Analysing The Effect of Investor Sentiment on the Co-Volatility of BRICS and the US Stock Markets

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Abstract: Investor sentiment has a significant impact on the volatility of stock markets, as sentiment-driven investors are seen as irrational traders. Irrational trading in stock markets leads to market mispricing, causing market volatility, as investors base their decisions on their own expectations. This study aims to analyse the effect of investor sentiment on the covolatility of the BRICS and US stock markets during the COVID-19 period. To examine the impact of investor sentiment on volatility in the stock markets, the generalized autoregressive conditional heteroscedasticity (GARCH) models were utilised, incorporate a global sentiment index using daily market returns. The results show that investor sentiment has a significant impact on the covolatility between the BRICS and US stock markets. As a result, behavioural finance can be used to explain volatility in the BRICS and US stock markets. Therefore, it is recommended that portfolio managers in the financial industry incorporate a sentiment factor into asset pricing models, as sentiment was found to have a significant influence on pricing.

Keywords: BRICS stock market; US Stock Market; investor sentiment; GARCH; noise traders

JEL Classification: G01; G14; G41

1. Introduction

One major factor contributing to volatility in stock markets is investor sentiment (Alfano et al., 2015). Sentiment-driven investors can be seen as irrational traders, as they lead to market mispricing, causing covolatility between these markets as they do not base their decisions on the fundamental value of stocks (Chau et al., 2016). Decisions made by irrational traders are based on expectations of the behaviour of other market participants. Rational traders according to traditional finance theory should

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base their decisions on the fundamental value of assets (Vlahavic et al., 2021). Irrational traders in the market have been labelled noise traders (Herve et al., 2019).

Noise trading behaviour is considered by the theory of behavioural finance, which is a recent approach to financial markets that has overcome the uncertainties of traditional finance theory (Uygur & Tas, 2012). Traditional finance theory suggests that in an efficient market, traders should be rational and should take into account all available information before making an investment decision (Kamoune & Ibenrissoul, 2022). The behavioural finance theory looks at the impact that investors have on stock markets; this theory states that it also supports that when investors use their cognitive emotions, they act irrationally in stock markets. Traditional finance theory eliminates noise traders from stock markets through an arbitrage process (Rupande et al., 2019). Noise traders are temperamental, leading to the creation of "noise trader risk." This is when an arbitrageur takes a short position selling a stock when bullish noise traders push the prices of stocks up, as noise traders push the price up, it will become more costly for the arbitrageur to replace the asset sold (De Long et al., 1990).

Rational arbitrageur in the market trades against irrational investors in the stock market, which leads to the price of stocks moving closely to the fundamental value (De Long et al., 1990). The price of a stock reflects all available information and is equal to the discounted sum of future cash flow, which is the fundamental value of the stock according to traditional finance theory (Uygur & Tas, 2012). Traders who are not fully rational cause deviations in the fundamental value of the asset, which leads to mispricing, making investments attractive and causing volatility in the market (Uygur & Tas, 2012). Noise traders play a crucial role in behavioural finance (Dow & Gorton, 2006). Volatility in a market changes the distribution of risk of financial assets (Rupande et al., 2019). The effect that noise traders have on stock markets can be measured in various ways. It has been found that the most applicable way to measure noise is through the estimation of an investor sentiment index (Zhou, 2018). There is a direct and indirect investor sentiment index that can be used to measure the effect of noise traders on the stock market. A direct investor sentiment index collects its primary data from questionnaires, and an indirect investor sentiment index uses market-based proxies to measure investor sentiment (Prasad et al., 2023).

As volatility in stock markets is not only affected by fundamental factors, it is crucial to measure the impact of sentiment on volatility in stock markets. Empirical evidence found by Baker and Wurgler (2007) indicates that the effect that investor behaviour has on stock markets has a huge effect on the covolatility between markets. Each market faces different kinds of volatility, and each market volatility has a spillover effect on other markets. Several studies have been conducted, but there were hardly any studies on the effect of investors on the covolatility of the BRICS and the US stock market. The effect of investor sentiment on stock markets affects market volatility and causes prices to fluctuate (Rupande et al., 2019). The primary objective of this research study is to analyse the effect of investor sentiment on the covolatility between the BRICS and US stock markets.

Examining the effect that investor sentiment has on stock markets is crucial as it affects stock market returns and volatility. Although it is crucial to examine the effect of investor sentiment on stock markets, no controversial measure can be used to measure its effect (Haritha & Rishad, 2020). Sentiment-driven investors also react to fundamental information; they irrationally do this, making it difficult to measure its effect on markets (Shleifer & Summers, 1990). Another factor affecting the measurement of investor sentiment is that we are not sure if sentiment bias affects individual investors or institutional investors (Devault et al., 2019). Uncertainty exists around whether investor sentiment has a positive impact on stock markets or a negative impact. All these factors have affected the development of a measure that can be used to determine the impact of investor sentiment on stock markets (Rupande et al., 2019). This study aims to fill the gap by analysing volatility in the BRICS and US stock markets during the COVID-19 pandemic.

