MSA-Management science journal
ISSN 2974-3036
Volume: 3, Issue:2, Year: 2024 pp.76-119

Assessing the Influence of Investor Sentiment on the Performance of the Stock prices: Analyzing Stock Returns and Volatility During the COVID-19 Pandemic and Periods of Market Fluctuations

Sara Sobhy[1]
Department Of Finance, Faculty of Management Sciences
October University for Modern Sciences and Arts (MSA), Egypt
Email: ssobhy@msa.edu.eg

Abstract *The primary objective of this study is to examine how investor sentiment affects stock market performance, with a particular focus on two indicators: stock returns and stock market volatility. The analysis takes into account the impact of the coronavirus pandemic and takes into account two market conditions: upside (bullish) and downside (bearish). Monthly closing prices for ten sector indices were analysed, including information technology, healthcare, financials, consumer credit, telecommunications services, industrials, energy, utilities, real estate, and materials. The study used three GARCH models (GARCH, GJR-GARCH, and E-GARCH) to predict the volatility of these sector indices and understand the impact of investor sentiment. The results indicate a negative impact of investor sentiment on stock returns and stock market volatility in most sectors. The coronavirus pandemic is having a positive impact on the relationship between investor sentiment, volatility, and stock returns.*

In addition, the results reveal a bidirectional link between investor sentiment and stock volatility across all US sectors. Regarding the market situation, it has been shown that in emerging markets, investor sentiment has a negative impact on volatility, and stock returns in the majority of sectors. However, in bear markets, the effect of investor sentiment on stock market returns and volatility is positive.

Keywords: *investor sentiment, stock price volatility, stock returns, GRCH, GJR-GARCH, E-GARCH, Corona pandemic, bullish and bearish markets.*

JEL Codes: G4

[1] ORCID iD 0000-0002-8044-321X

Introduction:

Investor sentiment has attracted growing scholarly attention over the last 10 years because of its ability to impact market performance. The term "investor sentiment" describes the general attitude or mood of investors towards the market. It is a general indicator of how investors feel about the economy's current status, the success of specific businesses or industries, and the likelihood of future growth. Investors and financial experts should be aware of investor mood since it can shed light on market patterns and behavior. A bullish market can result from higher demand for equities brought on by an optimistic investor attitude, which raises prices. On the other hand, poor investor sentiment might result in a decline in demand, which will lower prices and result in a bearish market. (Zhang and Li 2019; Niu, et.al 2021; He, et.al 2020).

According to (Xie, et.al 2021, Muguto, et.al 2022), Investor sentiment can influence market trends and act as a major driving element behind market movements. For instance, when investors are feeling optimistic, they might be more inclined to take risks and buy equities, which would raise demand and drive-up stock prices. In contrast, when investors are feeling pessimistic, they can become more cautious and risk-averse, which would reduce demand and drive down stock prices. Since investor sentiment is a complicated and nuanced topic, measuring it can be difficult. However, several instruments and indicators, including surveys, sentiment indexes, and social media analytics, have been developed to assist in capturing investor mood.

Based on the studies, it is crucial to examine investor sentiment and its impact on stock performance for several reasons. Firstly, understanding market behavior is important as investor sentiment provides insightful information about how the market will likely behave under specific circumstances (Huang and Liu, 2020; Liu et al., 2019). By monitoring changes in investor sentiment, analysts can forecast shifts in market demand and adjust their investment strategy accordingly. Secondly, predicting stock prices is essential, and including measurements of investor sentiment in forecasting models can significantly impact stock prices (Dang and Kim, 2021). Analysts can better forecast future stock prices and market movements by considering investor mood. Thirdly, shifts in investor attitude can lead to market volatility, increasing the risk of investment losses (Han et al., 2021; Wang et al., 2021). By keeping an eye on shifts in investor sentiment, investors can manage risk and reduce potential losses by adjusting their portfolios. Fourthly, policymakers need to consider the effect of investor sentiment on financial stability and the overall economy when making decisions on monetary or regulatory policy (Chen et al., 2021; Chen et al., 2022; Li et al., 2021; Lin et al., 2021). Researching investor sentiment and its influence on stock price volatility can help policymakers make more informed choices that support monetary stability and economic growth.

Despite the existing research on investor sentiment and its influence on financial markets, there are still gaps in the literature. One such gap is the causality problem (Baker and Wurgler, 2007; Chiang and Zheng, 2010). The relationship between investor sentiment and stock prices remains unclear, as it is uncertain which variable causes the other. Some studies suggest a unidirectional link, with sentiment affecting stock prices (Baker and Wurgler, 2007; Chiang and Zheng, 2010), while others indicate a bidirectional association (Da, Warachka, and Xing, 2011; Zhang and Li, 2019). Another gap in the literature is the heterogeneity problem (Baker and Wurgler, 2006). The impact of investor sentiment on stock price performance may vary across different market situations, periods, and investor groups. Different sectors and industries may be affected differently by sentiment (Baker and Wurgler, 2006), and the impact of sentiment can change depending on market conditions (Brown and Cliff, 2005; Zhou and Wong, 2017). Moreover, much of the existing work treats investors as a homogenous population, potentially overlooking significant variances in sentiment among different investor groups.

Lastly, the role of macroeconomic factors including interest rates, inflation, and economic growth, in influencing the relationship between investor sentiment and stock price volatility is not well understood. The extent to which these variables influence the link between stock price volatility and investor sentiment requires further investigation. Overall, even though a lot has been learnt about the association between investor sentiment and stock price, there is still much to be discovered about this intricate and complicated relationship. By filling in these gaps in the literature, we can better understand investor sentiment and how it affects stock prices. Based on the previously indicated discussion, the main objective of the current research is to investigate the association between investors' sentiment and stock price volatility and returns. To achieve this general objective, it is better to split this objective into the following sub-objectives:

A. To investigate the causality effect between investors' sentiment and stock price volatility. In other words, is there a bidirectional association between investors' sentiment and stock price volatility?
B. To investigate the influence of industry type on the association between investor sentiment and stock price volatility. In other words, does stock price react differently according to the industry type?
C. To investigate the role of market conditions (up and down markets) on the previously indicated association, taking into account the corona virus as one of the most important pandemics.

By achieving these research objectives, we can contribute to finance literature as follows. First, although there is ample evidence of the impact of investor sentiment on stock price volatility, the nature of the connection is not always clear-cut. For instance, shifts in mood might have a more significant effect on stock prices in some market segments than in others, or the effect might alter over time. The current research tries to abandon the idea that the financial markets are homogenous, and we will try to investigate the association in different sectors in the American financial market. More specifically, this study examines the variations in the relationship between overall investor sentiment and industry index return, focusing on the differences between industry sectors. It also examines whether there is a causal relationship between investor sentiment and stock prices across different industries, as well as the direction of the causal relationship. As a result, when building the sentiment index and choosing the data, the investor sentiment index (ISI) is an aggregate index representing the entire market, while the stock returns and volatilities are sectoral data representing various industries. However, the majority of earlier research (Baker et al., 2012; Maitra and Dash, 2017; Dash and Maitra, 2018a; Yao and Li, 2020) focused on the relationship between general market sentiment and overall market performance, and there is little proof of this.

Second, market conditions play a crucial role in shaping the association between investor sentiment and stock price volatility and returns. For this reason, we study investor sentiment in two states of the market bearish and bullish markets. Additionally, Previous studies revealed that there are some macroeconomic variables that should be considered when studying the association between investor sentiment and price volatility. Interest rates can significantly affect volatility and stock prices. Higher interest rates, for instance, could make it more expensive for businesses to borrow money, which might result in reduced profits and stock prices. Higher interest rates may also make bonds more appealing as an investment, which may decrease demand for stocks and increase volatility. Inflation can influence volatility and stock prices. High inflation can devalue corporate profits and weaken investors' purchasing power, which can result in falling stock prices and more volatility. Low inflation, on the other hand, can be advantageous for equities as it can raise consumer spending power and enhance business profits. De Long et al., 1990; Dash and Maitra, 2018a; Lao et al., 2018; Sun et al., 2016; Jing et al., 2021). Exchange rates: For businesses that depend on exports or imports, exchange rates can have an impact on stock prices and volatility. For instance, a stronger home currency may increase the cost of exports and decrease the demand for a company's goods, both of which may result in reduced profits and stock prices. Changes. For the previously indicated discussion, the current research has identified a group of macroeconomic variables which might influence the association.

The article is organized as follows: section 2 is assigned to display the literature review, section 3 to display research methods. section 4 is assigned to display data and methodology, section 5 for discussion of the results and section 6 to display the conclusion, recommendation and future research.

Literature review

Investor sentiment is how an investor feels about certain stocks or the stock market as a whole. Research from the past shows that investor sentiment influences stock prices, and this effect lasts for a long time in the financial markets (Mike, Farmer, 2010; de Sousa-Gabriel, et al., 2023).

Theories

Traditional finance theory maintains that stock prices reflect the discounted value of expected cash flows and that arbitrageur eliminates the impact of irrational investor behavior. The classical asset-pricing model (CAPM) says that, to varying degrees, financial markets are always efficient. No consideration is given to how investors' feelings affect the value of assets. The CAPM says that because there are smart investors, the price of a security will match its real worth (Domingues, et.al 2022; Karim, Zet al., 2022). It also says that arbitrageurs are very important for keeping irrationality to a minimum. After the market crash in October 1987, its usefulness was called into question. (Bathia & Bredin, 2013) Academics found evidence that stock prices sometimes didn't respond enough to earnings reports and always responded too much to some news articles. Researchers have tried to explain these price differences in the past (De Bondt and Thaler, 1995; Vahl, 2022; Rim and Zha Giedt, 2023) by saying that investors sometimes overreact and sometimes underreact. Researchers have found a link between the idea of "noise traders" and the way assets are priced wrongly. This shows that some investors trade based on noise rather than on what's really going on.

Behavioral finance contends that waves of irrational sentiment, such as optimistic or pessimistic expectations, can persist and influence asset prices for significant periods of time and ultimately lead to crises (Zouaoui et al., 2011; Reis and Pinho 2020). The study of investor behavior from a psychological angle is the focus of the discipline of behavioral finance, which is classified as a social science (Lopez-Cabarcos et al., 2019). Although there is still a lack of consensus in some areas, the field has seen an increase in attention as shown by the quick growth of papers published. Therefore, further study is necessary. Investor sentiment, which is defined as the investors' attitude toward a firm's potential in terms of cash flows and risks, not based on fundamental valuation criteria, is a particular aspect of this behavioral field (Baker and Wurgler, 2007). According to Baker and Wurgler (2006), this behavioral construct reflects the optimism or pessimism of investors. Numerous areas of sentiments have been the subject of studies. Baker and Wurgler (2007), for instance, investigated the use of sentiment to forecast stock returns, as well as its ability to forecast volatility and returns, was established by Gupta (2019). Sentiment and mood were differentiated by Rapp (2019), who found that their empirical effects were distinct. The balance between the two views and the level of rationality vs. non-rationality were the main topics of Mukherjee and De's (2019) research.

Zunara et al. (2022) showed that even arbitrageurs with a lot of experience may not always be able to get share prices back to where they should be. Krainer (2023) also wrote about the proof that the "risk arbitrage" theory is true. As the market gets closer to fundamental equilibrium, the market log dividend-price ratio will change in a way that is not linear. This will depend on how far away the market is from fundamental equilibrium. So, the importance of investor psychology in setting the prices of securities was shown by (Dreyer, Sharma & Smith, 2023).

Since investor sentiment can cause market bubbles and big drops in value afterward, it is important to find out if investor sentiment affects stock prices (Carnazza, 2023). In the past 10 years, there have been two major stock market crashes: the tech bubble crash in 2000 and the real estate bubble fall in 2008. These crashes show how much investor sentiment affects the value of assets. Several studies have also shown that there are good ways to trade based on changes in stock prices caused by how the market feels (Anbarasu, et al., 2023).

