The Investor Sentiment Impact on the Egyptian Stock Market Volatility: A Non-Linear Framework

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Abstract

Empirical evidence investigating the dynamics between investor sentiment and the stock mean-variance framework remains inconclusive and unsettled. Therefore, the current study aims to examine the role of sentiment in the formation of the Egyptian systematic risk. It constructs a top-down aggregate sentiment index for the Egyptian stock market to assess the impact and predictive power of investor sentiment on the Egyptian stock market volatility within a non-linear conditional mean-variance framework. The findings confirm the impact of investor sentiment on market volatility. However, regarding the predictive ability of the sentiment index, the study emphasizes the need to account for structural breaks in future research when examining the effect of investor sentiment on the stock market mean-variance framework.

Keywords

investor sentiment, stock market volatility, ARCH group models, emerging markets

Article history

Received: *07 June 2024* · **Accepted:** *04 July 2024*

1. Introduction

Market volatility has long been a major concern for traders, investors, and policymakers. In addition to its role as a key factor in setting asset prices, it is crucial for managing risk. The level of market volatility can significantly affect how smoothly capital markets operate. High volatility, for example, can elevate the cost of capital by increasing the risk premium, which may consequently reduce economic output and impact investment decisions. As a result, understanding and predicting market volatility remains a central research focus, which is unlikely to decline until it can be accurately predicted.

Many researchers have examined the factors driving market volatility. Schwert (1989) linked it to the fluctuations in the business cycle, while French and Roll in 1986 attributed it to trading activity. Black in 1976 highlighted the role of financial leverage. However, as traditional financial theories struggled to explain various stock market deviations and failed to fully comprehend market movements, behavioral finance emerged. This new approach examines how individual biases and heuristics influence the stock market around, extending beyond the rigid calculations of risk and return.

One notable perspective that has been explored is how traders' moods and irrational decisions—often referred to as 'noise trading'—as well as the overall investor sentiment contribute to market volatility. Jyoti Kumari in 2019 and others have examined the impact of emotional trading. A key study in this area was conducted by DeLong et al. in the 1990s, who developed a theory demonstrating the significance of sentiment in determining asset prices.

Recognizing the critical role of sentiment in asset pricing and the scarcity of studies focusing on its impact on risk in emerging markets like Egypt, this research aims to explore the influence of investor sentiment on market volatility in Egypt's stock market. To achieve this, an index will be developed to measure irrational investor sentiment in Egypt, adapting Baker and Wurgler's method for emerging markets. This approach will highlight the intricate dynamics of one of the region's key financial hubs.

The research has theoretical and practical implications. For theoretical implications, the research expands the literature by being the first to investigate the relevance and significance of investor sentiment as a factor embedded in the systematic risk of the emerging markets, precisely Egypt, and its role in the construction of conditional volatility in the Egyptian stock market within a non-linear framework. The research provides further support for the noise trader theory in Egypt by demonstrating the substantial ability of behavioral finance in explaining stock return volatility and resolving the eminent paradox of sentiment-volatility dynamics. By establishing sentiment as a significant factor in stock return volatility, the research facilitates future research addressing the augmentation of the asset pricing models to include sentiment. For practical implications, the research enables market participants to improve their predictability of Egypt's stock market volatility and refine asset pricing by incorporating the sentiment factor in the financial pricing models. Finally, the improvement of market prediction for Egypt's stock market can further attract both domestic and foreign investors.

2. Theoretical Background

2.1. From the Neo-classical to the Behavioral Finance and Noise Trade Theory

The neo-classical theory of finance, which gained prominence in the latter half of the 19th century, is a normative-approach-based theory on economic decision making and utility maximization (Jegadeesh, 1995; Nell, 1984), primarily based on the rational expectations hypothesis (REH). The theory suggests that economic agents are rational, risk-averse, and primarily focused on maximizing their expected utility based on economic factors. Moreover, it asserts that rational actions among market participants can correct asset mispricing through arbitrage, which realigns prices with their fundamental values (Kumari & Mahakud, 2015; Friedman, 1953). Central to this theory are the capital asset pricing model (CAPM), the arbitrage principle, and most importantly, the efficient market hypothesis (EMH). The EMH posits that a market achieves efficiency when prices at any moment fully reflect all available information (Fama, 1970). Fama (1965, 1970) provided key insights into the various forms of market efficiency and elaborated on the random walk hypothesis, which implies that stock prices fluctuate unpredictably as they immediately adjust to new information, rendering future prices unpredictable (Malkiel, 2003).