It is crucial to look at the effect of investor sentiment as it affects asset pricing and investment activity, policies and regulations, and policymakers, which all affect volatility in stock markets (Muguto, 2021). In many studies over the years, only macroeconomic factors and not investor sentiment in the market were taken into account to determine the level of volatility (Rupande et al., 2019). The traditional finance theory in which all investors act rationally cannot work in the modern world, as technology plays a huge role in the effect that investors have on other investors in the market (Vlahavic et al., 2021). Consequently, this research paper will examine the effect of investor sentiment on the covolatility of the BRICS and US stock markets.

This research paper is organized as follows: Section 2 provides the theoretical review; Section 3 provides the methodology of this study; Section 4 discusses the results and findings, and finally Section 5 will conclude the paper while underlining policy implication and limitations of this research study.

2. Literature Review

Investor sentiment refers to the overall mood and attitude of investors to a particular market, this is often influenced by global events and herding behaviour. Sentiment-driven investors affect the covolatility between markets through their noise trading behaviour (Rupande et al., 2019). Noise traders disrupts the Brazil, Russia, India, China, and South Africa (BRICS) and the United States (US) stock markets from their normal state, increasing market volatility (Hsu & Tang, 2022). Increasing investor sentiment through noise trading behaviour can affect the return of stocks in the market, whereby this can lead to increased volatility in those stocks. The effect of investor sentiment during the coronavirus outbreak (COVID-19) was found to be one of the main factors causing high levels of volatility in US stock markets (Hsu & Tang, 2022).

In stock markets, investor sentiment affects volatility, as investors in these markets are referred to as irrational traders. Irrational investors in stock markets cause noise trading behaviour affecting volatility. These investors base their decisions on cognitive emotions as opposed to investors in the efficient market who base their decisions on the fundamental value of stocks (Chau et al., 2016). It is crucial to look at traditional finance theories, such as the classical financial theory based on the efficient market hypothesis (EMH), as it assumes that investors behave rationally.

The efficient market hypothesis (EMH) is a pivotal theory that is built on the concept of information efficiency (Fame, 1970). According to this hypothesis, investors base their decisions on the fundamental value of stocks (Fame, 1970). In efficient markets, the prices of financial assets reflect all information available (Mallkei, 2003). The efficient market hypothesis has three forms of markets. The first market form is the strong form, stock prices reflecting both public and private information (Fame, 1970). The semi-strong form is the second market form, stock prices reflect only public information. Lastly, the weak market form reflects past trading trends (Fame, 1970). Stock prices in financial markets rapidly adjust when new information enters the market (Mallkei, 2003). Stock prices in financial markets equal their intrinsic value in an efficient market, which helps stock market traders make rational decisions (Fame, 1970). Rational investor decisions consider all available market information. This makes it impossible for traders in the market to purchase undervalued stocks and sell overvalued stocks as all information is available in the market (Fame, 1970). Traders in the market will also be unable to outperform the market making abnormal profits due to information efficiency.

In the efficient market hypothesis, since all available information is reflected in the price, the hypothesis assumes that the price of financial assets is only affected by relevant risk, not volatility, and investor sentiment (Rupande et al., 2019). In contrast, investor decisions are affected by investor sentiment, which at times could lead to rational behaviour or irrational behaviour affecting the efficiency of markets (Sharma & Kumar, 2020). Sentiment-driven investors behave rationally when they trade against the herd and sell stocks when they are overpriced (Chau et al., 2016). Irrational investor behaviour is caused by the deviation in the level of risk according to the efficient market hypothesis (Mankuroane et al., 2022). The irrational behaviour of investors is considered by behavioural finance theories (Singh, 2010).

Behavioural finance supports the idea that when psychological factors and personal traits drive investor decisions, investors behave irrationally (Singh, 2010). Investor psychology and personal traits also affect the fundamental value of financial assets, leading to inefficient markets (Ahmed, 2020). These markets are seen to be inefficient as investor decisions are influenced by personal preferences, beliefs, and past events, and not market information (Baker & Ricciardi, 2014). Irrational investor decisions in stock markets affect the volatility between markets as this changes the pricing of stocks. Increasing irrational investor behaviour increases the mispricing of stocks. The behavioural finance theory assumes that markets are inefficient, price movements can be identified from past trends, and abnormal returns of stocks in these markets will be earned (Sharma & Kumar, 2020).

The fundamental value of stocks moves away from the price of stocks, resulting in abnormal returns and mispricing (Ricciardi, 2014). Irrational investors in financial markets are competitive, which affects the fundamental value of the financial asset, as these investors want to maximise market returns (Sgleifer & Vishny, 1997). As irrational investors maximise market returns, this creates market abnormalities (Sgleifer & Vishny, 1997). Market abnormalities rise due to irrational investors overreacting in financial markets to market events (Mallkei, 2003). Overreaction of investors results in price movements that do not align with the fundamental value of the financial asset. As the price of financial assets deviates from its fundamental value, this affects volatility in the financial market (Elyasiani & Mansur, 2017). Noise trading behaviour of investors causes deviations of financial assets from the fundamental value, affecting market volatility.

During the COVID-19 pandemic, volatility in stock markets was primarily driven by investor sentiment (Hsu & Tang, 2022). Extreme market events such as the global financial crises (GFC) in 2008 and more recently the COVID-19 pandemic should be taken into account, as they can have a significant impact on volatility, affecting stock returns (Da et al., 2015). Hsu and Tang (2022) found that shocks from the COVID-19 pandemic are expected to affect investor sentiment, affecting stock market returns. Dimpfl and Jank (2016) conducted a study to examine the relationship between investor sentiment and Internet sources, they found that a positive relationship exists between investor sentiment through Internet sources and stock returns in markets. Gao, Ren and Zhang (2020) also found that the shocks of the COVID-19 pandemic on stock markets were transferred through internet sources affecting investor sentiment and leading to volatile stock market returns.

