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Computing the Investor Sentiment Index for Nigeria: Methodology and Applications

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Abstract

This study computed an Investor Sentiment Index (ISI) for the Nigerian stock market using the Hamilton Filter Decomposition method. The objective is to estimate an Index that reflect Nigerian investor sentiment over the period from January 15, 2009, to November 21, 2024. The Hamilton Filter allows for the separation of long-term trends from short-term cyclical fluctuations, which are then normalized using the min-max approach to create a sentiment index that spans from 0 to 1. The findings from the computed index suggest that investor sentiment generally follows the market's movements, exhibiting greater volatility during periods of crises, such as the 2008-2011 Global Financial Crisis and the 2020-2021 COVID-19 pandemic. Additionally, sentiment reacts swiftly to news and market changes, making it a leading indicator of market trends, though it does not always align perfectly with the underlying stock index. This research highlights the significant role of investor sentiment in driving market volatility and offers insights into the psychological factors influencing stock prices.

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1. Introduction

Investor sentiment plays a fundamental role in financial markets by influencing investor behavior and, consequently, market movements. Investor sentiment can drive markets beyond their intrinsic values during periods of excessive optimism or pessimism, leading to overvaluation or undervaluation of assets (**Shiller, 2000**). This relationship is particularly important in emerging markets like Nigeria, where the market is more susceptible to external shocks, such as fluctuations in global oil prices, geopolitical events, and economic uncertainties. These factors can significantly affect market participants' expectations and decisions, making the measurement and analysis of investor sentiment a key component in understanding and forecasting market behavior (**Bouri et al., 2021**; **Kumar & Lee, 2006**).

Despite the recognition of investor sentiment as an important determinant of stock market performance, there is a noticeable lack of a standardized, robust sentiment index for Nigeria. While sentiment indices have been successfully developed for developed economies, the unique dynamics of emerging markets—such as Nigeria—necessitate the development of a tailored sentiment index that takes into account local and external economic factors. This gap in existing research highlights the need for an investor sentiment index that can provide a clear, quantifiable measure of sentiment and its effects on the Nigerian stock market (**Baker & Wurgler, 2006**).

The objective of this study is to compute an investor sentiment index specifically for Nigeria, which is currently under-researched in the context of emerging markets. The Nigerian stock market is heavily influenced by oil price fluctuations, political instability, and global economic developments, making it essential to capture and quantify investor sentiment as a key variable in financial analysis (**Musa et al., 2022**). Existing methods for computing sentiment indices in other markets, including the use of financial news and surveys, often fail to account for the unique characteristics of Nigerian financial markets and the role of external shocks. Therefore, a more tailored computational method is necessary to accurately reflect sentiment in Nigeria's context.

This study proposes the use of the Hamilton Filter Decomposition method for computing the investor sentiment index. The Hamilton Filter is particularly effective in separating the cyclical and trend components of time series data, making it well-suited for understanding investor sentiment, which is influenced by both long-term trends and short-term market fluctuations. The method decomposes a time series into its cyclical components, allowing for the identification of underlying patterns and shifts in investor sentiment. This is crucial for analyzing sentiment in Nigerian markets, where shifts in sentiment can be influenced by both long-term economic trends, such as changes in oil prices, and short-term shocks, such as political events or global financial crises. The Hamilton Filter Decomposition method is chosen for its ability to model non-stationary data and capture the latent components of sentiment that are difficult to measure directly. By filtering out noise and identifying underlying trends and cycles, this method will provide a clearer representation of investor sentiment and its impact on the stock market. The use of the Hamilton Filter allows for a more robust and accurate quantification of sentiment, which is essential for understanding its influence on market performance in a highly volatile and external-shock-sensitive environment like Nigeria.

The justification for this approach lies in the fact that investor sentiment often reflects both short-term volatility and long-term structural trends in the market. The Hamilton Filter method is widely used in macroeconomic analysis for separating cyclical fluctuations from longer-term trends and has proven to be effective in financial time series analysis (**Hamilton, 1989**). By applying this method, the study will be able to capture both the short-term mood of investors and the long-term structural changes in market sentiment, offering a comprehensive view of how sentiment influences the Nigerian stock market over time.