Despite its foundational status, the EMH has received ongoing criticism, particularly for its assumption of 'rationality'. This criticism led to the emergence of behavioral finance, a field that challenges the neo-classical framework by demonstrating how individual biases and heuristics impact financial decision-making (Barberis & Thaler, 2003; Daniel et al., 2002; Shiller, 2000). Behavioral finance introduces the concept of 'noise traders;' market participants whose decisions are influenced by irrational beliefs or non-fundamental information, thereby distorting asset prices from their intrinsic values and amplifying market volatility (De Long et al., 1990; Black, 1986; Shleifer & Vishny, 1997). Hence, noise trading, or investor sentiment is a component of systematic risk and should be incorporated into asset pricing (Kumari and Mahakud, 2015; Baker and Wurgler, 2006, 2007; Black 1986). This perspective is supported by empirical research highlighting the significant effect of such trading on market dynamics and the critical role of investor sentiment in asset pricing (Kumari & Mahakud, 2015; Baker & Wurgler, 2006).

In summary, while the neo-classical theory of finance regards market participants as rational agents capable of correcting pricing inefficiencies through arbitrage, the emergence of behavioral finance challenges this perspective. It emphasizes the impact of psychological factors on market operations, presenting a more comprehensive understanding of financial markets that acknowledges both rational and irrational investor behavior.

2.1.1. Investor Sentiment and the Mean-Variance Relation in Stock Returns

The relationship between investor sentiment, stock returns, and market volatility has been a longstanding focus of research. Studies by Neal and Wheatley (1998), Simon and Wiggins (1999), and Wang et al. (2006) indicate that investor sentiment can effectively predict stock returns. Baker and Wurgler (2006, 2007) further invetsigated how investor sentiment affects different types of stocks. They concluded that value and small stocks, which are more difficult to arbitrage and evaluate, are particularly sensitive to sentiment shifts. Moreover, they found that stocks from unprofitable, highly volatile, or growth-seeking firms are also significantly influenced by investor sentiment and noise trading.

With regard to conditional volatility, Lee et al. (2002) and Aydogan (2016) demonstrated that sentiment is a key factor in explaining conditional volatility in both the US and European markets. This notion was further supported by Verma and Verma (2007), highlighting the role of noise trading in volatility formation. Beyond the stock market, Yang et al. (2019) and Qadan and Nama (2018) showed that investor sentiment could predict volatility in the crude oil market, a finding echoed by Chen et al. (2021) within the energy sector.

Despite these insights, the predictive power of investor sentiment on stock volatility remains debated, especially in emerging markets. Wang et al. (2006) observed a reverse causality, suggesting that return volatility influences investor sentiment rather than the reverse. Similarly, Spyrou (2012) and Kling and Gao (2008) questioned the influence of sentiment on volatility and stock prices, respectively. However, in contrast to these findings, Chandra and Thenmozhi (2013) noted a positive relationship between sentiment, excess returns, and market volatility. Wang and Duxbury (2021) further supported this perspective, suggesting that markets with a cultural inclination toward overreaction are more influenced by sentiment. Furthermore, Haritha and Abdul Rishad (2020) provided substantial evidence of sentiment's impact on market volatility, indicating that irrational sentiment increases market volatility and affects returns. Finally, Yu and Yuan (2011) explored how investor sentiment is integrated into systematic market risk and is reflected in asset pricing through its impact on excess returns and conditional volatility.

2.1.2. Predicting Volatility in Emerging Markets

Regarding the emerging markets, investor behavior has been observed to differ from that in developed markets (Kim and Nofsinger, 2008). This difference can be attributed to higher stock volatility, uncertain policies, and weaker market efficiency compared to the developed markets (Bekaert and Harvey, 2003; Lim and Brooks, 2011; Lesmond, 2005). Similarly, Wang and Duxbury (2021) found that emerging markets exhibit a more immediate reaction to changes in investor sentiment than developed markets. A notable study investigating emerging markets in the context of noise trading and conditional volatility is that of Kumari and Mahakud (2015). Their investigation of the Indian stock market validated the embeddedness of sentiment into the systematic market risk, its positive correlation with the excess returns, and its predictive power of stock return volatility within a conditional non-linear mean-variance framework.

In light of the discussed literature, the question of whether investor sentiment affects stock market volatility remains unresolved, with some studies attributing the inconclusive results to the false assumption of linearity under which certain investigations were conducted, highlighting the significance of accounting for news (Cagli et al., 2020). Building on the work of Cagli et al., (2020) and Van Hoang and Syed (2021), the research aims to address the existing paradox of the sentiment's predictive ability on stock market volatility by identifying structural breaks and conducting the analysis in a non-linear framework. Hence, the research aims to examine the predictive power of investor sentiment on the conditional volatility of the Egyptian stock market within a non-linear framework, addressing whether sentiment index truly predicts market volatility in emerging markets while considering the impact of news.

