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ARTICLE

Is there any connectedness Between Investor Sentiment and Nigeria Stock Market Performance?

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Abstract

This study investigates the dynamic connectedness between the Nigerian Stock Exchange (ASI) and investor sentiment (IS) over the period from January 2009 to November 2024. Using a Quantile Vector Autoregressive (QVAR) model, the study explores how shifts in investor sentiment influence stock market performance across different market conditions, namely bearish, normal, and bullish. The results reveal a significant spillover effect between stock market performance and investor sentiment, particularly during periods of extreme market conditions. During bullish and bearish phases, the connectedness between the two variables is stronger, with investor sentiment amplifying stock market movements in both directions. In contrast, during normal market conditions, the relationship is more balanced. The study's results emphasize the importance of investor sentiment in understanding stock market fluctuations and provide valuable insights for policymakers, regulators, and investors seeking to navigate the complexities of market dynamics in emerging economies like Nigeria. The policy implications suggest that regulatory measures and investor education should focus on mitigating the influence of extreme sentiment to enhance market stability and reduce volatility during times of uncertainty.

Keywords: connectedness, investor sentiment, Nigeria, stock market.

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1. Introduction

The Nigerian Exchange' (NGX) is one of the largest and most active stock markets in Sub-Saharan Africa, serving as a barometer for the economic performance of the country. The performance of the stock market is influenced by a multitude of factors, including macroeconomic variables such as oil prices, exchange rates, and inflation (**Ajala et al., 2021; Kolapo et al., 2018**). In an oil-dependent economy like Nigeria, changes in global oil prices can have a significant impact on the stock market, as fluctuations in oil prices affect government revenues, foreign exchange reserves, and overall economic stability (**Onuoha & Nwaiwu, 2016; Musa et al., 2022**).

In addition to these macroeconomic factors, investor sentiment has emerged as a critical determinant of stock market performance. Investor sentiment refers to the

general mood or attitude of investors towards the market, which can be either optimistic or pessimistic. This sentiment is shaped by a wide range of factors, including economic news, political events, and global crises. In the case of Nigeria, investor sentiment has often been influenced by external shocks such as fluctuations in oil prices, political instability, and global economic uncertainty (**Musa et al., 2022**). For example, the COVID-19 pandemic and its associated economic disruptions created significant uncertainty, leading to heightened volatility in global and domestic financial markets (**Tetteh et al., 2022**). Similarly, geopolitical tensions, such as the Russia-Ukraine conflict, have also impacted investor sentiment, leading to fluctuations in stock prices (**Umar et al., 2022**).

In Nigeria, where the stock market is highly susceptible to external shocks, the behavior of investors can be volatile due to factors such as changes in oil prices, exchange rates, and political instability (**Ajala et al., 2021; Musa et al., 2022**). Despite the growing importance of investor sentiment in financial markets, there remains a significant gap in understanding how sentiment connects with stock market performance in the Nigerian context. While some studies have explored the relationship between macroeconomic variables and stock market returns (**Kolapo et al., 2018; Onuoha & Nwaiwu, 2016**), few have specifically addressed the role of investor sentiment in influencing stock market movements in emerging markets like Nigeria.

While the connection between investor sentiment and stock market performance has been well-documented in developed markets, less attention has been paid to emerging markets like Nigeria, where market behavior is often more volatile and susceptible to external shocks (**Bouri et al., 2021; Kizys et al., 2021**). In these markets, the behavior of investors can be influenced not only by local economic conditions but also by global events, creating a complex interplay between sentiment and stock market performance. In recent years, there has been growing interest in understanding the role of investor sentiment in shaping stock market volatility, especially in emerging markets like Nigeria. Studies have shown that changes in investor sentiment can precede large market movements and may serve as an early indicator of future market trends (**Berger et al., 2019**). However, the precise mechanisms through which sentiment impacts stock market performance in the Nigerian context remain unclear. There is a need for empirical research that explores this relationship in greater detail, particularly in light of Nigeria's unique economic vulnerabilities and the global uncertainties that shape investor behavior.

This research aims to bridge this gap by investigating the connectedness between investor sentiment and stock market performance in Nigeria, with a particular focus on how shifts in sentiment influence stock prices, market volatility, and overall market stability. Using a Quantile Vector Autoregressive (QVAR) approach, the study examines the relationship across different market conditions, specifically during bullish, bearish, and normal periods. By capturing the effects of sentiment under these varying conditions, the study provides a more nuanced understanding of how investor sentiment drives market movements. Understanding this relationship is vital for investors, policymakers, and regulators, as it can help improve investment decision-making and market forecasting, particularly in an increasingly unpredictable global economic environment.

