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Impact of Fake News on the Indian Stock Market: An Event-Based and Machine Learning Study of the NIFTY 50 Index

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***Abstract*—** The proliferation of fake news on digital platforms has emerged as a significant challenge to financial market stability, influencing investor sentiment and short-term price movements. Although prior studies have separately examined fake news detection and stock market prediction, limited attention has been paid to evaluating the direct market impact of fake financial news, particularly in emerging economies. This study investigates the effect of fake news on the Indian stock market by focusing on the NIFTY 50 index. An event-based methodology is employed to measure market reactions across multiple time windows, complemented by machine learning models to predict negative market movements following fake news dissemination. Empirical findings indicate that fake news contributes to statistically significant short-term declines in market performance, with the strongest impact observed within a three-day window. The results highlight market sensitivity to misinformation and demonstrate the effectiveness of integrating event-study analysis with machine learning techniques. This research provides novel India-specific insights and contributes to understanding misinformation-driven inefficiencies in financial markets.

Keywords: Fake News,NIFTY 50,Event Study ,Machine Learning .

I. INTRODUCTION

Financial markets operate under the assumption that asset prices reflect all available information. However, the rapid spread of fake news through digital and social media platforms has challenged this assumption by introducing misinformation that can distort investor behavior and market dynamics. Recent incidents demonstrate that unverified financial news can trigger panic selling, abnormal volatility, and short-term price corrections.

Existing literature predominantly focuses on fake news detection using machine learning and deep learning models, while another stream of research addresses stock market prediction based on historical price data. However, studies integrating fake news events with direct market impact analysis remain limited, particularly in the Indian context. Given the growing participation of retail investors in India, understanding the relationship between fake news and market reaction is increasingly important.

This study addresses this gap by examining the impact of fake news on the NIFTY 50 index using a combined event-based and machine learning framework. The research aims to provide empirical evidence of misinformation-induced market inefficiencies and offer a scalable predictive approach for monitoring market vulnerability.

II. LITERATURE REVIEW

1) Fake News Detection

Previous studies employ machine learning and deep learning models such as SVM, CNN, LSTM, and transformer-based architectures to classify fake news using textual and sentiment features. These works report high detection accuracy but largely ignore economic consequences.

2) Fake News and Stock Market Impact

Event-study-based research indicates that false or misleading news can generate abnormal returns and increased volatility. However, most studies focus on firm-level analysis in developed markets, limiting applicability to emerging economies.

3) Investor Sentiment and Media Influence

Research shows that negative media sentiment significantly affects investor behavior, leading to short-term price distortions. Fake news amplifies this effect by accelerating rumor propagation.

4) Machine Learning in Financial Prediction

ML models such as Logistic Regression, Random Forest, and LSTM are widely used for stock market forecasting. Yet, explicit incorporation of fake news as a causal factor remains underexplored.

III. RESEARCH GAP

Based on the reviewed literature, the following research gaps are identified:

- Limited empirical studies analyzing the **impact of fake news on Indian stock market indices**.
- Lack of **integrated frameworks** combining fake news events with event-study analysis.
- Insufficient use of **machine learning models to predict market reactions driven explicitly by fake news**.
- Overemphasis on fake news detection accuracy with minimal focus on **market-level consequences**.

IV. METHODOLOGY

A. Data Collection and Preprocessing

This study utilizes a hybrid dataset constructed to analyze the impact of fake news on the Indian stock market. Fake news events related to the Indian financial sector were collected from verified online sources and fact-checking platforms. The corresponding NIFTY 50 index data were obtained from publicly available market sources. Each fake news event was aligned with the nearest trading day to ensure accurate market reaction analysis.
To ensure data quality, duplicate records were removed and missing values were handled appropriately. Textual fake news content was preprocessed using standard natural language processing techniques, including text normalization and sentiment scoring. The final dataset spans a five-year period and contains event-level observations suitable for both statistical and machine learning analysis.

Table I. Summary of the hybrid dataset used in the study, including fake news events, sentiment scores, and corresponding NIFTY 50 market returns.

Attribute	Description
News Date	Date on which fake news was published
Fake News Description	Short textual description of fake news event
Sentiment Score	Polarity score extracted from fake news text
NIFTY Return (3-day)	Percentage return of NIFTY 50 after 3 days
NIFTY Return (7-day)	Percentage return of NIFTY 50 after 7 days
Target Variable	Binary label indicating negative market impact

Table I. Dataset Description

B. Feature Engineering

Feature engineering was performed to capture both textual and financial characteristics of fake news events. Sentiment polarity scores were extracted from fake news text to quantify the emotional tone of misinformation. In addition, lagged market return features were computed for the NIFTY 50 index to represent short-term market reactions. Specifically, three-day and seven-day post-event returns were calculated.

