www.ijarp.com ISSN 2456-9992 Page: 01-11

Research Article

International Journal Advanced Research Publications

Volume: 02
Issue: 11

ARTIFICIAL INTELLIGENCE-DRIVEN INVESTMENT THEMES AND STOCK MARKET VOLATILITY IN INDIA: AN EMPIRICAL STUDY

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Article Received: 02 October 2026, Article Revised: 21 October 2026, Published on: 11 November 2026

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Doi: https://doi-doi.org/101555/ijarp.1469

ABSTRACT

Artificial intelligence has become an important investment theme, influencing expectations about technology services, data infrastructure, telecommunications, electronics and power demand. These expectations may affect the prices and risk characteristics of listed companies, even when the financial benefits of new technology have not yet appeared fully in reported earnings. This paper examines how an investment basket associated with artificial intelligence and its enabling infrastructure can be assessed against the wider Indian equity market. The proposed study covers January 2020 to December 2025 and relies exclusively on secondary data from exchange records, company disclosures and published financial information. The main measures are daily stock returns, rolling realised volatility, trading activity, Nifty 50 returns and India VIX. The study sets out a transparent company-selection approach and proposes descriptive statistics, correlation analysis, volatility comparisons and regression with robust standard errors. A central distinction is maintained between companies exposed to AI-related demand and the direct use of AI in securities trading. Since a verified daily dataset and completed statistical outputs are not available in this manuscript preparation, no numerical results are claimed. The paper provides the complete research rationale and empirical procedure, while the final results section must be populated from verified observations before the work is submitted as a completed empirical article.

KEYWORDS: Artificial Intelligence; Investment Themes; Stock Market Volatility; Indian Equity Market; Nifty 50; India Vix; Secondary Data; Financial Risk.

INTRODUCTION

Stock markets respond to changes in earnings, interest rates, economic conditions and expectations about future business opportunities. In recent years, artificial intelligence has become one such source of expectations. The possible use of AI in software, data analysis, automation and digital services has also increased interest in companies that supply the infrastructure required to support these activities. For investors, the challenge is to determine whether the market price of a company reflects sustainable earnings potential or an expectation that may change quickly.

The investment theme is wider than firms that develop AI products. Telecommunications companies, data-centre operators, electronics manufacturers, optical-fibre suppliers and power-related businesses may benefit indirectly from rising demand for digital infrastructure. Their exposure varies considerably, however. A company that reports a specific AI product or service should not be treated as equivalent to a company whose connection is limited to general technology demand. The quality of the research therefore depends on a clear definition of the companies included in the sample.

Volatility is important because it describes the extent to which returns fluctuate over time. High volatility does not necessarily mean that a stock is overvalued or that investors have behaved irrationally. It may reflect new information, uncertainty about future earnings, changes in liquidity or broader market shocks. Equally, a rise in the price of a company associated with AI does not establish that AI caused the rise. An empirical study must separate observed relationships from causal claims.

The International Monetary Fund has discussed the potential for AI to improve the speed and efficiency of capital-market activity while also creating risks when trading models react in similar ways or when market conditions become stressed (Abbas et al., 2024). In India, the Securities and Exchange Board of India has addressed responsible use of artificial intelligence and machine learning in securities markets (SEBI, 2025). These developments make it useful to examine how AI-related investment themes behave in relation to the broader equity market.

The present study uses a secondary-data approach to compare a defined basket of Indian listed companies associated with AI-related business activity or enabling infrastructure with the Nifty 50 benchmark. The purpose is not to prove that AI itself increases or decreases volatility. Rather, the study seeks to establish whether the selected securities display different return and volatility patterns and whether those patterns are associated with market uncertainty and trading activity.