Empirical evidence

Several authors who have investigated the relationship between mood and instability have found results consistent with sentiment models. For example, Chuang, Ouyang, and Lu (2010) find that changes in investors' market sentiment have a significant impact on the volatility of the Taiwan Stock Exchange. This was demonstrated by the number of transactions that took place. When confidence was high, the market was more volatile and there were more trades, indicating that noise traders were more common. Rahman et al. (2013) also looked at how “noise trading”, which is based on how people feel, affects expected returns and volatility in the Bangladeshi stock market. Their results revealed that changes in investor sentiment affected how well these companies performed and how much they changed. Rahman et al. (2013) and Uygur and Taş (2014) both find that sentiment has a significant impact on conditional volatility in financial markets in the United States, Japan, Hong Kong, the United Kingdom, France, Turkey, and Germany.

Naik and Padhi (2016) and Kumari and Mahakumar (2017) found that people's sentiment affects conditional volatility in the Indian stock market (2016). The later authors also found a link between the volatility of stock returns and investors' feelings towards them. This shows that the mood of investors in India has a significant impact on stock market volatility. Rupande, Muguto & Muzindutsi (2019) stated that sentiment can be used to predict Malaysian stock market volatility. Even after changes were made to deal with financial crises, this remained very important. Bahloul and Bouri (2016) looked at thirteen of the largest futures markets in the United States and found that there is a link between how people feel about the market and how volatile prices are, meaning that unstable markets are more likely to occur.

Evidence on the bidirectional association between investors' sentiment and stock price.

Many studies have looked at the correlation between stock price and investor sentiment. In general, this research examines the relationship between shifts in investor mood and stock price fluctuations, as well as vice versa. Below are some important conclusions drawn from previous studies. In the Chinese market, Wang et al (2021) investigate the correlation between investor sentiment and stock price volatility. Using the GARCH-MIDAS framework, the authors discovered evidence of a strong relationship between sentiment and bidirectional volatility. The relationship between investor sentiment and stock market volatility in developed and emerging countries is examined by

Aloui, C., et al. (2020). In both types of markets, the authors use a quantile regression approach and discover evidence of a bidirectional relationship between sentiment and volatility. Lee, J., et al. (2020), in this study the authors look at the interrelationship between the stock market flexibility and investor sentiment in various countries. Using a panel model VAR (Vector Autoregression), the authors found that sentiment and volatility had a strong two-way association in most of the countries they looked at. Based on the aforementioned studies, we can formulate the first hypothesis as follows:

H1: There is a significant bidirectional association between stock prices and investor sentiment.

Evidence on the variability of the association between investor sentiment and stock price volatility according to sector type

Baker & Wurgler (2006) This seminal study showed that in companies where investor sentiment contagion is more pronounced, stock returns and volatility are significantly influenced by investor sentiment. They discovered evidence that sentiment-based trading has a greater impact on stock prices in sectors such as technology stocks – which have higher investor sentiment than those with lower sentiment, such as utility stocks. Cliff and Brown (2004) looked at the predictability of stock returns and volatility based on industry-level sentiment. The authors discovered that the predictability and volatility of stock returns are significantly influenced by industry-specific sentiment, as measured by investor surveys and media coverage. They concluded that, in addition to company-specific characteristics, industry-level sentiment can help predict returns and volatility.

Aspres, et al. (2015) looked at the relationship between volatility industry returns, and investor sentiment focusing on the German stock market. The impact of investor mood on industry returns and volatility is greater than the impact of individual stock returns, according to the authors' research cross-sectional differences in returns and volatility are mostly explained by industry-level sentiment. In 2018, Kim and Kon used data from the Korean stock market to investigate how investor sentiment affects industry returns. The authors reported a significant effect of investor mood on industry returns and this effect varies by industry. They concluded that emotion and industry-specific variables combine to influence stock returns at the industry level.

Based on the aforementioned studies we can formulate the second hypothesis as follows:

> ***H2: The association between investors' sentiment and stock price volatility varies according to the industry type.***

Evidence on the variability of the association between investor sentiment and stock price volatility according to market status.

Lee, et al. (2018) examined the relationship between stock market volatility, investor sentiment, and market conditions (bullish and bear markets) in the United States. The authors show that in bear markets compared to bull markets, investor behavior has a greater impact on stock market volatility. They concluded that the relationship between emotions and volatility can be moderated by the market state. In Li (2017) the relationship between stock prices and investor sentiment in developed and emerging markets is examined. Comparing emerging markets with developed markets, the author concluded that sentiment generally had a greater impact on volatility in emerging markets. According to the study, mood and volatility may have different relationships depending on whether developed or emerging markets are in a better financial position.

In Wurgler and Baker (2007), researchers considered different market states, such as periods of high and low volatility, and considered the relevant relationship between investor behavior and stock market fluctuations. The authors found that during times of extreme volatility, sentiment has a greater impact on volatility. They concluded that the effect of investor sentiment on stock market volatility can be moderated by market conditions. Merika & Karim (2018) presented research confirming the importance of market position. The influence of investor sentiment on stock market returns in the Baltic countries – Estonia, Latvia and Lithuania – was studied in this study. The authors find that, unlike bull markets, there is a higher correlation between sentiment and returns during bear markets. They concluded that the relationship between sentiment and stock market returns can be affected by market conditions. Puri, et al. (2017) investigated the relationship between stock market volatility and investor sentiment in European countries. The authors discovered that during downturns in the market rather than in the market with highs, sentiment has a greater impact on volatility. They concluded that the relationship between investor sentiment and stock market volatility is partly shaped by market conditions. Based on the conclusion of the previous studies, we can formulate the third hypothesis as follows:

H3: The association between investors' sentiment and stock price volatility varies according to market status.

Data and Methodology

Monthly closing prices were collected for ten sector indices, namely Information Technology (IT), Financials (FN), Health Care (HC), Consumer Discretionary (CD), Telecommunication Services (TS), Industrials (ID), Energy (EG), Utilities (UT), Materials (MT), and Real Estate (RE) covering the period from January 2000 to December 2022, based on data availability. These sectors are classified according to the S&P sectors and industry indices, which are stock market indices maintained by S&P Dow Jones Indices. The purpose of these indices is to measure different segments of the U.S. stock market based on the Global Industry Classification Standard (GICS) (S&P Dow Jones Indices, 2023). The S&P sectors and industry indices provide a detailed breakdown of the stock market by dividing it into specific sectors and industries. Each index represents a group of companies operating within a particular sector or industry of the economy. These indices are widely used by investors and analysts for benchmarking, asset allocation, and investment analysis purposes. By monitoring the performance of these indices, investors can gain valuable insights into the relative strengths or weaknesses of different sectors and industries, which can inform their investment decisions (S&P Dow Jones Indices, 2023). Although the sector classification used in this study may differ from categorizations in other markets (Costa et al., 2022), it has been applied in several previous research studies (Mokoena & Nomlala, 2022; Vengesai et al., 2022).

Following the methodology of Muguto et al. (2022), the monthly volatility (σ) was calculated using the standard deviation (σ) of the monthly returns: $V_t = S_{Return} = \sqrt{\frac{\sum_{i=1}^{t} \left(Return_t - \overline{Return}\right)^2}{n-1}}$

Compared to volatility analysis, sentiment analysis was more challenging. There isn't a widely recognized measurement for the phenomenon, claim Baker and Wurgler (2007). Multiple techniques are therefore often used, such as lexicons, surveys, and proxies. Without the need for complex financial theories, surveys such as those employed in research by Lux (2011), Finter et al. (2012), and Brown and Cliff (2004) can measure an individual's psychological composition. They struggle to differentiate between various levels of optimism and pessimism, confusion, and prestige bias (Baker & Wurgler, 2007; Bormann, 2013; Beer and Zouaoui, 2018).

Conversely, proxy factors are variables that, through the use of basic market data, indirectly reflect the sentiment of investors at the moment (Pandey & Sehgal, 2019). Many studies have demonstrated that proxies are significantly more useful in assessing sentiment in the financial markets (Baker & Wurgler, 2006; Muguto et al., 2019 & 2022). The attraction of this strategy is rooted in how simple it is to gather proxies and how real-time proxy observation can reveal the degree of bullishness or bearishness among market participants (Murut et al., 2019 & 2022). On the other hand, proxies are not perfect. According to Muguto (2015), these explanations, for instance, incorporate both an emotion component and a unique non-emotion component and are based on controversial theoretical explanations for their relationship with emotions. A clear, comprehensive, and consistent understanding of investor sentiment is lacking, as evidenced by the vast array of sentiment proxies employed in the literature (Baker & Wurgler, 2006).

To avoid all of this complexity, the study considered the consumer confidence index (CCI) as a proxy for investor sentiment in each sector. CCI has been used extensively in the literature as a measure for domestic sentiment (See for example: Money, June 2021; Motley Fool, July 2021; Baker and Wurgler, 2006; Çevik et al., 2012; Perez-Liston et al., 2018; Salhin et al., 2016). The consumer confidence index series has been obtained from the OECD main economic indicators database.

Furthermore, various factors from the economic, financial, and socio-political realms, both at the domestic and global levels, have a significant influence on the behavior of stock prices in developed and emerging markets. Numerous empirical studies have identified several determinants at the firm, industry, country, and international levels that can be used to predict stock returns. These studies include research by Baker and Wurgler (2006), Brooks and Del Negro (2005), Campbell and Robert (1988), Dimic et al. (2015), Jones et al. (2017), Tian et al. (2018), and others. To account for the potential impact of local and global information variables, we adopt a multivariate approach. Our analysis incorporates a set of control variables, such as short-term interest rate, inflation rate, GDP, unemployment rate, broad money, and market stability. For more detailed information regarding measurement, data sources, and abbreviations, please refer to Table (1).

In a research study conducted by Rupande et al. (2020), the objective was to predict the volatility of sector indexes and explore the influence of investor sentiment. To achieve this, the researchers employed three GARCH models: GARCH (Bollerslev, 1986), E-GARCH (Nelson, 1991), and GJR-GARCH (Glosten et al., 1993). These models were selected to address the limitations of Engle's (1982) ARCH model, which required a large number of parameters and extended lag times. Unlike the ARCH model, the GARCH model incorporated squared residuals and conditional variance from previous periods to estimate the conditional variance. This allowed for the consideration of the impact of past volatility on current volatility. Additionally, the GARCH models had a simpler specification that only required one lag of historical volatility and squared residuals, eliminating the need for additional lags of the volatility component. Before employing the GARCH models, the researcher conducted various residual tests, including tests for heteroscedasticity, autocorrelation, normality, and ARCH-LM, to ensure the suitability of the models. The presence of ARCH effects confirmed the appropriateness of the GARCH models, as noted by Muguto and Muzindutsi (2022). The mean equation for the stock price returns in each model was identical across all specifications, while the variance equation for stock price volatility varied.

Each model Y mean equation for stock price returns was identical in all specifications and the V variance equation for stock price volatility was different in all specifications. The mean equation for the model was estimated as:

If Y_t is the index for stock price return, μ is the mean, ω represents the impact of previous shocks and returns, and investor mood is captured by α. By examining the size, sign, and importance of the coefficient, θ was ascertained. To ascertain the impact of investor mood on the significance and signs of the other variables in the equations, coefficients from Equation 1 were also compared. Next, by estimating the variance equation, the effect of investor sentiment on stock price volatility was ascertained. Equations 2, 3, and 4 were used to estimate the variance equations for the GARCH (1.1), GJR-GARCH (1.1), and E-GARCH (1.1):

$$Y_t = \mu + \omega Y_{t-1} + \alpha\varepsilon_{t-1} + \theta SentIV_t + \varphi DCV_t + \vartheta X_t + \varepsilon_t \quad (1)$$

$$V_t = \delta + \alpha\varepsilon_{t-1}^2 + \beta V_{t-1} + \theta SentIV_t + \varphi DCV_t + \vartheta X_t \quad (2)$$

$$V_t = \delta + \alpha\varepsilon_{t-1}^2 + \beta V_{t-1} + \gamma\varepsilon_{t-1}^2 D_{t-1} + \theta SentIV_t + \varphi DCV_t + \vartheta X_t \quad (3)$$

$$V_t = \delta + \alpha\left[\left[\frac{\varepsilon_{t-1}}{\sqrt{V_{t-1}}} - E\left(\frac{\varepsilon_{t-1}}{\sqrt{V_{t-1}}}\right)\right]\right] + \gamma\frac{\varepsilon_{t-1}}{\sqrt{V_{t-1}}} + \beta V_{t-1} + \theta SentIV_t + \varphi DCV_t + \vartheta X_t \quad (4)$$

Where δ is the intercept, V_t is the conditional variance, α and β represent the effects of historical and recent volatility shocks on the volatility of the stock price, respectively, and φ and ϑ show the effects of the corona virus and control variables, respectively, on the volatility of the stock price today. While an insignificant coefficient demonstrated that sector volatility was unresponsive to investor sentiment, a statistically significant coefficient of θ suggested that SentIV had a significant impact on stock volatility. Sentiment rises in response to increases in volatility if the coefficient is positive, and vice versa if it is negative. Shocks are handled symmetrically in Equation 2 since the GARCH (1.1) model implies that time-varying volatility responds to both positive and negative shocks in the same way. The GJR-GARCH (1.1) model, a GARCH (1.1) extension, takes this problem into account by allowing for asymmetries in volatility's response to both positive and negative shocks. To capture the impacts of leverage, Equation 3 incorporates a multiplicative dummy factor, γ, into Equation 2. (Shamiri & Hassan, 2007). The definition of the leverage effect is a positive, statistically significant effect (Brooks, 2019).