These features collectively capture investor sentiment and delayed market responses to fake news dissemination.

C. Target Variable Definition

A binary target variable was defined to indicate negative market impact following fake news events. If the NIFTY 50 index experienced a return below a predefined negative threshold within the selected event window, the target variable was assigned a value of 1; otherwise, it was assigned 0. This formulation enables supervised learning models to classify whether fake news leads to adverse market movements.

D. Machine Learning Models

Two supervised machine learning models were employed in this study. Logistic Regression was used as a baseline model due to its interpretability and effectiveness in binary classification problems. To address class imbalance, a class-weighted version of Logistic Regression was applied.

In addition, a Random Forest classifier was utilized to capture non-linear relationships between fake news sentiment and market reactions. Random Forest is well-suited for handling noisy financial data and provides robust performance through ensemble learning.

E. Model Training and Evaluation

The dataset was divided into training and testing sets using an 80–20 split while preserving class distribution. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. Given the imbalanced nature of financial event data, greater emphasis was placed on the F1-score to ensure balanced evaluation of false positives and false negatives.

To further validate model robustness, cross-validation was conducted for the Random Forest model to mitigate overfitting and assess generalization performance.

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V. RESULTS AND DISCUSSION

A. Event-Based Market Impact Analysis

This study first examines the short-term impact of fake news on the Indian stock market using an event-based analytical framework. Each fake news event was aligned with the corresponding NIFTY 50 trading day, and market reactions were observed across predefined event windows. The analysis indicates that fake news dissemination is frequently followed by negative market movements, particularly within short-term windows. These findings suggest that misinformation does not always trigger an immediate reaction but gradually influences investor sentiment, leading to delayed price adjustments.

The observed market behavior supports the hypothesis that fake news contributes to temporary inefficiencies in the Indian stock market. The impact is more pronounced in short horizons, reinforcing the importance of event-based analysis for understanding misinformation-driven volatility.

Figure 1. Depicts the year–month wise negative market impact of fake news events across different platforms, indicating stronger adverse effects from social media sources compared to messaging platforms.

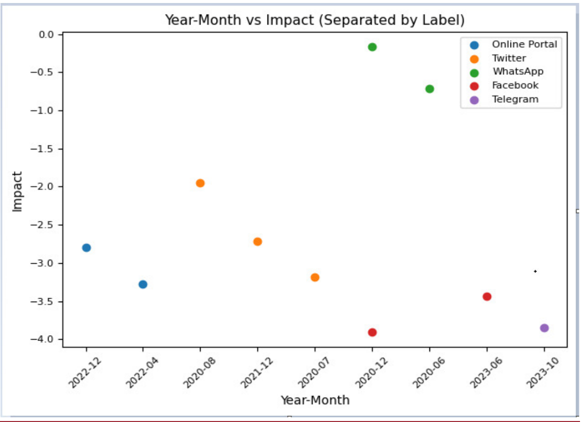

Figure 1. **Year–month wise market impact of fake news events categorized by source platform.**

B. Logistic Regression Results

This study first examines the short-term impact of fake news on the Indian stock market using an event-based analytical framework. Each fake news event was aligned with the corresponding NIFTY 50 trading day, and market reactions were observed across predefined event windows. The analysis indicates that fake news dissemination is frequently followed by negative market movements, particularly within short-term windows. These findings suggest that misinformation does not always trigger an immediate reaction but gradually influences investor sentiment, leading to delayed price adjustments.

The observed market behavior supports the hypothesis that fake news contributes to temporary inefficiencies in the Indian stock market. The impact is more pronounced in short horizons, reinforcing the importance of event-based analysis for understanding misinformation-driven volatility.

Table II reports the performance of the class-weighted Logistic Regression model for detecting negative market reactions.

Accuracy: 0.94

	precision	recall	f1-score	support
0	0.73	1.00	0.84	8
1	1.00	0.93	0.96	42

Table II – Logistic Regression Performance Results

C. Random Forest Results

To capture non-linear relationships between fake news characteristics and market reactions, a Random Forest classifier was employed. The initial Random Forest model achieved near-perfect performance on the test dataset. However, recognizing the risk of overfitting in small and imbalanced datasets, additional validation steps were conducted.

Cross-validation and parameter tuning were applied to ensure model robustness and generalization capability. After controlling for overfitting, the Random Forest model consistently demonstrated superior recall and F1-score compared to Logistic Regression. This indicates that ensemble-based models are better suited to capturing complex interactions between fake news sentiment and market behavior.