Based on Kumari and Mahakud (2015), it has been indicated that investor sentiment has significant predicting power on stock market volatility, especially in the emerging markets. Accordingly, the following hypothesis can be proposed:

H1: *Investor Sentiment has predictive power over the Egyptian stock market return volatility.*

3. Methodology

3.1. Sentiment Index Variables and Construction

To measure investor sentiment, the study adopts the macro-economic top-down approach proposed by Baker and Wurgler (2006, 2007), which consolidates sentiment proxies to observe the impacts of market volatility and market returns through aggregate sentiment proxies based on specific market indicators, a methodology employed by Brown and Cliff (2004) as well as Baker and Wurgler (2006, 2007). The approach is particularly suitable for Egypt, as an emerging market predominantly influenced by institutional rather than retail investors, thus facilitating the applicability of the macroscopic top-down strategy. This strategy is essentially a macro-economic method that consolidates measurement forms and sentiment proxies to analyze the influence of market returns and volatility, as described by Kumari and Mahakud (2015; p.31). Furthermore, due to the absence of a universally accepted theory regarding the number and selection of proxies for a sentiment index, this study adopts proxies employed by Kumari and Mahakud (2015), emphasizing the relevance of the chosen sentiment proxies to emerging markets, while remaining constrained by data availability. Additionally, aiming for a broader understanding of market sentiment, the study incorporates two macro-economic proxies: IPO volume and the bank deposit-to-market cap ratio, following the approach of Piyush Pandey and Sanjay Sehgal (2019) in their analysis of emerging markets. Table 1 summarizes the variables and their measurements of the sentiment proxies for the construction of sentiment index.

Following Baker and Wurgler (2006), and as further applied by Rupande et al. (2019), Haritha and Rishad (2020), and Kumari and Mahakud (2015), the sentiment index is constructed in two steps. In the first step, each of the sentiment proxies is orthogonalized by regressing it against economic and business cycle fundamentals to eliminate business cycle fluctuations, as presented in Equation 1, assuming that each proxy contains information about the current economic conditions (Sibley et el., 2016; Baker and Wurgler, 2006). Table 2 summarizes the macroeconomic variables utilized for orthogonalization.

In the second step, the errors of the orthogonalized proxies are used to construct the sentiment index, as presented in Equation 2. To capture the irrational component of the sentiment index after adjusting it for the business cycle, the first principal component in Equation 2 is applied to the extracted residuals from Equation 1. Specifically, Equation 2 shows the irrational sentiment index, as the independent variable.

$$Sentindex_{it} = \alpha_0 + \gamma_j \sum_{j=1}^{10} Fund_{jt} + \varepsilon_{jt} \qquad (1)$$

whereas,
α_0 = constant
γ_j = parameter to be estimated for each proxy
$Fund$ = business cycle fundamentals (Table 2)
ε_{jt} = random error

$$Sentindex_t = \theta_1 ADR_t + \theta_2 BSI_t + \theta_3 DP_t + \theta_4 ES_t + \theta_5 FF_t + \theta_6 NIPO_t + \theta_7 TV_t + \theta_8 TVOL_t + \theta_9 VIPO_t + \theta_{10} BMR_t \qquad (2)$$

whereas,
θ_j = factor loading on the first principal component of the lagged proxies

Table 1: Sentiment Proxies: Variables and Measurements

Variable	Variable Measurement	Expected relationship with Sentiment & supporting Lit.
Advance Decline Ratio (ADR)	Number of advancing shares/number of declining shares	Positive *(Brown and Cliff, 2004); (Kumar and Lee, 2006); (Kumari and Mahakud, 2015)*
Dividend Premium (DP)	Log of average market to book ratio of (div. payers less the non div payers)	Negative *(Kumari and Mahakud, 2015)*
Equity Share (ES)	Gross equity issuance/(gross equity + gross long-term debt issuance)	Positive *(Baker and Wurgler, 2000)*
Net IPO (NIPO)	Difference between the returns based on IPO offer p rice and the initial price of the stock at the beginning of the first trading day	Positive *(Kumari and Mahakud, 2015)*
Trading Volume (TV)	Index Turnover or OBV (On-Balance-Volume)	Positive *(Kumari and Mahakud, 2015)*
Turnover volatility (TVOL)	(Turnover ratio)/(standard deviation of market returns); whereas the turnover ratio = trading volume/market cap	Positive *(Kumari and Mahakud, 2015)*

IPO Volume (VIPO)	Number of IPOs per period t	Positive *(Pandey and Sehgal, 2019)*
Bank deposit/market cap ratio (BMR)	Bank deposits/Market Capitalization	Negative *(Pandey and Sehgal, 2019)*

