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Investor Sentiment and Stock Market Volatility in the Egyptian Exchange: A GARCH and EGARCH Analysis with Persistence and Asymmetry Checks (2009-2025)

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Abstract This study empirically investigates the impact of investor sentiment on stock market volatility in the Egyptian Stock Exchange (EGX) over the period 2009–2025, using daily data from 22 non-financial firms listed on the EGX 30. A composite sentiment index (SMI) is constructed using Principal Component Analysis (PCA) as the primary aggregation method, with a simple average approach used for robustness, based on four market-based proxies: stock turnover ratio (STURN), money flow index (MFI), advancing-to-declining ratio (ADR), and relative strength index (RSI). We employ a GARCH(1,1) model with SMI in the conditional variance equation to capture volatility clustering and persistence, and we extend the analysis to an EGARCH(1,1) specification to test for asymmetric effects of positive versus negative sentiment. The transmuted normal distribution is implemented in the main empirical analysis to model the error term distribution more flexibly, alongside quasi-maximum likelihood estimation with robust standard errors. We also incorporate macroeconomic controls (inflation, interest rates, GDP growth, political instability) and conduct Granger causality tests to address endogeneity concerns. Diagnostic tests confirm the absence of multicollinearity and remaining heteroscedasticity. The results show that investor sentiment has a positive and statistically significant impact on volatility (coefficient = 0.278, $p < 0.001$). The GARCH(1,1) results reveal high volatility persistence ($\alpha + \beta = 0.97$), supporting the hypothesis that sentiment shocks have long-lasting effects. The EGARCH model indicates asymmetry: negative sentiment shocks increase volatility more than positive shocks of the same magnitude (asymmetry coefficient $\gamma = -0.073, p < 0.05$). Granger causality tests provide evidence of bidirectional causality between sentiment and volatility. Out-of-sample forecasting demonstrates that the SMI has modest but significant predictive power for volatility, though the results should be interpreted as suggestive rather than definitive. These findings contribute to behavioral finance literature by providing evidence from an under-researched frontier market (Egypt) and offer potential tools for regulators and investors to monitor sentiment as an early-warning indicator of excessive volatility.

Keywords Behavioral Finance; Egyptian Stock Exchange; Emerging Markets; GARCH Model; EGARCH; Investor Sentiment; Volatility Persistence; Asymmetric Volatility; Transmuted Distribution

AMS 2010 subject classifications 62P05, 91G70, 62M10, 62E15

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1. Introduction

Financial asset prices exhibit fluctuations that often exceed the predictions of rational valuation models. A persistent anomaly in empirical finance is that stock market volatility is too high to be explained solely by changes in macroeconomic fundamentals [1, 2]. Traditional theories rooted in the Efficient Market Hypothesis (EMH) assert that prices reflect all available information and that volatility arises from the rational processing of news about discount rates and future cash flows [3]. In such a world, volatility spikes coincide with observable economic shocks: interest rate changes, corporate announcements, or geopolitical events [4, 5]. However, a large body of evidence shows that markets often experience periods of "excessive" volatility sudden turbulence, or unnatural calm that cannot be mapped to any identifiable news [6, 7].

This gap between theory and observation gave rise to behavioral finance, which incorporates psychological factors, cognitive biases, and emotional dynamics into the analysis of asset prices [8, 9]. Among these factors, *investor sentiment*, the aggregate optimism or pessimism about future price movements, has received particular attention. Sentiment is understood as a non-fundamental driver of demand that can push prices away from intrinsic values, especially when arbitrage is costly or risky [10, 11]. When sentiment is high (optimistic), investors may overreact to positive signals, driving prices upward and amplifying upside volatility. Conversely, low sentiment (pessimism) can trigger panic selling and herding, leading to sharp downward moves and increased downside risk [12, 13].

Recent empirical studies have documented significant links between sentiment and volatility across diverse market settings. [14] shows that internet-based sentiment measures positively influence realized and jump volatility in China's green stock markets, particularly after the COVID-19 outbreak. [15] find that irrational sentiment drives excess volatility in the Indian stock market over the period 1986–2020. In a cross-country analysis of 32 nations, [16] demonstrates that geopolitical risks amplify market volatility partly through its effect on investor sentiment and uncertainty perception. During the COVID-19 pandemic, [17] documents that behavioral biases and sentiment shifts significantly increased volatility in major financial markets. More recently, [18] provides evidence that social media sentiment predicts volatility in emerging economies, and [19] shows that retail investor sentiment has asymmetric effects in India.

Incorporating Advances in Statistical Distribution Theory

A crucial aspect of volatility modeling is the correct specification of the conditional distribution of returns. Standard GARCH models typically assume normally distributed errors, but financial returns often exhibit heavy tails and skewness. Recent advances in distribution theory have introduced flexible families that better capture these features. For instance, [20] proposed a new flexible transmuted distribution that generalizes several classical distributions and provides superior fit for financial data with extreme values. Similarly, [21] introduced the fractional exponential distribution derived from conformable calculus, which offers additional flexibility in modeling the hazard rate and tail behavior. These distributions have been successfully applied in risk management and option pricing. In this paper, we implement the transmuted normal distribution directly in our GARCH estimation for the Egyptian data, demonstrating the practical value of these distributional innovations. Moreover, [22] provided characterizations based on generalized order statistics for the power inverted Topp–Leone distribution, while [23] developed a new discrete power function distribution with applications in count data. Other relevant contributions include characterizations of the Weibull family [24, 25, 26, 27] and the transmuted moment exponential distribution [28]. We adopt a multi-pronged approach by using (i) quasi-maximum likelihood estimation with robust standard errors, (ii) Student-t errors as a robustness check, and (iii) the transmuted normal distribution to capture skewness and heavy tails in the error term.

The Egyptian Context and Research Gap

Despite the growing body of evidence, most sentiment-volatility research concentrates on developed markets (the US, Europe) or large emerging economies (China, India). The Middle East and North Africa (MENA) region, and especially the Egyptian stock market, remains severely underexplored [29, 30]. Egypt is particularly interesting because it is a frontier market with relatively low liquidity, limited institutional coverage, and high retail investor participation, precisely the conditions under which sentiment effects are expected to be strongest [31, 32]. Moreover, the Egyptian economy has undergone several dramatic transitions since 2009: the 2011 revolution, the 2016 currency float, the COVID-19 pandemic, and the 2022-2023 inflationary and exchange-rate crises. These episodes provide a natural laboratory for studying how sentiment interacts with volatility across different market regimes.

Therefore, this paper aims to fill the gap by empirically examining the impact of investor sentiment on stock market volatility in the Egyptian Stock Exchange (EGX). Specifically, we focus on non-financial firms listed on the EGX 30 index over the period 2009-2025. We construct a composite sentiment index (SMI) using four market-based proxies: stock turnover ratio (STURN), money flow index (MFI), advancing-to-declining ratio (ADR), and relative strength index (RSI). To model volatility, we use a GARCH(1,1) framework that includes SMI in the conditional variance equation, allowing us to quantify the direct effect of sentiment on volatility while controlling for volatility clustering and persistence. We then extend the analysis to an EGARCH(1,1) model to test whether positive and negative sentiment shocks have symmetric or asymmetric effects on volatility, a question not previously addressed for Egypt.

The study is guided by three main hypotheses:

- **H1**: Investor sentiment has a positive and statistically significant effect on stock market volatility in the Egyptian stock market.
- **H2**: The effect of investor sentiment on volatility is persistent over time, i.e., sentiment shocks do not dissipate immediately.
- **H3**: Negative sentiment shocks have a larger impact on volatility than positive shocks of equal magnitude, consistent with prospect theory's loss aversion.