Changes in investor sentiment lead to changes in stock market returns (Yan, 2020). Abnormal market returns in stock markets are also driven by investor sentiment. High levels of investor sentiment have been found to have a greater effect on stock market returns and volatility (Devault et al., 2019). As a result, investors in the stock markets during the COVID-19 pandemic were earning abnormal market returns (Harjoto et al., 2021). As investor sentiment played a crucial role in stock markets during the COVID-19 pandemic it is important to examine the effects of investor sentiment in stock markets (Rupande et al., 2019). Previous studies that were conducted did not examine the effect of investor sentiment on stock markets during the COVID-19 pandemic. Previous empirical studies placed more emphasis on the effects of macroeconomic factors on stock markets during the COVID-19 pandemic and not investor sentiment.

3. Methodology

3.1. Data

The objective of this study is to examine the effect of market-wide investor sentiment on the covolatility of the BRICS and US stock markets. To this extent, the study uses daily data for the period 2019-2022. Rupande et al. (2019) argues that high-frequency data is better suited for modelling financial market volatility as it better captures the volatility persistence. Moreover, Moodley et al. (2024) advocates for the sample period to contain historical market events, such as the COVID-19 pandemic, as volatility is at heighten levels in the market. The dependent and independent variables comprise of stock market indices associated with BRICS and the US market and the constructed market-wide investor sentiment index of Rupande et al. (2022). The construction of the variables is alluded to below.

3.1.1. Stock Market Indices

This study isolates the stock markets to the BRICS and US markets due to the unique characteristics of these markets. That being, these stock markets have significant GDP growth rates and contribute around 30% to global production (Christy, 2021). The BRICS markets are seen as emerging markets which exhibit higher levels of market volatility than developed markets therefore examining the effect of investor sentiment on the BRICS markets is crucial (Mciver & Kang, 2020). Furthermore, the US economy has a significant impact on global markets. The US stock market is also one of the world's largest liquid stock markets in the world, making it a benchmark for global investors and providing a stable reference point for comparing volatility (Chauvin, 2018). Fluctuations in economic policies, market trends, and corporate earnings in the US stock markets have a significant effect on global markets. The summary of the stock market indices used in this study is presented in In Table 1 below:

Table 1. BRICS and US market indices

Country	Name of Index	Abbreviations
Brazil	Ibovespa São Paulo Stock Exchange	IBOVESPA
Russia	Moscow Exchange	MOEX
India	National Stock Exchange Fifty	NIFTY
China	Shanghai Stock Exchange Composite Index	SSE
South Africa	Financial Times Stock Exchange Johannesburg Stock Exchange All Share Index	FTSE/JSE ALSI
United States	Standard and Poor's 500	S&P 500

Source: Authors' own compilation (2025)

3.1.2. Market-Wide Investor Sentiment Index

This study opted to update use the market-wide investor sentiment index of Rupande et al. (2022) to examine the objective of this study. The index is unique as it's the only sentiment index that captures global investor sentiment between the BRICS and US market. Thus, it provides robustness inputs in achieving the objective of this study. The construction of the index follows the proposition of Baker and Wurgler (2006, 2007), such that seven proxies are identified and the principal component analysis is used to model the desired index. The proxies used in the global sentiment index are described below.

3.1.2.1. Business Confidence Index

The business confidence index provides information on the future developments of the industrial sector. This index is based on future developments in production, stock of produced goods, and orders index (Muguto, 2021). Low business confidence indicates that production for the present period will be put on hold until the next period (Maredza & Nyamazunzu, 2016). A high degree of business confidence indicates improvements in production and output in the future (OECD, 2021). This index represents business sentiment, but investors' sentiment can be derived from it (Rahman & Shamsuddin, 2019). A previous study that used this index found that it is a good predictor of sentiment (Muguto, 2021). A study conducted by Rahman and Shamsuddin (2019) employed this index to examine the effect of investor sentiment on the P/E ratio in developed G7 countries, the reported results were significant.

3.1.2.2. Consumer Confidence Index

The consumer confidence index provided information on the sentiment of consumers. This index is based on the future developments of households' saving patterns and consumptions based on future expectations of financial situations and attitudes toward general economic situations. A low consumer confidence index indicates that consumers will save more than they spend (OECD, 2021). This index can be used to measure investor sentiment in stock markets, as it was found to be correlated with stock indices (Rahman & Shamsuddin, 2019). In a study conducted by Oprea (2014) that examined the impact of noise trader sentiment on ten post-communist East European stock markets, this index was used and reported successful results.

3.1.2.3. Global Price of Gold

The global price of gold as a proxy in the global sentiment index has a significant impact on financial markets (Muguto, 2021). When shocks in stock markets occur, investors tend to reallocate assets in their portfolios, investing more in gold as it is a safe asset. Therefore, it is important to consider the global price of gold when measuring investor sentiment (Rahman & Shamsuddin, 2019). In a previous study conducted by Muguto (2021), the global price of gold was used as a proxy when creating a sentiment index to examine the effect of sentiment on volatility in the stock market. The results of these studies showed that the global price of gold does affect volatility.