2. Review of Literature

2.1 Investor Sentiment and Stock Market Behavior

Investor sentiment refers to the prevailing mood or attitude of investors toward the market, often categorized into two primary forms: optimism (bullish sentiment) and pessimism (bearish sentiment). It reflects the collective psychological state of market participants, influencing their perceptions, expectations, and subsequent actions. When sentiment is positive, investors exhibit confidence, leading to an increase in buying activity, which can drive stock prices up. Conversely, when sentiment turns negative, investors tend to become risk-averse, engaging in more selling activity, which can lead to declines in stock prices. This interplay between sentiment and market behavior highlights the importance of psychological factors in financial markets.

The traditional Efficient Market Hypothesis (EMH), introduced by Eugene Fama in the 1960s, posits that stock prices always reflect all available information, and as a result, markets are inherently rational. According to EMH, asset prices are driven solely by fundamentals and investors' rational expectations. In this framework, there is no room for sentiment-driven price movements because any information, whether positive or negative, is immediately incorporated into stock prices, ensuring that they always reflect their true value (**Fama, 1970**).

However, this view has been increasingly questioned by scholars in the field of behavioral finance. Behavioral finance suggests that markets are not always efficient, and that investor psychology plays a significant role in driving market movements. Investor sentiment, which can be driven by emotions, overconfidence, and cognitive biases, often leads to deviations from the rational pricing

suggested by EMH (**Shiller, 2000**). For instance, over-optimism during bullish periods can lead to excessive risk-taking, driving prices above their intrinsic value, while heightened pessimism during bearish periods can cause panic-selling and significant undervaluation (**Barberis et al., 1998**).

Investor sentiment influences stock prices by shaping the collective expectations and actions of market participants. When sentiment is positive (bullish), investors generally believe that prices will continue to rise, leading to more buying activity. This increase in demand pushes stock prices higher, creating a self-reinforcing cycle of rising prices and further optimism. As more investors enter the market, hoping to benefit from the price increases, this optimism fuels even more buying, often driving prices beyond their fundamental value. Conversely, during periods of negative sentiment (bearish), investors tend to become more cautious, fearing further losses. As a result, they are more likely to sell their holdings, which leads to an oversupply of stocks in the market, causing prices to fall. This downward spiral is often exacerbated by fear, uncertainty, and the possibility of further declines, which can create a self-fulfilling prophecy of falling prices.

The prospect theory (**Kahneman & Tversky, 1979**) offers a psychological explanation for the asymmetry in investor responses to gains and losses. According to prospect theory, investors are generally risk-averse when faced with gains and tend to prefer sure, smaller gains over uncertain, larger gains. However, in the face of losses, investors become risk-seeking, preferring a gamble that may lead to a larger loss in the hopes of breaking even. This asymmetry in risk preferences suggests that investors may overreact to negative news, leading to larger price movements during market downturns than during periods of growth. For example, during market crises or economic downturns, negative sentiment can cause an exaggerated reaction, with investors disproportionately selling off assets, amplifying market declines. In contrast, during periods of optimism, investors may ignore potential risks, driving prices upward even when the underlying fundamentals may not fully support such price increases.

Thus, investor sentiment plays a crucial role in influencing stock market returns, particularly during times of heightened uncertainty, financial crises, or periods of economic instability. During such times, market participants' emotional responses and cognitive biases can significantly distort their decisions and drive market outcomes. Sentiment-induced price movements are often observed during events such as financial bubbles, where irrational exuberance can lead to an unsustainable rise in asset prices, followed by sharp declines when sentiment shifts (**Shiller, 2000**). Similarly, during bear markets, excessive pessimism can lead to asset prices falling far below their intrinsic values, resulting in market inefficiencies.

2.2 The Role of Investor Sentiment in Stock Market Volatility

Investor sentiment plays a crucial role in shaping market volatility, which refers to the degree of fluctuation in stock prices over time. Volatility is an inherent feature of financial markets, but it is often magnified during periods of extreme investor sentiment, whether it is positive (bullish) or negative (bearish). The effect of sentiment on market volatility is particularly significant in environments where emotional and psychological factors drive investor decision-making, often leading to market behavior that deviates from rational expectations.

In bullish market conditions, where investor sentiment is highly positive, stock prices tend to rise as a result of increased buying activity. However, this positive sentiment can also trigger speculative behavior among investors, who may become overly optimistic and disregard potential risks. Speculation is fueled by the belief that stock prices will continue to rise indefinitely, often leading to excessive demand for stocks. This speculative frenzy can drive prices above their intrinsic value, causing prices to become detached from their fundamental value. Such behavior creates an environment of market inefficiency, where prices are driven more by emotional reactions rather than rational analysis (**De Long et al., 1990**). This excessive optimism can also lead to increased volatility as the market becomes highly sensitive to shifts in sentiment. For instance, if any piece of news—whether positive or negative—affects investor sentiment, stock prices can change dramatically. The sudden onset of panic selling or the collapse of a speculative bubble can trigger sharp declines in prices, which only increases market volatility further (**Kumar & Lee, 2006**). The dot-com bubble of the late 1990s and the housing market bubble leading to the 2008 financial crisis are prime examples of how speculative behavior during periods of bullish sentiment can create volatile market conditions.