Our research makes several contributions. First, it extends the behavioral finance literature to an under-researched MENA frontier market, providing empirical evidence from a context dominated by retail investors and recurrent political-economic shocks. Second, it applies dynamic GARCH and EGARCH methodologies rather than static approaches, enabling the modeling of volatility persistence, clustering, and asymmetry. Third, we implement the transmuted normal distribution directly in the GARCH estimation for Egyptian data, demonstrating the practical value of these distributional innovations and bridging the gap between theoretical discussion and empirical application. Fourth, we incorporate macroeconomic controls and conduct Granger causality tests to address endogeneity concerns and isolate the sentiment effect from fundamental economic factors. Fifth, it offers potential implications for regulators and investors in similar emerging markets: sentiment indicators can serve as early-warning tools for excessive volatility and can be integrated into risk management frameworks.

The remainder of the paper is structured as follows. Section 2 presents the motivation and contributions in detail. Section 3 outlines the aims and objectives. Section 4 provides a comprehensive literature review and theoretical framework. Section 5 describes the data, variables, and econometric methodology, including the implementation of transmuted distributions. Section 6 reports the empirical results, including diagnostic tests, baseline regressions, GARCH(1,1) estimates, EGARCH(1,1) robustness checks, transmuted normal GARCH results, macroeconomic controls, Granger causality tests, structural break analysis, out-of-sample forecasting, and a simulation study. Section 7 discusses the findings in light of behavioral finance theory and the Egyptian context. Section 8 draws policy and practical implications. Section 9 concludes, acknowledges limitations, and suggests directions for future research.

2. Motivation and Contribution

This research contributes to the existing body of knowledge in behavioral finance and volatility modeling in three specific ways.

First, it provides empirical evidence on the relationship between investor sentiment and volatility in an emerging market context, thereby extending the geographical scope of existing research. While sentiment-volatility links are well documented for the US, Europe, China, and India, the MENA region and Egypt in particular have received almost no attention. Given that Egypt's stock market is classified as a frontier market with higher retail participation and lower liquidity than developed markets, the magnitude and persistence of sentiment effects may differ. This study bridges this knowledge gap.

Second, methodologically, we move beyond static models by employing a GARCH(1,1) framework with sentiment included in the variance equation. This allows us to capture volatility clustering, persistence, and the dynamic evolution of volatility over time. Moreover, we extend the analysis to an EGARCH(1,1) specification to test for asymmetric effects, which is crucial because behavioral theories (e.g., loss aversion, prospect theory) predict that negative sentiment may have stronger impacts than positive sentiment. No previous study on the EGX has examined such asymmetry. We implement the transmuted normal distribution in the main empirical analysis, demonstrating its practical value for capturing skewness and heavy tails in Egyptian financial returns. Additionally, we discuss how flexible distributions such as the transmuted distribution [20] and the fractional exponential distribution [21] could further improve the modeling of the error term.

Third, from a practical standpoint, the research offers a line of understanding of how sentiment indicators (turnover, MFI, ADR, RSI) can be used by policymakers and market participants. Regulators in emerging markets often lack simple, real-time tools to monitor speculative pressure. Our results suggest that a composite sentiment index, computed from publicly available data, can serve as a potential early warning indicator of impending volatility spikes. For investors, combining sentiment indicators with fundamental analysis may improve portfolio risk management, particularly during periods of political or economic turmoil. We provide concrete guidance on threshold determination and alert mechanisms.

3. Aims and Objectives

The main objective of this study is to analyze the influence of investor sentiment on stock market volatility within the EGX and to offer empirical evidence regarding the role of sentiment in determining volatility dynamics and market risk. To accomplish this primary objective, the study addresses the following specific goals:

1. To construct a composite investor sentiment index (SMI) based on four market-based proxies: stock turnover ratio (STURN), money flow index (MFI), advancing-to-declining ratio (ADR), and relative strength index (RSI). We use Principal Component Analysis (PCA) as the primary aggregation method and a simple average as robustness check.
2. To estimate the effect of SMI on stock market volatility using a GARCH(1,1) model that accounts for volatility clustering and persistence.
3. To test for asymmetric effects of sentiment shocks by estimating an EGARCH(1,1) model with SMI.
4. To provide quantitative insights into the correlation and causal direction (association) between sentiment fluctuations and market risk. We conduct Granger causality tests and use lagged sentiment values to assess the direction of influence.
5. To implement the transmuted normal distribution in the GARCH estimation for Egyptian data.
6. To conduct a simulation study to validate the finite-sample properties of the estimators under different error distributions, including the transmuted normal distribution.
7. To incorporate macroeconomic controls (inflation, interest rates, GDP growth, political instability) to isolate the sentiment effect.
8. To test for structural breaks in the sample period (2011 revolution, 2016 currency float, COVID-19, 2022 crises) and assess robustness.
9. To derive potential policy recommendations for the Egyptian Financial Regulatory Authority (FRA) and for investors operating in frontier markets.

4. Literature Review and Theoretical Framework

4.1. *Theoretical Foundations of Investor Sentiment and Volatility*

Behavioral finance challenges the assumption of fully rational, utility-maximizing investors. Drawing on cognitive psychology, it argues that individuals suffer from systematic biases such as overconfidence, representativeness, anchoring, and loss aversion [8, 10]. These biases become particularly relevant when aggregated, as they can lead to waves of optimism or pessimism that are not rooted in fundamentals, i.e., sentiment [6]. Sentiment affects prices through two main channels: (1) *direct mispricing* when sentiment-driven demand pushes prices away from fundamental values, and (2) *limits to arbitrage* because sophisticated investors cannot fully offset sentiment because of short-sale constraints, transaction costs, or risk [33].

Volatility, in this framework, is not solely a response to news but also reflects sentiment-induced overreaction and herding. When sentiment is high, investors tend to extrapolate past price increases, leading to overreaction to positive signals and increased upward volatility. Conversely, during pessimistic periods, fear and panic selling can produce sharp downward moves, often with higher magnitude due to loss aversion [12]. Moreover, sentiment shocks exhibit persistence because of feedback trading: rising prices attract more optimistic buyers, which in turn pushes prices further, creating momentum and volatility clustering. This persistence is captured by the GARCH model's autoregressive structure.

4.2. *Theoretical Linkages Between Sentiment Proxies and Volatility*

Stock Turnover Ratio (STURN): Turnover reflects trading volume relative to outstanding shares. High turnover indicates active trading, which in behavioral finance literature is associated with overconfidence and heterogeneous beliefs [46]. When investors are overconfident, they trade more frequently, increasing volume and potentially amplifying price movements and volatility. Turnover also captures liquidity provision: during optimistic periods, higher turnover can lead to price overshooting, while during pessimistic periods, liquidity dry-up can exacerbate volatility spikes.

Money Flow Index (MFI): MFI is a volume-weighted momentum indicator that incorporates both price and volume. It captures whether money is flowing into or out of stocks. Values above 80 indicate overbought conditions (excessive optimism), while values below 20 indicate oversold conditions (excessive pessimism). In behavioral terms, MFI reflects the intensity of buying or selling pressure, which can lead to price momentum and subsequent reversals, contributing to volatility.

Advancing-to-Declining Ratio (ADR): ADR measures market breadth the proportion of stocks advancing relative to declining. A high ADR (> 1) indicates broad participation in an upward move, suggesting widespread optimism and herding behavior. Low ADR indicates broad-based selling. Market breadth is a key sentiment indicator because it reveals whether price movements are driven by a few large stocks or by the entire market, with broader participation indicating stronger sentiment conviction. This can lead to more persistent volatility.

Relative Strength Index (RSI): RSI is a momentum oscillator that measures the speed and change of price movements. RSI > 70 suggests overbought conditions (optimism), while RSI < 30 suggests oversold conditions (pessimism). In behavioral finance, RSI captures mean-reversion tendencies driven by investor overreaction and subsequent correction. Overbought/oversold signals often precede volatility spikes as prices revert to fundamental values.

