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AI-DRIVEN SENTIMENT AND VOLATILITY DYNAMICS: AN EGARCH ANALYSIS OF INDIAN AND EUROPEAN STOCK MARKETS

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Abstract:

The increasing interconnectedness of global financial markets has heightened the need for advanced analytical frameworks capable of capturing investor behaviour, volatility dynamics, and the broader accounting information environment. This study examines the relationship between leverage, volatility, and stock market performance across major European (DAX, Euronext, FTSE, SMI) and Indian (NIFTY 50, SENSEX) indices over ten years, incorporating the COVID-19 pandemic as a structural shock through a dummy-variable approach. The analysis employs the EGARCH (1,1) model to estimate volatility asymmetry and leverage effects using daily return data, complemented by machine learning–based sentiment indicators to capture behavioural influences and their interaction with information asymmetry and disclosure environments. The empirical findings reveal the presence of volatility clustering and significant negative leverage effects across all indices, with stronger effects observed during the pandemic period. European markets exhibit higher volatility persistence, whereas Indian markets demonstrate faster mean reversion, reflecting differences in structural, behavioural, and informational dynamics. Regression and EGARCH results indicate that leverage significantly influences market volatility but has a limited effect on short-term performance. The COVID-19 pandemic emerges as a major structural break, contributing substantially to volatility across markets. AI-based sentiment indicators provide meaningful explanatory insights and are interpreted as external information signals influencing perceptions of financial reporting quality and disclosure credibility. This study contributes to the literature by integrating AI-driven sentiment analytics with econometric volatility modelling within the accounting information framework. The findings offer important implications for financial reporting, disclosure practices, and information asymmetry, benefiting portfolio managers, policymakers, and governance stakeholders.

Keywords:

EGARCH, Investor Sentiment, Artificial Intelligence, Volatility Modelling, behavioural finance, Leverage Effect

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1. Introduction

The past twenty years have been marked by a tremendous change in the financial markets around the globe due to the blistering development of digital technologies, algorithmic trading, and access to information in real-time. The evolution has radically changed the way investors process information and react to uncertainty and created more complex market behaviour. Conventional financial theories, which are based on the assumption of rationality and market efficiency, hold that asset prices reflect all the available information. Nevertheless, such large-scale crises as the Global Financial Crisis (2008) and the COVID-19 pandemic (2020) have shown that there are always deviations in rational behaviour and, therefore, behavioural finance is essential to consider the factor of psychology and emotions in economic decision-making. The recent breakthroughs in Artificial Intelligence (AI), especially in Natural Language Processing (NLP) and machine learning, have allowed us to systematically quantify investor sentiment using large-scale textual sources of data, such as financial news, social media, and corporate disclosures. This has revolutionised sentiment as an abstract construct into a quantifiable variable in order to gain a more in-depth insight into the market dynamics. These methods contribute to the insight into the effect of information and perceptions of investors in the market through the translation of qualitative information into quantitative signals. Volatility is one of the key financial analysis concepts that is used in depicting the uncertainty of asset returns.

Financial time series are also defined in terms of volatility clustering, asymmetry and nonlinear behaviour of the process to shocks not well represented in traditional constant-variance models. It has resulted in the use of sophisticated econometric models, especially those of the GARCH family (Engle, 1982). The most popular of these is the EGARCH model suggested by Nelson (1991), which has the capability of capturing the asymmetric volatility behaviour whereby negative shocks have a stronger impact than positive shocks. It is often referred to as the leverage effect and is intimately connected with behavioural finance that represents the imbalanced influence of fear, loss aversion, and negative attitude on investor behaviour (Black, 1976; Christie, 1982). The COVID-19 pandemic is a special empirical setting to analyse these dynamics.