To address the violation of non-negativity criteria in the GJR-GARCH (1.1) model, the research study deliberately imposed a set of non-negativity conditions, including $\delta > 0$, $\alpha > 0$, $\beta \geq 0$, and $\alpha + \gamma \geq 0$. These conditions were imposed to ensure that the coefficients in the model remained positive. On the other hand, the E-GARCH (1.1) model in Equation 4 circumvented this issue by utilizing logarithms, which guaranteed that the non-negativity conditions were always satisfied. Similar to the GJR-GARCH (1.1) model, the E-GARCH (1.1) model effectively accounted for the influence of leverage on stock return volatility. This was accomplished by including a statistically significant and negative parameter (γ) in Equation 4 to capture the leverage effects. Moreover, it was imperative for all equations to meet the requirement for stationarity ($\alpha + \beta < 1$) to be considered as valid models. The research study employed three distribution assumptions, namely generalized error distribution (GED), student-t, and normal distributions. The selection of the most appropriate model for each sector was based on the Schwarz-Bayesian Information Criterion (SBIC), which served as the criterion for model selection. Additionally, diagnostic tests were conducted on the standardized residuals to ensure that the selected GARCH models provided accurate descriptions of the data (Brooks, 2019).

Table (1): Descriptions of the variables.

Variables	**Symbols**	**Measurements**	**Data Source**
Dependent variables			
Stock price return	Y	The variance of monthly stock returns.	OECD
Independent variables			
Investor sentiment	SentIV	Consumer confidence index (CCI)	OECD
Corona virus	CV	Dummy variable takes 0 before the corona and 1 after the corona	
control variables			
Interest rate	IR	Real interest rate (% GDP)	WBI
Gross domestic product	GDP	GDP (constant 2015 US$)	WBI
Unemployment	Unemp		WBI
Inflation rate	INF	Consumer price index (annual %)	WBI

In addition, the granger causality test (Granger and Lin, 1995) was then used to determine the direction and causal relationship between variables. The null hypothesis affirms that the independent variable doesn't granger cause the dependent variable, against does granger cause the dependent variable as an alternative.

Upside and downside volatility measures

The modelling and forecasting of asset volatility play a crucial role in financial research and practice, as they have implications for asset pricing, portfolio selection, hedging strategies, and risk management (Andersen et al., 2010). Various parametric and nonparametric models have been developed for this purpose, including GARCH-type models, stochastic volatility models, and implied volatilities derived from option pricing models. However, the effectiveness of these models relies on specific assumptions regarding distribution, functional form, and available information (Andersen et al., 2010).

In recent years, data-driven posterior volatility estimators have emerged as an alternative. These estimators utilize high-frequency instantaneous data and the quadratic variance theorem, providing flexible and consistent volatility estimates without imposing strict assumptions. Empirical studies have demonstrated that these nonparametric volatility estimators outperform random volatility and GARCH models in out-of-sample forecasting (Parndorf-Nielsen and Sch Everard, 2002; Andersen et al., 2001; Comte and Reno, 1998), particularly in frictionless and non-arbitrage environments. Andersen et al. (2010) emphasize that nonparametric volatility assessments do not impose restrictions on the functional form, thereby enabling flexible and reliable volatility estimates. Additionally, Koopman et al. (2005) find that realized volatility models exhibit superior predictive performance compared to random volatility or GARCH models when evaluated using out-of-sample data.

To establish notation, let P represent the stock price at the i-th time point within a trading month t, where t ranges from 1 to T. The monthly prices are sampled q times at equal intervals. The i-th continuously compounded return from time point t to ti on day t can be calculated as the natural logarithm of the price ratio between these two points: Rt = ln(Pti/Pt). Assuming that price evolution follows a jump-diffusion process in continuous time, it can be decomposed into two components: the continuous (diffusive) component and the discontinuous (jump) component.$dP_t = \mu_t\, dt + \sigma_t dW_t + \emptyset_t\, dN_t$, t ∈ (0, T) (5)

$$QV_{t+1} = \int_t^{t+1} \sigma_t^2 dt + \sum_{i=N_t}^{N_{t+1}} \emptyset_{t,i}^2 = IV_t + \sum_{i=N_t}^{N_{t+1}} \emptyset_{t,i}^2 \quad (6)$$

In the present context, the variable "d" represents the price change, "dt" denotes a small time increment, "μt" represents the locally bounded drift term characterized by finite variation processes, and "σt" refers to the cadlag stochastic volatility process. The term "Wt" represents the standard Brownian motion, while "dNt" denotes a pure jump process. In the limit as the time increment (Δt) approaches infinitesimally small, the drift term (μt) can be neglected, and the martingale component becomes the primary driver of price variation. Following the framework proposed by Barndorff-Nielsen and Shephard (2002), the quadratic variation (QV) of Bitcoin returns between time t and t + 1 can be decomposed into the sum of variations arising from a continuous diffusive Brownian component, also known as the integrated variance (IV), and a discrete jump component.

When stock price dynamics do not involve jumps, the aggregation term in Equation (6) becomes irrelevant, resulting in the quadratic variation (QV) being equivalent to the integrated variance (IV). However, in real-world situations, stock prices are observed only at discrete time intervals, which poses challenges in directly estimating the QV. In their influential study, Andersen and Bollerslev (1998) introduced a model-free and nonparametric measure of volatility known as realized variance (RV). RV is computed by summing the squared intra-period returns within a trading day, as depicted in Equation (7).

$$RV_t = \sum_{i=1}^{q}(P_{t,i} - P_{t,i-1})^2 = \sum_{i=1}^{q} r_{t,i}^2 \qquad (7)$$

When an ultra-high sampling frequency is employed, RV becomes a consistent and unbiased estimate of the underlying unobserved volatility process of returns across any time interval, as demonstrated by Andersen et al. (2001) in their research.

$$\operatorname*{plim}_{q\to\infty} RV_t = \operatorname*{plim}_{q\to\infty} \sum_{i=1}^{q} r_{t,i}^2 = \sigma_{rt}^2 \qquad (8)$$

However, the realized variance (RV) estimator, which solely relies on total realized variation, fails to capture the well-documented empirical phenomenon of asymmetry in returns. This asymmetry refers to the asymmetrical impact of positive and negative price changes, which has been highlighted by studies such as Bekaert and Wu (2000) and Brandt and Kang (2004). Investors generally exhibit a greater concern for potential losses (downside risk) compared to potential gains (upside risk), as emphasized by Ang et al. (2006) and Koonce et al. (2005). Recognizing this behavioral aspect, Patton and Sheppard (2015) argue that, in certain cases, the variation in negative returns can provide more informative insights than the overall return variation. To address these limitations, Barndorff-Nielsen et al. (2010) propose the use of downside and upside-realized semivariance measures. These measures differentiate between variations caused by negative price movements (indicating poor volatility) and those caused by positive price movements (indicating good volatility). The following are the definitions of both model-free estimators:

$$RS_t^- = \sum_{i=1}^{q} r_{t,i}^2 \, I\,(r_{t,i} < 0) \qquad (9)$$

$$RS_t^+ = \sum_{i=1}^{q} r_{t,i}^2 \, I\,(r_{t,i} > 0) \qquad (10)$$

$$RV_t = RS_t^+ + RS_t^- \qquad (11)$$

MSA-Management science journal
ISSN 2974-3036
Volume: 3, Issue:2, Year: 2024 pp.76-119

The definitions of both model-free estimators are as follows: (insert equations here), where I(.) is an indicator function that returns one if the respective conditions ( ) and (> 0) hold true, and zero otherwise. Indeed, an increasing body of research has utilized the breakdown of realized variance into variance of negative returns and variance of positive returns to enhance realized volatility forecasts (Chen et al., 2019; Patton and Sheppard, 2015), predict cross-sectional variation in stock returns (Bollerslev et al., 2020), explore the asymmetric volatility connectedness of financial markets (Barunik et al., 2016; Barunik et al., 2017), and develop option pricing models (Feunou and Okou, 2019). The decomposition of RS_t^- into variance of negative returns, RS_t^+ and variance of positive returns, RSt +, in our analysis, enables us to provide a comprehensive evaluation of the relevance and relative importance of Price stock's downside and upside volatility dynamics of the S&P sectors and industry indices.