Table 2: Macro-economic Variables

Variable	**Variable Measurement**
Volatility (Market_Vol)	Deviation of stock market return from its mean value
Risk free rate (Rf)	30 days T-bill
Economic Growth (Gdpg)	IIP – Industrial Production Index (Proxy)
Exchange rate (Delta_Ex.)	EGP to USD exchange rate
Inflation (CPI)	CPI – Consumer Price Index (Proxy)
Market risk premium (mrp)	Market return less the risk free rate
Small to Large stocks (SMB)	Excess stock return of small cap companies over large cap companies
High to Low stocks (HML)	Excess return of value stocks (high book to price) over growth stocks (low book to price)
Momentum factor (WML)	Difference between average return on winners and losers portfolio

3.2. GARCH Models for Market Volatility Prediction

In estimating the impact of investor sentiment on the volatility of stock market, and following Kumari and Mahakud (2015) and Haritha and Rishad (2020), the GARCH set models are used in a time series analysis to analyze volatility. Specifically, three volatility models will be used: the GARCH model, the EGARCH (exponential GARCH) model, and the Power ARCH (PARCH) model.

While the GARCH model is the most widely used in empirical research, and captures the volatility clustering and symmetry of conditional variance, it does not account for the asymmetric effects between negative and positive returns. Hence, the EGARCH model is further employed to address this limitation. Finally, the study applies the PARCH model, allowing a more flexible approach to the non-linear effects of shocks on volatility and confirming the results of the EGARCH model.

To assess the predictive power of sentiment index on stock market return volatility, the sets of GARCH models will be estimated with and without the irrational sentiment index.

$$Y_t = \alpha_0 + \beta_0 Y_{t-1} + \beta_1 Sentindex_{t-1} + u_t \quad (1)$$

$\varepsilon_t / \Omega \sim$ i.i.d. $(0, h_t)$

$$h_t = \omega_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-1} + \beta_3 Sentindex_{t-1} \quad (2)$$

$$\omega_0 > 0 \ and \ \alpha_j + \beta_i < 1$$

whereas,

Y_t= index stock returns

Y_{t-1}= lagged values of index returns

$Sent_{t-1}$= lagged investor sentiment

h_t= conditional variance

β_0= model coefficient

α_j= coefficient of lagged squared residuals

β_i= lagged conditional variance

and,

$$Y_t = \alpha_0 + \beta_0 Y_{t-1} + \beta_1 Sent_{t-1} + u_t \ (3)$$

$\varepsilon_t / \Omega \sim$ i.i.d. $(0, h_t)$

$$\log(h_t) = \omega + \sum_{j=1}^{q} \alpha_j \left[\left| \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} - E\left(\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right) \right| \right] + \sum_{k=1}^{m} \delta_k \frac{\varepsilon_{t-j}}{\sqrt{h_{t-k}}} + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \Psi_j Sent_{t-1} \ (4)$$

$\omega > 0$, $\alpha_j + \beta_i < 1$, $\delta_k < 0$

whereas,

$\log(h_t)$ = log of the conditional variance

ε_t= white noise

$$r_t = \mu + \epsilon_t \ (5)$$

whereas,

r_t = the asset returns at time t

μ = the constant mean of returns, and

ϵ_t = the error term or innovation at time t

$$\sigma_t^d = \omega + \alpha(\epsilon_{t-1}^2)^\delta + \beta(\sigma_{t-1}^d) + \gamma Sent_{t-1} \ (6)$$

whereas,

σ_t^d= conditional variance of returns raised to the power of d

ω= constant

α, β, γ = model parameters

$Sent$= Sentiment Index at t-1

4. Empirical Results and Discussion

The research relies on monthly data from January 2005 to May 2023 for the Egyptian stock market. The data were obtained from Datastream Thomson Reuters Eikon and the Egyptian Stock Exchange. Market volatility is measured as the difference between closing prices at the beginning and end of period *t*.

4.1. Descriptive Statistics

Table 3: Descriptive Statistics of the Sentiment Proxies

	ADR	BMR	ES	DP	NIPO	TV	TVOL	VIPO
Mean	2.279837	3.81E-07	5.702187	5.824663	0.012549	7101478.	17845348	0.511312
Median	1.011628	2.67E-07	5.000000	5.830898	0.000000	6311792.	14000000	0.000000
Maximum	18.66667	1.47E-06	15.25892	5.947592	1.169377	19500000	2.09E+08	5.000000
Minimum	0.027397	4.15E-11	-4.532778	4.605170	-0.440000	1459909.	2853509.	0.000000
Std. Dev.	3.271336	4.30E-07	3.502554	0.102073	0.111032	3624500.	18780315	0.912593
Skewness	2.561868	0.751790	0.737325	-7.740460	5.183470	1.245841	6.543450	2.340173
Kurtosis	9.903693	2.272742	4.169924	93.26963	57.96988	4.387053	59.31276	9.348214
Jarque-Bera	680.6215	25.68811	32.62803	77241.93	28814.35	74.88578	30777.88	572.8087
Probability	0.000000	0.000003	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	503.8439	8.43E-05	1260.183	1287.250	2.773296	1.57E+09	3.94E+09	113.0000
Sum Sq. Dev.	2354.360	4.08E-11	2698.934	2.292156	2.712181	2.89E+15	7.76E+16	183.2217
Observations	221	221	221	221	221	221	221	221