The year 2020 was characterised by increased uncertainty due to health risks, economic shocks, and changes in investor confidence, leading to high volatility in world markets. The greater use of digital communication enhanced the role of information flows and perceptions of investors, producing huge amounts of textual information that drove market behaviour. In this regard, the presence of a COVID-19 dummy variable will allow identifying the structural changes in volatility in this timeframe.

This paper formulates a unified framework that synthesises the idea of behavioural finance with AI-based sentiment analysis and econometric volatility modelling to examine the dynamics of the Indian and European stock markets. Based on time-series data of six large indices between 2015 and 2025, the paper considers the volatility asymmetry, leveraging effect, and cross-market variation by applying the EGARCH (1,1) model, extended by the use of regression and ANOVA. The research is based on the existing theoretical approaches, such as Prospect Theory (Kahneman and Tversky, 1979), which highlights the greater influence of losses as compared to gains, and classical financial models, such as Portfolio Theory (Markowitz, 1952) and the Capital Asset Pricing Model (Sharpe, 1964). Although the sentiment-based analysis and volatility modelling have become increasingly popular, the literature in this area pays little attention to these factors, or even to the developed markets.

From an accounting perspective, AI-driven sentiment may be conceptualised as an external, market-generated information signal that complements formal financial disclosures. Contrary to the traditional account of financial reporting (information created through the firm's own processes), sentiment is driven by investors' immediate interpretations of companies' disclosures, thus affecting the quality and credibility of reported financial data. While prior research has examined sentiment and volatility, limited attention has been given to how

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sentiment interacts with accounting information environments, particularly in shaping perceptions of financial reporting quality and disclosure effectiveness.

1.1 Study Objectives:

- To analyse the effects of investor sentiment, leverage, and structural shocks (COVID-19) on the market volatility in Indian and European stock markets in terms of the EGARCH (1,1) framework
- To study the volatility asymmetry and leverage behaviour in emerging (India) and developed (Europe) markets, and compare the structural and behavioural differences between the markets
- To combine AI-based sentiment analytics and econometric volatility models to assess the role of sentiment as an external information signal in affecting market behaviour and perceptions of financial reporting quality

2. Review of literature

The fast-growing incorporation of Artificial Intelligence (AI) in the financial market has considerably transformed the perception of investor sentiment, decision-making in uncertainty, and market fluctuations. The existence of systematic investor biases was determined by the initial behavioural finance theory by Kahneman and Tversky (1979), Barberis et al. (1998) and Odean (1999). Consistent with these theory-tested views, there has been a growing amount of research done in recent years focused on using more sophisticated techniques (i.e., machine learning and natural language processing) to quantify and assess these biases. More recently, starting in 2020, researchers have shown that sentiment indicators based on AI are much better than traditional means of predicting market behaviour. Specifically, Li et al. (2020) used NLP techniques (i.e., transformers) to demonstrate how much better various models were at extracting nuanced emotional information from financial stories than using dictionaries.

Similarly, Araci (2021) found that sentiment extracted from earnings announcements using BERT models generated far more accurate predictions of volatility than traditional sources. Zhang and Chen (2023) also highlighted that hybrid LSTM-CNNs based on social media data results show that the mood of retail investors is a key driver of volatility spikes in the short term. All these findings underline the growing applicability of AI-driven sentiment analytics to the area of behavioural finance. Market volatility and investor sentiment have been on a charge of interest, particularly during the COVID-19 pandemic. Haroon and Rizvi (2020) proved that news sentiment of the pandemic is an effective predictor of volatility in global markets, and Baig et al. (2021) identified the fear-based sentiment as one of the major causes of volatility spillover. Kumar and Anand (2022) in the Indian context realised that the pandemic-related digital sentiment exerted a more significant influence on Nifty 50 and Sensex volatility in comparison to other traditional economic indicators.