In contrast, during bearish market conditions, where investor sentiment turns negative, volatility can be exacerbated by panic selling and fear-driven decision-making. As sentiment shifts from optimism to pessimism, investors may begin to perceive higher risks and, as a result, become more risk averse. This shift often leads to mass selloffs, where a large number of investors attempt to liquidate their positions at once, causing significant downward pressure on stock prices. The fear of further

declines can intensify selling activity, driving prices even lower and creating a self-reinforcing negative cycle of selling and price depreciation. The panic response to negative sentiment can result in dramatic price swings, as investors react emotionally to market news rather than considering long-term fundamentals. In these conditions, stock prices may fall below their true value, contributing to market inefficiency. For example, during the global financial crisis of 2008, widespread fear and uncertainty surrounding the collapse of major financial institutions led to panic selling, creating extreme volatility in the stock markets. Similarly, during the COVID-19 pandemic, negative sentiment surrounding the economic impact of the virus led to large-scale sell-offs, significantly increasing volatility in global equity markets (**Sharif et al., 2020**).

Investor sentiment does not operate in isolation; it interacts with broader macroeconomic factors such as oil prices, exchange rates, and economic policy uncertainty, further influencing market volatility. For instance, oil price fluctuations have long been known to impact stock markets, particularly in oil-exporting countries like Nigeria. When investor sentiment is already negative, a sharp decline in oil prices can amplify the effects of this sentiment on stock market performance, leading to more significant volatility. In addition, periods of global uncertainty, such as geopolitical crises or pandemics, can increase market volatility by intensifying investor sentiment. For example, during the onset of the COVID-19 pandemic, investor sentiment turned sharply negative as the global economy faced unprecedented disruption. This negative sentiment amplified the effects of economic policy uncertainty, leading to massive swings in stock market performance (**Bouri et al., 2021**). Similarly, economic shocks such as changes in interest rates or political instability can interact with negative sentiment, further heightening market volatility.

The role of investor sentiment in shaping long-term market volatility trends is also noteworthy. Over time, the buildup of positive or negative sentiment can lead to secular trends in market volatility. During periods of prolonged optimism, market volatility may be relatively low as investors continue to drive prices higher. However, when sentiment shifts abruptly, as it often does follow economic or financial crises, volatility can surge dramatically, marking the transition from periods of stability to instability. Additionally, long-term shifts in sentiment can influence broader market trends, such as the transition from bull to bear markets. The adaptive market hypothesis (**Lo, 2004**) suggests that markets are constantly evolving, and investor sentiment is one of the key factors that determine how quickly and severely markets respond to new information. Over time, sentiment can shape market cycles, influencing volatility in both the short and long term.

2.3 Empirical Review

A growing body of empirical research has examined the relationship between investor sentiment and stock market performance, particularly in the context of market volatility, returns, and inefficiencies. The findings from these studies highlight the significant role sentiment plays in shaping market behavior, with varying impacts depending on market conditions and external shocks.

For instance, numerous studies have found a strong link between investor sentiment and stock market volatility. For instance, **Baker and Wurgler (2006)** demonstrated that positive sentiment leads to an increase in market liquidity, reducing volatility, while negative sentiment is associated with increased volatility, as seen during economic downturns. Similarly, **Kumar and Lee (2006)** found that extreme positive sentiment results in speculative behavior, while extreme negative sentiment leads to panic selling, both of which heighten volatility. These findings suggest that sentiment-driven market movements contribute to both short-term and long-term fluctuations in stock prices.

Moreover, empirical research has also shown that investor sentiment has a direct effect on stock returns, with sentiment-driven behavior often leading to price deviations from fundamental values. **De Long et al. (1990)** argued that emotional reactions to market conditions rather than rational calculations often drive stock returns, particularly during periods of heightened sentiment. In a similar vein, **Lee et al. (2002)** demonstrated that investor sentiment plays a crucial role in explaining cross-sectional variations in stock returns. This is particularly true during market bubbles or crashes, where sentiment can lead to both overvaluation (during bullish periods) and undervaluation (during bearish periods) of stocks.

In addition, research has also highlighted the interaction between investor sentiment and macroeconomic factors in influencing stock market performance, especially during periods of global uncertainty. Studies by **Bouri et al. (2021)** and **Sharif et al. (2020)** have shown that external shocks such as the COVID-19 pandemic and fluctuations in oil prices significantly amplify the effects of negative sentiment on stock market performance. These studies argue that during periods of global economic stress, investor sentiment serves as a moderating factor, exacerbating market volatility and driving larger-than-expected market movements. The global nature of such shocks, combined with negative sentiment, results in

synchronized declines across markets, highlighting the importance of sentiment in market interconnectedness.