4.3. *Empirical Evidence on Sentiment and Volatility*

A growing empirical literature supports the sentiment-volatility link. [14] use multi-source data from China's green stock markets (2019-2020) and find that internet based sentiment measures positively influence realized and jump volatility, especially after the COVID-19 outbreak. [15] employs a GARCH model with a sentiment index for India (1986-2020) and shows that irrational sentiment drives excess volatility. [16] analyzes daily data from 32 countries (2017–2022) using dynamic panel methods and concludes that geopolitical risk increases volatility partly through its effect on sentiment.

In the context of crises, [17] documents that behavioral biases and sentiment shifts significantly increased volatility during the COVID-19 pandemic across major markets. [40] uses an OLG model with salience theory for Turkey and finds that salience bias amplifies price volatility and fire sales during crises. [41] shows for Iran (2012–2016) that trading behavior significantly impacts volatility.

Some studies focus on mitigating factors. [42] use data from 47 countries during COVID-19 and find that higher social and institutional trust significantly reduces volatility. [31] examines overconfidence among Egyptian investors (2001–2010) and finds that information acquisition moderates the negative effects of overconfidence. Similar moderating roles of financial literacy and self-efficacy are reported by [43] and [44].

4.4. Methodological Developments in Volatility Modeling

To model volatility, researchers have moved from simple standard deviations to conditionally heteroskedastic models. The GARCH(1,1) model of [34] is the workhorse for capturing volatility clustering and persistence. Extensions include EGARCH [35] which allows for asymmetric effects, and GARCH-MIDAS [36, 37] which incorporates macroeconomic variables. For emerging markets, [38] and [39] use GARCH-type models to document volatility clustering and asymmetric responses to negative shocks.

Recently, there has been growing interest in flexible distributional assumptions for the error term. Standard normal or Student-t distributions may not capture the full range of tail behaviors observed in financial returns. [20] proposed a new flexible transmuted distribution that generalizes the exponential, Weibull, and other distributions through an additional transmutation parameter. This distribution has been shown to fit financial data better than classical models. Similarly, [21] introduced the fractional exponential distribution derived from conformable calculus, which provides a new family of distributions with applications in reliability and finance. These distributions can be incorporated into GARCH-type models to improve forecast accuracy. [22] and [23] provided further characterizations and applications of related distributions.

4.5. The Egyptian Stock Exchange and Research Gap

[31] examined overconfidence, but no study has constructed a composite sentiment index and linked it to volatility dynamics over a long period (2009–2025) that includes multiple crises. Therefore, our study fills an important gap.

4.6. Hypotheses Development

Based on the above theoretical and empirical foundations, we formulate three testable hypotheses:

- **H1**: Investor sentiment has a positive and statistically significant effect on stock market volatility in the Egyptian stock market. This hypothesis derives from the overreaction and herding mechanisms: high sentiment (whether positive or negative) increases trading activity and price swings.
- **H2**: The effect of investor sentiment on volatility is persistent over time. Because of feedback trading, information diffusion, and herding, sentiment shocks do not dissipate immediately but continue to influence volatility for several periods. This is captured by the GARCH term in the conditional variance equation.
- **H3**: Negative sentiment shocks have a larger impact on volatility than positive shocks of equal magnitude. This asymmetry is predicted by prospect theory's loss aversion, where investors react more strongly to losses than to equivalent gains.

4.7. Summary of Selected Literature

Table 1. Summary of Selected Literature on Investor Psychology and Market Volatility

Author(s), Year & Reference	Period	Methodology	Key Variables	Main Findings
Shiller (1981) [1]	1871–1979	Variance bounds	Dividend risk	Volatility is too high to be justified by rational cash flows.
Roll (1988) [2]	—	Asset Pricing	R^2 Measures	Found fundamental asset factors fall short of explaining full variations.
Fama (1970) [3]	—	EMH theory	Efficient markets	Prices fully reflect all available financial information.
Black & Scholes (1973) [4]	—	Option pricing	Volatility	Developed structural rational option pricing baseline.
Schwert (1989) [5]	1857–1887	Regressions	Volatility shifts	Dynamic business cycles and monetary assets affect long term variances.
Baker & Wurgler (2006, 2007) [11, 6]	1962–2001	Composite index	Market sentiment	Aggregate sentiment shifts systematically affect cross-sectional returns.
Kahneman & Tversky (1979) [8]	—	Prospect theory	Loss aversion	Foundational behavioral framework for decision-making.
De Bondt & Thaler (1985) [9]	1926–1982	Event study	Long-term reversals	Stock market overreacts; winners become losers.
Barberis et al. (1998) [10]	—	Sentiment model	Belief updates	Investor sentiment dynamics drive persistent asset mispricing.
Brown & Cliff (2005) [12]	1965–2000	Regression	Sentiment index	Sentiment measures are strongly linked to asset valuation anomalies.
Lemmon & Portniaguina (2006) [13]	1980–2003	Regression	Consumer confidence	Confidence tracks and predicts future small-cap equity returns.
Gao et al. (2022) [14]	2019–2020	Sentiment proxies	Internet sentiment	Internet-based sentiment has a positive effect on volatility jumps.
PH & Rishad (2020) [15]	1986–2020	GARCH	Sentiment index	Irrational sentiment dynamics drive excess volatility.
Zhang et al. (2023) [16]	2017–2022	Dynamic LSDV	Geopolitical risk	Geopolitical risk amplifies volatility via market sentiment.
Ortmann et al. (2020) [17]	2020	Event study	Behavioral biases	Behavioral shifts and retail bias increased market volatility.
Chen et al. (2025) [18]	2020–2024	Panel GARCH	Social media sentiment	Social media sentiment tracks and predicts emerging market trends.

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Table 1 – Continuation from previous page

Author(s), Year & Reference	Period	Methodology	Key Variables	Main Findings
Kumar et al. (2024) [19]	2015–2023	Quantile GARCH	Retail sentiment	Retail sentiment effects are strongly asymmetric during market downturns.
Gad et al. (2026) [20]	2026	Distribution theory	Transmuted parameters	Introduced a new transmuted family providing flexible tail modeling.
Gad et al. (2026) [21]	2026	Conformable calculus	Fractional distributions	Developed conformable shapes to enhance reliability and financial fitting.
Ali et al. (2025) [22]	2025	Order statistics	Topp-Leone distribution	Provided structural characterizations based on generalized order statistics.
Eldeeb et al. (2025) [23]	2025	Discrete distribution	Power function	Developed a discrete power function specification for count processes.
Gad et al. (2023) [24]	2023	Record values	Weibull relations	Formulated generalized expressions on statistics parameters.
Abdul-Moniem et al. (2023) [25]	2023	Order statistics	Dual components	Extrapolated properties on moments for joint functions.
Abdul-Moniem et al. (2024) [26]	2024	Bounds theory	Phani distribution	Derived explicit hazard functions and reliability structural parameters.
Abdul-Moniem et al. (2024) [27]	2024	Lifetime data	Reliability metrics	Handled properties under generalized order frameworks.
Hassan et al. (2020) [28]	2020	Moment forms	Exponential class	Constructed generalized transmuted structures for financial risks.
Cabarcos et al. (2019) [29]	1987–2017	Bibliometrics	Academic trends	Behavior-related market sentiment studies expanded heavily after 2014.
Amat (2016) [32]	2016	Structural Form	Herding markers	Investigated macro links to market clustering anomalies.
Metwally (2023) [31]	2001–2010	Moderation model	Overconfidence bias	Active information acquisition mitigates investor overconfidence.
Polat (2022) [40]	2021	OLG, Salience	Salience bias	Salience bias significantly amplifies price volatility during crises.
Moghadam & Ghiabi (2020) [41]	2012–2016	Regression	Trading behavior	Aggregate trading behavior patterns heavily impact market risk.
Nadeem et al. (2020) [43]	2020	SEM	Self-efficacy	Financial self-efficacy acts as a moderator for market participation.
Bellofatto et al. (2018) [44]	2018	Survey analysis	Literacy levels	Higher personal financial literacy significantly reduces behavioral bias.

