent studies have explored the relationship between greenhouse gas (GHG) emissions and stock market volatility. A global study of 50 countries revealed that lower CO2 and other GHG emissions are negatively associated with stock market volatility (Aharon et al., 2024). In China, volatility spillover effects were observed from regional carbon prices to stock prices of companies regulated by emission trading markets (Ma et al., 2024). At the firm level, carbon productivity was found to be negatively associated with total and idiosyncratic volatilities in U.S. companies, particularly after the implementation of binding intergovernmental regulations like the Paris Agreement (Jung et al., 2023). These findings collectively suggest that carbon risk is priced into financial markets and that reducing emissions could potentially lead to more stable equity markets. Positive and negative shocks in stock markets reduce carbon emissions, while positive and negative shocks in exchange rate volatility have a positive significant effect on carbon emissions in Pakistan (Sana Ullah et al., 2020). Stock market index price (MSCI) has a negative relationship on CO2 emissions in India (Younis, I et al., 2021). Volatility in regional carbon prices positively impacts the stock volatility of companies in the corresponding emission trading region in China (Jinwang Ma, 2024). Stocks of firms with higher carbon emissions earn higher returns, suggesting investors demand compensation for carbon emission risk (P. Bolton. Et al., 2020). Carbon price changes have a positive and significant effect on stock market returns in all four industries studied, except for the oil & gas industry (Scholtens, B., & Goot, F., 2014). India is the second-largest emitter of black carbon in the world, with emissions projected to rise steadily in the coming decades (Rana, A., Jia, S., & Sarkar, S., 2019).

Recent studies have explored the interconnections between water, energy, and financial markets. Research has shown significant volatility spillovers between water, energy, and food sectors, particularly during the 2008 crisis (Peri et al., 2017). Energy companies' water management policies have been found to influence volatility integration with natural gas markets, but not with oil markets (Gormus & Harrell, 2024). Additionally, firms with higher energy efficiency tend to have higher stock market valuations and lower stock return volatility (Jadiyappa & Krishnankutty, 2022). Research has shown strong bidirectional volatility transmission between energy funds and natural gas prices, with water management policies influencing this integration (Gormus & Harrell, 2024). Energy-related uncertainty indexes predict stock market volatility (Salisu, A.A., 2024).

Resource depletion theory posits that as finite resources are depleted, production costs increase, leading to higher prices and reduced economic growth (Hardin G., 1968). This, in turn, can affect stock market volatility as investors become uncertain about future profits and economic stability. Climate change, driven by greenhouse gas emissions, poses significant risks to various industries and economies. As the impacts of climate change become more severe, investors may become increasingly concerned about the long-term viability of businesses that are vulnerable to climate-related risks. This can lead to increased stock market volatility (Stern N., 2006). Systemic risk refers to the risk of a widespread collapse of the financial system. Extreme events, such as climate-related disasters or resource shortages, can have a cascading effect on the economy and financial markets, leading to increased volatility (Financial Stability Board., (2021). Studies also found that not all eco-strategies are positively related to better performance, at least not in the short term (Jové-Llopis, et al.,2018). Most industries have no significant relationships between eco-efficiency and financial performance (Suh, Y et al., 2014).

The literature on resource efficiency, emissions, and stock market volatility reveals critical research gaps. Most studies focus on global or developed markets, neglecting firms within the Nifty 100 index, which hinders localized strategy development. Additionally, there is a methodological gap regarding the integration of environmental performance metrics, such as resource efficiency and emission changes, in understanding their collective impact

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on volatility. Lastly, a lack of sector-specific analysis prevents a comprehensive understanding of how different industries within the Nifty 100 respond to resource efficiency and emissions changes. Hence, this research aims to examine the impact of resource efficiency and emissions on stock market volatility within the Nifty 100 index firms, addressing the gaps in existing literature that largely focuses on global or developed markets. This study aims to integrate environmental performance metrics, such as resource efficiency and emission changes, to analyse their collective influence on market volatility.