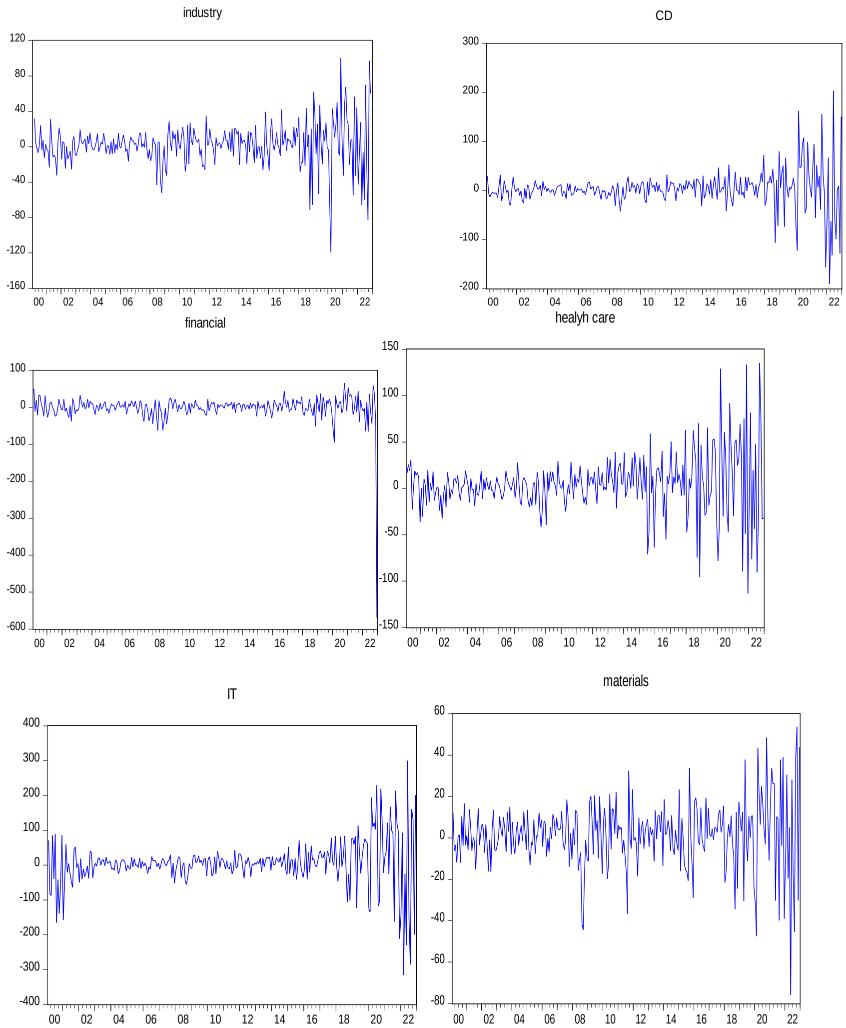
Results and analysis

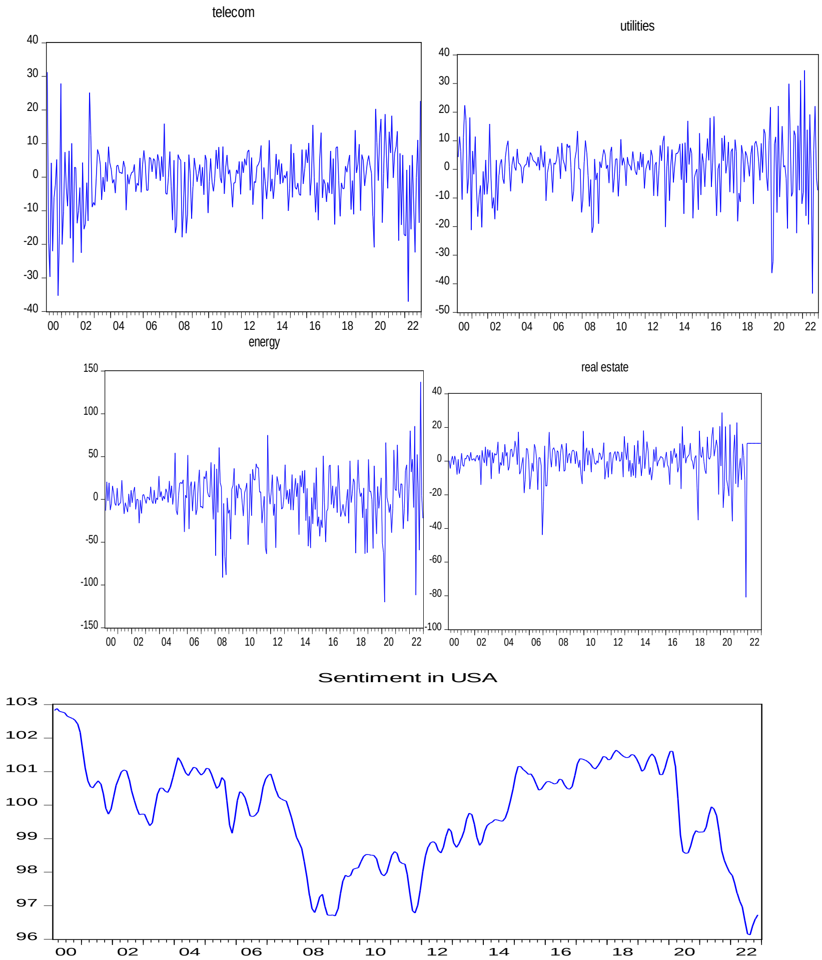
This part presents the study's findings, covering everything from the initial tests to the analysis of the variance and mean equations.

Preliminary analysis

Table 2 presents descriptive statistics for the sentiment index and sectoral returns. Throughout the study period, all industries exhibited positive average daily returns. Information technology had the highest average return of 5.55%, while finance had the lowest average return of -1.00%. The standard deviation of returns was lowest for utilities at 10.19% and highest for information technology at 69.0%. These differences in sector returns indicate that cross-sector diversification can provide benefits due to the heterogeneity of industries. The variations in returns also suggest that different sectors respond differently to macroeconomic shocks and public opinion. Furthermore, all return series displayed positive skewness, indicating a period characterized by higher average daily returns and a non-normal distribution. The Jarque-Bera test and the kurtosis results confirm the departure from normality.

Figure 1. Sector index returns and investor sentiment





Furthermore, the study revealed the presence of serial correlation among all return series, indicating the necessity of modelling the mean equations using the autoregressive moving average (ARMA) process (Brooks, 2019). The existence of ARCH effects in all sectors was confirmed through the results of the ARCH-LM and Ljung-Box tests, which justified the utilization of GARCH models to examine the impact of investor sentiment on S&P sectoral returns and volatility. The outcomes of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root and stationarity tests are presented in Table 2. These tests indicated that all stock return series were either stationary at levels or became stationary after taking the first difference. Therefore, the variables were considered to possess a unit root of order 1, and differencing was employed before estimation, as the PP test is regarded as a more robust test compared to the ADF test. The return plots depicted in Figure 1 further support certain descriptive statistics, demonstrating that the variance of stock returns did not remain constant over the entire sample period but displayed an autoregressive pattern that led to the phenomenon of volatility clustering.

Table 2: summery of descriptive statistics and preliminary tests:

Series	ID	CD	FN	HC	EG	IT	TS	RE	UT	MT	SentIV	INF	GDP
Mean	2.27	3.26	-1.00	4.52	1.68	5.55	-0.37	0.68	0.74	1.47	99.79	2.4	99.8
Median	3.06	3.19	2.77	4.31	2.90	6.10	0.56	1.84	1.69	2.01	100.1	2.3	99.9
Maximum	100.24	203.7	66.36	135.2	137.2	299.6	31.28	28.8	34.6	53.6	102.8	6.4	101.8
Minimum	-119.2	-190.5	-569.7	-113.4	-120.1	-316.1	-37.06	-80.8	-43.4	-75.9	96.1	0.6	91.6
Std. Dev.	24.34	38.77	40.24	31.79	30.60	69.0	9.45	10.65	10.19	16.09	1.5	0.8	1.2
Skewness	-0.33	0.07	-10.36	0.24	-0.30	-0.36	-0.49	-2.18	-0.48	-0.46	-0.4	1.6	-2.3
Kurtosis	7.55	11.60	146.4	6.57	5.75	8.21	4.77	16.16	5.08	5.83	2.4	9.5	14.1
JB	240.7**	848.7***	24084***	148.9**	91.53**	317.9***	47.24***	2205***	60.4**	101.8*	10.5**	619.9**	18.0***
LB	56.60***	91.47***	30.34***	106.8***	35.54***	83.01***	45.05***	73.44***	57.97***	64.68***	-	-	-
ARCH-LM	0.229***	0.032***	0.217***	0.154***	0.135***	5.370***	1.03***	0.000***	0.012***		-	-	-
ADF-I(0) C+T	3.5	1.50	1.25	1.8	-1.5	5.4	2.0	-2.6	2.5	4.1	-2.2	-0.85	-4.2**
ADF-I(1) C+T	5.0***	-3.95**	-14.7***	-16.7***	-13.7***	-3.0	-3.3*	-13.4***	-14.1***	-1.3	-7.2***	-5.7***	-7.5
PP-I(0) C+T	6.5	2.93	0.88	1.7	-1.3	10.8	6.9	-2.6	2.3	3.6	-1.9	0.22	-3.4*
PP-(1) C+T	15.6***	-14.7***	-14.7***	17.1***	-17.5***	-15.0***	-15.7***	-13.4***	-14.5***	14.7***	-4.5***	-9.7***	-11.6***
Order	I(1)	I(1)		I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

Most times volatility clustering occurred with significant financial market occurrences, the most noteworthy of which was the Covid-19 epidemic. Because of the lack of constant averages during the sample period, the plots further show that the series was not stationary. As a result, they had to be divided once before being estimated. Furthermore, there were significant disparities in return patterns between industries. These distinctions suggest that cross-sector diversification is feasible in the USA. Due to the 2008 financial crisis, investor sentiment was negative from 2009 to 2015 (Rupande et al., 2019). From 2010, attitude gradually improved as the market recovered, and from 2015, sentiment shifted to positive until 2019 (Muguto et al., 2022). Investor sentiment fell sharply between 2019 and 2020, maybe as a result of the COVID-19 epidemic. Overall, USA investor sentiment demonstrates substantial volatility, as evidenced by the index's fast ups and downs during the study period.

The SBICs under the three distribution assumptions used to choose the best model for each sector are displayed in Table 3 for the three GARCH models. It should be mentioned that none of the models that were assessed under the premise of a normal distribution were selected. The distribution statistics and the visual proof offered by the graphs in Figure 1 both corroborate this. Conversely, the differences indicate the existence of arbitrage depending on public sentiment. Leverage effects were present as the E-GARCH (1.1) with the generalized error distribution was the most often selected model. The model selection results show some agreement with the USA market findings of Rupande et al. (2019) and (Muguto et al., 2022). Their chosen model, however, was the GJR-GARCH (1.1) and the E-GARCH (1.1). The disparity was caused by the different study periods.

Table (3): Model selection

Sectors	GARCH(1,1)			E-GARCH			GJR-GARCH		
	Normal	Student-t	GED	Normal	Student-t	GED	Normal	Student-t	GED
ID	8.909427	8.888349	8.923856	8.898187	8.877568	8.891747	8.928674	8.931302	8.921541
CD	9.266052	9.230618	9.236558	9.190537	9.298819	9.192057	9.373904	9.316127	9.221561
FN	8.845591	8.897420	8.846329	8.864327	8.855968	8.825221	8.902194	8.899690	8.908555
HC	9.311018	9.303737	9.314786	9.312499	9.403982	9.365488	9.359073	9.393491	9.358305
EG	9.636288	9.601227	9.596640	9.620783	9.574462	9.599671	9.699131	9.624683	9.613387
IT	10.21730	10.24891	10.18830	10.19471	10.24961	10.21522	10.24738	10.31211	10.42384
RE	7.571160	7.428643	7.452312	7.455773	7.385667	7.376928	7.509270	7.450088	7.393454
UT	7.438616	7.467277	7.496110	7.427381	7.402591	7.396003	7.422575	7.384730	7.426342
MT	8.282236	8.298284	8.295432	8.187585	8.213888	8.197060	8.289190	8.273596	8.278439

Discussion of the mean equations results

The results of the selected models for each sector index are presented in Table 4. The positive and statistically significant serial correlation coefficient, ω, observed in the mean equation for all six sector indices indicates the presence of return serial correlation. This suggests that market frictions, such as non-synchronous trading, contribute to the autocorrelation observed in these indices (Hounyo, 2017).

Among the four sectors analyzed (CD, IT, MT, and TS), no evidence of serial correlation was found in their returns. The impact of previous shocks on current returns was also examined. In all seven sector indices, the coefficient α, which measures the influence of past shocks on present returns, was statistically significant and negative. This indicates that, except for CD and MT, the current returns of these sectors can be explained by previous negative shocks.

Two out of the seven sectors examined, namely information technology and real estate, exhibited statistically significant negative values for the investor sentiment metric (θ), which was determined using the Schwarz Bayesian information criterion (SBIC). These findings align with the results of studies conducted by Corredor et al. (2015) in the US market and Yang et al. (2017) in the Korean market, which also found that investor sentiment influenced sector returns in the stock market. The negative coefficients show that variations in investor mood are accompanied by comparable changes in these sectors' returns. Put differently, a rise in investor sentiment is correlated with a decline in future returns. This pattern is consistent with the idea of mean reversion to market fundamentals, which has been covered in papers by Chakraborty and Subramaniam (2020) and Da et al. (2011).

Nonetheless, certain studies found that sentiment and returns had favorable contemporaneous connections. This is probably because optimism increases positive expectations and reduces uncertainty and volatility in stock market returns (McGurk et al., 2020; AlNasseri et al., 2021; Abdul Karim et al., 2022). The findings show that overpricing happens when mood increases rather than when volatility and uncertainty decrease in the South African market. This could be the result of differences in the characteristics and makeup of investors. This is consistent with some oddities in the financial markets concerning market sentiment (Mahlophe & Muzindutsi, 2017). However, the utilities, finance, and industry sectors' negligible coefficients suggest that each sector includes a range of investor types, which causes variability (Curatola et al., 2016). It causes differences in how sensitive each sector is to emotion (Cakan & Balagyozyan, 2016). This presents an opportunity for arbitrage and diversification, based on the consensus.