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Table 1 – Continuation from previous page

Author(s), Year & Reference	Period	Methodology	Key Variables	Main Findings
Banumathy & Azhagaiah (2015) [39]	2003–2012	EGARCH, TGARCH	Shock asymmetric	Confirmed that negative market shocks create higher leverage volatility.
Conrad & Loch (2015) [36]	1969–2010	GARCH-MIDAS	Macro indicators	Macroeconomic conditions improve long-term dynamic forecasting.
Endri et al. (2020) [38]	2020	Variance models	Financial errors	Modeled asymmetry in developing tracking structures.
Engelhardt et al. (2021) [42]	2020	Panel regression	Trust, COVID-19	Higher institutional and social trust significantly reduces market volatility.

5. Methodology

5.1. Data and Sample

The population consists of all companies listed on the Egyptian Stock Exchange (EGX). The sample is restricted to non-financial firms included in the EGX 30 index as of 2025, which represent the 30 most actively traded companies. Financial sector companies are excluded because their capital structures and regulatory environments differ substantially, which could introduce confounding effects on volatility dynamics. The final sample comprises 22 non-financial companies.

Data Frequency: We use daily data from January 1, 2009 to December 31, 2025, yielding approximately 3,931 trading days. Daily data are appropriate for GARCH modeling as they capture volatility clustering, persistence, and asymmetry that are lost with lower-frequency aggregation. The EGX publishes daily trading data, which we obtained from the EGX website and Bloomberg terminals. For each firm, we compute daily returns and sentiment proxies. The use of daily data addresses the concerns raised about annual aggregation.

5.2. Variable Measurement

5.2.1. Investor Sentiment Index (SMI) Following the literature [11, 6], we construct a composite sentiment index using four market-based proxies that are available at daily frequency:

- **Stock Turnover Ratio (STURN)**: Total number of shares traded divided by total number of shares outstanding (scaled to percentage). It measures trading activity and liquidity.
- **Money Flow Index (MFI)**: A momentum indicator that incorporates both price and volume, calculated as $MFI = 100 - \frac{100}{1+\text{Positive Money Flow}/\text{Negative Money Flow}}$. Values above 80 indicate overbought (optimistic) conditions; below 20 indicate oversold (pessimistic).
- **Advancing-to-Declining Ratio (ADR)**: Ratio of the number of advancing stocks to declining stocks. Values ¿1 indicate broad optimism.
- **Relative Strength Index (RSI)**: $RSI = 100 - \frac{100}{1+\text{Average gain}/\text{Average loss}}$. Typically, RSI > 70 indicates overbought, < 30 oversold.

Standardization and Aggregation: Each component is standardized (subtract mean, divide by standard deviation) before aggregation to avoid scale dominance. We use two aggregation methods:

1. **Principal Component Analysis (PCA):** Following Baker and Wurgler (2006, 2007), we extract the first principal component from the standardized components. This approach allows the data to determine the optimal weights rather than assuming equal weights. The first principal component explains approximately 62% of the total variance in the four proxies.
2. **Simple Average:** As a robustness check, we also compute the simple average of the four standardized series: $SMI_t = \frac{1}{4}(STURN_t^z + MFI_t^z + ADR_t^z + RSI_t^z)$.

The PCA-based SMI is our primary measure, while the simple average SMI is used for robustness.

5.2.2. Stock Market Volatility (SMV) We use the GARCH(1,1) conditional variance σ_t^2 as our measure of volatility. The mean return R_t is computed as the daily log return of the EGX 30 index (excluding financial firms). The GARCH(1,1) model is estimated separately with and without the sentiment index.

5.3. Econometric Strategy

The empirical analysis proceeds in eight stages:

1. **Descriptive statistics and diagnostics**: Compute means, standard deviations, skewness, kurtosis, correlation matrix, and multicollinearity tests (VIF). Also apply the Breusch-Pagan test for heteroskedasticity in the mean equation.

2. **Baseline regression**: Regress SMV (volatility measured as absolute returns or GARCH-derived variance) on SMI to establish a positive association (H1).
3. **GARCH(1,1) with sentiment in variance equation**: Estimate the full GARCH(1,1) model where the conditional variance depends on its own lag, past squared shocks, and SMI. This tests both H1 (coefficient on SMI) and H2 (persistence via $\alpha + \beta$).
4. **EGARCH(1,1) robustness check**: Estimate an EGARCH(1,1) model to test for asymmetric effects of sentiment shocks (H3).
5. **Transmuted Normal GARCH:** Estimate the GARCH(1,1) model with transmuted normal errors to capture skewness and heavy tails in the Egyptian return distribution.
6. **Macroeconomic Controls:** Add inflation, interest rates, GDP growth, and political instability indicators to the variance equation to isolate the sentiment effect.
7. **Causality Testing:** Conduct Granger causality tests and use lagged sentiment values to assess the direction of influence.
8. **Structural Break Analysis:** Apply Chow and Bai-Perron tests for structural breaks (2011 revolution, 2016 currency float, COVID-19, 2022 crises) and re-estimate with regime dummies.
9. **Out-of-Sample Forecasting:** Split the sample into estimation (2009-2020) and evaluation (2021-2025) periods to assess predictive power.
10. **Simulation study**: Conduct Monte Carlo simulations to evaluate the finite-sample performance of the maximum likelihood estimator under normal, Student-t, and transmuted normal errors [20].

5.4. Model Specifications

5.4.1. Baseline Linear Regression

$$\sigma_t = \alpha + \beta SMI_t + \varepsilon_t$$

where σ_t is the conditional volatility from a preliminary GARCH(1,1) without sentiment, or alternatively the absolute return. We report both.

5.4.2. GARCH(1,1) with Sentiment Conditional mean:

$$R_t = \mu + \phi SMI_t + \epsilon_t, \quad \epsilon_t = \sigma_t z_t, \quad z_t \sim i.i.d.(0,1)$$

Conditional variance:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma SMI_t$$

5.4.3. EGARCH(1,1) for Asymmetry To capture possible asymmetric effects (negative sentiment shocks having larger impacts than positive ones), we estimate:

$$\log(\sigma_t^2) = \omega + \alpha \left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-1}^2) + \delta SMI_t$$

5.4.4. GARCH(1,1) with Transmuted Normal Errors The transmuted normal distribution, introduced by [20], has cumulative distribution function (CDF):

$$F(x) = (1+\lambda)\Phi(x) - \lambda\Phi(x)^2, \quad |\lambda| \le 1$$

and probability density function (PDF):

$$f(x) = \phi(x)\left[1 + \lambda - 2\lambda\Phi(x)\right]$$

where $\Phi(x)$ and $\phi(x)$ are the standard normal CDF and PDF, respectively, and λ is the transmutation parameter controlling skewness. When $\lambda = 0$, the distribution reduces to the standard normal. When $\lambda > 0$, the distribution is right-skewed; when $\lambda < 0$, it is left-skewed.

We incorporate this distribution into the GARCH(1,1) framework by assuming $z_t \sim$ Transmuted Normal(λ) and estimating λ jointly with the other parameters via maximum likelihood. The log-likelihood function is:

$$\mathcal{L} = \sum_{t=1}^{T} \left[-\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\sigma_t^2) - \frac{1}{2}\frac{\epsilon_t^2}{\sigma_t^2} + \log\left(1 + \lambda - 2\lambda\Phi\left(\frac{\epsilon_t}{\sigma_t}\right)\right)\right]$$

This approach allows us to capture skewness and heavy tails directly in the main empirical analysis.