III. METHODOLOGY

This study employs a quantitative approach to investigate the relationship between environmental factors, specifically GHG emissions and resource efficiency, and stock price volatility in Nifty 100 firms. The research is based on cross-sectional data for the year 2023-24, focusing on the influence of these independent variables on firm-specific volatility. By collecting data from reliable financial and environmental sources, this study aims to assess the impact of emissions score and resource efficiency score on stock price volatility. The sample consists of firms listed on the Nifty 100 index, which represents the top 100 companies by market capitalization in the National Stock Exchange of India (NSE). These firms were chosen for their significant economic influence and availability of relevant financial and environmental data. Volatility data were sourced from Yahoo Finance. The volatility for each firm was calculated using daily stock price fluctuations, which were then aggregated to derive the annual volatility for the 2023-24 period. This measure reflects the market risk and uncertainty faced by each company. Data on GHG emission score, which represents reduction in greenhouse gas emissions and carbon footprint, were obtained from the London Stock Exchange (LSE) website. Similarly, Resource efficiency score, representing the reduced energy consumption and water usage, were also collected from the LSE website, reflecting each firm's total resource utilization during the same period. The analysis used a multiple regression model to evaluate the relationship between the independent variables (GHG emissions and resource efficiency) and the dependent variable (Volatility). The regression model is structured as follows:

$$\textbf{Volatility} = \beta 0 + \beta 1 * \textbf{GHG Emissions} + \beta 2 * \textbf{Resource Efficiency} + \epsilon$$

The intercept term, β0, indicates the baseline volatility when both emissions and resource efficiency are at zero levels. The coefficient β1 measures the impact of emissions on volatility, showing how changes in emissions affect the stock market's stability. Similarly, β2 represents the relationship between resource efficiency and volatility, indicating the influence of resource consumption on market fluctuations. GHG Emissions score (Matsumura E.M et al., 2014), (Hardiyansah, M et al., 2021) and Resource efficiency score (Leung W.S. et al., 2014), (Choi B et al., 2017) are the independent variables in this model, while ϵ is the error term, accounting for any unexplained variations in volatility that cannot be attributed to emissions or resource efficiency.

Three null hypotheses were formulated for this study. The first null hypothesis posits that there is no significant relationship between emissions score and stock volatility, implying that higher emissions do not have a measurable effect on market volatility. The second null hypothesis suggests that resource efficiency score does not significantly influence stock volatility, indicating that variations in resource management have no impact on market stability. The third null hypothesis proposes that the combined effect of emissions score and resource efficiency score does not significantly affect stock volatility, meaning the interaction between these environmental factors does not contribute to any notable change in market behaviour.

Table – 1 (Descriptive Statistics)

	Volatility	Resource Efficiency Score	GHG Emission Score
Mean	33.96	74.38	79.74
Median	29.5	79.5	86.5
Maximum	70	100	100
Minimum	22	22	18
Std. Dev.	11.7	21.8	21.4

The descriptive statistics summarize the volatility, resource efficiency, and GHG emissions scores for Nifty 100 firms. Volatility has a mean of 33.96 and a standard deviation of 11.71, with a range from 22 to 70, indicating moderate variability. Resource efficiency has a mean of 74.38 and a larger standard deviation of 21.82, ranging from 22 to 100, reflecting significant differences in resource utilization. The GHG emissions score shows a mean of 79.74, with a minimum of 18 and a maximum of 100, and a standard deviation of 21.35, highlighting diverse environmental impacts among the firms.