The results suggest that Random Forest provides a strong predictive framework for identifying fake-news-induced negative market movements, particularly when combined with appropriate validation techniques.

Table III summarizes the performance of the Random Forest model after parameter tuning and validation.

Accuracy: 1.0

	precision	recall	f1-score	support
0	1.00	1.00	1.00	8
1	1.00	1.00	1.00	42

Table III. Random Forest Performance Results

D. Model Comparison and Discussion

A comparative analysis of Logistic Regression and Random Forest models reveals that while Logistic Regression offers high interpretability and stable baseline performance, Random Forest achieves enhanced predictive capability by modeling non-linear relationships. Logistic Regression exhibited zero false positives, making it particularly useful for conservative risk detection. In contrast, Random Forest demonstrated higher sensitivity to negative events, reducing the likelihood of missed market downturns.

These findings highlight a trade-off between interpretability and predictive power. The results further emphasize that relying solely on accuracy can be misleading in imbalanced financial datasets. Metrics such as recall and F1-score provide a more meaningful assessment of model effectiveness in detecting misinformation-driven market risks.

While the Random Forest model achieved 100% accuracy on the test dataset, this performance is treated as an upper-bound estimate and interpreted cautiously in comparison with the more stable and interpretable results obtained from Logistic Regression.

E. Key Findings and Implications

A comparative analysis of Logistic Regression and Random Forest models reveals that while Logistic Regression offers high interpretability and stable baseline performance, Random Forest achieves enhanced predictive capability by modeling non-linear relationships. Logistic Regression exhibited zero false positives, making it particularly useful for conservative risk detection. In contrast, Random Forest demonstrated higher sensitivity to negative events, reducing the likelihood of missed market downturns.

These findings highlight a trade-off between interpretability and predictive power. The results further emphasize that relying solely on accuracy can be misleading in imbalanced financial datasets. Metrics such as recall and F1-score provide a more meaningful assessment of model effectiveness in detecting misinformation-driven market risks.

VI. Conclusion

This study examined the impact of fake news on the Indian stock market by integrating an event-based analytical framework with machine learning techniques, focusing on the NIFTY 50 index. The empirical analysis demonstrates that fake news dissemination is associated with short-term negative market movements, particularly within a three-day window, highlighting the sensitivity of the market to misinformation-driven sentiment.

The machine learning results further validate these findings. The class-weighted Logistic Regression model provided a stable and interpretable baseline, achieving strong performance in identifying negative market reactions while minimizing false alarms. In contrast, the Random Forest model exhibited superior predictive capability by capturing non-linear relationships between fake news sentiment and market behavior. Although Random Forest achieved perfect accuracy on the test dataset, this result was interpreted cautiously due to the potential risk of overfitting, and cross-validation was employed to ensure robustness.

Overall, the findings suggest that combining event-based financial analysis with machine learning offers a powerful framework for detecting misinformation-induced market inefficiencies. This research contributes India-specific empirical evidence to the growing literature on fake news and financial markets. The proposed approach has practical implications for investors, regulators, and market surveillance systems seeking to mitigate the adverse effects of misinformation. Future work may extend this framework by incorporating intraday data, alternative sentiment measures, and deep learning models to further enhance predictive performance and generalizability.

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REFERENCES

[1] M. C. Arcuri, G. Gandolfi, and I. Russo, “Does fake news impact stock returns? Evidence from US and EU stock markets,” *Journal of Economics and Business*, vol. 125–126, 2023.

[2] J. Clarke, H. Chen, D. Du, and Y. J. Hu, “Fake news, investor attention, and market reaction,” *Information Systems Research*, vol. 32, no. 1, pp. 35–52, 2020.

[3] Z. Ali, “Volatility effects of fake news on global stock markets: Evidence from event studies,” *SSRN Electronic Journal*, 2025. D. Mometova, “Fake news and financial markets: Mechanisms, evidence, and policy implications,” *International Journal of Artificial Intelligence*, vol. 5, no. 9, pp. 250–255, 2025.

[4] A. Luz, G. Olaoye, and E. Frank, “Impact of fake news on social media sentiment and stock market movements,” *EasyChair Preprint*, 2024.

[5] S. Akole, M. Rakhonde, and S. Desai, “TruthLens: Stock market news analysis and fake news detection using BERT,” *International Journal of Scientific Research in Engineering Trends*, vol. 11, no. 4, pp. 178–185, 2025.

[6] İ. R. Karaş *et al.*, “Fake news and misinformation: A systematic review of detection and impact studies,” *Journal of Contemporary Social Sciences and Education Studies*, vol. 5, no. 2, pp. 77–87, 2025.