In emerging markets, such as Nigeria, investor sentiment has been shown to play a particularly prominent role due to the higher susceptibility of these markets to external shocks and the prevalence of less mature market structures. Research by **Ajala et al. (2021)** and **Onuoha & Nwaiwu (2016)** found that in Nigeria, external shocks such as oil price fluctuations significantly influence investor sentiment, which in turn drives stock market volatility and returns. Moreover, investor sentiment in emerging markets can often lead to inefficient pricing, where market prices deviate significantly from their intrinsic values due to overreaction or herding behavior.

3. Methodology

Data and Source

Daily data on Nigeria All Share Index from January 2009 to November 2024 are used in this study. The returns of the Nigerian stock market are calculated as the first difference of the natural logarithm of the price level series (P_t). Hence, expressed in equation (1);

$$R_t = (\Delta \log(P_t)) * 100 \dots\dots\dots\dots\dots\dots\dots (1)$$

Where R_t represents the calculated returns of the series, P_t is the level series return, and Δ is the first difference lag operator. Thus, a positive/negative return will represent an increase or decrease in the quoted indices compared to the base indices. The Investor Sentiment (IS) was computed using the Hamilton Filter Decomposition method.

The Hamilton Filter is an econometric method used to extract cyclical components from time series data, which helps in identifying turning points in economic indicators. Originally developed by James D. Hamilton in 2017 (**Hamilton, 2018**), it has become a popular alternative to the Hodrick-Prescott (HP) filter. The Hamilton Filter is useful in scenarios where the goal is to separate trends from cycles in time series data, including stock prices. By applying it to stock price data, we can derive insights into cyclical variations that will reflect investor sentiment. Unlike the Hodrick-Prescott (HP) filter, which often requires a stationary series, the Hamilton Filter is well-suited for non-stationary data such as stock prices (**Chiu et al., 2018**). A common problem with other filtering techniques like the HP filter is the "end-point bias," which refers to distortions near the end of the data series. The Hamilton Filter is less prone to this problem because it looks forward rather than only using past data. Hence, it does not introduce spurious dynamics into the model (**Hamilton, 2018; Phillips et al., 2021**).

Stock price data generally reflects investor behaviour, where fluctuations in prices are often linked to shifts in sentiment due to macroeconomic changes, earnings reports, or market speculation. As such, the investment sentiment index would be computed from the stock price dataset. Since the Hamilton Filter essentially extracted the cyclical component of the stock price time series by regressing the stock price data on its past values and some lagged periods. The Hamilton equation is written as follows:

$$Y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \dots \beta_k y_{t-k} + \delta_{t+h}$$

Where: y_t represent stock price at time t; β_i represent the regression coefficients; h represents the forecast horizon; k is the lag length (usually a multiple of the seasonality or the economic cycle period) and δ_{t+h} is the cyclical component of the series.

The idea is to forecast future values of the stock price based on its historical values, and the cyclical (or residual) component can be interpreted as the deviation from the expected trend. This residual represents the investor sentiment since it captures the short-term fluctuations (e.g., optimism or pessimism) that are not explained by the long-term trend. Once the cyclical component is isolated, this series of residuals can be normalized (using z-scores or another scaling method) to construct an investor sentiment index. This index will reflect periods of bullish or bearish sentiment. That is, while positive residuals suggest investor optimism, often leading to upward trends in prices (bull markets), negative residuals indicate investor pessimism, often associated with downward trends (bear markets).

3.2 Quantile Vector Autoregressive (QVAR)

A Quantile VAR (QVAR) is an extension of the standard Vector Autoregressive (VAR) model. It allows us to estimate the relationship between multiple time series variables at different quantiles of their joint distribution, rather than focusing only on the conditional mean (as in traditional VAR models). The QVAR model captures the asymmetric effects and tail behavior of the variables, providing a more comprehensive analysis, especially in volatile market periods.