IV. EMPIRICAL RESULT

The Variance Inflation Factor (VIF) is a widely used measure for detecting collinearity in multiple linear regression (Román Gómez et al., 2016). The Centred Variance Inflation Factors (CVIF) for both Resource efficiency and GHG Emissions are found to be approximately 3, indicating a moderate level of multicollinearity between these independent variables. According to Menard (2002), a VIF value greater than 5 raises concerns, while values exceeding 10 suggest a serious collinearity problem. Since the CVIF values in this analysis are below the threshold of 5, there is no immediate cause for concern regarding multicollinearity in this regression model. This moderate correlation implies that while Resource efficiency and GHG emissions may share some common variance, they are not overly correlated to the extent that it would compromise the stability or interpretability of the regression coefficients. Therefore, the model can proceed without significant adjustments for multicollinearity. A Durbin-Watson (DW) statistic of 2.09 indicates a slight deviation from the ideal value of 2, which suggests that there is no autocorrelation present in the residuals of your regression model. According to Turner (2020), a DW statistic that is approximately 2 signifies the absence of autocorrelation, meaning that the residuals are not correlated with each other over time. The p-value associated with the F-statistic is 0.2590, which is greater than the common significance level of 0.05. This means we fail to reject the null hypothesis of homoskedasticity. In other words, there is no strong evidence of heteroskedasticity in your model based on this test. suggesting that the residuals have constant variance.

Table-2 - Result (OLS Model)

Dependent Variable: Volatility				
Method: Least Squares				
Sample: 1 100				
Included observations: 100				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
GHG emissions	-2.331	0.068	-3.41	0.000
Resource efficiency	-1.928	0.066	-2.91	0.005
C	36.746	3.065	21.78	0.000
Model Summery				
R-squared	0.652	Mean dependent var		33.96
Adjusted R-squared	0.643	S.D. dependent var		11.71
S.E. of regression	7.825	Akaike info criterion		6.98
Sum squared resid	5939.517	Schwarz criterion		7.06
Log likelihood	-346.104	Hannan-Quinn criter.		7.01
F-statistic	62.258	Durbin-Watson stat		2.099
Prob(F-statistic)	0.000			

The results from the least squares regression analysis provide valuable insights into the relationship between GHG emissions score, resource efficiency score, and stock volatility for the Nifty 100 firms. The coefficient for GHG emissions is -2.331, resulting in a p-value of 0.000. This indicates a statistically significant negative relationship between GHG emissions score and stock volatility. Specifically, for each unit increase in GHG emissions score, stock volatility decreases by approximately 2.331 units, suggesting that higher GHG emissions are associated with lower market volatility for these firms. The coefficient for resource efficiency is 1.928, with a standard error of 0.066 and a t-statistic of -2.91, resulting in a p-value of 0.005. This also suggests a statistically significant negative relationship at the 5% significance level, an increase in resource efficiency score is associated with a decrease in stock volatility by about 1.928 units. This indicates that more efficient resource management contributes to lower market fluctuations among Nifty 100 firms. The model's R-squared value is 0.652, indicating that approximately 65.2% of the variance in stock volatility can be explained by the independent variables. The adjusted R-squared value of 0.643 indicates that the model has a good fit after adjusting for the number of predictors. The F-statistic of 62.258 (with a p-value of 0.000) indicates that the overall model is statistically significant, rejecting the null hypothesis that the model coefficients are equal to zero.

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Figure – 1 (CUSUM Test)