Review of Literature

Fama (1970) reviewed the theory and empirical evidence on efficient capital markets and explained that security prices incorporate available information to varying degrees. This perspective is relevant to technology-related investment themes because new information about future demand can be reflected in prices before it is visible in financial statements. However, the speed at which information is incorporated into prices does not determine whether volatility will rise or fall; the effect depends on the information and the response of market participants. Engle (1982) developed the autoregressive conditional heteroskedasticity model to represent time-varying variance in financial and economic series. Bollerslev (1986) extended this approach through the generalised ARCH model, allowing past conditional variance to affect current volatility. These methods remain relevant to stock-market research because financial returns often exhibit periods of unusually high or low volatility rather than a constant variance over time. Black (1976) discussed changes in stock-price volatility and the relationship between price movements and risk. Christie (1982) examined the leverage effect, under which falling share prices may be associated with increases in volatility. This literature suggests that positive and negative returns may not have symmetrical effects on market risk. A study of AI-related shares should therefore avoid relying only on average returns and should consider the distribution and persistence of price movements. Andersen, Bollerslev, Diebold, and Labys (2003) advanced the measurement and forecasting of realised volatility using high-frequency financial data. Their work provides a useful conceptual distinction between volatility calculated from observed returns and expectations of future volatility implied by derivative prices. In the Indian market, India VIX represents expected near-term volatility derived from Nifty options; it should therefore be interpreted as a different measure from the historical volatility calculated from share returns. Bekaert and Wu (2000) examined asymmetric volatility and risk in equity markets and demonstrated that volatility behaviour can vary across market conditions. Their work supports the use of alternative specifications and robustness checks when assessing whether a particular group of stocks differs from a broad-market index. It also reinforces the need to consider market-wide conditions before attributing volatility patterns to a specific investment theme. Taylor (1986) provided a systematic treatment of financial time-series modelling, including the properties of asset returns and the statistical challenges involved in analysing them. Tsay (2010) similarly set out methods for modelling financial time series, volatility and dependence. These contributions support the use of carefully specified time-series methods and the reporting of model diagnostics alongside statistical significance. The International Monetary Fund (2024)

considered the implications of AI for capital-market activities and financial stability. Its discussion highlights potential gains in information processing and market efficiency, alongside concerns about opacity, common model use and correlated trading during periods of stress. This analysis provides a useful background for the present study, but it does not establish that all companies associated with AI will have higher share-price volatility. The Securities and Exchange Board of India (2025) issued a consultation paper on responsible AI and machine-learning use in Indian securities markets. The paper illustrates the regulatory importance of accountability, governance and risk controls when AI is used in market-related activities. Its relevance to this study is institutional: it establishes the context in which AI adoption is being considered by the Indian securities regulator, rather than providing direct evidence about the returns of an AI-related stock portfolio. The National Stock Exchange of India provides historical index values, security-wise price and volume information, and historical India VIX data. These official records allow researchers to construct return series and compare securities across common trading dates. The availability of exchange data does not remove the need for careful processing. Researchers must account for corporate actions, missing observations, trading calendars and changes in company business exposure over the study period.

Taken together, the literature offers established methods for measuring volatility and identifies several ways in which technology may affect capital-market activity. Yet three concepts should remain distinct: a company's exposure to AI-related demand, the use of AI in securities trading, and the volatility of its share price. A company can benefit from AI-related infrastructure demand without using AI to trade its own shares, while the share price may fluctuate because of general market conditions. The present study addresses this distinction through a transparent company-selection process and a comparison with the Nifty 50.

The research gap lies in the need for an India-focused, reproducible comparison of selected AI-related and AI-enabling companies with the broad market, using a consistent observation period and explicit measures of volatility. The study contributes by defining the variables and statistical tests in advance, documenting the limits of the sample and avoiding a causal interpretation unless the research design can support one.

Research Gap

Prior work has established a range of methods for analysing volatility and has discussed the opportunities and risks associated with AI in financial markets. However, the investment

theme covers firms with very different business models, and a broad label such as 'AI stock' may obscure these differences. A transparent comparison of a documented basket with the Nifty 50 can provide useful evidence about relative volatility, provided that the company classifications and statistical procedures are disclosed. The study therefore focuses on measurable market behaviour rather than treating AI exposure as a direct cause of price changes.

Objectives of the Study

1. To examine the return and volatility characteristics of selected Indian companies associated with AI-related activities or enabling infrastructure.
2. To compare the volatility of the selected basket with the Nifty 50 benchmark.
3. To examine the association between India VIX, trading activity and the absolute returns of the selected basket.
4. To determine whether the observed relationships differ across periods of relatively high and low market uncertainty.
5. To provide evidence-based implications for investors, listed companies and market regulators.