Diebold and Yilmaz (2009) introduced the connectedness framework, widely used to analyze spillover effects in financial markets. However, a limitation of this traditional approach is its focus on mean relationships, which may overlook tail risks and asymmetric spillover effects under different market conditions. To address this, **Chatziantoniou et al. (2021)** expanded the framework by incorporating Quantile Vector Autoregression (QVAR), which allows for spillover

analysis across different quantiles (τ) in the conditional distribution of variables (**Yaya et al., 2024**). The QVAR model is particularly suitable for situations where the relationship between the variables of interest is expected to differ in periods of high volatility (bullish or bearish markets) compared to normal conditions. This ability to analyze the relationship at different points in the distribution (such as the 10th, 50th, and 90th percentiles) makes the QVAR model an ideal tool for understanding connectedness in the context of financial markets, where investor behavior and market dynamics often shift drastically between positive and negative sentiments. The basic Quantile Vector Autoregressive (QVAR) model, as introduced by **Chatziantoniou et al. (2021)**, can be expressed in the following form:

$$Q_\tau(Y_t) = \alpha(\tau) + \sum_{i=1}^{p} \beta_{i,\tau} Q_\tau(Y_{t-i}) + \sum_{j=1}^{q} \gamma_{j,\tau} Q_\tau(X_{t-j})\ \mu_t(\tau) \ldots (2)$$

where $Q_\tau(Y_t)$ is the quantile τ of the dependent variable (in this instance, Nigeria Stock market) at time t, $Q_\tau(X_t)$ represent the quantile τ of the assumed independent variable(s) – investor sentiment at time, t, and $\alpha(\tau)$ is the conditional mean vector having n × 1 dimension.

4. Result and Analysis

In this section, we present the results of the descriptive statistics for the variables analyzed in this study, which include the Nigerian Stock Exchange (ASI) and Investor Sentiment (IS). The statistics provide a preliminary overview of the data distribution, central tendencies, and variability before proceeding with the more complex modeling analysis.

Table 1: Descriptive Statistics and Preliminary Test

	ASI	IS
Mean	37160.6***	1.22***
Mean (returns)	0.038**	0.033**
Variance	337135116.7***	33.5***
Skewness	2.17***	-0.12***
Skewness (returns)	0.540***	0.03***
Ex.Kurtosis	4.63***	-0.35***
JB	6600.5***	9.72***

The average value for ASI (37,160.6) indicates a generally positive trend in the stock market index over the sample period. For IS, the mean of 1.22 reflects an average level of investor sentiment, indicating moderate optimism. The positive returns for both variables (ASI returns: 0.038, IS returns: 0.033) suggest relatively steady growth over time, though investor sentiment is slightly less volatile than the stock market performance. Similarly, the variance of the ASI is much higher (337,135,116.7) compared to IS (33.5), showing that stock market returns exhibit much higher variability. This is expected, as stock markets are generally more volatile compared to sentiment measures, which tend to follow broader economic and political trends.

The ASI has a skewness of 2.17, which indicates a rightward skew (positive skew), meaning that the distribution of ASI values is concentrated towards the lower end, with a few extremely high values. In contrast, IS has a slight negative skew of -0.12, suggesting that investor sentiment is more evenly distributed but slightly tilted towards more pessimistic sentiments. The returns for ASI show a positive skew (0.540), indicating that stock returns tend to have higher positive returns relative to negative ones. IS returns, however, exhibit a near-zero skewness (0.03), suggesting a relatively balanced distribution of sentiment changes.

The ASI has an excess kurtosis of 4.63, which indicates that the distribution has heavier tails than a normal distribution, meaning that extreme values (both high and low) are more likely to occur than in a normal distribution. IS, on the other hand, has a negative excess kurtosis (-0.35), indicating that its distribution is relatively flatter than

the normal distribution, with fewer extreme values. The JB statistic for ASI (6600.5) is significantly high, suggesting that the distribution of ASI deviates substantially from normality, particularly due to its heavy tails and skewness. The JB statistic for IS (9.72) is much smaller but still indicates a departure from normality, though to a lesser extent than ASI.

Table 2: The Preliminary Tests

	ASI	IS
ARCH1	3922.2***	395.4***
ARCH15	3908.4***	365.0***
ERS	-10.196***	-7.25***
ADF	-5.347***	-8.43***
Q.20.	40179.5***	3946.7***
Q2.20.	39954.9***	4244.1***
Hurst_Simple	0.861	0.726
Hurst_Empirical	0.993	0.855
Hurst_Corrected_Empirical	0.978	0.968
Hurst_Theoretical	0.532	0.632

Pearson	ASI	IS
ASI	1.000***	0.343***
IS	0.343***	1.000***

The preliminary tests provide crucial insights into the characteristics of the Nigerian Stock Exchange (ASI) and Investor Sentiment (IS) series. The ARCH tests (both ARCH1 and ARCH15) show highly significant value for both ASI and IS, indicating the presence of heteroskedasticity in the data. This suggests that volatility clustering exists in both series, meaning that periods of high or low volatility tend to follow each other over time. Such behavior is typical in financial markets, and it highlights the need for models, such as GARCH or QVAR, that can account for conditional heteroskedasticity.