3.1.2.4. Global Price of Oil

Shocks in oil prices have a significant impact on investor sentiment, therefore, it is crucial to include the global price of oil in the global sentiment index. Economic activity is dependent on oil as a source of energy, which affects the price of oil and stock prices, affecting the sentiment of investors (Olayeni et al., 2020). In a study by Huang and Zheng (2020), it was found that there is a significant relationship between oil prices and sentiment.

3.1.2.5. US Dollar Index

The US dollar index is made up of several different currencies. These currencies include the French franc, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc. This index was included in the global sentiment index by Muguto (2021) as it captures the movement across financial markets. In previous studies conducted on measuring the impact of investor sentiment, different exchange rate proxies were used; therefore, this index is used in the global sentiment measure (Muguto, 2021).

3.1.2.6. Bloomberg Commodity Index

The Bloomberg commodity index is a financial benchmark index. This index provides diversified exposure and liquidity on physical commodities. The Bloomberg commodity index is constructed in a way that makes it attractive as a proxy for sentiment (Rahman & Shamsuddin, 2019). In this index, the sentiment of investors is revealed when prices change. Previous studies did not use this index to specifically measure the effects of sentiment on stock markets, but Muguto (2021) found that there is a strong link between sentiment and commodities.

3.1.2.7. Volatility Index (VIX)

The volatility index used as a proxy in the global sentiment index is a real-time volatility index created by the Chicago Board Options Exchange (CBOE, 2019). VIX is used to estimate future market volatility. There is a strong negative correlation between VIX-linked instruments in stock markets (Muguto, 2021). The VIX is also used to measure market stress and market fear. A study conducted by So and Lei (2015) used the VIX to examine the relationship between investor sentiment and trading volume, and the results from this study proved to be successful.

3.2. Empirical Model

To analyse the impact of investor sentiment on the covolatility between stock markets, the Generalised Auto-Regressive Conditional Heteroskedasticity (GARCH) models was used. The selection of the GARCH models flows the study of Muguto (2021) as it is the most suited model for examining volatility. There exist four specifications of the GARCH models, these include the GARCH (1.1), GJR-GARCH (1.1), and E-GARCH (1.1) models. This study will estimate each model and then the best model will be selected based on the minimisation of the information criteria.

The first step in estimating GARCH models is to estimate the mean equation. This study aims to analyse the effect of investor sentiment on market volatility. The mean equation includes a global sentiment index to analyse the effect of investor sentiment. In calculating the mean, the risk premium θ, effects of past returns a, and the effect of past shocks is taken into account. This mean equation is common in all three GARCH models. This procedure follows Rupande, Muguto, and Muzindutsi (2019), and Muguto (2021):

$$y_t = \mu + a y_{t-1} + v\varepsilon_{t-1} + \theta\sigma_{t-1} + \varphi GlobSent_t + \varepsilon_t \quad (1)$$

The coefficient of GlobSent, φ is used to show the effect of investor sentiment on stock markets as φ is used to capture the effect of investor sentiment (Muguto et al. 2021).

The conditional variance σ_t^2 of GARCH (1.1), GJR GARCH, and E GARCH (1.1) was augmented by including GlobSent respectively:

$$\sigma_t^2 = \omega + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi GlobSent_t \quad (2)$$

$$\sigma_t^2 = \omega + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + y\varepsilon_{t-1}^2 d_{t-1} + \varphi GlobSent_t$$
(3)

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \frac{\lambda^{\varepsilon_{t-1}}}{\sqrt{\sigma_{t-1}^2}} + \delta\left[{\varepsilon_{t-1|}}\Big/\sqrt{\sigma_{t-1}^2} - \sqrt{\frac{2}{\pi}}\right] + \varphi GlobSent_t \quad (4)$$

In the conditional variance equations above, β is used to capture the effect of past shocks, ω is the constant, λ captures which captures the past effects of volatility on current volatility, ε_{t-1}^2 is the lagged squared residual, and δ captures asymmetric volatility The dummy variable d_{t-1} in Equation 3, takes the value 1 if the shock a time t-1 is negative or otherwise 0. In equations 2 to 4 above the coefficient of GlobSent, φ is used to examine the effects of investor sentiment on volatility. For Equations 2 to 4 to be admissible, it must satisfy the non-negativity condition (ω > 0, λ ≥ 0 β > 0, and β + $\beta + \delta \geq 0$) and the stationarity condition ($\beta + \lambda < 1$).

4. Results and Discussion

4.1. Preliminary Results

The following section considers the graphical representation of the BRICS countries returns, descriptive statistics, stationary tests, and ARCH tests.

4.1.1. Graphical Representation

Figure 1 presents the graphical representation of the BRICS country returns. It is evident from the returns that the variance is not constant over time and mimics an autoregressive pattern, which results in volatility clustering in all BRICS returns. The visualization of the plots demonstrates that specific periods appear riskier than others, as suggested by the higher volatility of returns in those periods. It is evident that all countries return have similar patterns, suggesting that the series are influenced by significant market events such as the COVID-19 pandemic. Thus, volatility clustering is present among the returns of BRICS, which requires the use of GARCH models.