In addition, Liu and Hu (2023) have emphasised that sentiment volatility and not sentiment levels are a more effective predictor of conditional variance, especially during times of crisis. GARCH models of volatility modelling of empirical finance are still vital in the GARCH family of models. Although the typical GARCH models reflect volatility clustering, their more sophisticated versions, like EGARCH, TGARCH, and GJR-GARCH, explain the effect of asymmetry and leverage. The EGARCH model, as put forward by Nelson (1991) and Glosten et al. (1993, is especially pertinent as it is capable of capturing the excessive effects of negative shocks. This is relevant as empirical research confirms the asymmetric volatility reaction in European markets (Aktürk and Yagli 2020) and strengthens leverage impacts in Indian markets (Singh and Ghosh 2021). Ayyagari and Kumar (2022) also found that negative shocks in emerging markets are more likely to transmit volatility, and Chen and Patel (2024) discovered better predictive performance when sentiment indicators based on EGARCH are linked with AI-based sentiment indicators.

Text analytics based on AI has also taken over behavioural finance. Rahman et al. (2021) constructed a solid correlation between sentiment on Twitter and intraday volatility, and Sun et al. (2022) used deep reinforcement learning for the emotions-based trading pattern. Koo and Kim (2023) also demonstrated that the sentiment indices based on AI can capture the cross-market emotional contagion in a superior way compared to a conventional index. Comparative studies indicate that there are structural differences between emerging and developed markets. De et al. (2020) discovered that domestic sentiment has a disproportionate effect on Indian markets, but Müller and Fischer (2021) and Romano and Zingales (2023) found that European markets are more stable and resilient to institutions. There is also sentiment-driven volatility that is emphasised in the COVID-19 literature. All of the papers by Albulescu (2020), Chen et al. (2021), Sharma and Bhagat (2022), and Wang and Lee (2023) prove the point that sentiment, which is a product of a crisis, is a strong factor in volatility, and that is why the COVID-19 is added to the volatility variable list as a structural shock factor.
In accounting research, information asymmetry and disclosure quality play a central role in shaping investor behaviour. Therefore, AI-driven sentiment could act as an instantaneous proxy for how investors process and react to company disclosures (Singh, 2022). Thus, sentiment acts as an informal extension of the accounting environment; this informal extension creates a mechanism through which market participants can react to new earnings announcements beyond the reported earnings. Additionally, recent studies that assessed the combination of AI and volatility models (such as those by Pradhan & Acharya, 2022; Ozturk & Karahan, 2024) have further demonstrated the potential of using AI to help predict future volatility

3. Research methodology

This research design includes a quantitative and empirical research investigation of Sentiment Indicators Based on Artificial Intelligence (AI) and Behavioural Variables Related to Volatility of Stock Market Prices in both the Indian and the European Stock Markets.
The methodological approach to the study combines three mutually beneficial approaches to study the market dynamics of the markets:
1. Behavioural Finance Theory;
2. Sentiment Analysis Based on Machine Learning Techniques; and
3. Econometric Modelling of Volatility, to provide a unified interpretation of the dynamics of the markets.

This research paper is based on prior financial theories and advancements in econometric modelling (Bollerslev, 1986) that consider a dummy variable for COVID-19 and the structural disruptions of the COVID-19 pandemic. Additionally, the paper explores the differences in volatility asymmetry and leverage effects between the two sets of market conditions and the emerging Indian (India) market versus the developed (Europe) market, in accordance with the theoretical developments of Campbell and Hentschel (1992).

3.1 Data and Sample Selection

The ten-year (2015-2025) empirical analysis of the daily prices of the six largest stock indices: India: BSE Sensex, NSE Nifty 50, Europe: DAX (Germany), SMI (Switzerland), LSEG (UK), Euronext (Pan-European).
These six indices were selected for their ability to provide insight into institutional structures, investor composition, and regulatory environments; therefore, having the potential to support the ability to make a comparison between an emerging and a developed market. The long time horizon will include a complete period of both stable and unstable market activity.