Table 4: Descriptive Statistics of the Sentiment Proxies

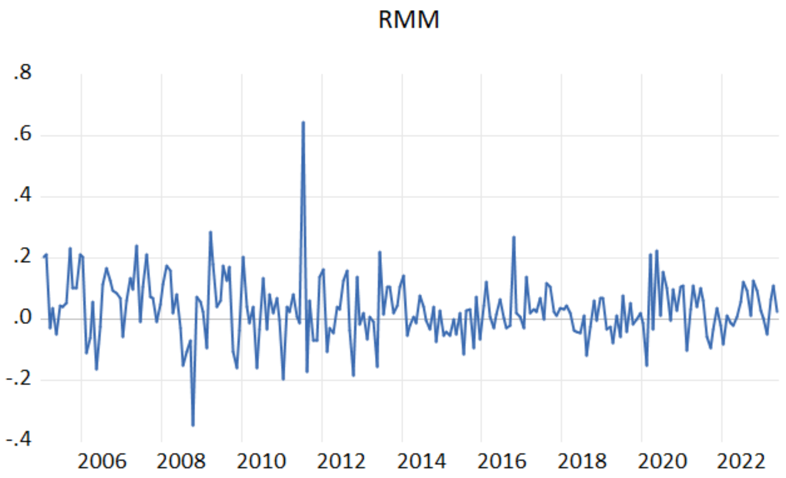
	CPI	DELTA_EX...	GDPG	HML	MARKET_...	MRF	MRP	SMB	WML
Mean	63.59050	0.111782	0.046599	0.033370	0.010766	0.010620	0.017538	-0.001228	-0.043065
Median	49.10000	0.000150	0.020832	0.020954	0.009131	0.010079	0.014019	-0.000784	-0.020833
Maximum	173.5000	9.096800	0.317094	0.396602	0.045242	0.019826	0.521823	0.195260	0.428854
Minimum	20.40000	-3.006500	-0.088589	-0.143296	0.002639	0.000000	-0.398374	-0.145118	-1.295967
Std. Dev.	37.98279	0.840277	0.102638	0.077891	0.006448	0.003246	0.127618	0.057782	0.162340
Skewness	0.788882	7.373807	0.911872	1.462023	2.141286	0.502080	0.445167	0.368217	-2.489386
Kurtosis	2.610046	72.10257	2.881888	7.395452	9.819602	3.146245	5.779079	4.151846	18.89266
Jarque-Bera	24.32290	45974.05	30.75575	256.6367	597.1363	9.482047	78.41796	17.21116	2554.066
Probability	0.000005	0.000000	0.000000	0.000000	0.000000	0.008730	0.000000	0.000183	0.000000
Sum	14053.50	24.70375	10.29846	7.374671	2.379373	2.347053	3.876005	-0.271298	-9.517335
Sum Sq. Dev.	317392.4	155.3345	2.317593	1.334758	0.009148	0.002318	3.582981	0.734531	5.797934
Observations	221	221	221	221	221	221	221	221	221

**With 'MARKET..' referring to Market Volatility*

4.2. Testing for Market Efficiency

In testing for market efficiency, the study applied the random walk hypothesis to the price return, following Fama (1965, 1970). The price return (RMM) exhibits stationarity, showing that past stock movements predict future movements, as they do not follow a random walk. Thus, the efficient market hypothesis for the Egyptian stock market is rejected, suggesting that the Egyptian stock market is weak-form efficient, as demonstrated in Figure 1. These findings confirm the choice of the sentiment construction method and sentiment proxies employed in the study.

Graph 1: Plot of Market Return



4.3. Sentiment Index Construction

Before the Sentiment proxies are orthogonalized to eliminate the business cycle fluctuations, all variables are tested for their stationarity using the ADF unit root test. The results indicate that all variables are stationary at level I(0), except for the monthly risk-free rate, core inflation rate (CPI), equity share (ES), and book-to-market ratio (BMR), which were found to be non-stationary at level but stationary at first difference, and hence exhibit order one integration, I(1). The results are further confirmed through the PP and KPSS unit root tests. Table 3 summarizes the unit root test results.