Furthermore, the corona virus coefficient (φ) for five out of nine sectors (industry, CD, information technology, utilities, and real estate) was positive and statistically significant. Only the energy industry was negatively but statistically insignificantly different from the other sectors, which were all favourable. The GDP was then positive and statistically significant for four of the eight sectors (material, CD, information technology, and real state) for the control variables coefficients. Second, the inflation for six out of ten sectors—ID, HC, Energy, Real state, TS, and Utility—was negative and statistically significant. From the aforementioned discussions, we can accept the second hypothesis stating that ***the association between investors' sentiment and stock price volatility varies according to the industry type.***

Table (4): the selected model outputs

Sectors	Mean Equation						
	μ	ω	α	θ	φ	ϑ_1	ϑ_2
ID	-79.74148	0.911739***	-0.984160***	0.727079	2.710926**	0.157038	-3.000184***
CD	314.7478***	-0.016388	-0.070510	-0.959570	7.005481*	2.107895***	-2.212733
FN	62.50254	0.648143***	0.778806***	1.155720	1.798417	1.721028	-2.196208
HC	75.14740	0.750518***	-0.757611***	-0.563599	6.954044	-0.084617	-3.404188*
EG	-74.04334	0.803735***	0.734094***	-0.659356	-3.234924	1.527538	-3.845389**
IT	638.6984	-0.266109	0.198813***	-0.433851***	11.26959***	5.890324***	-1.425677
RE	19.33093***	0.893517***	-0.936921***	-0.630582***	2.038455***	0.419663***	-0.984694***
TS	92.53697**	0.145392	-0.260951	-0.057594	0.334179	-0.848341	-0.730944**
UT	-25.39471	0.938612***	-0.999990***	0.243213	1.101042***	0.033488	-0.732296***
MT	140.4449***	-0.048429	-0.076251	-0.193560	0.834231	1.190450***	-0.397202

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

Discussion of the variance equation results

In Table 5, it can be observed that all of the variance equation parameters for the selected models in six sectors, namely Information Technology (IT), Consumer Discretionary (CD), Telecommunication

Services (TS), Energy (EG), Industrials (ID), and Utilities (UT), were found to be statistically significant (Brooks, 2019). This indicates that the current volatility can be explained by both past volatility and historical innovations. However, there were differences in the coefficients, indicating that the ability of past volatility to explain current volatility was stronger than the impact of earlier innovations. Except for the consumer discretionary and healthcare sectors, the asymmetry parameter was found to be significant and negative in all sectors. This finding suggests the presence of the leverage effect, where positive shocks have a greater impact on volatility compared to negative shocks of the same magnitude.

The degree of volatility persistence in sector returns was quantified by the coefficients $\alpha + \beta$, which for all sectors was high but less than one. This suggests that there is volatility clustering in the returns, which is typical of time series data related to finance. This conclusion is supported by the graphs of sector returns across the sample period in Figure 1. According to Engle and Patton (2001), significant volatility persistence indicates that recent volatility shocks have an impact on volatility predictions for several future periods. A high degree of volatility persistence suggests that mean reversion to average volatility occurs slowly and that stock return volatility has a major effect on stock prices. This was true of the results for the information technology sector (1.000), which showed the greatest persistence and consequent susceptibility to outside influences. A certain amount of diversification, however restricted, could be offered by the differences in volatility persistence among the indices.

Except for real estate, every sector showed statistically significant negative values for the investor mood measure, θ. This suggests that behavioral variables were important in causing the volatility in these industries and that volatility is reduced when investor sentiment rises. This is in opposition to other research (Gao et al., 2022; Gong et al., 2022; Jiang & Jin, 2021) and indicates that sentiment reduces volatility in the US stock market. As a result, market volatility falls as sentiment means returns. Nonetheless, this validates the results of Rupande et al. (2019) and Naik and Padhi (2016), who observed negative coefficients. This discrepancy could be explained by variations in the prevalence of sentiment-driven investors across various periods and markets.

In addition, the coronavirus coefficient, φ, was positive and statistically significant for eight out of ten sectors, except real state and utility. This means that the corona virus increases the volatility in the USA markets. Then, for the control variables coefficients, first the GDP, ϑ_1 , was positive and statistically significant for three out of eight sectors— financial, energy and telecommunication service. Second the inflation, ϑ_2 , was negative and statistically significant for three out of five sectors— Energy, Real state and Information Technology.

Both the stationarity constraint ($\alpha + \beta < 1$) and the non-negativity conditions in the volatility equation ($\delta > 0$, $\beta > 0$, $\alpha \geq 0$ and $\beta + \gamma \geq 0$) were met. This indicates that for every sector index, every model chosen for the conditional variance was acceptable. In addition to confirming that the mean and variance equations of the chosen models were appropriately constructed, diagnostic residual tests were performed to verify the conclusions drawn from the estimated models on sector returns and broad market indexes. It was determined that these tests were successful.

Table (5): the selected model outputs

Sectors	Variance Equation								
	δ	α	γ	β	θ	φ	ϑ_1	ϑ_2	$\alpha+\beta$
ID	12.04343	0.286126	-0.273297***	0.441343**	-0.176414**	1.114708***	0.079582	0.071470	0.727469
CD	11.66297	0.578000***	-0.082458	0.523851***	-0.156135	1.319781***	0.056096	0.131115	0.3022
FN	1.877761	0.047413	-0.310514***	0.291605	-0.113452*	0.837713***	0.125181***	0.261641	0.339
HC	2.383826	0.114811	-0.110705	0.198170	-0.107780	1.925557***	0.123304	0.111336	0.3129
EG	-1.288779	-0.059053	-0.240350***	0.553566***	-0.239136***	0.742781***	0.280442***	-0.089959***	0.4945
IT	0.574740	-0.035825	0.101705***	1.000317***	-0.010358***	0.052566***	0.004994	-0.007480***	0.9642
RE	1.829187	1.135496***	-0.251426**	-0.251426	0.058603	-0.276060	-0.008757	-1.277562***	0.8836
TS	-0.652329	-0.036026	-0.069805***	0.998804***	-0.007168***	0.048704***	0.013997***	-0.004317	0.9628
UT	2.574696	0.143316***	-0.266911***	0.0981556***	-0.019121***	0.048738	-0.007918	0.035370	0.2413
MT	12.40883	0.094701	-0.303811***	0.324381	-0.244173***	1.111737***	0.148874	0.007944	0.419

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

MSA-Management science journal
ISSN 2974-3036
Volume: 3, Issue:2, Year: 2024 pp.76-119

Discussion of granger causality test

The outcomes of the pairwise causality test are reported in Table 6. The significant results of this test determine that there a bi-directional causal links between the Financials sector and sentiment index; the Industrials sector and sentiment index; Information technology and SentIV; and Telecommunication services and sentiment index which assure the feedback hypothesis. Besides, the one-way causality of sentiment index to all the sectors except HC and RE. On the other hand, the results also show that there is no causal relationship between HC and sentiment index and RE and sentiment index. From the aforementioned discussion, we can accept the first hypothesis stating that ***there is a significant bidirectional association between stock prices and investor sentiment.***

Table (6): granger causality results

Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
CD does not Granger Cause SentIV	273	0.22334	0.6369
SentIV does not Granger Cause CD		1.91308	0.0078
EG does not Granger Cause SentIV	273	0.87255	0.3511
SentIV does not Granger Cause EG		1.12540	0.0097
FN does not Granger Cause SentIV	273	7.85550	0.0054
SentIV does not Granger Cause FN		0.28542	0.0036
HC does not Granger Cause SentIV	273	0.15836	0.6910
SentIV does not Granger Cause HC		0.00605	0.4381
ID does not Granger Cause SentIV	272	14.8412	0.0001
SentIV does not Granger Cause ID		0.12646	0.0224
IT does not Granger Cause SentIV	273	0.25877	0.0114
SentIV does not Granger Cause IT		0.23189	0.0305
RE does not Granger Cause SentIV	273	0.19572	0.6586
SentIV does not Granger Cause RE		0.85513	0.5559
MT does not Granger Cause SentIV	273	0.71102	0.9999
SentIV does not Granger Cause MT		0.00678	0.0344
TS does not Granger Cause SentIV	273	0.30232	0.0429
SentIV does not Granger Cause TS		0.24881	0.0183
UT does not Granger Cause SentIV	273	0.42455	0.5152
SentIV does not Granger Cause UT		0.96722	0.0263

Upside and downside volatility effects

In this section, we address the issue of whether the association between stock returns of various sectors and investor sentiment is affected by the upside and downside components of realized variance. The total realized variance measure does not distinguish between upward and downward price flactuations, which could potentially hide valuable insights into how investors respond to positive and negative price returns.

Discussion of the mean equation's results of the upside

The selected models' upside results for each sector index are displayed in Table 7. The financial, information technology and materials sector indices are the three based on the mean equation that exhibits return serial correlation, as indicated by the positive and statistically significant serial correlation coefficient, ω. This suggests that market frictions, like non-synchronous trading, which results in autocorrelation, have an impact on these indices (Hounyo, 2017). However, there is no proof of serial association in the other areas. The impact of previous shocks on current returns is likewise applicable. Except for the financial sector, which had a negative and statistically significant coefficient, all sector indices showed statistical insignificance for the coefficient α, which measures the influence of previous shocks on current returns. This suggests that, except for the financial industry, historical shocks cannot be utilized to explain the current returns of these sectors.

Six of the seven sectors for which the investor sentiment was selected using the SBICs had a negative and statistically significant value for the investor sentiment parameter, θ. The negative coefficients imply that an alteration in investor sentiment causes a corresponding shift in the sector returns. In other words, low future returns follow a rise in emotion. Although the results for the telecommunication services sector were statistically significant and positive, they are consistent with the findings of the following studies: McGurk et al., 2020; AlNasseri et al., 2021; Abdul Karim et al., 2022). These studies show that optimism lowers uncertainty and volatility in stock market returns and generates optimistic expectations, which explains the positive relationship between the two. They were statistically insignificant for the utilities and banking sectors, indicating that different investor types exist in each industry, leading to variations in sentiment proneness.

In addition, for the corona virus coefficient, φ, was negative and statistically significant for five out of eight sectors, namely, FN,UT,RE,HC and TS . While the other sectors were negative and statistically insignificant. Then, for the control variables coefficients, first the GDP ,ϑ_1 , was negative and statistically significant for six out of seven sectors— except the financial sector which was negative also but statistically insignificant. while, there were only three sectors- RE, EG and UT were positive and statistically significant. Second the inflation, ϑ_2 , all the sectors are statistically significant but with different sign, four out of ten were positive-ID,IT,RE and FN while, the other were negative.

Table (7): the selected model outputs

Sectors	Mean Equation						
	μ	ω	α	θ	φ	ϑ_1	ϑ_2
ID	282.7439***	0.004579	0.012780	-1.353982***	-0.108950	-1.459176***	0.435535***
CD	463.3461***	0.083738	-0.041039	-1.031482***	-0.037447	-3.502526***	-2.075900***
FN	113.4447*	0.843198***	-0.863294***	-0.365058	-6.607566**	-0.727979	1.424279**
HC	144.1446***	0.044718	0.029402	-1.361426***	-3.131824***	-0.084617***	-3.404188***
EG	121.5194***	-0.071642	0.030296	-3.282910***	-0.977990	2.130105***	-0.865546***
IT	665.3034***	0.093860***	-0.011909	-1.541261***	-0.926123	-5.124683***	2.689368***
RE	40.24222***	-0.015717	0.003643	-0.481770***	-2.155590***	0.049853***	1.519400***
TS	38.94136***	0.009094	0.012131	0.092992***	-0.069172***	-0.479666***	-0.120625**
UT	-8.092362***	0.012865	-0.000448	0.204382	-0.086025***	0.012865***	-0.130819***
MT	65.35602***	0.032304**	0.011794	-0.010011***	-0.189704	-0.605105***	-1.143588***

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

<u>Discussion of the variance equations results of the upside</u>

Table 8 reveals that all of the variance equation parameters for five out of ten sectors, namely Health Care (HC), Real Estate (RE), Consumer Discretionary (CD), Industrials (ID), and Energy (EG), were found to be statistically significant indicating that the current volatility can be explained by both past volatility and historical innovations. However, there were discrepancies in the coefficients, indicating that the predictive power of past volatility was stronger than the impact of earlier innovations. With the exception of the Telecommunication Services (TS), Utilities (UT), and Information Technology (IT) sectors, the asymmetry parameter was found to be significant and negative in all sectors. This finding suggests the presence of the leverage effect, where positive shocks have a greater influence on volatility compared to negative shocks of the same magnitude.