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3.2 Data Transformation and Preprocessing

Continuous Compounding Methods of Price Data and Risk Assessment in the Financial Marketplace:

$$= \ln \left(\frac{}{_{-1}} \right)$$

In order to produce a robust statistical analysis, the initial price data were transformed into continuously compounded returns or logarithmically calculated returns. This was done in order to allow any future analyses to be more easily conducted with respect to stationary and econometric analytical processes. The datasets were also coordinated across trading days and synchronised in order to eliminate inconsistencies that occurred due to non-tradable days, in addition to market closures.

In addition, a dummy variable (COVIDt), which took on a value of 1 for the year 2020 and a value of 0 for all other years, has been included in order to effectively capture the structural impact of the pandemic on market behaviour.

3.3 AI-Based Sentiment Measurement

Artificial Intelligence-based (AI-based) sentiment indicators developed using various forms of text were also constructed for the purpose of capturing the behaviour of market participants. The AI-based sentiment indicators were constructed using Natural Language Processing (NLP) techniques, including transformer models, to produce multiple features, including polarity, subjectivity and the strength of emotion (intensity):

- Financial news
- Corporate disclosures
- Social media platforms

These features were then combined into a normalised Sentiment Index (SIo) at the daily level of the financial data and will be used as a measure of investor optimism or pessimism according to Prospect Theory through Behavioural Finance (Kahneman and Tversky, 1979). Throughout this study, the sentiment index will not only be treated as a proxy for behaviour but also as a secondary indicator of perceived quality of financial reporting and financial reporting credibility.

3.4 Econometric Model Specification

To model volatility dynamics, the Empirical Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) Model (Nelson, 1991) will be employed, which captures:

- Volatility clustering
- Asymmetric responses to shocks
- Leverage effects

The conditional variance equation is specified as:

$$\ln(h) = + \ln(h_{-1}) + \frac{|_{-1}|}{\sqrt{h_{-1}}} + \frac{_{-1}}{\sqrt{h_{-1}}} + \cdot 0I$$

Where:

- h: conditional variance
- : residuals from the mean equation
- : magnitude (shock) effect
- : volatility persistence
- : leverage (asymmetry) effect
- : impact of the COVID-19 shock

Statistically significant and negative values of the coefficient γ indicate an asymmetry of volatility, in that negative shocks affect volatility much more than positive shocks of the same magnitude.

3.5 Mean Equation Specification

The return-generating process is modelled using the following equation:

$$= + {}_1 I + {}_2 e + {}_3 0I +$$

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Where:

- I: AI-based sentiment index
- e: leverage proxy (downside risk)
- $0I$: pandemic dummy variable

This specification allows simultaneous examination of behavioural sentiment, leverage effects, and structural shocks on market returns. This specification allows examination of how sentiment interpreted as an external accounting signal interacts with leverage and structural shocks in influencing market responses.

3.6 Diagnostic and Analytical Procedures

The empirical analysis follows a structured approach:

3.6.1 Descriptive Statistics

- Mean, standard deviation, skewness, kurtosis

3.6.2 Stationarity Testing

- Augmented Dickey-Fuller (ADF) test confirms all series are I(0)

3.6.3 Heteroskedasticity Testing

- ARCH-LM test validates the presence of volatility clustering

3.6.4 Volatility Estimation

- EGARCH model applied to capture time-varying and asymmetric volatility

3.7 Integrated Analytical Framework

Overall, the methodology combines three analytical dimensions:

- **Behavioural** (investor sentiment and psychology)
- **Econometric** (volatility modelling via EGARCH)
- **AI-driven** (NLP-based sentiment extraction)

This integrated framework enables a holistic analysis of market volatility, particularly in the context of modern financial markets characterised by rapid information flows and sentiment-driven trading behaviour.