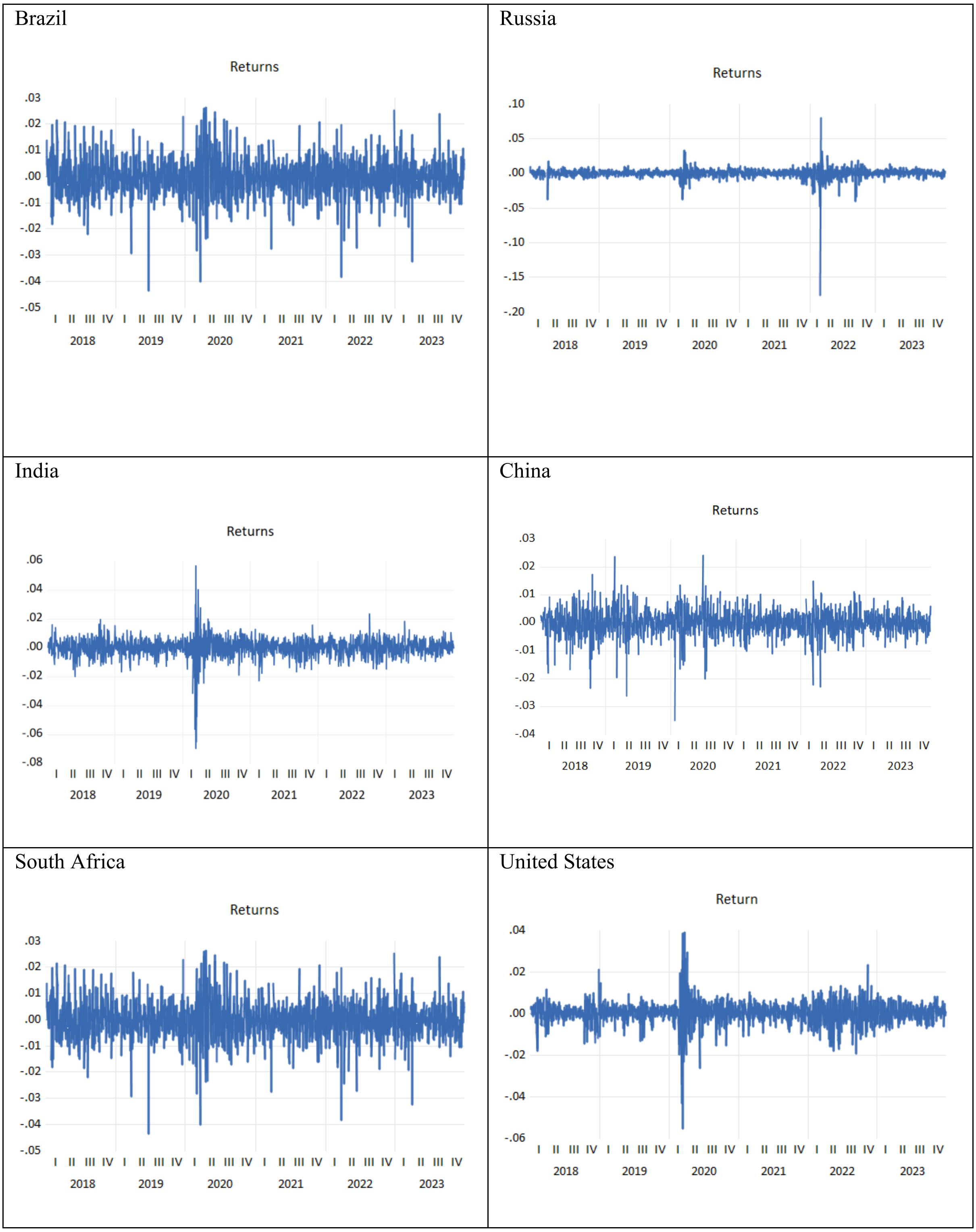

Figure 1. Returns of BRICS Country Returns

Source: Author's own estimation (2025)

4.1.2. Descriptive Statistics and Stationarity Results

The descriptive statistics and the results of the stationarity test for investor sentiment are shown in Table 2 below. Daily mean returns were positive for most of the BRICS and US stock markets, except

China and South Africa. This suggests that there was a bullish trend during the period 2019 to 2022 for these markets. The mean returns for this period were close to zero; this could have been affected by the COVID-19 pandemic. China had the lowest stock returns in 2019 to 2022 as the COVID-19 pandemic originated in China. India recorded the highest daily mean returns among the BRICS and US stock markets. Domestic demand for goods and services continued to increase in India during the COVID-19 pandemic, which could have had high returns (Hussain et al., 2023).

The volatility in stock markets can be examined by the standard deviation. South Africa has the highest standard deviation (0.026192), but the second lowest returns. This indicates that risk is not one of the common factors used to price these markets (Rehman, 2013). According to Lawlor (2020), the BRICS stock markets are known to have high risk and volatility. The BRICS stock markets had the highest overall risk (0.0064) compared to the US stock market (0.0057) in this research study.

The skewness of a normally distributed series should have a measure near zero. The returns of both the BRICS stock market (-2.3072) and the US stock markets (-0.7885) were negatively skewed. A negatively skewed market return is an undesirable property; this indicates that more of the daily market returns were below the mean than above the mean (Hussain et al., 2023). This was a result of the COVID-19 pandemic, stock markets crashed, negatively affecting returns.