The degree of volatility persistence in sector returns was quantified by the coefficients $\alpha + \beta$, which for all sectors was high but less than one. This suggests that there is volatility clustering in the returns, which is typical of time series data related to finance. A high degree of volatility persistence suggests that mean reversion to average volatility occurs slowly and that stock return volatility has a major effect on stock prices. This was true of the industry sector returns (0.934), which showed the greatest persistence and were hence most susceptible to outside influences. A certain amount of diversification, however restricted, could be offered by the differences in volatility persistence among the indices.

Out of seven sectors, four showed statistically significant negative values for the investor sentiment metric, θ, while the remaining three showed statistically negligible values. This suggests that behavioural variables were important in causing the volatility in these industries and that volatility is reduced when investor sentiment rises. This indicates that sentiment reduces stock market volatility in the United States. As a result, market volatility falls as sentiment mean returns.

In addition, for the corona virus coefficient, φ, was positive and statistically significant for six out of ten sectors, except energy, telecommunication services, real state and utility. Which means that the corona virus increases the volatility in the USA markets. Then, for the control variables coefficients, first the GDP ,$\boldsymbol{\vartheta_1}$, was statistically insignificant with different directions, except for two only sectors- ID and CD were negative and statistically insignificant. Second the inflation, $\boldsymbol{\vartheta_2}$, was statistically insignificant for all the sectors except for the ID sector which was positive and statistically significant.

Both the stationarity constraint ($\alpha + \beta < 1$) and the non-negativity conditions in the volatility equation ($\delta > 0$, $\beta > 0$, $\alpha \geq 0$ and $\beta + \gamma \geq 0$) were met. This indicates that for every sector index, every model chosen for the conditional variance was acceptable.

Table (8): the selected model outputs

Sectors	Variance Equation								
	δ	α	γ	β	θ	φ	ϑ_1	ϑ_2	$\alpha+\beta$
ID	3.970057***	-0.119598***	-0.189463***	0.934382***	-0.018552***	0.230464***	-0.017282***	0.004970***	0.727469
CD	6.172294***	-0.266827***	0.142721***	0.913303***	-0.015305	0.157615**	-0.040224**	-0.027897	0.3022
FN	3.761669	0.171781	-0.223649***	0.921833***	0.003160	0.136937**	-0.040318	0.006438	0.339
HC	5.186564	2.258143**	-2.058326**	0.198170	-0.009109	2.01161 *	-0.006111	-0.030658	0.3129
EG	4.674107	1.416941***	-1.565257***	0.680183***	-0.022725**	0.269983	-0.003638	-0.2281**	0.4945
IT	13.76166	-0.340504	-0.158983	-0.305225	-0.031593	3.578272***	-0.038679	0.318439	0.9642
RE	3.439187	0.585496***	-0.921426**	0.201426	-0.000603**	0.545560	0.002997	-0.464317	0.8836
TS	3.132329	0.018026	-0.379805	0.118804	0.001468	0.610004	0.001278	0.072460	0.9628
UT	3.524552	0.435258	-0.553589	0.057147	0.000873	1.364996	0.000834	0.135151	0.2413
MT	7.891869	2.031375	-2.399535*	0.573060**	-0.118966*	0.765586*	0.055012	0.101683	0.419

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

<u>*Discussion of the mean equation's results of the downside*</u>

Table 9 displays the models' negative outcomes for each sector index. Based on the mean equation, the CD is the only sector in which return serial correlation is demonstrated by the positive and statistically significant serial correlation coefficient, ω, whereas all other sectors were found to be statistically insignificant. The impact of previous shocks on current returns is likewise applicable. For just two sector indices—the CD and TS—the coefficient, which measures the impact of previous shocks on current returns, was statistically significant and negative. The statistical significance of the other sectors was negligible, though. This implies that, with the exception of CD and TS, it is not possible to estimate the current returns using the previous returns and shocks.

With the exception of information technology, where investor sentiment was determined by looking at SBICs, all sectors had positive and statistically significant values of the investor sentiment metric, θ. The positive coefficients indicate that when investor sentiment shifts, the sector returns also tend to shift in the same direction. In other words, rising sentiment is accompanied by large future rewards. These outcomes are consistent with the research conducted by McGurk et al. (2020), AlNasseri et al. (2021), and Abdul Karim et al. (2022).

In addition, for the corona virus coefficients, φ, six out of seven were negative and statistically significant — CD, EG, MT, IT, HC and FN, only the energy sector was also negative but insignificant. While the other sectors were positive and statistically significant. Then, for the control variables coefficients, first the GDP, ϑ_1 , was negative and statistically significant for seven out of nine sectors except the RE was positive and statistically significant. Second the inflation, ϑ_2 , was negative and statistically significant for eight sectors— ID, CD, FN, HC, IT, TS, UT and MT, while the other two sectors were positive and statistically significant.

Table (9): the selected model outputs

Sectors	Mean Equation						
	μ	ω	α	θ	φ	ϑ_1	ϑ_2
ID	-188.0204***	0.003347	0.002987	1.947561***	-0.511380	-0.002278	-3.395906***
CD	-137.6788***	0.674302***	-0.453715***	3.784120***	-3.377945 ***	-2.312983 ***	-3.415496***
FN	60.56564***	-0.007832	-0.007080	1.429622***	-1.166412***	-1.997056***	-2.209174***
HC	-18.46535***	0.037470	0.037117	1.611493***	-1.046531***	-1.377988***	-2.295742 ***
EG	37.24543***	0.004925	-0.008091	2.340191***	-2.021837***	-2.730570***	0.457880***
IT	-1.779677	0.005000	0.005000	3.709648	-16.65962	-3.357927	-18.76778***
RE	-22.63868 ***	0.011861	0.014660	0.069759***	0.399734***	0.280894 ***	0.525803 ***
TS	58.89237 ***	0.080244	-0.002249***	0.196908***	0.935629***	-0.359157***	-1.649816 ***
UT	-16.12555***	-0.001848	0.001461	0.218488***	0.088653***	-0.031657***	-1.207388***
MT	-8.855206***	-0.004805	-0.003621	1.610022***	-1.269609***	-1.498139***	-1.416492***

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

Discussion of the variance equations results of the downside

For every model chosen from the ten sectors in Table 10, the variance equation parameters of the downside were all statistically insignificant. This implies that past innovations and volatility cannot adequately account for the volatility we are currently experiencing. The explanatory power of volatility in the previous period, however, was higher than the explanatory power of previous innovations, except for the RE and IT, as shown by the differences in the coefficients. The asymmetry parameters were then found to be positive and statistically not significant. This proves that the leverage effect doesn't exist.

The coefficients $\alpha + \beta$ measured the degree of volatility persistence in sector returns, and they were all high but less than one for every sector. This implies that the returns exhibit volatility clustering, which is common for time series data pertaining to finance. Significant volatility persistence, according to Engle and Patton (2001), suggests that recent volatility shocks affect volatility projections for several future periods. A high degree of volatility persistence indicates that stock return volatility has a significant impact on stock prices and that mean reversion to average volatility happens slowly. This was especially true for the CD sector returns (0.1014), which were the most persistent and therefore most vulnerable to external factors.

The investor sentiment parameter, θ, was negative and statistically insignificant in all sectors This indicates that the sentiment investor doesn't have any impact on the downside variance equation for all the sectors under study. In addition, for the corona virus coefficient, φ, was statistically insignificant for all sectors, except CD which was positive and statistically significant. Then, for the control variables coefficients, first the GDP ,ϑ_1 , was statistically insignificant for all the sectors. Second the inflation, ϑ_2 , was positive and statistically significant for CD and RE sectors, while the other sectors were positive but statistically insignificant.

Both the stationarity constraint ($\alpha + \beta < 1$) and the non-negativity conditions in the volatility equation ($\delta > 0$, $\beta > 0$, $\alpha \geq 0$ and $\beta + \gamma \geq 0$) were met. This indicates that for every sector index, every model chosen for the conditional variance was acceptable. From the aforementioned discussion we can accept the third hypothesis stating that ***the association between investors sentiment and stock price volatility varies according to market status.***

MSA-Management science journal
ISSN 2974-3036
Volume: 3, Issue:2, Year: 2024 pp.76-119

Table (10): the selected model outputs

Sectors	Variance Equation								
	δ	α	γ	β	θ	φ	ϑ_1	ϑ_2	$\alpha+\beta$
ID	4.714354	0.403784	0.279610	-0.035615	-0.007139	0.981486	-0.006133	0.563670	0.727469
CD	4.788855	0.679227	0.194586	0.101495	-0.016795	1.504917**	-0.011469	0.796264**	0.3022
FN	4.300995	0.458498	0.113314	-0.040865	-0.009452	0.419218	0.007181	0.921833	0.339
HC	4.710109	0.723011	0.420049	0.021870	-0.011121	1.322557	-0.008646	0.836236	0.3129
EG	5.781318	0.174553	-0.001083	0.002366	-0.001033	0.483181	-0.000787	0.048159	0.4945
IT	7.373291	0.010000	0.010000	0.010000	0.000000	0.000000	0.000000	0.000000	0.9642
RE	3.781531	-0.017296	-0.654912	-0.064926	-0.002974	-0.274060	-0.002944	0.058962***	0.8836
TS	2.982010	0.794726	0.722652	0.049604***	-0.006611	-0.151861	-0.005861	0.729617	0.9628
UT	3.198148	0.368916	0.292591	0.0606556	-0.006927	0.171738	-0.005023	0.892970	0.2413
MT	3.870801	0.725901	0.358075	0.072581	-0.008401	0.408037	-0.005173	0.739672	0.419

Note: ***, ** and * denotes 1%, 5% and 10% significant level.

Conclusion

Investor sentiment plays a crucial role in shaping stock returns and stock volatility within financial markets. It refers to the collective psychological outlook and feelings of investors towards a particular asset or market. Investor sentiment includes various factors, including optimism, fear, greed, and market expectations.

Existing research has found evidence that investor sentiment has a significant negative impact on stock returns in seven sectors, meaning that any change in investor sentiment causes the sectors to change in the opposite direction. The impact of the coronavirus on the association between investor sentiment and stock returns was positive and significant in five out of 10 sectors (Industrials, IT, Consumer Discretionary, Utilities, and Real Estate). While the other sectors were positive and not statistically significant, and in only one sector was the impact of Corona negative and insignificant, which is the energy sector. On the other hand, the results confirmed that the effect of investor sentiment on stock market fluctuations was negative and significant, which means that any increase in investor sentiment reduces stock market fluctuations in all sectors except the real estate sector. The results also showed that the Coronavirus increases volatility in all sectors except (real estate and utilities). The mutual correlation between stock returns in each sector and investor sentiment is confirmed in the following sectors (financial, industrial, information technology, and communications services). This confirms that investor sentiment has an impact on stock market returns and fluctuations and that stock market fluctuations also have an impact on investor sentiment in the American markets.

Regarding the impact of investor sentiment on the performance of selected US sectors in emerging and declining countries. The results showed that in the case of a bull market, investor sentiment has a negative and statistically significant impact on stock returns, as any increase in sentiment is followed by lower future returns. While the impact of the previously mentioned relationship was positive in the communications sector. The impact of the Coronavirus on the relationship in the event of a rising market was negative and statistically significant in the following sectors (financial, real estate, healthcare, and communications. While the impact on other sectors was negative but insignificant).

From an alternative perspective, the influence of investor sentiment on stock market volatility in the upside market exhibited a negative and statistically significant effect in only four sectors, while it was insignificant in the remaining sectors. In contrast, the impact of the coronavirus was positive and significant across all sectors, except for the energy, telecommunications, real estate, and utility sectors. This suggests that the coronavirus outbreak has led to increased volatility in the US market. Regarding the impact of investor sentiment on stock returns in the downside market, the results indicate that investor sentiment has a positive and statistically significant effect on stock returns in all sectors, except for the information technology sector. This implies that any change in investor sentiment results in corresponding changes in sector returns in the same direction.