The stationarity tests, including the ERS test and the ADF test, indicate that both the ASI and IS series are stationary. The significant negative values for both tests (ERS: -10.196 for ASI and -7.25 for IS; ADF: -5.347 for ASI and -8.43 for IS) suggest that the mean and variance of the series do not change over time, making the data suitable for time-series modeling, which requires stationarity. The autocorrelation tests reveal a significant serial correlation in both ASI and IS series, as indicated by the high Q-statistics at lag 20 (Q.20: 40,179.5 for ASI and 3,946.7 for IS). These results suggest that the past values of both series have predictive power over future values, reinforcing the appropriateness of using time-dependent models like VAR. Additionally, the significant autocorrelation at lags 2 to 20 (Q2.20) further supports the idea that both series exhibit serial dependence over extended periods.

The Hurst exponent tests provide an understanding of the long-term memory of the series. The simple Hurst exponent values (0.861 for ASI and 0.726 for IS) indicate long-term persistence, meaning that trends in both the stock market and investor sentiment tend to continue over time. The empirical and corrected empirical Hurst exponents are even closer to 1 (0.993 for ASI and 0.855 for IS), which suggests very strong persistence and long memory in both series. However, the theoretical Hurst exponent values (0.532 for ASI and 0.632 for IS) are closer to 0.5, indicating that they exhibit characteristics of a random walk, although the empirical results show stronger long-memory behavior.

Finally, the Pearson correlation between ASI and IS is 0.343, which is statistically significant. This indicates a moderate positive relationship between stock market performance and investor sentiment, suggesting that

changes in sentiment do influence the stock market, but this connection is not overwhelmingly strong. The moderate correlation highlights that while investor sentiment plays a role, other factors likely contribute to stock market movements.

The results from Table 3 provide valuable insights into the average dynamic connectedness between the Nigerian Stock Exchange (ASI) and Investor Sentiment (IS) across different quantiles, highlighting the spillover effects under various market conditions, including bearish, normal, and bullish periods. The connectedness values between ASI and IS show that ASI contributes 63.12% to its own volatility, which suggests that the stock market has a dominant role in driving its own behavior, particularly in periods of heightened volatility that are typically observed in bearish or bullish conditions. On the other hand, the spillover from IS to ASI is relatively lower at 36.88%, indicating that although investor sentiment influences stock market performance, its impact is less pronounced compared to the stock market's own volatility, especially in stable market conditions.

Investor sentiment, in turn, has a strong influence on itself, with IS contributing 68.00% to its own volatility. This high percentage suggests that investor sentiment is particularly volatile, especially during bullish market conditions when investor optimism is often amplified. The spillover from ASI to IS is 32.00%, indicating that stock market performance does influence sentiment, but to a lesser extent than the influence of sentiment on itself, particularly during periods of market instability or extreme sentiment. Furthermore, the net spillover value of -4.88% from ASI to IS and 4.88% from IS to ASI suggests asymmetry in the transmission of shocks between the stock market and investor sentiment. This asymmetry is further reflected in the non-positive transmission (NPT), which is 1.00 during normal market conditions, indicating no significant non-positive transmission effects in periods of market stability.

Figure 1, the Total Connectedness Index (TCI) heatmap, which averages the connectedness across quantiles from 0.05 to 0.95, reinforces these findings. The heatmap indicates that connectedness between ASI and IS is more pronounced during periods of extreme market conditions, both bullish and bearish, as evidenced by the thick areas in the graph that represent higher spillovers. During these periods, investor sentiment and stock market performance exhibit stronger interdependence, suggesting that the influence of sentiment on stock prices and vice versa is heightened when market conditions are either overly optimistic or pessimistic. In contrast, during periods of normal market conditions, the connectedness between ASI and IS decreases, reflecting a more stable and balanced relationship where investor sentiment has a lesser impact on stock market returns, which aligns with the assumptions of the Efficient Market Hypothesis (EMH).

Table 3: Average dynamic connectedness across quantile

	ASI	**IS**	**FROM**
ASI	63.12	36.88	36.88
IS	32.00	68.00	32.00
TO	32.00	36.88	68.88
Inc.Own	95.12	104.88	68.88/34.44
NET	-4.88	4.88	
NPT	0.00	1.00	