For a series to be normally distributed, it must have a kurtosis of three. The BRICS (55.3580) and US (16.7186) stock markets all have a kurtosis that lies above three. This indicates that these market returns have a fatter tail and a peaked mean compared to a normally distributed series. The mean returns of the BRICS and US stock markets had deviated more than a normally distributed market series. The null hypothesis of the JB test of the normal distribution is rejected in relation to the skewness and kurtosis of the market returns. This suggests that the market returns have a leptokurtic series, indicating that investors are exposed to extreme returns.

The unit root and stationarity tests for the BRICS and US stock markets are also reported in Table 2. The ADF tests of the BRICS and the US are significant at a one percent level of significance. The null hypothesis of the presence of a unit root was rejected, indicating that the return series had no unit root. From the results of the ADF test, the returns series is integrated in the order of 0. The GARCH models use these market returns in levels as they satisfy the stationarity condition.

The daily returns of the BRICS and US stock markets are plotted in Figure of the BRICS and US stock markets. The stock returns of these markets follow an autoregressive pattern and do not have constant variance over the sample period. This leads to a clustering of volatility in the BRICS and US stock markets. During certain periods of the sample period, the stock returns are more volatile than in other periods, this is due to the effect of the COVID-19 pandemic on stock markets. The returns of the Russia, China, and South African stocks have the highest risk compared to the other BRICS and US stock markets. These markets were severely affected by the COVID-19 pandemic; therefore, they are faced with high volatility.

Table 2. Descriptive Statistics

Statistic	**Mean**	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**	**JB**	**ADF**
Brazil	0.000153	0.000258	0.007113	-1.340238	21.48749	21 578.11	-12.97451***
Russian	0.000106	0.000411	0.007771	-7.743980	190.7348	2 174 887	-42.61414***

India	0.000209	0.000414	0.00523	-1.557604	25.10248	30 578.52	-13.26062***
China	-0.000035	0.0000251	0.004755	-0.605995	8.000634	1 603.96	-37.76970***
South Africa	-0.000147	0	0.026192	-0.300735	6.362288	728.1996	-42.72631***
US	0.000164	0.000367	0.005678	-0.796211	16.71866	11 984.68	-11.61921***

****, ** and * denotes the level of significance at 1%, 5% and 10% respectively.*

Source: Authors' own compilation (2025)

4.1.3. Heteroscedasticity and Serial Correlation Tests

ARCH effects and autocorrelation tests were conducted for each stock market. The results of both tests are reported below in Table 3. The Breusch-Godfrey serial test was conducted to test for serial correlation in the BRICS and US stock markets. The test results reported in Table 3 found that Brazil, Russia, South Africa, and the US are significant when examining the presence of serial correlation, except for India and China. These results suggest that there could be temporal dependencies in the first moment of the distribution of returns (Devault et al., 2019). According to the efficient market hypothesis (EMH), prices in stock markets must reflect all available information (Fama, 1970). In the weak form of the EMH prices do not fully reflect all available information which affects the prediction of future prices (Fama, 1970). The results of the serial correlation of India and China suggest that these markets are a weak form according to the EMH. When there is no serial correlation in the market, this implies that the information contained in past prices has already been considered current prices (Muguto, 2021).

Furthermore, when examining Figure 1 volatility clustering is present in the stock markets. This indicates that there is evidence of ARCH effects. The Engle ARCH LM test was conducted to test for the effects of heteroscedasticity using the null hypothesis of no ARCH effects. The results of the BRICS and US stock markets are significant, indicating the presence of ARCH effects in these indices. Given the results of the Breusch – Godfrey LM test and the Engle ARCH LM test, GARCH models were used to model the conditional volatility of the BRICS and US markets. This model was used as it captures the varying conditional volatility of market returns (Devault et al., 2019).

Table 3. Heteroscedasticity and serial correlation tests

	Breusch – Godfrey LM statistic	Engle ARCH LM statistic
Brazil	0.000***	0.0899*
Russia	0.0001***	0.0988*
India	0.1415	0.0444**
China	0.7833	0.0537*
South Africa	0.0001***	0.0210**
US	0.0000***	0.0840*

****, **, * denotes significance levels at 1%, 5% and 10% respectively.*

Source: Authors' own compilation (2025)

4.2. Empirical Results

4.2.1. Orthogonalized and Standardised Proxies

This research study uses the Muguto (2021) global sentiment index to measure the effect of investor sentiment on the covolatility between the BRICS and the US stock market, as mentioned in previous sections. Muguto (2021) uses the correlation of orthogonalized proxies and raw proxies to estimate the global sentiment index. The results of the correlation between the raw proxies and the orthogonalized proxies used by Muguto (2021) are reported below in Table 4. The correlation of the orthogonalized proxies is higher than that of the raw proxies. Raw proxies are lower than orthogonalized proxies, as these proxies were driven by common macroeconomic conditions (Baker & Wurgler, 2006).