Concerning the influence of investor sentiment on stock market volatility in the upside markets, the results reveal that investor sentiment was negative and insignificant across all sectors. This suggests that investor sentiment does not have a significant impact on volatility in the downside market

Implications, recommendations, and future research

This study has implications for academia, investors, policymakers or portfolio managers, and the government. First, Understanding the role of sentiment can help investors make more informed decisions by considering not only fundamental factors but also the prevailing sentiment in the market. Investors can use sentiment analysis to gauge market sentiment, identify potential market trends, and adjust their investment strategies accordingly. Second, Investor sentiment plays a crucial role in shaping market volatility, especially during periods of heightened uncertainty such as the coronavirus pandemic and market fluctuations. Recognizing the impact of sentiment on stock market performance can assist risk managers in developing effective risk management strategies. By incorporating sentiment analysis into risk models, risk managers can better assess and manage market risks arising from shifts in investor sentiment. Third, the research findings on investor sentiment provide valuable insights for financial market regulators. Regulators can utilize sentiment analysis to monitor market sentiment and identify potential market manipulation or excessive speculation driven by sentiment. Understanding the impact of sentiment on stock market performance can aid in the development of appropriate regulations and policies to maintain market integrity and stability. Fourth, the research on investor sentiment's influence on stock market performance provides valuable information for market analysts and researchers. By incorporating sentiment analysis into their analysis, analysts can gain a deeper understanding of market dynamics and improve their forecasts of stock returns and volatility.

Current research recommends the following points. First, to better understand the impact of investor sentiment on stock market performance, it is crucial to continuously improve sentiment analysis techniques. Researchers should explore advanced natural language processing (NLP) algorithms, machine learning models, and deep learning approaches to accurately capture and analyze investor sentiment from various sources such as social media, news articles, and financial reports. This will enable a more nuanced understanding of sentiment dynamics and its relationship with stock returns and volatility. Second, Investor sentiment is a multifaceted concept that encompasses various dimensions, including optimism, fear, uncertainty, and risk aversion. Future studies should explore the impact of these different dimensions of sentiment on stock returns and volatility individually and collectively. This will allow for a more comprehensive understanding of how specific sentiment dimensions drive market dynamics during different market conditions.

While existing studies often focus on short-term effects, future research should explore the long-term impact of investor sentiment on stock market performance. By analyzing sentiment dynamics over extended periods, researchers can identify persistent patterns and trends that may have lasting effects on stock returns and volatility. Investigating the impact of investor sentiment on stock market performance in different countries and regions is crucial for understanding the global dynamics of sentiment-driven markets. Future research should compare sentiment patterns across international markets and assess how cultural, economic, and political factors influence the relationship between sentiment, stock returns, and volatility. Market anomalies, such as bubbles, crashes, and herding behavior, have been extensively studied in finance. Future research should explore the links between investor sentiment and these market anomalies, investigating how sentiment contributes to the formation and bursting of bubbles and the occurrence of other market irregularities.

Reference

Alfano, S. J., Feuerriegel, S., & Neumann, D. (2015, May). Is news sentiment more than just noise? In *ECIS*.

Anastasiou, D., Ftiti, Z., Louhichi, W., & Tsouknidis, D. (2023). Household deposits and consumer sentiment expectations: Evidence from Eurozone. *Journal of International Money and Finance*, *131*, 102775.

Anbarasu, N., Karuppusamy, S., Prabhu, S., & Sobana, P. (2023). Experimental Work and Discussion of Results on Deepfakes in Stock Prices Using Sentiment Analysis and Machine Learning. In *Handbook of Research on Advanced Practical Approaches to Deepfake Detection and Applications* (pp. 44-54). IGI Global.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016). Investor sentiment, beta, and the cost of equity capital. *Management Science*, *62*(2), 347-367.

Bahloul, W., & Bouri, A. (2016). The impact of investor sentiment on returns and conditional volatility in US futures markets. *Journal of Multinational Financial Management*, *36*(1), 89-102.

Bai, M., & Qin, Y. (2023). SENTIMENT AND INDIVIDUAL STOCK PERFORMANCE: EVIDENCE FROM CHINA. *International Journal of Business and Economics (IJBE)*, *8*(1), 9-32.

Bathia, D., & Bredin, D. (2013). An examination of investor sentiment effect on G7 stock market returns. *The European Journal of Finance*, *19*(9), 909-937.

Black, F. (1986). Noise. *The journal of finance*, *41*(3), 528-543.

Campbell, J. Y., & Kyle, A. S. (1993). Smart money, noise trading and stock price behaviour. *The Review of Economic Studies*, *60*(1), 1-34.

Carnazza, G. (2023). The Impact of the Social Mood on the Italian Sovereign Debt Market: A Twitter Perspective. *Italian Economic Journal*, 1-30.

Chau, F., Deesomsak, R., & Koutmos, D. (2016). Does investor sentiment really matter?. *International Review of Financial Analysis*, *48*, 221-232.

Cheng, W. K., Bea, K. T., Leow, S. M. H., Chan, J. Y. L., Hong, Z. W., & Chen, Y. L. (2022). A review of sentiment, semantic and event-extraction-based approaches in stock forecasting. *Mathematics*, *10*(14), 2437.

Chi, L., Zhuang, X., & Song, D. (2012). Investor sentiment in the Chinese stock market: an empirical analysis. *Applied Economics Letters*, *19*(4), 345-348.

Chuang, W. J., Ouyang, L. Y., & Lo, W. C. (2010). The impact of investor sentiment on excess returns: A Taiwan stock market case. *International Journal of Information and Management Sciences*, *21*(1), 13-28.

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. *Handbooks in operations research and management science, 9*, 385-410.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990a). Noise trader risk in financial markets. *Journal of political Economy*, *98*(4), 703-738.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990b). Positive feedback investment strategies and destabilizing rational speculation. *the Journal of Finance*, *45*(2), 379-395.

de Sousa-Gabriel, V. M., Lozano-García, M. B., Matias, M. F. L. I., Neves, M. E., & Martínez-Ferrero, J. (2023). Global environmental equities and investor sentiment: the role of social media and Covid-19 pandemic crisis. *Review of Managerial Science*, 1-25.

DeVault, L., Sias, R., & Starks, L. (2019). Sentiment metrics and investor demand. *The Journal of Finance*, *74*(2), 985-1024.

Domingues, C. H. S., Aronne, A., Pereira, F., & Magalhães, F. (2022). Piotroski, Graham and Greenblatt: an Empirical Approach to Value Investing in the Brazilian Stock Market. *BBR. Brazilian Business Review*, *19*, 475-491.

Dreyer, J. K., Sharma, V., & Smith, W. (2023). Warm-glow investment and the underperformance of green stocks. *International Review of Economics & Finance*, *83*, 546-570.

Elahi, M., Kholgh, D. K., Kiarostami, M. S., Oussalah, M., & Saghari, S. (2023). Hybrid Recommendation by Incorporating the Sentiment of Product Reviews. *Information Sciences*.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of financial economics*, *88*(2), 299-322.

Gong, X., Zhang, W., Wang, J., & Wang, C. (2022). Investor sentiment and stock volatility: New evidence. *International Review of Financial Analysis*, *80*, 102028.

Guerra, A., & Karakuş, O. (2023). Sentiment Analysis for Measuring Hope and Fear from Reddit Posts During the 2022 Russo-Ukrainian Conflict. *arXiv preprint arXiv:2301.08347*.

Hessary, Y. K., & Hadzikadic, M. (2017). Role of behavioral heterogeneity in aggregate financial market behavior: An agent-based approach. *Procedia Computer Science*, *108*, 978-987.

Abdul Karim, Z., Muhamad Fahmi, F. S. R., Abdul Karim, B., & Shokr, M. A. (2022). Market sentiments and firm-level equity returns: panel evidence of Malaysia. *Economic Research-Ekonomska Istraživanja*, *35*(1), 5253-5272.

Kim, J. S., Kim, D. H., & Seo, S. W. (2017). Investor sentiment and return predictability of the option to stock volume ratio. *Financial Management*, *46*(3), 767-796.

Krainer, R. E. (2023). Financial Contracting as Behavior towards Risk: The Corporate Finance of Business Cycles 8/3/22. *Journal of Financial Stability*, 101104.

Li, S. (2023). Algorithmic Financial Regulation: Limits of Computing Complex Adaptive Systems. *Available at SSRN 4335913*.

Li, Z., Wen, F., & Huang, Z. J. (2023). Asymmetric response to earnings news across different sentiment states: The role of cognitive dissonance. *Journal of Corporate Finance*, *78*, 102343.

Liapis, C. M., Karanikola, A., & Kotsiantis, S. (2023). Investigating Deep Stock Market Forecasting with Sentiment Analysis. *Entropy*, *25*(2), 219.

Liu, W., Yang, J., Chen, J., & Xu, L. (2023). How Social-Network Attention and Sentiment of Investors Affect Commodity Futures Market Returns: New Evidence From China. *SAGE Open*, *13*(1), 21582440231152131.

Liu, S. (2015). Investor sentiment and stock market liquidity. *Journal of Behavioral Finance*, *16*(1), 51-67.

Ma, Y., Mao, R., Lin, Q., Wu, P., & Cambria, E. (2023). Multi-source aggregated classification for stock price movement prediction. *Information Fusion*, *91*, 515-528.

Mike, S., & Farmer, J. D. (2008). An empirical behavioral model of liquidity and volatility. *Journal of Economic Dynamics and Control*, *32*(1), 200-234.

Mili, M., Sahut, J. M., Teulon, F., & Hikkerova, L. (2023). A multidimensional Bayesian model to test the impact of investor sentiment on equity premium. *Annals of Operations Research*, 1-21.

Naik, P. K., & Padhi, P. (2016). Investor sentiment, stock market returns and volatility: evidence from National Stock Exchange of India. *International Journal of Management Practice*, *9*(3), 213-237.

Neal, R., & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns?. *Journal of Financial and Quantitative Analysis*, *33*(4), 523-547.

Parra-Moyano, J., Partida, D., & Gessl, M. (2023). Your Sentiment Matters: A Machine Learning Approach for Predicting Regime Changes in the Cryptocurrency Market.

Piccoli, P., da Costa Jr, N. C., da Silva, W. V., & Cruz, J. A. (2018). Investor sentiment and the risk–return tradeoff in the Brazilian market. *Accounting & Finance*, *58*, 599-618.

Pillada, N., & Rangasamy, S. (2023). An empirical investigation of investor sentiment and volatility of realty sector market in India: an application of the DCC–GARCH model. *SN Business & Economics*, *3*(2), 55.

Rahman, M. A., Shien, L. K., & Sadique, M. S. (2013). Swings in sentiment and stock returns: Evidence from a frontier market. *International Journal of Trade, Economics and Finance*, *4*(6), 347.

Rim, H. J., & Zha Giedt, J. (2023). Mistaking Bad News for Good News: Mispricing of a Voluntary Disclosure. *Available at SSRN 4322045*.

Sapkota, N., & Grobys, K. (2023). Fear sells: On the sentiment deceptions and fundraising success of initial coin offerings. *Journal of International Financial Markets, Institutions and Money*, *83*, 101716.

Song, Z., Gong, X., Zhang, C., & Yu, C. (2023). Investor sentiment based on scaled PCA method: A powerful predictor of realized volatility in the Chinese stock market. *International Review of Economics & Finance*, *83*, 528-545.

Ung, S. N., Gebka, B., & Anderson, R. D. (2023). Is sentiment the solution to the risk-return puzzle? A (cautionary) note. *Journal of Behavioral and Experimental Finance*, 100787.

Uygur, U., & Taş, O. (2014). The impacts of investor sentiment on returns and conditional volatility of international stock markets. *Quality & Quantity*, *48*(3), 1165-1179.

Vahl, J. (2022). *New directions in empirical asset pricing: information, innovation, and stock returns* (Doctoral dissertation, University of British Columbia).

Verma, R., & Soydemir, G. (2006). The impact of US individual and institutional investor sentiment on foreign stock markets. *The Journal of Behavioral Finance*, *7*(3), 128-144.

Wang, J., Huang, Y., Feng, H., & Yang, J. (2023). The effect of customer concentration on stock sentiment risk. *Review of Quantitative Finance and Accounting*, *60*(2), 565-606.