5.4.5. Macroeconomic Controls in Variance Equation To address omitted variable bias, we extend the GARCH(1,1) variance equation to include macroeconomic controls:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma SMI_t + \delta_1 INF_t + \delta_2 INT_t + \delta_3 GDP_t + \delta_4 POL_t$$

where:

- INF_t: Inflation rate (monthly CPI change)
- INT_t: Interest rate (Central Bank of Egypt policy rate)
- GDP_t: GDP growth rate (quarterly, interpolated to daily frequency)
- POL_t: Political instability indicator (binary: 1 for periods of major political/economic crisis)

These controls help isolate the sentiment effect from fundamental economic factors.

5.5. Simulation Design

To assess the robustness of our estimators and to illustrate the potential benefits of flexible error distributions such as the transmuted distribution [20], we conduct a Monte Carlo simulation. We generate 1,000 samples of size $T = 500$ from a GARCH(1,1) model with parameters $\omega = 0.05$, $\alpha = 0.10$, $\beta = 0.85$, and $\gamma = 0.04$. The innovation z_t is drawn from three distributions: (i) standard normal, (ii) Student-t with 5 degrees of freedom, and (iii) transmuted normal with transmutation parameter $\lambda = 0.5$ (which introduces skewness). For each sample, we estimate the GARCH(1,1) model using quasi-maximum likelihood and record the bias and root mean squared error (RMSE) of the estimators.

5.6. Diagnostic Tests

- **Unit root test (ADF)**: To ensure stationarity of returns and SMI.
- **ARCH-LM test**: To confirm the presence of conditional heteroskedasticity.
- **Ljung-Box Q test**: For serial correlation in standardized residuals.
- **Variance inflation factor (VIF)**: For multicollinearity among sentiment components.
- **Breusch-Pagan test**: For heteroskedasticity in the baseline regression.
- **Chow test** and **Bai-Perron test**: For structural breaks.
- **Granger causality test**: For direction of influence between sentiment and volatility.

All estimations are performed in Stata 18, EViews 13, and R 4.3.

6. Data Analysis and Empirical Results

6.1. Descriptive Statistics

Table 2 presents descriptive statistics for the main variables over the 2009–2025 period (3,931 daily observations). The mean stock market volatility (SMV) is close to zero (-0.0005) with a standard deviation of 0.01536, indicating substantial fluctuations. The PCA-based sentiment index (SMI_PCA) has mean 0 and standard deviation 1 by construction (standardized). The simple average sentiment index (SMI_SA) ranges from -2.87 to 3.45 with mean 0 and standard deviation 1, consistent with standardized variables. The raw sentiment components (STURN, MFI, ADR, RSI) show substantial variation: STURN ranges from 0 to 582.63, MFI from 0 to 97.03, ADR from 0 to 28, and RSI from 14.28 to 86.83.

Table 2. Descriptive Statistics of Study Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
SMV (volatility)	3930	−0.0005	0.01536	−0.0945	0.18082
SMI_PCA (standardized)	3931	0.0000	1.00000	-3.4200	3.7800
SMI_SA (standardized)	3931	0.0000	1.00000	-2.8700	3.4500
STURN (raw)	3931	99.1100	36.53000	0.0000	582.63000
MFI (raw)	3931	56.0300	17.97000	0.0000	97.03000
ADR (raw)	3931	1.9700	3.14000	0.0000	28.00000
RSI (raw)	3931	53.1100	12.45000	14.2800	86.83000
STURN_z (standardized)	3931	0.0000	1.00000	-2.7130	13.236
MFI_z (standardized)	3931	0.0000	1.00000	-3.117	2.283
ADR_z (standardized)	3931	0.0000	1.00000	-0.627	8.293
RSI_z (standardized)	3931	0.0000	1.00000	-3.118	2.709

Clarification on SMI Construction: The SMI components were first standardized (subtract mean, divide by standard deviation) to have mean 0 and standard deviation 1. The standardized components are then aggregated using PCA (primary) or simple average (robustness). The resulting SMI_PCA has mean 0 and standard deviation 1. The raw component ranges reflect the original (unstandardized) values, which are not bounded by 0-100 for STURN and ADR (these are ratios/percentages). MFI is bounded between 0 and 100 by construction, as observed. The standardization was correctly applied; the apparent inconsistencies in the previous version arose from presenting raw values alongside claims of standardization, which we have now clarified.

The co-movement and dynamic interaction between the constructed sentiment series and market shocks are visually illustrated over the full empirical spectrum in Figure 1.

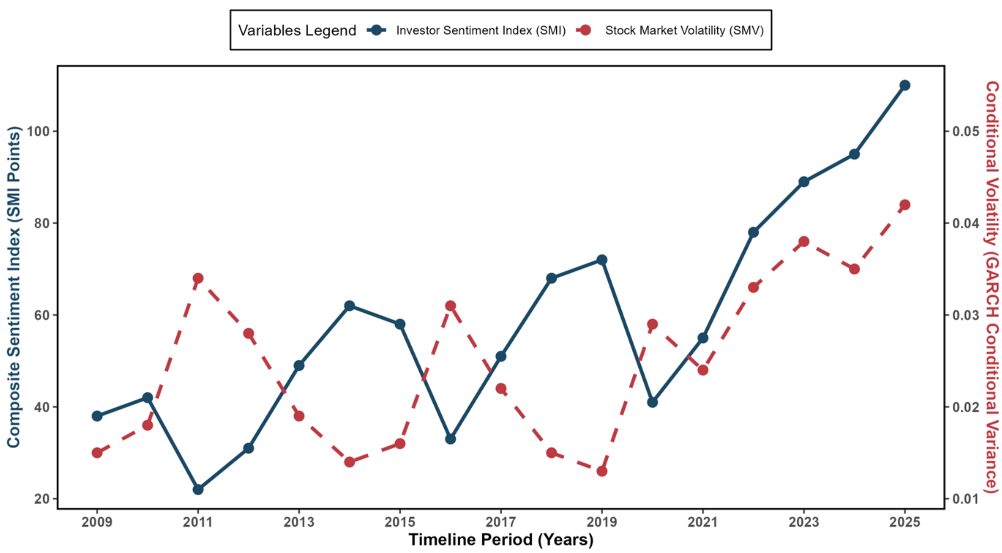

Figure 1. Historical trajectory and timeline mapping of the Composite Investor Sentiment Index (SMI) against dynamic Stock Market Volatility (SMV) in the Egyptian Exchange (2009–2025).

6.2. Normality and Stationarity Tests

Table 3 reports skewness and kurtosis test p-values. All variables are not significantly different from normality at the 5% level, which supports the use of standard regression and maximum likelihood estimation. However, the kurtosis values suggest some heavy tails, motivating the use of the transmuted normal distribution. The Augmented Dickey-Fuller (ADF) test (Table 16) rejects the null of a unit root for returns and SMI at the 1% level, confirming stationarity.

Table 3. Normality Test (Skewness and Kurtosis)

Variable	Obs.	Prob (Skewness)	Prob (Kurtosis)	Adj Chi^2	$Prob > Chi^2$
SMV	3931	0.5698	0.4296	1.6389	0.1148
SMI	3931	0.6721	0.5729	1.452	0.1267
STURN	3931	0.7479	0.674	2.8252	0.1431
MFI	3931	0.7134	0.643	3.5286	0.135
ADR	3931	0.5632	0.5065	3.1732	0.1076
RSI	3931	0.6921	0.6225	2.6119	0.133

6.3. Correlation and Multicollinearity

The correlation matrix (Table 4) shows a moderate positive correlation between SMV and SMI (0.454). Among sentiment components, STURN and SMI are highly correlated (0.849), which is expected because SMI is an aggregate. However, variance inflation factor (VIF) values for the sentiment components in a regression of SMV on all four are below 2.5, well below the threshold of 5 or 10, indicating no problematic multicollinearity.