Fig. 1: Total directional connectedness for Multiple Quantile

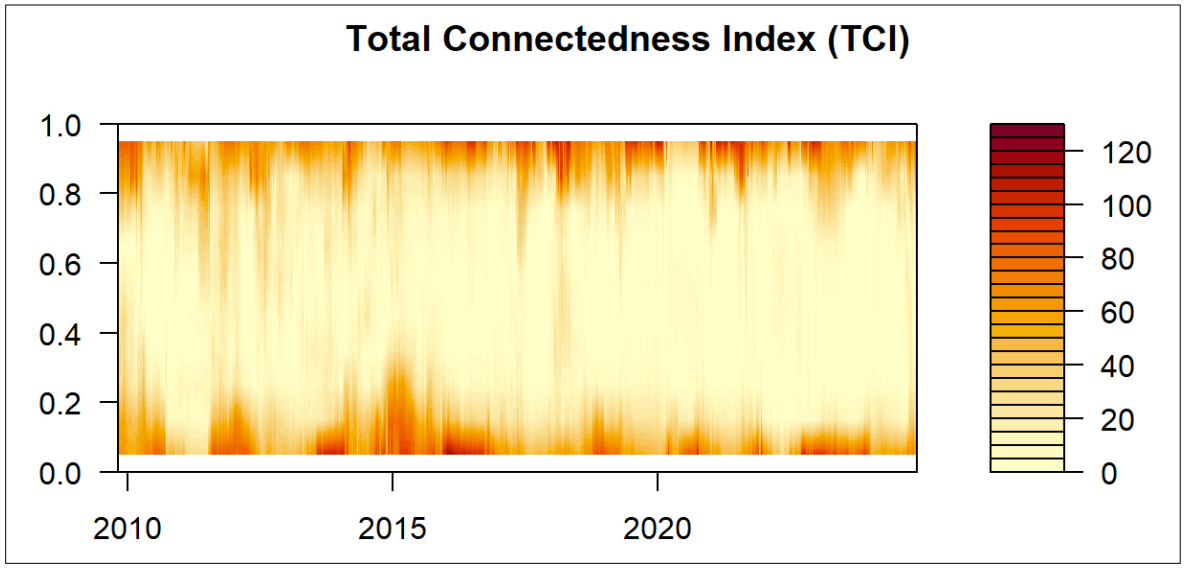
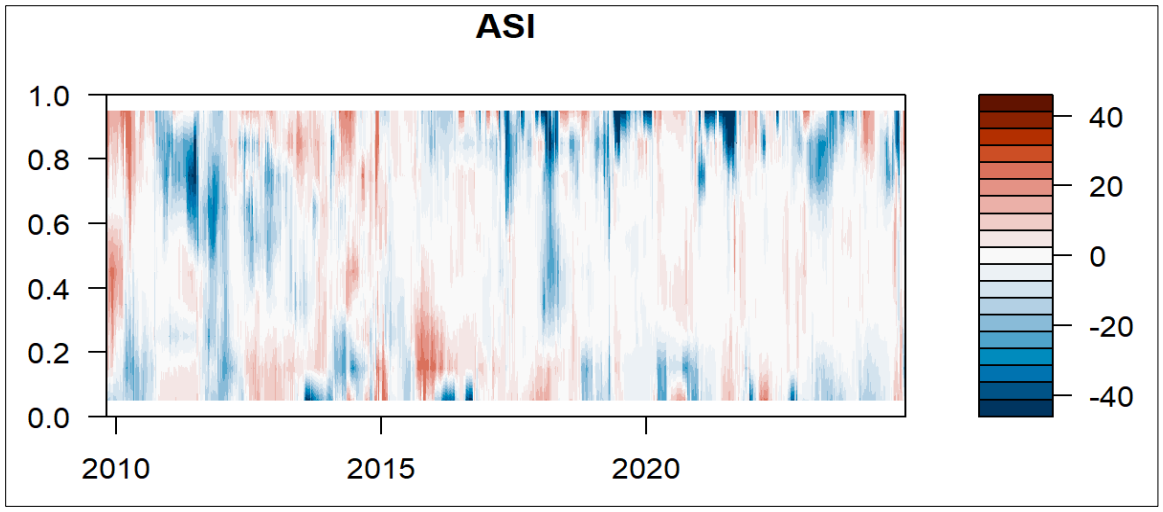


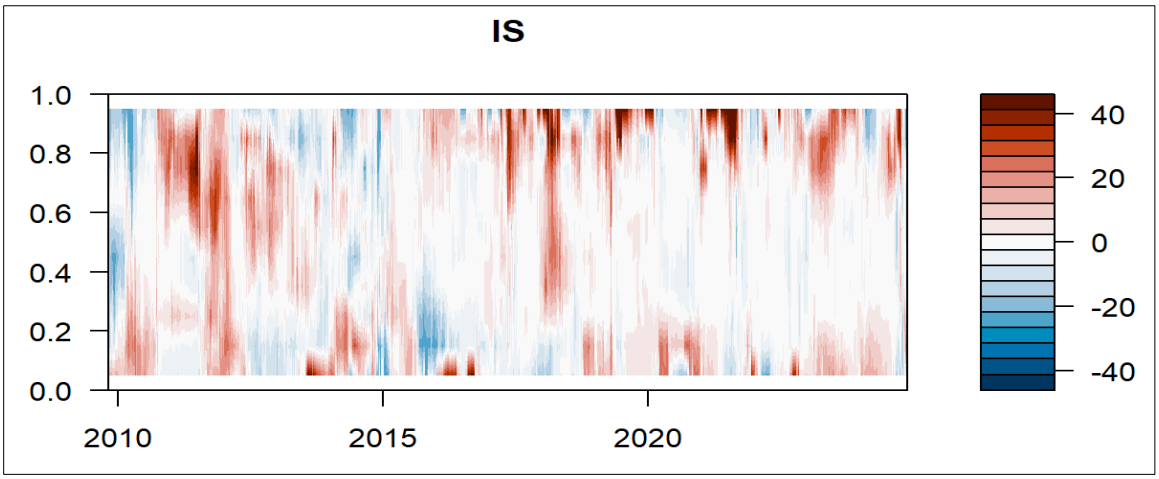
Fig. 2: Net Directional connectedness for ASI across quantile