Table 5a: Sentiment Proxies Unit Root Test Result

Variable	I(0)	I(1)
ADR	***	
BMR	-	***
ES	-	***
DP	***	
NIPO	***	
TV	***	
TVOL	***	
VIPO	***	

Table 5b: Macroeconomic Variables Unit Root Test Resul

Variable	I(0)	I(1)
CPI	-	***
Delta Ex.	***	
GDPG	**	
HML	***	
SMB	***	
WML	***	
MRF	-	***
MRP	***	
Market Vol	***	

*Where *** denotes significance at 1% and, ** denotes significance at 5% and * denotes significance at 10%. A (-) denotes that results are insignificant at all p values.*

Equation 1 has been further tested and corrected for OLS assumptions. Where applicable, heteroskedasticity has been corrected through the heteroskedasticity-robust standard errors. To capture the irrational component of the sentiment proxies, random errors were extracted from Equation 1 and used to construct a sentiment index using the principal component analysis. The results of the principal component analysis and coefficient loadings are presented in Table 5 and Equation 3, respectively. Regression results for equity issuance (ES) indicate insignificant coefficients and spurious findings. To avoid spurious results in the index construction, the equity issuance variable has been excluded as a proxy at this step, and the sentiment index has been constructed using the seven remaining proxies.

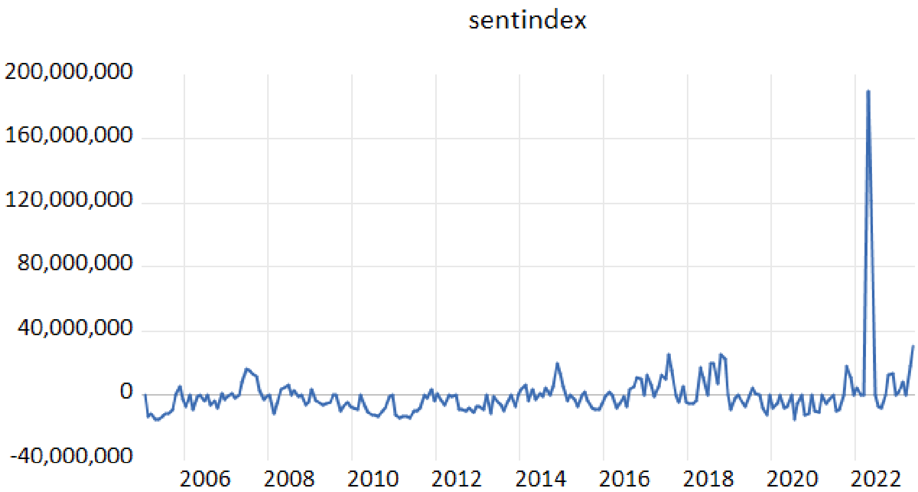
Table 5: Principal Component Results

Component	*Eigenvalue*	*Difference*	*Proportion*	*Cumulative*
Comp1	3.65639e+14	3.56234e+14	0.9749	0.9749
Comp2	9.40539e+12	9.40539e+12	0.0251	1.0000
Comp3	0.0000	0.0000	1.0000	1.0000

$$Sentindex_t = -0.0000\ RADR_t - 0.0000\ \mathrm{R}VIPO_t - 0.0000\ RNIPO_t - 0.0000\ \mathrm{R}BMR_t + 0.0657 RTV_t + 0.9978\ RTVOL_t - 0.0000 TVDP_t \qquad \text{(Eq. 3)}$$

The first principal component captures 97% of the variation in the underlying variables, aligning with the literature and confirming that the index effectively represents the sentiment proxies. However, the coefficient loadings indicate minimal negative values for almost all variables, except for the trading volume (tv) and turnover volatility (tvol), which exhibit the highest coefficients and weights in the index construction.

Graph 2: Plot of Sentiment Index



The unit root test for the sentiment index (Sentindex) suggests that the index is stationary at level I(0). With all selected variables of I(0), the study proceeds with the non-linear univariate GARCH models to investigate the impact of the sentiment index on market volatility.

4.4. Impact of Sentiment on Stock Market Volatility

Before conducting the GARCH tests, the LM test is first performed to identify the presence of serial correlation in the residuals. The results reveal homoskedasticity of the residuals, indicating the presence of a serial correlation and hence supporting the application of the GARCH models. For assessing the impact of the sentiment index on the Egyptian stock market volatility, the study employs two sets of conditional volatility models: GARCH and EGARCH, both with and without the sentiment index. Tables 5a and 5b summarize the results for the GARCH models without the sentiment index, while Tables 6a and 6b summarize the results with its inclusion.