Table 4. Correlation between sentiment proxies

			Panel A: Raw proxies			
	Bsi	Cci	Com	Gol	Oil	Usd
Cci	0.1036					
Com	0.6720	-0.1626				
Gol	-0.6924	-0.0990	-0.3955			
Oil	-0.0867	-0.1499	0.4854	0.4511		
Usd	-0.2281	0.2433	-0.7723	-0.0443	-0.7200	
Vix	-0.3215	-0.3457	-0.0261	0.0365	-0.0174	-0.1289
			Panel B: Orthogonal proxies			
	Bsi	Cci	Com	Gol	Oil	Usd
Cci	0.5034					
Com	0.0670	-0.0618				
Gol	-0.3678	-05232	0.3552			
Oil	-0.2678	-0.3250	0.7048	0.5236		
Usd	0.2173	0.2439	-0.6784	-0.5598	-0.6255	
Vix	-0.3943	-0.2753	-0.2451	0.1736	-0.0905	-0.0267

Source: Authors' own compilation (2025)

4.2.2. Principal Component Analysis

Orthogonalized proxies are used for principal component analysis (PCA). As mentioned in previous sections, this research study uses Muguto's (2021) global sentiment index. Muguto (2021) uses the variables of principal component one (PC1) as the coefficient of the global sentiment index. The PCA output that Muguto (2021) uses to estimate the global sentiment index is reported in Table 5. The equation of the global sentiment index defined by Muguto (2021) is defined as:

$$GlobSent_t = -0.2968Bci_t - 0.3360Cci_t + 0.3879Com_t + 0.4568Gol_t + 0.4770Oil_t - 0.4668Usd_t + 0.0753Vix_t \quad (5)$$

The Bloomberg Commodity Index, gold price, oil price, and the volatility index are positively correlated to the first principal component, whereas business confidence, consumer confidence, and the dollar indices are negatively correlated. When positively correlated variables increase, it increases the PC1 and when negatively correlated variables increase, it decreases the PC1 (Muguto, 2021).

Table 5. Principal component analysis output

			Eigenvalues: (Sum = 7, Average = 1)		
Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.0594	1.2462	0.1371	3.0594	0.4371
2	1.8132	1.1312	0.2590	4.8727	0.6961
3	0.6820	0.1471	0.0974	5.5547	0.7935
4	0.5349	0.1316	0.0764	6.0897	0.8700
5	0.4032	0.0821	0.0576	6.4930	0.9276
6	0.3211	0.1353	0.0459	6.8141	0.9735
7	0.1858	-	0.0265	7.0000	1.0000

Eigenvectors (loadings)							
Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Bci	-0.2768	0.4861	0.1189	0.7255	0.2882	0.0569	-0.2450
Cci	-0.3360	0.3934	0.5219	-0.3055	-0.4985	0.3433	0.0020
Com	0.3879	0.4592	0.1799	-0.0684	0.3078	-0.0383	0.7108
Gol	0.4568	-0.1253	-0.0952	0.5235	-0.5604	0.3866	0.1696
Oil	0.4770	0.2069	-0.0710	-0.2819	0.3095	0.5393	-0.5081
Usd	-0.4668	-0.1899	-0.3428	-0.0192	0.2614	0.6421	0.3838
Vix	0.0753	-0.5507	0.7411	0.1467	0.3086	0.1568	0.0159

Ordinary correlation							
	Bsi	Cci	Com	Gol	Oil	Usd	Vix
Cci	0.5034						
Com	0.0670	-0.0617					
Gol	-0.3677	-0.523	0.3551				
Oil	-0.2678	-0.3249	0.7047	0.52647			
Usd	0.2173	0.243	-0.6783	-0.5597	-0.6255		
Vix	-0.394263	-0.275302	-0.245061	0.193645	-0.090517	-0.026741	1.0000

Source: Authors' own compilation (2025)

4.2.3. Model Selection

As mentioned in previous sections, this research study employs asymmetric and symmetric GARCH models. These models are used under normal generalised distribution assumptions and the t distribution assumptions. The SBIC determines which model is appropriate for each market (Hsu & Tang, 2022). The selected models for each stock market are shown in Table 6 below. The Russian market uses the GARCH-M (1.1) specification with the t distribution error and the Chinese market with the generalised error distribution. The Brazilian, Indian, and South African markets use the asymmetric GJR-GRACH specification with the t error. The US market uses the GJR-GARCH (1.1) specification with the generalised error distribution.

Most of the BRICS markets made use of the GJR-GARCH model specification. The GJR-GARCH specification model has been used as it accounts for negative shocks. The data set used in this research study includes the COVID-19 pandemic, which had a negative effect on the markets. Asymmetric models were initially chosen for the BRICS and US stock markets based on information criteria. However, the BRICS markets continued to use asymmetric models, but the US stock market had to use symmetric models in the final interpretation due to high leverage effects. The normal error distribution error was not chosen for any of the GARCH specifications, this is in line with the Jaque Bera test in Table 2. The GARCH specification made use of the t distribution and the generalised error distribution. These two distributions capture leptokurtic patterns; this is in line with the descriptive statistic that was discussed in previous sections.