The heatmap reveals overall minimal connectedness between the Nigerian stock market and investor sentiment in normal condition. This is particularly evident as there is significant evidence of lighter regions outside the 0.05 and 0.95 quantiles. There are also significant variations in the connectedness between the two variables across time and that connectedness is more prominent in period of higher volatility often orchestrated by major global events.

Figure 2 of the ASI net connectedness plot revealed an alternating period of being a net transmitter and receiver of shocks over time. As mentioned earlier, Figure 2 revealed that ASI in terms of its connectedness with investor sentiment (IS) explained that Nigeria stock market tends to receive more volatility spill from investors sentiment than it propels out as revealed by more prominent blue heatmap. What we could see also is the fact that ASI connected with IS changes across time and across quantile essentially revealing that the relationship does not remain constant justifying the choice of dynamic connectedness approach.

Fig. 3: Net directional connectedness for IS across quantiles



As revealed in the connectedness table in Table 3, we could see that IS, is a net giver of shock than it receives from Nigeria stock market. This is clearly revealed by the largely dominated reddish heatmap in Figure 3. This is theoretically consistent as investors' sentiment is driven by global events and influences the stock market.

Again, the findings are consistent with studies that emphasize the importance of investor sentiment in driving stock market performance. For instance, **Liu et al. (2020)** demonstrated that fear sentiment during the COVID-19 pandemic significantly influenced global stock market volatility, a phenomenon also observable in Nigeria's case. Similarly, **Ahmed and Huo (2021)** and **Bai et al. (2021)** highlighted how investor expectations during periods of uncertainty contribute to heightened market sensitivity to external shocks. The bidirectional relationship between ASI and IS mirrors the findings from **Demirer et al. (2020)** and **Harjoto et al. (2021)**, who noted the dual role of investor sentiment as both a driver and a consequence of market movements. This bidirectionality underscores the complex feedback mechanisms inherent in financial markets, where sentiment and performance reinforce each other.

5. Conclusion and Policy Implications

This study examined the dynamic connectedness between the Nigerian Stock Exchange (ASI) and Investor Sentiment (IS) over the period from 2009 to 2024. The analysis utilized both descriptive statistics and the Total Connectedness Index (TCI) to explore how these two variables influence each other across different market conditions, specifically during bearish, normal, and bullish periods. The results revealed that investor sentiment and stock market performance exhibit stronger connectedness during periods of extreme sentiment, either bullish or bearish—while the relationship is weaker during normal market conditions. This finding suggests that during times of heightened market volatility, driven by optimism or pessimism, investor sentiment plays a crucial role in shaping stock market outcomes, with sentiment amplifying market movements in both directions. Conversely, in stable market conditions, stock market performance and investor sentiment show more balanced interactions, consistent with the Efficient Market Hypothesis, where information is more evenly priced, and the market behaves more predictably.

The findings of this study carry significant implications for policymakers, regulators, and investors. First, understanding that investor sentiment plays a critical role in market fluctuations, particularly during volatile periods, suggests that policymakers should consider the psychological state of market participants when formulating regulations. During times of heightened investor sentiment, whether positive or negative, regulators should ensure that market interventions are in place to prevent irrational exuberance or panic-driven selloffs, both of which can exacerbate market instability. For regulators, ensuring the stability of financial systems during periods of extreme sentiment is essential. Measures that promote market liquidity, reduce information asymmetry, and foster confidence in the financial system can help cushion the effects of extreme market movements. Furthermore, the findings highlight the importance of macroeconomic policy stability in moderating investor sentiment. As sentiment can be influenced by external factors such as oil price fluctuations or global economic uncertainty, policymakers

should aim for stability in key macroeconomic variables to reduce sentiment-driven volatility.

For investors, the results underscore the importance of monitoring market sentiment alongside traditional financial indicators. Understanding the influence of sentiment on market performance, especially during periods of heightened optimism or pessimism, can help investors make more informed decisions and avoid falling victim to market overreactions. Long-term investors could benefit from considering sentiment analysis in their portfolio diversification strategies to better navigate periods of market volatility.

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