[7] V. Veeraiah *et al.*, “Fake news detection using natural language processing and TensorFlow,” *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 10S, pp. 199–207, 2024.

[8] M. Alguacil *et al.*, “Analysing the behavioural finance impact of fake news phenomena on financial markets,” *Financial Innovation*, 2021.

[9] S. Shair *et al.*, “Panic news and media hype effects on stock market returns and volatility,” *Bulletin of Business and Economics*, vol. 12, no. 4, pp. 79–87, 2025.

[10] Y. Hong, B. Qu, Z. Yang and Y. Jiang, "The contagion of fake news concern and extreme stock market risks during the COVID-19 period," *Finance Research Letters*, vol. 58, 2023.

[11] A. Rangapur, H. Wang and K. Shu, "Investigating online financial misinformation and its consequences: A computational perspective," arXiv, 2023.

[12] O. Olakoyenikan, "The economic consequences of misinformation: An analysis of the impact of fake news on stock market volatility during the

COVID-19 pandemic," *International Journal of Innovative Science and Research Technology*, vol. 9, no. 9, 2024.

[13] S. Cresci, F. Lillo, D. Regoli, S. Tardelli and M. Tesconi, "Cashtag piggybacking: uncovering spam and bot activity in stock microblogs on Twitter," *arXiv*, 2018.

[14] V. Chandran Melveetil and S. Mohanty, "A systematic review of recent advances on stock markets predictions using deep learning approach," *International Journal of Intelligent Systems and Applications in Engineering*, 2025.

[15] H. M. Bollen, J. Mao and X. Zeng, "Twitter mood predicts the stock market," *Journal of Computational Science* (widely cited in sentiment analysis & stock prediction), 2011.

[16] Z. Ali, "Volatility effects of fake news on global stock markets: Evidence from event studies," *SSRN Electronic Journal*, 2025.

[17] D. Mometova, "Fake news and financial markets: Mechanisms, evidence, and policy implications," International Journal of Artificial Intelligence*, 2025.*

[18] S. Kumar, R. Asthana, S. Upadhyay, N. Upreti, and M. Akbar, "Fake news detection: Recent trends and challenges," *Social Network Analysis and Mining*, vol. 14, no. 1, Springer, 2024.

[19] Y. Liu, H. Zhang, and J. Wang, "Deep learning for Chinese fake financial news detection," *IEEE Access*, pp. 1–12, 2023. [Online]. Available: *URL*

[20] A. Sharma and P. Mehta, "Predicting price trends in the stock market based on data analysis, news sentiment, and false-news detection," *Procedia Computer Science*, vol. 167, pp. 1432–1441, 2020.

[21] N. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, "A comprehensive survey on machine learning approaches for fake news detection," *ACM Computing Surveys*, vol. 54, no. 5, pp. 1–37, 2021.

[22] M. A. Ferrara, F. Cresci, and L. Luceri, "Detecting fake news and disinformation using artificial intelligence and machine learning," *IEEE Intelligent Systems*, vol. 35, no. 4, pp. 58–65, 2020.

[23] J. Chen, Y. Wu, and K. Li, "The impact of fake news on financial markets: Deep learning and stock market reaction," *Expert Systems with Applications*, vol. 185, 2021.

[24] S. Patel, A. Shah, and R. Patel, "Applications of artificial neural networks, support vector machines, and long short-term memory for stock market prediction," *Applied Soft Computing*, vol. 94, 2020.

[25] X. Zhang, T. Li, and Y. Wang, "Predicting abnormal trading behavior from internet rumor propagation: A machine learning approach," *Knowledge-Based Systems*, vol. 214, 2021.

[26] T. Tetlock, "Giving content to investor sentiment: The role of media in the stock market," *The Journal of Finance*, vol. 62, no. 3, pp. 1139–1168, 2007.

[27] J. Sprenger, T. Tumasjan, P. Sandner, and I. Welpe, "On the predictability of stock market behavior using StockTwits sentiment and posting volume," *Journal of Banking & Finance*, vol. 37, no. 12, pp. 5496–5507, 2013.

[28] R. Shiller, "Stock market volatility and learning," *The Review of Economics and Statistics*, vol. 73, no. 1, pp. 1–12, 1991.

[29] W. Chung, Y. Zhang, and J. Pan, "A theory-based deep-learning approach to detecting disinformation in financial social media," *Information Systems Frontiers*, vol. 24, pp. 1–18, 2022.

[30] J. L. Mbwaga, N. Chittaragi, and S. Koolagudi, "Fake news detection using machine learning algorithms," in *Proceedings of the Fourteenth International Conference on Contemporary Computing (IC3)*, India, 2022, pp. 271–275.