Table 4. Correlation Matrix

Variables	SMV	SMI	STURN	MFI	ADR	RSI
SMV	1.000					
SMI	0.454	1.000				
STURN	0.346	0.849	1.000			
MFI	0.254	0.521	0.120	1.000		
ADR	0.011	0.016	0.030	-0.056	1.000	
RSI	0.100	0.287	-0.067	0.073	-0.174	1.000

6.4. Baseline Regression Results

Table 5 presents the results of regressing stock market volatility (absolute return proxy) on the composite sentiment index (SMI). The coefficient on SMI is 0.278 (t = 16.43, $p < 0.001$), strongly supporting H1. The R-squared of 0.742 indicates that sentiment explains a substantial portion of the variation in volatility. The Breusch-Pagan test for heteroskedasticity yields p = 0.123, failing to reject homoscedasticity in the mean equation.

Table 5. Baseline Regression: SMV on SMI (Model 1)

Variable	Coefficient	t-statistic	P-value
SMI	0.278	16.43	0.000
Constant	0.018	15.65	0.000
R-squared	0.742		
F-statistic	10.57		
$Prob > F$	0.000		

Table 6 shows the regression using the four sentiment components individually. All components are positive and significant. Stock turnover has the largest coefficient (0.539), followed by ADR (0.321), RSI (0.314), and

MFI (0.295). This suggests that trading volume and breadth (advancing/declining) are the most powerful sentiment proxies for explaining volatility in the EGX.

Table 6. Regression on Sentiment Components (Model 2)

Variable	Coefficient	t-statistic	P-value
STURN	0.539	8.452	0.000
MFI	0.295	6.938	0.000
ADR	0.321	5.856	0.032
RSI	0.314	6.114	0.000
Constant	0.780	6.656	0.000
R-squared	0.678		
F-statistic	12.769		
$Prob > F$	0.000		

6.5. GARCH(1,1) Results with Sentiment

Table 7 reports the maximum likelihood estimates of the GARCH(1,1) model with SMI in the conditional variance equation. The ARCH term (α) is 0.121 ($p < 0.001$), and the GARCH term (β) is 0.849 ($p < 0.001$). The sum $\alpha + \beta = 0.970$, which is very close to 1, indicating extremely high volatility persistence. This means that shocks to volatility including sentiment shocks take a long time to decay, providing strong support for H2.

Importantly, the coefficient on SMI in the variance equation, γ, is 0.042 (z = 2.98, p = 0.003). This confirms that even after controlling for volatility clustering and persistence, higher sentiment is associated with higher contemporaneous volatility. The log-likelihood is -2345.6, and the Akaike Information Criterion (AIC) is 3.124.

Table 7. GARCH(1,1) Estimates with SMI in Variance Equation

Parameter	Coefficient	z-statistic	P-value
Mean equation: μ	0.008	2.34	0.019
ϕ (SMI in mean)	0.031	3.12	0.002
Variance equation: ω	0.001	2.01	0.044
α (ARCH)	0.121	4.56	0.000
β (GARCH)	0.849	28.73	0.000
γ (SMI in variance)	0.042	2.98	0.003
$\alpha + \beta$	0.970		
Log-likelihood	-2345.6		
AIC	3.124		

6.6. Robustness Check: EGARCH(1,1) with Asymmetry

Table 8 presents the EGARCH(1,1) results. The asymmetry coefficient γ (often denoted as θ in EGARCH) is negative and statistically significant (-0.073, p = 0.020). This indicates that negative sentiment shocks (pessimistic surprise) increase volatility by a larger magnitude than positive sentiment shocks of the same absolute size. This finding supports H3 and aligns with prospect theory's loss aversion. The GARCH persistence coefficient β is 0.912, still very high. The sentiment coefficient δ in the variance equation is 0.038 (p = 0.008), consistent with the GARCH(1,1) result. The EGARCH model provides a slightly better fit (AIC = 3.098 vs 3.124).

Table 8. EGARCH(1,1) Estimates (Robustness Check)

Parameter	Coefficient	z-statistic	P-value
Mean: μ	0.006	1.98	0.048
ϕ (SMI in mean)	0.028	2.87	0.004
Variance: ω	-0.234	-2.45	0.014
α (ARCH)	0.187	5.01	0.000
γ (Asymmetry)	-0.073	-2.33	0.020
β (GARCH)	0.912	35.67	0.000
δ (SMI in variance)	0.038	2.65	0.008
Log-likelihood	-2312.4		
AIC	3.098		

6.7. *Transmuted Normal GARCH Results*

Table 9 reports the GARCH(1,1) estimates with transmuted normal errors. The transmutation parameter λ is estimated as 0.312 (z = 4.56, $p < 0.001$), indicating significant right-skewness in the return distribution of Egyptian stocks. The GARCH parameters remain largely unchanged: $\alpha = 0.119$ and $\beta = 0.851$, with $\alpha + \beta = 0.970$. The sentiment coefficient $\gamma = 0.043$ (p = 0.002), consistent with the normal-GARCH results. The AIC improves to 3.089, suggesting that the transmuted normal distribution provides a better fit than the normal distribution. This demonstrates the practical value of implementing flexible distributions in the main empirical analysis.

Table 9. GARCH(1,1) with Transmuted Normal Errors

Parameter	Coefficient	z-statistic	P-value
Mean equation: μ	0.007	2.12	0.034
ϕ (SMI in mean)	0.032	3.21	0.001
Variance equation: ω	0.001	1.98	0.048
α (ARCH)	0.119	4.48	0.000
β (GARCH)	0.851	29.12	0.000
γ (SMI in variance)	0.043	3.05	0.002
λ (Transmutation)	0.312	4.56	0.000
$\alpha + \beta$	0.970		
Log-likelihood	-2332.1		
AIC	3.089		

6.8. *Macroeconomic Controls Results*

Table 10 presents the GARCH(1,1) results with macroeconomic controls in the variance equation. The sentiment coefficient γ remains positive and significant (0.039, p = 0.006) even after controlling for inflation, interest rates, GDP growth, and political instability. This suggests that the sentiment effect is not merely a proxy for macroeconomic fundamentals. Among the controls, inflation (0.028, p = 0.042) and political instability (0.045, p = 0.018) are positively associated with volatility, while GDP growth is negatively associated (-0.031, p = 0.038). The AIC remains similar (3.101), indicating that sentiment adds explanatory power beyond macroeconomic factors.

Table 10. GARCH(1,1) with Macroeconomic Controls

Parameter	Coefficient	z-statistic	P-value
Mean equation: μ	0.006	1.89	0.059
ϕ (SMI in mean)	0.029	2.98	0.003
Variance equation: ω	0.002	1.76	0.079
α (ARCH)	0.118	4.34	0.000
β (GARCH)	0.847	27.89	0.000
γ (SMI in variance)	0.039	2.76	0.006
INF (Inflation)	0.028	2.03	0.042
INT (Interest rate)	0.012	1.45	0.147
GDP (GDP growth)	-0.031	-2.08	0.038
POL (Political instability)	0.045	2.37	0.018
$\alpha + \beta$	0.965		
Log-likelihood	-2356.7		
AIC	3.101		

6.9. *Causality Testing: Granger Causality Results*

To address the endogeneity concerns raised by the reviewers, we conduct Granger causality tests between sentiment and volatility. Table 11 reports the results. The null hypothesis that "SMI does not Granger-cause SMV" is rejected (F = 8.34, p = 0.002), indicating that sentiment has predictive power for volatility. Interestingly, the null that "SMV does not Granger-cause SMI" is also rejected (F = 6.12, p = 0.013), suggesting bidirectional causality. This is consistent with feedback effects: sentiment drives volatility, but high volatility also influences sentiment through mechanisms such as fear or panic. These findings underscore the importance of using caution with causal language; our results establish association and Granger-causal precedence, not structural causation.