Research Hypotheses

- H01: There is no statistically significant difference between the volatility of the selected AI-related equity basket and the Nifty 50.
- H02: India VIX has no statistically significant association with the absolute daily returns of the selected basket.
- H03: Trading activity has no statistically significant association with the absolute daily returns of the selected basket after controlling for broad-market movements.
- H04: The association between market uncertainty and the volatility of the selected basket does not differ between high-uncertainty and normal-market periods.

RESEARCH METHODOLOGY

The study adopts a quantitative, descriptive and analytical design based entirely on secondary data. The proposed observation period is 1 January 2020 to 31 December 2025. This period includes sharply different market conditions and provides a basis for examining whether return and volatility patterns vary over time. The study uses daily observations because

monthly data may conceal short-lived movements and would provide fewer observations for statistical analysis.

Data should be collected from the National Stock Exchange of India's historical index reports, security-wise price and volume archives, and India VIX history. Company annual reports, investor presentations and official corporate disclosures should be used to determine whether each company has a documented connection to AI-related products, services or infrastructure. BSE records may be used to verify or supplement company disclosures. The source file, download date, date range and any adjustments should be recorded so that the analysis can be reproduced.

The sample should consist of approximately eight to twelve listed companies. Inclusion criteria should be set before examining returns. Direct exposure may include disclosed AI products or services; enabling exposure may include businesses supplying telecommunications, data-centre, electronics or power infrastructure associated with digital computing demand. General technology companies should not automatically be classified as AI companies. The final company list should include a short evidence note for each inclusion and should acknowledge that business exposure may change during the sample period.

A transparent equal-weighted portfolio is suitable for an initial analysis because it avoids allowing the largest company to dominate the result. Daily portfolio return is calculated as the arithmetic mean of the constituent daily returns when all required observations are available. The portfolio construction and rebalancing rule should be stated explicitly. If a constituent lacks a valid observation on a given date, the treatment of that date should be documented rather than concealed through an automatic fill.

For each security, the daily logarithmic return is calculated as $r(t) = \ln(P(t)/P(t-1))$, where $P(t)$ is the adjusted closing price on trading day t. Adjusted prices should account for relevant corporate actions where the source permits. The same method is applied to the Nifty 50 benchmark. A twenty-trading-day rolling standard deviation of daily returns is used to estimate realised volatility. Annualised volatility is calculated by multiplying the daily standard deviation by the square root of 252. This convention assumes approximately 252 trading days in a year.

India VIX is included as a measure of expected near-term market volatility derived from Nifty option prices. It is not the same as realised volatility in the selected shares. Trading activity may be measured by daily traded volume or turnover; a logarithmic transformation can reduce the influence of extreme values. Broad-market absolute returns are included as a

control so that the analysis does not mistake a general market shock for a pattern unique to the selected portfolio.

The statistical analysis begins with descriptive statistics, cumulative returns and rolling-volatility plots. Correlation analysis is used to examine the direction and strength of association between the selected variables. A difference-in-means test may compare volatility between the portfolio and benchmark, but overlapping rolling windows create dependence; inference should therefore be treated cautiously or based on non-overlapping periods or suitable time-series procedures. Regression models should use heteroskedasticity- and autocorrelation-consistent standard errors.

The baseline regression is specified as follows: $|r(p,t)| = \alpha + \beta1\ VIX(t) + \beta2\ \ln(1 + Volume(p,t)) + \beta3\ |r(m,t)| + \varepsilon(t)$. Here, $|r(p,t)|$ represents the absolute daily return of the selected portfolio, VIX(t) is the India VIX close, Volume(p,t) is portfolio trading activity, and $|r(m,t)|$ is the absolute Nifty 50 return. The model estimates conditional associations. It cannot establish that AI causes volatility, because market uncertainty, stock returns and trading activity may respond to the same information.

Before estimation, the dataset should be checked for duplicate dates, missing observations, non-positive prices, incorrect corporate-action adjustments and inconsistent date formats. Model diagnostics should consider multicollinearity, serial correlation, heteroskedasticity and influential observations. Robustness checks may change the rolling window, compare alternative portfolio definitions and exclude selected extreme periods using a rule justified in advance. Results should include coefficients, standard errors, confidence intervals, p-values, sample size and model fit.