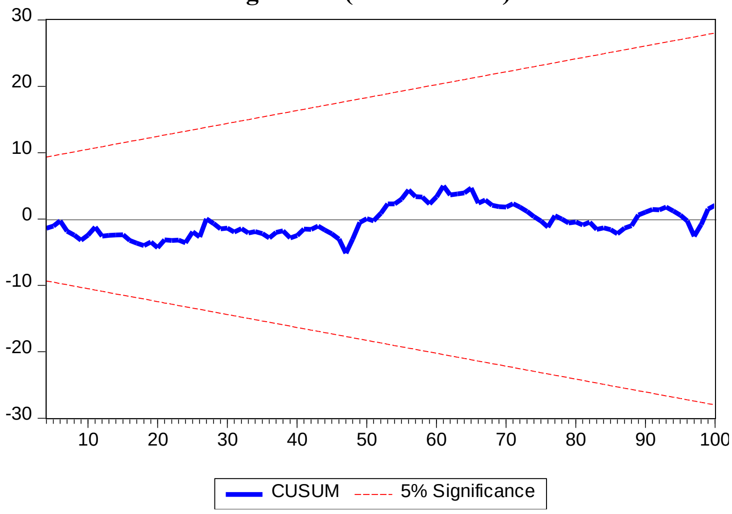
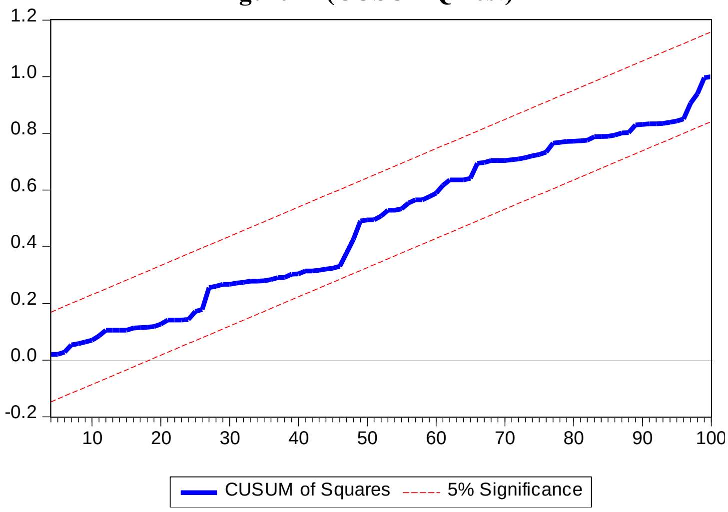


Figure -2 (CUSUMQ Test)



The results of the CUSUM (Cumulative Sum) test and CUSUMQ (Cumulative Sum of Squares) test indicate that both tests remain well within the boundary lines, suggesting that the regression model is stable over time and that the coefficients of the independent variables (GHG emissions and Resource efficiency) are reliable. The stability of the model implies that the relationship between these environmental factors and stock volatility in Nifty 100 firms is consistent and not subject to significant changes or structural breaks. This is significant as it reinforces the validity of the findings, ensuring that the observed impacts of GHG emissions and resource efficiency on volatility are robust. Therefore, stakeholders can confidently use these insights for decision-making related to investment strategies and corporate sustainability practices.

V. FINDINGS

The regression analysis reveals a statistically significant negative relationship between GHG emissions and stock volatility, with a one-unit increase in GHG emissions Score resulting in a decrease in volatility by approximately 2.331 units. Similarly, an increase in resource efficiency score by one unit correlates with a decrease in volatility of about 1.928 units. These findings indicate that both higher GHG emissions and more efficient resource management contribute to reduced market fluctuations, potentially reflecting investor confidence in firms perceived as stable. The model's strong explanatory power, with an R-squared value of 0.652, demonstrates that 65.2% of the variance in stock volatility is attributed to GHG emissions and resource efficiency. The F-statistic further confirms the model's statistical significance, underscoring the critical role of environmental factors in shaping market behaviour.

VI. CONCLUSION

The aim of this study is to investigate the relationship between resource efficiency, GHG emissions, and stock volatility among Nifty 100 index firms, with a focus on understanding how these environmental factors influence market fluctuations. For investors and financial analysts, these findings emphasize the importance of incorporating environmental factors into investment strategies. Firms that manage GHG emissions and resource efficiency effectively may exhibit greater market stability, making them attractive investment options. Companies should prioritize sustainability practices to enhance their appeal to investors. Policymakers should consider the relationship between environmental practices and market volatility when designing regulations. Encouraging sustainable resource management and reducing GHG emissions could not only benefit the environment but also contribute to market stability. Implementing incentives for firms to adopt greener practices may enhance overall economic resilience. While this study provides valuable insights into the relationship between GHG emissions, resource efficiency, and stock volatility in Nifty 100 firms, several limitations must be acknowledged. First, the analysis is constrained by the availability and reliability of data, particularly regarding GHG emissions and resource efficiency metrics, which may vary in accuracy across firms. Additionally, the study focuses on a specific time, which may limit the generalizability of the findings to other economic conditions or longer-term trends. Furthermore, the model does not account for other potential factors influencing stock volatility, such as macroeconomic variables or industry-specific dynamics, which could provide a more comprehensive understanding of market behaviour.

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