Wang, S., Zhou, B., & Gao, T. (2023). Speculation or actual demand? The return spillover effect between stock and commodity markets. *Journal of Commodity Markets*, *29*, 100308.

Xiao, D., Wang, J., & Niu, H. (2016). Volatility analysis of financial agent-based market dynamics from stochastic contact system. *Computational Economics*, *48*, 607-625.

Yu, D., Chen, C., Wang, Y., & Zhang, Y. (2023). Hedging pressure momentum and the predictability of oil futures returns. *Economic Modelling*, 106214.

Zunara, E., Achsani, N. A., Hakim, D. B., & Sembel, R. (2022). The The Effect of Rational and Irrational Sentiments of Individual and Institutional Investors on Indonesia Stock Market. *Jurnal Aplikasi Bisnis dan Manajemen (JABM)*, *8*(3), 802-802.

Rupande, L., Muguto, H. T., & Muzindutsi, P. F. (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance*, *7*(1), 1600233.

Peters, G. W., Chudtong, M., & De Gaetano, A. (2023). Analysis of option-like fund performance fees in asset management via Monte Carlo actuarial distortion pricing. *Annals of Actuarial Science*, 1-43.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives, 21(2), 129-152.

Da, Z., Warachka, M., & Xing, Y. (2011). Stock market volatility, excess returns, and the role of investor sentiment. Journal of Empirical Finance, 18(3), 289-305.

Zhang, X., & Li, Y. (2019). Investor sentiment and stock price volatility: Evidence from the Chinese stock market. International Review of Economics & Finance, 64, 424-437.

Chiang, T. C., & Zheng, D. (2010). The volatility–sentiment hypothesis in the Taiwan Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. Journal of Finance, 61(4), 1645-1680.

Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 12(5), 537-560.

Han, B., Lee, C. M., & Wang, Q. (2018). Individual investor sentiment and stock returns—What do we learn from option data? Journal of Banking & Finance, 94, 238-250.

Zhou, W. X., & Wong, W. K. (2017). Does investor sentiment affect the implied volatility? Evidence from equity options. Journal of Futures Markets, 37(9), 978-999.

Massa, M., Simonov, A., & Stenkrona, A. (2017). Limits of arbitrage and sentiment volatility on asset pricing. Journal of Financial Economics, 123(1), 19-45. stock market. Journal of Banking & Finance, 34(5), 1057-1066.

Abdul Karim, Z., Muhamad Fahmi, F. S. R., Abdul Karim, B., & Shokr, M. A. (2022). Market sentiments and firm-level equity returns: Panel evidence of Malaysia. Economic Research-Ekonomska Istraživanja, 1(1), 1–20. https://doi.org/10.1080/1331677X.2021.2025126

Andersen, T. G., & Bollerslev, T. (1998). Deutsche mark–dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies. The Journal of Finance, 53(1), 219–265. https://doi.org/10.1111/0022-1082.85732

Andersen, T., Bollerslev, T., & Lange, S. (1999). Forecasting financial market volatility: Sample frequency vis-a-vis ` forecast horizon. Journal of Empirical Finance, 6(5), 457–477. https://doi.org/10.1016/S0927-5398(99)00013-4

Anderson, E. W., Ghysels, E., & Juergens, J. L. (2005). Do heterogeneous beliefs matter for asset pricing? The Review of Financial Studies, 18(3), 875–924. https://doi. org/10.1093/rfs/hhi026

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. The Review of Financial Studies 19 (4), 1191–1239. https://doi.org/10.1093/rfs/hhj035.

Al-Nasseri, A., Ali, F. M., & Tucker, A. (2021). Investor sentiment and the dispersion of stock returns: Evidence based on the social network of investors. International Review of Financial Analysis, 78(1), 101910. https://doi.org/10.1016/j.irfa.2021.101910

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. Journal of Financial Economics, 104(2), 272–287. https://doi.org/10.1016/ j.jfineco.2011.11.002

Baruník, J., Koˇcenda, E., V´acha, L., 2016. Asymmetric connectedness on the U.S. stock market: bad and good volatility spillovers. J. Financ. Mark. 27, 55–78. https:// doi.org/10.1016/j.finmar.2015.09.003.

Baruník, J., Koˇcenda, E., V´acha, L., 2017. Asymmetric volatility connectedness on the forex market. J. Int. Money Financ. 77, 39–56. https://doi.org/10.1016/j. jimonfin.2017.06.003.

Barndorff-Nielsen, O. E., Kinnebrock, S., Shephard, N. (2010). Measuring downside risk: realised semivariance. In: Bollerslev, T., Russell, J., Watson, M. (Eds.), Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle. Oxford University Press

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and equity market contagion. The Journal of Finance, 69(6), 2597–2649. https://doi.org/ 10.1111/jofi.12203

Bekaert, G., Harvey, C. R., & Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. The Review of Financial Studies, 20(6), 1783–1831. https://doi.org/10.1093/rfs/hhm030

Beer, F., Hamdi, B., & Zouaoui, M. (2018). Investors' sentiment and accruals anomaly: European evidence. Journal of Applied Accounting Research, 19(4), 500–517. https://doi.org/10.1108/JAAR-03-2017-0043

Bormann, S. K. (2013). Sentiment indices on financial markets: What do they measure? Economics Discussion Papers, No. 2013-58.

Bollerslev, T. (1986). Generalised autoregressive conditional heteroskedasticity. Journal of Econometrics, 31 (3), 307–327. https://doi.org/10.1016/0304-4076(86) 90063-1

Brandt, M.W., Kang, Q., 2004. On the relationship between the conditional mean and volatility of stock returns: a latent VAR approach. J. Financ. Econ. 72 (2), 217–257. https://doi.org/10.1016/j.jfineco.2002.06.001.

Brown, G., & Cliff, M. (2004). Investor sentiment and the near-term stock market. Social Science Research Network Electronic Journal, 11(4), 627–643. https://doi.org/10.1016/j.jempfin.2002.12.001

Brooks, C. (2019). Introductory Econometrics for Finance (4th ed.). Cambridge University Press.

Cakan, E., & Balagyozyan, A. (2016). Sectoral herding: Evidence from an emerging market. Journal of Accounting and Finance, 16(4), 87–96.

Chakraborty, M., & Subramaniam, S. (2020). Asymmetric relationship of sentiment with stock return and volatility: Evidence from India. Review of Behavioral Finance, 12(4), 435–454. https://doi.org/10.1108/RBF07-2019-0094

Chen, Y., Ma, F., Zhang, Y., 2019. Good, bad cojumps and volatility forecasting: new evidence from crude oil and the U.S. stock markets. Energy Econ. 81, 52–62. https://doi.org/10.1016/j.eneco.2019.03.020.

Corredor, P., Ferrer, E., & Santamaria, R. (2015). The impact of investor sentiment on stock returns in emerging markets, the case of central European markets. Eastern European Economics, 54(4), 328–355. https://doi.org/10.1080/00128775.2015.1079139

Costa, A., Matos, P., & da Silva, C. (2022). Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics. Finance Research Letters, 45(1), 102124. https://doi.org/10.1016/j.frl. 2021.102124

Comte, F., Renault, E., 1998. Long memory in continuous-time stochastic volatility models. Math. Financ. 8 (4), 291–323. https://doi.org/10.1111/1467-9965.00057.

Curatola, G., Donadelli, M., Kizys, R., & Riedel, M. (2016). Investor sentiment and sectoral stock returns: Evidence from world cup games. Finance Research Letters, 17(1), 267–274. https://doi.org/10.1016/j.frl. 2016.03.023

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. Journal of Finance, 66(5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

Engle, R. F., & Patton, A. J. (2001). What good is a volatility model?. Quantitative Finance, 1(2), 237–245.

Feunou, B., Okou, C., 2019. Good volatility, bad volatility, and option pricing. J. Financ. Quant. Anal. 54 (2), 695–727. https://doi.org/10.1017/S0022109018000777.

Finter, P., Niessen-Ruenzi, A., & Ruenzi, S. (2012). The impact of investor sentiment on the German stock market. Zeitschrift für Betriebswirtschaft, 82(2), 133– 163. https://doi.org/10.1007/s11573-011-0536-x

Han, X., & Li, Y. (2017). Can investor sentiment be a momentum time-series predictor? Evidence from China. Journal of Empirical Finance, 42, 212–239.

Hounyo, U. (2017). Bootstrapping integrated covariance matrix estimators in noisy jump-diffusion models with non-synchronous trading. Journal of Econometrics, 197(1), 130–152. https://doi.org/10. 1016/j.jeconom.2016.11.002

Gao, Y., Zhao, C., Sun, B., & Zhao, W. (2022). Effects of investor sentiment on stock volatility: New evidence from multi-source data in China's green stock markets. Financial Innovation, 8(1), 1–30. https://doi.org/ 10.1186/s40854-022-00381–2

Gong, X., Zhang, W., Wang, J., & Wang, C. (2022). Investor sentiment and stock volatility: New evidence. International Review of Financial Analysis, 80(1), 102028. https://doi.org/10.1016/j.irfa.2022.102028

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance, 48(5), 1779–1801. https://doi.org/ 10.1111/j.1540-6261.1993.tb05128.x

Jiang, S., & Jin, X. (2021). Effects of investor sentiment on stock return volatility: A spatio-temporal dynamic panel model. Economic Modelling, 97(1), 298–306. https://doi.org/10.1016/j.econmod.2020.04.002

Koonce, L., Lipe, M., McAnally, M., 2005. Judging the risk of financial instruments: problems and potential remedies. Account. Rev. 80 (3), 871–895. https://www. jstor.org/stable/4093180.

Koopman, S.J., Jungbacker, B., Hol, E., 2005. Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements.

J. Empir. Financ. 12 (3), 445–475. https://doi.org/10.1016/j.jempfin.2004.04.009.

Mokoena, S., & Nomlala, B. (2022). Analysis of the relationship between COVID-19 and the stock market performance in South Africa. International Journal of Finance & Banking Studies, 11(2), 25–33. https://doi. org/10.20525/ijfbs.v11i2.1477

Muguto, H. T., Rupande, L., & Muzindutsi, P. F. (2019). Investor sentiment and foreign financial flows: Evidence from South Africa. Zbornik Radova Ekonomski Fakultet u Rijeka, 37(2), 473–498. https:// doi.org/10.18045/zbefri.2019.2.473

Muguto, L., & Muzindutsi, P. F. (2022). A comparative analysis of the nature of stock return volatility in BRICS and G7 markets. Journal of Risk and Financial Management, 15(2), 1–27. https://doi.org/10.3390/ jrfm15020085

Naik, P. K., & Padhi, P. (2016). Investor sentiment, stock market returns and volatility: Evidence from National Stock Exchange of India. International Journal of Management Practice, 9(3), 213–237. https://doi.org/ 10.1504/IJMP.2016.077816

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347–370. https://doi.org/10.2307/2938260

Pandey, P., & Sehgal, S. (2019). Investor sentiment and its role in asset pricing: An empirical study for India. IIMB Management Review, 31(2), 127–144. https:// doi.org/10.1016/j.iimb.2019.03.009

Rupande, L., Muguto, H. T., Muzindutsi, P. F., & Yang, Z. (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. Cogent Economics and Finance, 7(1), 1600233. https://doi.org/10.1080/23322039.2019.1600233

Shamiri, A., & Hassan, A. (2007). Modelling and forecasting volatility of the Malaysian and the Singaporean stock indices using asymmetric GARCH models and non-normal densities. Journal of Malaysian Mathematical Sciences, 46(1), 83–102

Vengesai, E., Obalade, A. A., & Muzindutsi, P. F. (2022). Country risk dynamics and stock market volatility: Evidence from the JSE cross-sector analysis. Journal of Economics and Financial Analysis, 5(2), 63–84. https://doi.org/10.1991/jefa.v5i2.a46

Yang, H., Ryu, D., & Ryu, D. (2017). Investor sentiment, asset returns and firm characteristics: Evidence from the Korean stock market. Investment Analysts Journal, 46(2), 132–147. https://doi.org/10.1080/ 10293523.2016.1277850