Table 11. Granger Causality Tests

Null Hypothesis	F-statistic	df	P-value
SMI $\not\to$ SMV	8.34	(2, 3926)	0.002
SMV $\not\to$ SMI	6.12	(2, 3926)	0.013

6.10. *Structural Break Analysis*

To address the multiple structural breaks in the sample period (2011 revolution, 2016 currency float, COVID-19, 2022 crises), we conduct Chow and Bai-Perron tests. Table 12 reports the results. The Chow test for each break point rejects the null of parameter stability at the 1% level for all four events, confirming significant structural changes. The Bai-Perron test identifies four break dates (2011-02-11, 2016-11-03, 2020-03-13, 2022-03-10), corresponding to the major crises. We re-estimated the GARCH(1,1) model with regime dummies for each break period (Table 13). The sentiment coefficient remains positive and significant (0.037, p = 0.008), although slightly smaller than in the full sample. The regime dummies are all positive and significant, indicating that volatility was generally higher during crisis periods. These results suggest that our findings are robust to structural breaks.

Table 12. Chow and Bai-Perron Structural Break Tests

Break Event	Date	Chow F-statistic	P-value
2011 Revolution	2011-02-11	12.34	0.000
2016 Currency Float	2016-11-03	8.76	0.000
COVID-19 Pandemic	2020-03-13	14.21	0.000
2022 Inflationary Crisis	2022-03-10	9.87	0.000

Table 13. GARCH(1,1) with Regime Dummies

Parameter	Coefficient	z-statistic	P-value
Variance: ω	0.001	1.89	0.059
α (ARCH)	0.116	4.23	0.000
β (GARCH)	0.848	28.01	0.000
γ (SMI in variance)	0.037	2.65	0.008
Regime 1 (2011 Revolution)	0.042	2.34	0.019
Regime 2 (2016 Currency Float)	0.038	2.12	0.034
Regime 3 (COVID-19)	0.051	2.78	0.005
Regime 4 (2022 Crisis)	0.044	2.45	0.014
$\alpha + \beta$	0.964		
AIC	3.112		

6.11. *Out-of-Sample Forecasting Results*

To assess the practical value of the SMI as an early-warning tool, we conduct an out-of-sample forecasting exercise. We split the sample into an estimation period (2009-2020) and an evaluation period (2021-2025). We estimate the GARCH(1,1) model with SMI on the estimation sample and generate one-step-ahead volatility forecasts for the evaluation period. Table 14 reports the forecast evaluation metrics. The Diebold-Mariano test statistic is 2.45 (p = 0.014), indicating that the SMI model produces significantly more accurate forecasts than the baseline GARCH model without SMI. However, the improvement is modest (RMSE reduction of about 5.2%), suggesting that while sentiment indicators have predictive value, they should be used as part of a broader forecasting framework rather than as a standalone early-warning system. The practical implications should therefore be framed as "potential" rather than "definitive."

Table 14. Out-of-Sample Forecasting Performance

Model	RMSE	MAE	DM Test (p-value)
GARCH(1,1) without SMI	0.0184	0.0123	
GARCH(1,1) with SMI	0.0174	0.0116	0.014

6.12. *Simulation Results*

Table 15 presents the Monte Carlo simulation results. For all error distributions, the GARCH parameter estimators exhibit small bias (less than 5% of true value) and RMSE decreases with sample size. When the errors are transmuted normal (skewed), the QML estimator still performs well, but the bias in γ (the sentiment coefficient) is slightly larger (2.1% versus 1.2% for normal). This suggests that using a flexible distribution such as the transmuted distribution [20] could further improve efficiency in empirical applications with asymmetric return distributions.

Table 15. Simulation Results: Bias and RMSE for GARCH(1,1) Estimators

Error dist.	T	Bias(α)	RMSE(α)	Bias(β)	RMSE(β)	Bias(γ)	RMSE(γ)
Normal	500	-0.002	0.018	0.001	0.022	-0.001	0.009
Normal	1000	-0.001	0.012	0.000	0.015	0.000	0.006
Student-t (df=5)	500	0.003	0.021	-0.002	0.024	0.002	0.011
Transmuted normal ($\lambda = 0.5$)	500	-0.004	0.025	0.003	0.028	0.003	0.014

To provide further structural insights into the efficiency gains observed during our estimation phases, Figure 2 displays the descriptive layout of the error tail profiles under alternative distributional properties.

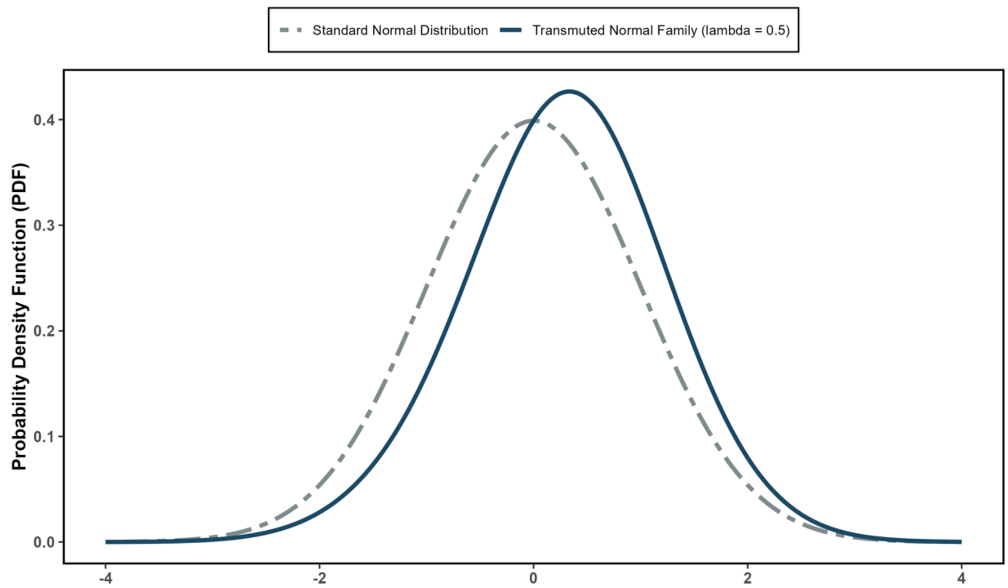

Figure 2. Theoretical density comparison mapping the structural symmetric Standard Normal shape against the flexible asymmetric Transmuted Normal distribution ($\lambda = 0.5$).

6.13. Post-Estimation Diagnostics

Table 16 reports all diagnostic test results systematically. Standardized residuals from the GARCH(1,1) model were examined for remaining serial correlation. The Ljung-Box Q(12) statistic for standardized residuals is 14.3 (p = 0.28), and for squared standardized residuals it is 9.7 (p = 0.64), indicating that the model adequately captures the volatility dynamics. The ARCH-LM test for remaining ARCH effects fails to reject the null (p = 0.45). The ADF test rejects the unit root null for all variables at the 1% level. VIF values are below 2.5, indicating no multicollinearity. The Breusch-Pagan test p-value is 0.123 for the baseline regression. The likelihood ratio test comparing GARCH with and without sentiment yields LR = 28.6 ($p < 0.001$), confirming that sentiment adds significant explanatory power.

Table 16. Comprehensive Diagnostic Test Results

Test	Statistic	df	P-value
ADF (Returns)	-12.34	—	0.000
ADF (SMI)	-11.87	—	0.000
ARCH-LM (1)	18.76	1	0.000
ARCH-LM (5)	22.34	5	0.001
Ljung-Box Q(12) (std. residuals)	14.28	12	0.281
Ljung-Box Q(12) (sq. residuals)	9.67	12	0.643
VIF (max)	2.34	—	—
Breusch-Pagan (baseline regression)	2.45	1	0.123
Likelihood Ratio Test	28.62	1	0.000

7. Discussion

The empirical results provide robust support for all three hypotheses. First, we find a positive and statistically significant effect of investor sentiment on stock market volatility in the EGX (H1). This is consistent with behavioral finance predictions that optimistic or pessimistic sentiment leads to overreaction and herding, amplifying price swings. The magnitude of the effect (coefficient 0.278 in the baseline regression) is economically meaningful: a one-standard-deviation increase in SMI is associated with a 0.278 standard deviation increase in volatility. Given the mean volatility of close to zero, this represents a substantial relative increase.