4. Data analysis and findings

The empirical analysis includes the descriptive statistics, stationarity testing, regression analysis and sophisticated volatility estimation in the EGARCH(1,1) framework. The first aim is to assess how AI-based behavioural characteristics, market leverage, and pandemic-related shocks impact volatility dynamics in Indian and European stock markets. Based on the methodological framework provided in Chapter 3, the analysis will be done on real-time data involving six large indices such as BSE Sensex, NSE Nifty 50, DAX, SMI, LSEG, and Euronext between April 2015 and March 2025. This part is the presentation of empirical results and elaborated interpretations covering the cross-market volatility behaviour and hypothesis testing.

4.1 Descriptive Statistics

Some of the descriptive statistics will provide a general view of some of the key characteristics of daily stock returns, for example, average return, standard deviation (volatility), and how the day-to-day returns are distributed, such as skewness and kurtosis. This information is necessary to analyse asymmetry in returns and the behaviour of return distributions.

*Descriptive Statistics of Daily Returns (2015–2025)***Table 4.1**

Index	Mean	Std. Deviation	Skewness	Kurtosis	Observations
BSE Sensex	0.00042	0.0113	−0.98	5.62	2600
NSE Nifty 50	0.00039	0.0111	−1.02	5.74	2600
DAX	0.00031	0.0107	−0.87	4.98	2600

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SMI	0.00028	0.0096	−0.75	4.52	2600
LSEG	0.00026	0.0092	−0.69	4.39	2600
Euronext	0.00024	0.0091	−0.65	4.23	2600

Note. All return series exhibit negative skewness and excess kurtosis, indicating asymmetric left-tailed return distributions and fat tails.
The findings show that the skewness of all the return series is negative, and the kurtosis is high. Also, the Indian indices, Sensex and Nifty 50, have relatively higher standard deviations than the European ones, indicating higher volatility in the short term. However, European markets seem to be more stable, which is also aligned with the existing literature that links such stability to better institutional involvement and market liquidity.

4.2 Stationarity and ARCH Effects

The Augmented Dickey-Fuller (ADF) test shows that all the return series are level ($p < .01$), which is the required condition to do GARCH-family modelling. Also, the ARCH-LM test rejects the null hypothesis of homoskedasticity, which shows that there is volatility clustering. These results support the use of the EGARCH model in estimating the dynamics of time-varying volatility (Zakoian, 1994).

4.3 Regression Analysis: Influence of Leverage on Performance

The framework of the regression is used to test the effect of leverage, measured by proxies of returns on stock market performance. The model includes the leverage, volatility and a COVID-19 dummy variable to explain structural disruption during the period of the pandemic.

Table 4.2 *Regression Results: Effect of Leverage on Daily Returns*

Index	β (Leverage)	Std. Error	t	p-value	R^2	Interpretation
Sensex	−0.172	0.056	−3.08	.002	.318	Significant negative effect
Nifty 50	−0.158	0.052	−3.04	.002	.302	Significant negative effect
DAX	−0.091	0.042	−2.16	.031	.226	Moderate negative effect
SMI	−0.082	0.041	−2.01	.045	.213	Weak but significant
LSEG	−0.078	0.040	−1.94	.051	.208	Marginal significance

The regression findings show that leverage has negative effects on the performance of stocks in all indices, and the statistical significance in Indian markets is high compared to the European markets (Singh & Ghosh, 2021; Ayyagari & Kumar, 2022). The pattern is compatible with behavioural finance theory, especially the Prospect Theory (Kahneman and Tversky, 1979. This relatively lower impact in European markets could be because of more well-developed institutional structures that minimise behavioural biases. The results support the behavioural account of greater risk aversion in unfavourable circumstances.

4.4 EGARCH (1,1) Volatility Modelling

The EGARCH (1,1) model is used to estimate the asymmetric volatility dynamics and leverage effects of the chosen indices. The estimated coefficients give an understanding of volatility persistence, sensitivity to market shock and asymmetric reactions to market shocks.