The study has limitations. AI-related revenue is not separately disclosed by every company, so the classification of enabling firms necessarily involves judgement. The selected sample may not represent the full universe of Indian listed companies. Stock returns are influenced by global conditions, interest rates, earnings announcements, foreign investment flows and liquidity. These factors make causal conclusions difficult, and the findings should be interpreted as historical associations for the specified sample and period.

Empirical Analysis and Interpretation

The empirical section should report the results only after the daily data have been downloaded, aligned and checked. The first table should present the number of observations, mean daily return, standard deviation, minimum return, maximum return and annualised volatility for the selected portfolio and the Nifty 50. The second table should show annual or

subperiod cumulative returns and realised volatility. The third table should present correlations among portfolio returns, absolute returns, India VIX, trading activity and broad-market returns.

The regression table should report the estimated coefficients, robust standard errors, confidence intervals, p-values, observation count and model fit. A positive and statistically significant coefficient on India VIX would indicate that higher implied market uncertainty is associated with larger absolute portfolio returns, conditional on the included controls. A statistically significant trading-activity coefficient would indicate an association between trading activity and absolute returns, but would not prove that volume causes volatility. The sign and magnitude must be interpreted in the context of the variable definitions and the model specification.

The hypotheses should be evaluated using a pre-specified significance level, conventionally five per cent, while also considering effect size and confidence intervals. A failure to reject a null hypothesis does not prove that no relationship exists; it means the available data do not provide sufficient evidence against the null under the chosen model. Results should be compared with prior research and interpreted in light of possible sample-selection and omitted-variable limitations.

No numerical coefficients, p-values or hypothesis decisions are reported in this manuscript because the complete daily dataset and the final company sample have not been verified and analysed. Reporting invented statistics would undermine the reliability of the paper. The empirical tables must be populated from actual observations before the paper is presented as a completed empirical study.

Findings Expected from the Study

The proposed analysis will establish whether the selected basket has a different volatility profile from the Nifty 50 over the chosen period. It will also assess whether absolute portfolio returns move with India VIX and whether trading activity adds explanatory value after broad-market movements are considered. These are research questions, not predetermined conclusions. The final findings may support, reject or provide insufficient evidence for the stated hypotheses.

A further contribution will be the documentation of how the sample was selected. By separating direct AI activity from enabling infrastructure, the study can show whether the results depend on a broad thematic definition or a narrower group of firms. This distinction will help readers judge the extent to which the results can be generalised.

Suggestions and Implications

Investors should assess AI-related investment opportunities through business fundamentals, cash flows, valuation, competitive position and concentration risk. A company's association with a growing technology theme does not guarantee that its share price is attractively valued. Historical volatility and India VIX can be used as complementary risk indicators, but neither should be treated as a reliable prediction of future returns.

Listed companies should disclose material AI-related activities and their financial significance clearly. Statements about future opportunities should be distinguished from realised revenue, operating savings or committed capital expenditure. Where companies use AI in internal processes, appropriate controls over data, cybersecurity, model validation and accountability are important.

Market regulators and exchanges should continue to support transparent disclosures, orderly trading and appropriate oversight of automated market activity. Reliable historical data access is also important for independent academic research. Recommendations should be refined after the statistical results are available rather than presented as consequences of findings that have not yet been established.

CONCLUSION

Artificial intelligence has become a significant investment theme, but the relationship between this theme and stock-market volatility cannot be assumed in advance. Companies associated with AI differ in their products, infrastructure roles and financial exposure. Their share prices also respond to broader economic conditions, investor expectations and market liquidity. A credible study must therefore define its sample carefully and distinguish association from causation.

This paper sets out a secondary-data framework for comparing selected AI-related and AI-enabling Indian equities with the Nifty 50 over January 2020 to December 2025. It specifies the data sources, return and volatility measures, hypotheses and statistical methods required for a reproducible analysis. The manuscript is written in a conventional academic style and avoids unsupported claims. It should be considered ready for empirical completion, but not camera-ready for an empirical journal until the verified dataset has been analysed and the actual results have been inserted.

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