Table 6a: GARCH Model without Sentiment Index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LAGDRMM	-0.540099	0.065149	-8.290231	0.0000
C	0.001918	0.007745	0.247608	0.8044
Variance Equation				
C	0.000352	0.000188	1.867572	0.0618
RESID(-1)^2	0.065652	0.030668	2.140741	0.0323
GARCH(-1)	0.908356	0.031257	29.06131	0.0000

Table 6b: EGARCH Model without Irrational Sentiment Index

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LAGDRMM	-0.480030	0.083404	-5.755477	0.0000
C	-0.000422	0.007712	-0.054725	0.9564
Variance Equation				
C(3)	-3.408017	1.565488	-2.176968	0.0295
C(4)	0.399287	0.131610	3.033857	0.0024
C(5)	-0.087441	0.104925	-0.833370	0.4046
C(6)	0.271868	0.358876	0.757554	0.4487

For the validity of the GARCH-M model, Table 6a demonstrates that the sum of the ARCH(1) and GARCH(1) respective coefficients is below 1. This confirms the stationarity and volatility persistence of the GARCH model, validating its goodness of fit, while being close to 1 (at 0.96) indicates a high degree of volatility persistence. Furthermore, the GARCH model shows significance at 1%, further emphasizing the presence of conditional variance and revealing the model's ability to capture volatility clustering and persistence efficiently. Additionally, the positive values of both the

ARCH and GARCH models indicate that past residuals and past conditional variance of returns can effectively forecast volatility persistence. As presented in Table 6b, the results from the EGARCH (1,1) model reveal the presence of volatility asymmetry, since the coefficient of the market return is less than 0. This suggests that negative shocks affect volatility more than positive shocks of the same size. The persistence of these negative shocks, or this asymmetry in volatility, highlights that investors are more affected by negative news compared to positive ones. Consequently, this suggests an uneven volatility transmission or the presence of a leverage effect.

Table 7a: GARCH with Sentiment Index[1]

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LAGDRMM	-0.540159	0.065220	-8.282058	0.0000
LAGDSENTINDEX	-9.20E-12	5.73E-10	-0.016075	0.9872
C	0.001918	0.007818	0.245354	0.8062
Variance Equation				
C	0.000352	0.000188	1.868585	0.0617
RESID(-1)^2	0.065673	0.030701	2.139161	0.0324
GARCH(-1)	0.908330	0.031305	29.01543	0.0000

Table 7b: EGARCH with Sentiment Index

LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LAGDRMM	-0.478653	0.083463	-5.734886	0.0000
LAGDSENTINDEX	8.03E-11	7.65E-10	0.104978	0.9164
C	-0.000415	0.007782	-0.053329	0.9575
Variance Equation				
C(4)	-3.433824	1.582815	-2.169441	0.0300
C(5)	0.400766	0.132693	3.020250	0.0025
C(6)	-0.086567	0.105350	-0.821706	0.4112
C(7)	0.266087	0.363211	0.732596	0.4638

[1] ARCH LM test has been conducted on the GARCH residuals to further validate the model's goodness of fit, with results indicating heteroskedasticity of the residuals implying that the model captured all ARCH effect.

Table 7c: PARCH with Sentiment Index

@SQRT(GARCH)^C(8) = C(4) + C(5)*(ABS(RESID(-1)) - C(6)*RESID(
-1))^C(8) + C(7)*@SQRT(GARCH(-1))^C(8)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LAGDRM	-0.542781	0.058193	-9.327279	0.0000
LAGDSENTINDEX	-8.63E-11	2.91E-10	-0.296044	0.7672
C	-0.002691	0.006348	-0.423894	0.6716
Variance Equation				
C(4)	6.80E-11	5.96E-10	0.114195	0.9091
C(5)	0.003393	0.008706	0.389783	0.6967
C(6)	0.287778	0.192851	1.492234	0.1356
C(7)	0.665998	0.165939	4.013498	0.0001
C(8)	8.718328	3.602850	2.419842	0.0155

Regarding the sentiment index, Table 7a shows insignificant results for its impact on the mean equation, implying that past sentiment index does not influence future returns. Conversely, the conditional variance equation presents highly significant results, with positive coefficients in the ARCH and GARCH models, demonstrating high significance at 5% and 1%, respectively, revealing that both bullish and bearish sentiment increase market volatility. Likewise, the sum of the ARCH and GARCH parameters is 0.96, indicating that shocks to conditional variance are highly persistent. These results imply that noise traders contribute to higher risk, supporting the noise trade theory. However, the insignificance of the sentiment index in the mean equation demonstrates its inability to reflect the volatility persistence and clustering, signifying that investors' past psychological beliefs do not drive the market volatility persistence.