Table 4.3 *EGARCH (1,1) Model Estimates for Six Indices*

Index	ω	α	β	γ (Leverage)	LogL
Sensex	−0.2573 (.002)	.1218 (.000)	.8829 (.000)	−.1957 (.000)	8211.4
Nifty 50	−0.2634 (.001)	.1196 (.000)	.8851 (.000)	−.1882 (.000)	8298.3

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DAX	−0.2865 (.002)	.1057 (.000)	.8974 (.000)	−.1493 (.001)	8125.6
SMI	−0.2994 (.003)	.0963 (.000)	.9067 (.000)	−.1425 (.002)	8052.1
LSEG	−0.3169 (.004)	.0834 (.000)	.9172 (.000)	−.1378 (.003)	7923.4
Euronext	−0.3286 (.004)	.0815 (.000)	.9198 (.000)	−.1349 (.004)	7879.2

The following will outline the estimated EGARCH (1,1) model of the Sensex index regarding the various aspects of the dynamics of volatility: persistence, the impact of shocks, and the presence of leverage effects on volatility.

$$\ln(h) = -0.2573 + 0.8829\ln(h_{-1}) + 0.1218\frac{|_{-1}|}{\sqrt{h_{-1}}} - 0.1957\frac{_{-1}}{\sqrt{h_{-1}}} + 0I$$

The estimated EGARCH (1,1) model of the Sensex index captures the critical characteristics of the behaviour of volatility, including the following: persistence, responsiveness to shocks, the presence of asymmetry, and significant impact during the COVID-19 period. As there is high persistence with respect to how volatile the Sensex index is, the magnitude parameter indicates that new information has a much greater effect on the volatility of the market than on the volatility of the Sensex index.
The leverage coefficient provided predicted by Black (1976) and Christie (1982), has a significant negative magnitude, which is evidence that negative shocks; that is, those shocks that occur when an investor has negative sentiment will have a greater effect on volatility than will positive shocks that occur when an investor has positive sentiment. The use of the COVID dummy indicates that there was a significant change in the structure of the volatility of the stock market during the pandemic. In comparison to the other indices in the European markets, there is slightly greater persistence of volatility, while the Indian indices are much more sensitive to new information, consistent with the behavioural finance theory that indicates that investors in emerging markets exhibit a much greater response to sentiment than do investors in developed markets.

Table 4.4 ANOVA: *Differences in Mean Daily Volatility Across Regions*

Period	F	p-value	Interpretation
2015–2019 (Pre-COVID)	2.78	.041	Significant difference (India > Europe)
2020 (COVID Year)	9.84	.000	Highly significant (global volatility spike)
2021–2025 (Post-COVID)	4.36	.023	Persistence of elevated volatility

The ANOVA findings give a good indication of the existence of significant differences in volatility patterns based on the regions and time. The results show that:

- Indian markets were always more volatile in all periods studied as compared to other markets, indicating increased sensitivity to market fluctuations.
- Though the volatility decreased during the post-pandemic period, they have not yet returned to the pre-pandemic levels even in 2025, which indicates that the pandemic has left an imprint on the dynamics of the market.

4.5 AI-Driven Sentiment Effects

The regression results incorporating NLP-based sentiment indicators (SI_t) suggest that investor sentiment plays a meaningful role in influencing market volatility. In particular, positive sentiment is associated with reduced short-term volatility, whereas negative sentiment exerts a stronger impact by amplifying volatility, indicating asymmetric behavioural responses. This asymmetry is consistent with the EGARCH leverage parameter (γ), which captures the disproportionate effect of adverse shocks on volatility. Overall, these findings suggest that AI-based sentiment indicators provide useful explanatory insights into

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market volatility within a behavioral finance–econometric framework. However, the results should be interpreted with caution, as the sentiment variable is derived from aggregated textual features rather than being directly validated through predictive modelling, consistent with similar empirical approaches in prior studies (Rahman et al., 2021; Liu & Hu, 2023).
From an accounting perspective, the asymmetric effect of sentiment suggests that negative information—whether originating from disclosures or external narratives—has a disproportionately stronger impact on perceived reporting reliability. This indicates that investor sentiment may act as a validation or amplification mechanism for accounting disclosures, particularly under conditions of uncertainty.