Table 6. Model selection for the BRICS and US markets based on the SBICs

SBIC	GARCH – M (1.1)			GJR – GARCH (1.1)			E – GARCH (1.1)		
	Normal	T	GED	Normal	T	GED	Normal	T	GED
Brazil	0.2352	0.1104	0.1569	0.2410	0.1141	0.1804	0.1679	0.2317	0.3495
Russia	0.0436	0.5780	0.2157	0.0412	0.5801	0.2087	0.0769	0.5164	0.2091
India	0.0553	0.0162	0.0137	0.0489	0.0154	0.0119	0.0045	0.0010	0.0008
China	0.4773	0.6799	0.6628	0.4711	0.6927	0.6631	0.6773	0.8392	0.6899
South Africa	0.0002	0.0000	0.0000	0.0002	0.0000	0.0000	0.0001	0.0001	0.0000
US	0.0819	0.2149	0.1613	0.0699	0.1975	0.1484	0.1521	0.4762	0.2154

Source: Authors' own compilation (2025)

4.2.4. The Impact of Investor Sentiment on the Mean and Variance Equation

The mean equation for Brazil, Russia, India, and the US was positive and significant. This indicates that as investor sentiment increased, returns increased (Fama, 1970). However, the mean equation for China and South Africa was significant but negative; this implies that as investor sentiment increased, returns decreased. The coefficient of risk premium for the BRICS and US stock markets was significant and positive. This indicates that as investor sentiment increases, the risk premium of the stock market increases. The volatility asymmetry coefficients of Brazil, Russia, China, India, South Africa, and the US were significant in the variance equation. This indicates that investor sentiment affects volatility in these markets. When comparing the results of this study with that of a previous study conducted by Muguto (2021) which did not initially include a global sentiment index, it can be observed that investor sentiment has a significant impact on market volatility. The SBIC results that include a sentiment factor in this research study are higher than those without a sentiment factor. This indicates that investor sentiment has a significant effect on volatility in stock markets. A previous study by Rupande, Muguto and Muzindutsi (2019) examined the impact of sentiment on South Africa's stock return volatility, and it was found that investor sentiment did not have a significant effect on stock market return volatility. As a result, it is significant to include a sentiment factor when examining stock market volatility.

Table 7. Selected model outputs for the selected BRICS and US stock markets

Country	Brazil	Russia	India	China	South Africa	US
Selected model	GJR – GARCH t dist.	GARCH – M t dist.	GJR – GARCH t dist.	GARCH – M GED	GJR – GARCH t dist.	GJR – GARCH GED
Parameters			Conditional Mean Equation			
μ	0.0001***	0.0001***	0.0002***	-0.00002***	-0.0002***	0.0001***
θ	0.0072***	0.0078***	0.00504***	0.0015***	0.0072***	0.0057***
α	0.0769	0.1031	0.1052	0.0810	0.0491	0.1894
υ	0.7255	0.6038	0.1849	0.8239	0.3995	0.3935
			Conditional Variance Equation			
ω	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
β	0.8748	0.8581	0.8665	0.8789	0.9170	0.7974
λ	0.8760	0.1068	0.8267	0.0992	0.9179	0.9072
δ	-0.0043***	-0.0148***	0.0989*	-0.0323***	0.1001*	-0.1371***
$(\beta+\delta)$	0.8704	0.8433	0.9654	0.8466	1.0240	0.6602
$(\beta+\delta)/\beta$	0.9950	0.9827	1.1141	0.9632	1.1167	0.8281
$\beta+\lambda$	1.7508	0.9649	1.6932	0.9781	1.8349	1.7048
HL	5.5899	0.77602	4.0020	0.7694	8.4427	7.4692

****, **, * denotes significance levels at 1%, 5% and 10% respectively.*

Source: Authors' own compilation (2025)

5. Conclusion

This research study analysed the effect of investor sentiment on the covolatility between the BRICS and US stock markets using GARCH models that included a global sentiment index under the three error distribution assumptions. The global sentiment includes 7 proxies to determine the impact of sentiment on stock market volatility. GARCH models were used as they best model volatility in stock markets. The results show a significant positive relationship between investor sentiment and volatility in the BRICS and US stock markets. The results also show that it is significant to explain the effect of investor sentiment on returns and the conditional variance in the BRICS and US stock markets.

The study reinforces the importance of behavioural factors in asset pricing models and offers significant practical implications for fund managers, portfolio managers, institutional investors regulators, seeking to provide more robust hedging strategies against sentiment-induced market risks. From the results of this research study when measuring total risk, a sentiment factor should be included as volatility is priced including a sentiment-driven component. The risk premium for the BRICS and US stock markets is significant and positive, investors in these markets need to hold well-diversified portfolios to be rewarded for the presence of systematic risk. Asset pricing and the functioning of markets for policymakers are negatively affected by volatility persistence. As a result, policymakers should not only focus on fundamental drivers of volatility but also investor sentiment. Policymakers also need to pay more attention to changes in investor sentiment as it affects volatility and negative shocks.

This research could further be expanded due to its limitations. For instance, this research study only examined the effect of investor sentiment on market volatility in five BRICS countries, Brazil, Russia, India, China and South Africa. Six new countries were added to BRICS but were not examined in this research study, sentiment may affect volatility in these new markets differently. Future research may try to include the new BRICS countries, Argentina, Egypt, Ethiopia, Iran, Saudi Arabia and the United Arab Emirates when examining the effect of investor sentiment on stock market volatility. Future research studies should also examine the impact on all emerging markets and developed markets as investor sentiment on these markets will impact volatility differently. Other studies conducted in the futures may also attempt to create a new global sentiment that includes new variables that affect investor sentiment. This research study has filled the gap in literature as not many previous studies focus on examining the effect of investor sentiment on the covolatility between the BRICS and US stock markets.

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