Table 7b demonstrates the EGARCH model results for the shock asymmetry, with c(5) representing the ARCH model term, c(6) reflects the asymmetric effect, and c(7) denotes the GARCH term. The ARCH term is significant at 1% with a positive coefficient, underscoring the higher effect of sentiment magnitude on market volatility. Accordingly, in the Egyptian stock market, and in line with other emerging markets (Kumari & Mahakud, 2015), if investors exhibit psychological pessimism or optimism, market volatility will rise on an average, with higher sentiment levels leading to greater volatility. However, the results show the absence of an asymmetric effect and a leverage effect, indicating that investors' sentiment in general, whether bearish or bullish (pessimistic or optimistic), will have the same impact on market volatility. In conclusion, despite the significant impact and magnitude of sentiment on the Egyptian stock market volatility, the irrational sentiment index showed insignificant results in predicting future volatility.

Finally, Table 7c reports the PARCH model results. In terms of goodness of fit, the Durbin-Watson statistics hold a value of 2.265247, suggesting no autocorrelation in the residuals and signifying that the model effectively represents the data's time-series properties. The variable results of PARCH align with the GARCH and EGARCH results, showing significance of the lagged market return at the 0% level with a negative coefficient, emphasizing the strong predictive power of past returns over current returns. The negative coefficient implies that past market returns negatively influence the current market returns. Furthermore, the lagged values of the sentiment index are not significant, revealing that the past sentiment index within this model, does not predict current market returns. c(5), which reflects the immediate impact of the last period's shock on current volatility, and c(6), which captures asymmetric effects of shocks on volatility, are both insignificant, highlighting the significant impact of past shocks and their asymmetric effects on volatility in this model. However, c(7), which represents the persistence of volatility over time and the impact of past volatility on current volatility, exhibits high significance at the 0% level ($p = 0.0001$), indicating a strong influence of lagged conditional volatility on current volatility. Additionally, c(8), which also contributes to volatility persistence, is significant, highlighting the model's benefit from a non-linear transformation of residuals and lagged volatility terms, enhancing the model's fit to the actual data distribution.

The ARCH group models appear well-specified in terms of volatility dynamics, as evidenced through the significance of the coefficients of the lagged volatility and power parameter in the variance equation. However, the model's results indicate that the sentiment index lacks predictive power, which is counterintuitive and inconsistent with the behavioral theory. Hence, the model can be further improved through the inclusion of structural breaks that justified the periods of economic distress or crises.

With respect to market implications, the results demonstrate a market overreaction, as explained by the negative coefficient on lagged returns, which may be indicative of overreaction to past information, causing corrections the following day. This behavior aligns with behavioral finance theories, which propose that investors tend to overreact to news, leading to momentum followed by reversals in stock prices. These dynamics can help policymakers and financial regulators devise strategies that mitigate excessive volatility and irrational trading behaviors to stabilize the market. Moreover, the insignificance of the sentiment index in influencing stock market returns can be considered as counterintuitive and inconsistent with the behavioral theory. However, this could suggest that while sentiment influences trading decisions, its direct impact on returns may be obscured by other factors such as past returns and economic fundamentals. Moreover, it highlights the importance of considering economic changes during the period of investigation.

5. Conclusion

When investigating the impact of irrational sentiment index on market volatility within a mean-variance framework, the findings revealed moderate results, showing that although a non-linear framework reflects the effect of sentiment index on market volatility, it failed to demonstrate the predictability of sentiment on future volatility. A probable explanation can be the lack of structures in the analysis. Prior literature exhibited the importance of considering structural breaks in the sample to accommodate the financial distressed periods, as the predictive power of the sentiment index varies depending on the presence of a financial crisis. Thus, the paper argues that no definitive conclusion can be established on the predictive power of the sentiment index on market volatility, and recommends that future research incorporates structural breaks and differentiates between crisis periods to provide a more comprehensive assessment of the impact and predictability of investors' sentiment on market volatility. The significance of such research is based on its theoretical and practical implementation. Theoretically, the research underscores the ability of behavioral finance and confirms the noise trade theory's crucial role in resolving the paradox of sentiment's effect on market volatility. Therefore, through exhibiting the eminent role and effect of sentiment on market volatility and, consequently, asset pricing models, the research recommends further investigations addressing the amendment of the asset pricing models to incorporate sentiment. Practically, such augmentation improves the predictability of stock market volatility, assisting central banks in fully understanding the financial markets' stability and reactiveness to policy changes. For instance, regulators could use such models to monitor systemic risks. A persistent volatility as concluded from the results might imply the country's need for improved regulatory framework or adjustments to the capital adequacy requirements of financial institutions. Finally, examining the effect of past variables on current market conditions could enhance tools for sentiment analysis, aiding in the prediction of market movements based on broader investor behavior metrics.

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