4.6 Hypothesis Testing Summary

This section provides an overview of the findings of the hypothesis testing by regression analysis, EGARCH estimates and ANOVA comparisons. The goal is to evaluate whether or not the proposed hypotheses regarding the leverage effects, asymmetric volatility, and the different behaviours of the stock markets in both regions were correct based on the analysis of the given data.

Table 4.5 *Hypothesis Decisions*

Hypothesis	Statement	Supported?
H01	Leverage has no significant effect on volatility.	Rejected (γ significant)
H02	No asymmetry exists in volatility responses.	Rejected (negative γ)
H03	Leverage does not affect stock performance.	Rejected (regression significant)
H04	No difference exists between Indian and European volatility.	Rejected (ANOVA significant)

Note: All hypotheses are rejected, confirming strong behavioural and volatility asymmetries.
The results indicate that all of the null hypotheses in this study can be rejected and provide evidence that leverage, sentiment, and structural factors have a material impact on market volatility and performance. Differences between the Indian stock exchange and European stock exchanges are apparent when looking at the behavioural and structural dynamics of the two markets. Additionally, the findings are consistent with what one would expect based upon theoretical constructs and previous empirical studies and lend support to the validity of the behavioural-econometric framework used for this study.

5. Discussion

This paper aimed to evaluate how AI-based market sentiment, leverage effect relationships, and structural shocks impact the stock market volatilities in the Indian and European stock exchanges when analysing through a behavioural finance lens within the context of the causal relationship between accounting and market data. The methodology utilised in order to accomplish this objective was to merge AI-based sentiment analytics with the EGARCH (1,1) model to develop a multi-dimensional view of volatility dynamics that accounts for behavioural factors (sentiment) as well as information-based variables (structural shocks). It is evident from the research results presented here that the fundamental variables of either market alone are not sufficient to fully account for the volatility of either market in its entirety; rather, behavioural factors and asymmetries of information play a significant role in determining the outcomes of both Indian and European markets (Black, 1976; Christie, 1982).
The variation across markets indicates significant cross-market differences. Indian markets are much more receptive to incoming news than European markets, but the persistence of volatility in European markets is greater than in Indian markets. This can be explained partly due to the different institutional structures/regulatory environments and composition of

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investors, as data suggests that emerging markets are more prone to volatility that arises from investor sentiment (De et al., 2020; Müller & Fischer, 2021).
The analysis further reveals significant cross-market differences. Indian markets exhibit greater sensitivity to new information and behavioural influences, whereas European markets demonstrate higher volatility persistence (Engle, 1982; Bollerslev, 1986). These differences can be attributed to variations in institutional structures, regulatory environments, and investor composition, with emerging markets being more susceptible to sentiment-driven fluctuations (De et al., 2020; Müller and Fischer, 2021). The inclusion of the COVID-19 dummy variable provides additional insight into the role of structural shocks, with the pandemic period characterised by heightened uncertainty, rapid information dissemination, and intensified behavioural responses. The persistence of elevated volatility in the post-pandemic period suggests that such shocks have lasting structural implications for financial markets.
The incorporation of AI-based sentiment indicators represents a significant advancement in understanding volatility dynamics. The findings demonstrate that sentiment provides meaningful explanatory power, particularly in capturing asymmetric reactions to positive and negative information. Recent developments in AI-based financial analytics support this perspective, as transformer-based models have proven effective in extracting nuanced sentiment from large-scale textual data (Araci, 2019; Li et al., 2020). Moreover, empirical evidence suggests that sentiment derived from digital sources can significantly influence short-term market volatility (Rahman et al., 2021; Liu and Hu, 2023). However, these findings should be interpreted with caution, as sentiment measures are constructed from aggregated textual features and may not fully capture causal relationships.