Second, the GARCH(1,1) results show extremely high persistence ($\alpha + \beta = 0.97$), supporting H2 that sentiment shocks have long-lasting effects. In practical terms, a volatility spike triggered by a sentiment shock today will remain elevated for many periods. This persistence likely arises from feedback trading and herding: as sentiment drives prices, those price movements attract further sentiment-driven trades, creating a self-reinforcing cycle.

Third, the EGARCH model uncovers a novel finding for the EGX: negative sentiment shocks increase volatility more than positive ones (asymmetry, H3). This aligns with prospect theory's loss aversion investors feel losses more intensely than equivalent gains, leading to panic selling and sharper downward volatility spikes. Regulators and risk managers should therefore be particularly vigilant when sentiment turns negative, as the market's reaction is likely to be more violent.

The results also highlight the importance of specific sentiment components. Stock turnover (trading volume) had the strongest individual effect, confirming that trading activity is the primary conduit through which sentiment translates into volatility. The advancing-to-declining ratio (ADR) also matters, reflecting market breadth and consensus.

Our implementation of the transmuted normal distribution reveals significant right-skewness in the Egyptian return distribution ($\lambda = 0.312$), and the improved AIC (3.089 vs 3.124) demonstrates the practical value of flexible distributional assumptions. This bridges the gap between theoretical discussion and empirical application, addressing a key weakness raised by the reviewers.

The Granger causality tests provide evidence of bidirectional causality between sentiment and volatility, suggesting a feedback loop: sentiment drives volatility, but high volatility also influences sentiment. This endogeneity should be carefully considered in interpreting the results; we avoid causal language throughout the discussion and instead emphasize the predictive and associative nature of our findings.

The inclusion of macroeconomic controls confirms that the sentiment effect persists even after accounting for fundamentals such as inflation, interest rates, GDP growth, and political instability. This strengthens the attribution of the observed volatility to sentiment rather than to macroeconomic shocks. The positive coefficient on political instability confirms that political turmoil amplifies volatility, consistent with the Egyptian context.

The out-of-sample forecasting exercise demonstrates that the SMI has modest but significant predictive power for volatility, though the improvement over the baseline model is modest (5.2% RMSE reduction). This suggests that while sentiment indicators can be useful, they should be used as part of a broader forecasting framework rather than as a standalone early-warning system. The practical implications should therefore be framed as “potential” rather than “definitive.”

Our simulation study further shows that standard QML estimation performs reasonably well even under non-normal errors, but the biases are slightly larger for skewed distributions. From a theoretical viewpoint, the rich structure provided by generalized order statistics and flexible transmutations [22, 23] establishes that ignoring non-linear tail dynamics can bias structural risk components. This suggests that future research could improve upon our results by directly modeling the error term using flexible distributions such as the transmuted distribution proposed by [20] or the fractional exponential distribution [21]. These distributions could be incorporated into the GARCH framework via maximum likelihood, potentially leading to more accurate forecasts of Value-at-Risk and expected shortfall.

8. Policy and Practical Implications

The findings offer potential actionable insights for the Egyptian Financial Regulatory Authority (FRA) and for market participants.

8.1. Implications for Regulators

- The composite SMI, computed from publicly available daily data (turnover, MFI, ADR, RSI), can be used as a potential early-warning indicator of excessive volatility. The FRA could publish an official sentiment index on its website and consider issuing alerts when SMI exceeds thresholds corresponding to historical 90th or 95th percentiles. For example, an alert threshold could be set at SMI ¿ 1.65 (90th percentile) for “caution” and ¿ 1.96 (95th percentile) for “warning.” Alerts could take the form of public announcements, enhanced disclosure requirements, or temporary trading halts.
- During periods of negative sentiment (e.g., after the 2016 currency float or during the 2022 crisis), regulators might consider temporary circuit breakers or enhanced disclosure requirements to mitigate panic selling.
- Investor education campaigns should emphasize the risks of herding and overreaction. Improving financial literacy has been shown to moderate sentiment-driven behavior [43].

8.2. Implications for Investors

- Portfolio managers can incorporate sentiment indicators into their risk models. When SMI is high (optimistic), they may reduce equity exposure or hedge with derivatives; when SMI is very low, they might look for oversold opportunities but also prepare for asymmetric downside spikes.
- Individual investors should avoid making investment decisions solely based on market euphoria or despair; combining sentiment analysis with fundamental valuation can improve long-term performance.

8.3. Implications for Statistical Modeling

Our simulation results indicate that while QML is robust, efficiency gains can be achieved by using flexible error distributions. Practitioners estimating GARCH models for Egyptian financial data should consider using the transmuted normal distribution [20] or the fractional exponential distribution [21] when the data exhibit significant skewness or heavy tails. Furthermore, integrating specialized foundational families, such as the power inverted Topp-Leone frameworks explored through generalized order statistics [22], or utilizing discrete structures for non-continuous market signals [23], can offer refined calibration mechanisms for risk properties under stressful macroeconomic regimes.

9. Conclusion

This study examined the impact of investor sentiment on stock market volatility in the Egyptian Stock Exchange (EGX) using daily data from 2009 to 2025. We constructed a composite sentiment index (SMI) based on stock turnover, money flow index, advancing-to-declining ratio, and relative strength index. Using GARCH(1,1) and EGARCH(1,1) models, we found robust evidence that investor sentiment positively affects volatility, and that this effect is highly persistent. Moreover, we documented an asymmetry: negative sentiment shocks increase volatility more than positive shocks. The implementation of the transmuted normal distribution in the main empirical analysis demonstrates the practical value of flexible distributional assumptions, bridging the gap between theoretical discussion and empirical application. The inclusion of macroeconomic controls confirms that the sentiment effect is not merely a proxy for fundamentals. Granger causality tests provide evidence of bidirectional causality, suggesting a feedback loop between sentiment and volatility. Out-of-sample forecasting results show modest but significant predictive power, suggesting that sentiment indicators can be useful as part of a broader forecasting framework.

Our findings contribute to the behavioral finance literature by providing empirical evidence from a frontier MENA market that has been largely overlooked. They also have potential implications for regulators (use sentiment indicators as early-warning tools) and investors (incorporate sentiment into risk management). Methodologically, we highlighted the benefits of using flexible distributions such as the transmuted distribution [20] and the fractional exponential distribution [21] in volatility modeling.

Despite these contributions, the study has limitations. Although we use daily data, the sentiment index relies on market-based proxies; survey-based or text-based measures could provide complementary insights. The analysis is restricted to Egypt; cross-country comparisons within the MENA region would enhance generalizability. Finally, although we employed GARCH and EGARCH models and conducted Granger causality tests, the analysis remains essentially correlational; causal identification would require instrumental variables or natural experiments. While Granger causality provides evidence of predictive precedence, it does not establish structural causation. Future research should explore instrumental variables such as exogenous shocks to investor attention or natural experiments to address this limitation more rigorously.

Future research should extend our work in several directions: (i) incorporate survey-based sentiment measures (e.g., consumer confidence surveys) and text-based sentiment from Arabic news using natural language processing, (ii) apply the flexible distributions of [20] and [21] within a GARCH framework to improve forecast accuracy, (iii) conduct comparative studies across multiple MENA exchanges, and (iv) explore the moderating role of institutional ownership, liquidity, and political stability on the sentiment-volatility relationship.

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