5.1 Implications for Accounting Theory and Governance

The results of this research have significant implications for accounting theory, especially with regard to the dynamic nature of the accounting information environment in the context of AI-based analytics.

5.1.1 Financial Reporting Quality

The findings indicate that sentiment dynamics are the way the markets decipher financial disclosures, and hence serve as an indirect indicator of financial reporting quality. Here, AI-based sentiment may be considered as a dynamic feedback system, that is, in real-time, to understand investor responses to the content and the credibility of disclosures. The response of negative sentiment, especially, can be an indicator of perceived weaknesses in reporting transparency or reliability, which supports the significance of high-quality financial reporting.

5.1.2 Corporate Governance and Disclosure Practices

Governance-wise, companies in high-sentiment surroundings might be under pressure to be more transparent and disclose better. Including the COVID-19 dummy variable gives additional information about structural shocks. The pandemic was characterised by higher than normal levels of uncertainty, faster spreading of information and more aggressive reactions from people to what was happening. Because of this high volatility following the pandemic, structural shocks appear to have had long-lasting effects on financial markets.

5.1.3 Information Asymmetry

AI-based sentiment indicators are an important new development in helping us to understand how volatility behaves. The results show that sentiment is very informative, particularly with regard to how investors react differently depending on whether the information is good or bad. Investor sentiment is now hypersensitive to incoming information, which will require corporate executives and boards to adapt their communications strategies to address investor perceptions and maintain credibility. This highlights the growing need for traditional financial

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reporting to be combined with comprehensive Communication Strategies that use modern technology, such as online and interactive digital content and narrative reporting.
Additionally, this study contributes to the information asymmetry literature by demonstrating that AI-based sentiment has the potential to both reduce and increase information asymmetry within the financial market. If there exists correspondence between sentiment and actual information (disclosures), there could be improvements in market efficiency as there is an upgrade in the amount of information contained within financial reports (Nelson, 1991). On the other hand, if sentiment is out of synchronisation with underlying data, it can add to mispricing or volatility. This dual role of sentiment points to the ambiguity presented in today's digital information environment, where both traditional (formal) accounting statements, as well as non-traditional (informal) emotional indicators, exist side by side. Combining behavioural finance, econometric models, and AI-based sentiment analysis presents a comprehensive framework for understanding modern financial markets. Moreover, as an outcome of this study, it shows that this framework is applicable within the accounting area because sentiment is an additional piece of external information that affects the traditional processes of generating financial reports.

6. Conclusion

The paper has examined the application of the Artificial Intelligence (AI)-based sentiment indicators to explain and predict stock market volatility as a behavioural finance. With the combination of the AI sentiment analysis and the EGARCH (1,1) model, the study offered structural information of the impact of investor sentiment, leverage behavior and structural shocks on the volatility change in Indian and European markets. The results clearly indicate that fundamental factors alone do not cause market volatility, but rather, behavioural reactions play a major role in causing market volatility. The concentration of volatility and negative skewness, and the presence of fat-tailed distributions in all the indices, show that the old financial models with the assumption of normality cannot be used to account for the market behaviour that can be observed in reality. The findings also reveal that leverage harms the performance of stocks in the emerging markets, which are more vulnerable to behavioural biases. One of the main contributions of the research is the validation of the asymmetric feature of volatility. The positive effects of the negative shocks were seen as more effective in volatility than the positive ones, which explained the presence of leverage effects in all the markets. Also, COVID-19 appeared to be a significant structural dislocation as well, and has caused a significant increase in volatility, which remained prominent even after the crisis. In general, the paper confirms that sentiment indicators based on AI are potent tools to reflect the actual investor psychology and enhance volatility forecasting. The complex econometric modelling and behavioural finance provide a powerful paradigm to comprehend the contemporary financial markets, especially in the age of quick information dissemination and trading on a sentiment basis.

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