2. Literature Review

The measurement of investor sentiment is rooted in both psychological and market-based theories. Behavioral finance theories, including Prospect Theory (**Kahneman & Tversky, 1979**), posit that investor sentiment is shaped by emotional biases, cognitive errors, and irrational behavior. For instance, investors often exhibit loss aversion, where they react more strongly to losses than to gains, leading to market inefficiencies. This asymmetry in investor behavior creates opportunities for sentiment-driven price movements. In contrast, Efficient Market Hypothesis (EMH) (**Fama, 1970**) argues that financial markets are rational, and investor sentiment has little or no effect on asset prices since prices always reflect all available information.

While EMH is useful for understanding the role of information in price formation, behavioral finance emphasizes that markets often deviate from rational expectations, particularly in the presence of extreme sentiment. Thus, understanding investor sentiment becomes essential for explaining market anomalies, overreactions, and price bubbles, which can lead to significant mispricing of assets (**Shiller, 2000**).

The methods employed to measure investor sentiment can be broadly classified into direct and indirect approaches. Direct methods typically involve surveys or sentiment indicators, while indirect methods infer sentiment from market data or news sources.

Survey-based methods have been a traditional approach to measuring sentiment. These methods rely on asking investors about their market expectations, views on the economy, or confidence in future returns. For instance, the University of Michigan Consumer Sentiment Index and the AAII Investor Sentiment Survey are commonly used to assess sentiment in developed markets. These surveys provide a direct reflection of investor optimism or pessimism, capturing psychological factors and personal beliefs. However, surveys are limited by their subjective nature and the lag in data collection, as they typically capture only broad opinions, not real-time sentiment or sentiment fluctuations (**Baker & Wurgler, 2006**).

Sentiment indicators derived from financial news and social media have gained traction in recent years. Sentiment analysis using natural language processing (NLP) techniques allows researchers to extract sentiment from large volumes of unstructured data, such as tweets, financial news articles, or forum discussions. This approach has proven effective in understanding investor sentiment in real time. For example, **Tetlock (2007)** found that media sentiment is a significant predictor of stock price movements. However, the accuracy of sentiment analysis depends heavily on the quality of the NLP algorithms and the ability to correctly interpret sentiment from diverse language sources, which can be challenging (**Engelberg & Parsons, 2011**).

Volatility indices, such as the VIX (Volatility Index), are another widely used market-based method to gauge sentiment. The VIX measures implied volatility in the options market and is often interpreted as a gauge of market fear or uncertainty. A high VIX is associated with negative sentiment, while a low VIX reflects investor optimism. **Whaley (2000)** demonstrated that the VIX correlates strongly with investor sentiment and can be used as a predictor of market volatility. Although effective, the VIX is a broader market sentiment indicator and does not directly capture the specific sentiments of individual investors. Its reliance on options prices also means that it can be influenced by factors other than investor sentiment, such as liquidity conditions or market expectations about future volatility.

Market liquidity and trading volume have also been used as proxies for sentiment. Studies have found that higher trading volumes are often associated with positive sentiment, while lower volumes signal investor caution or negative sentiment (**Baker & Wurgler, 2006**). However, these indicators do not explicitly measure sentiment but rather infer it based on the behavior of market participants. Trading volume can also be influenced by other factors, such as market liquidity or institutional trading, which may not be directly related to sentiment.

Principal Component Analysis (PCA) and factor models have been employed to derive composite sentiment indices by analyzing multiple financial variables, such as stock returns, volatility, and volume (**Lee et al., 2002**). PCA decomposes these variables into principal components that capture the underlying factors driving sentiment. This approach is effective in aggregating various sources of sentiment data into a single measure, but it requires a large amount of data and may be sensitive to the choice of variables included in the model.

While the methods discussed above have their merits, they also have limitations. For example, survey-based methods are often infrequent, and sentiment indicators derived from news or social media may lack the nuance necessary to capture shifts in sentiment accurately. Additionally, volatility indices like the VIX focus on overall market fear but fail to account for the specific sentiment of investors toward the stock market or the economy. The Hamilton Filter Decomposition method offers several advantages in this context. Developed by **Hamilton (1989)**, the Hamilton Filter allows for the decomposition of a time series into trend and cyclical components. This is particularly useful for analyzing investor sentiment, which often exhibits both short-term fluctuations (cyclical) and long-term trends (trend). Investor sentiment is influenced by a variety of factors, including both long-term structural changes in the economy and short-term shocks, such as political events or economic crises. By using the Hamilton Filter, researchers can separate these two components, providing a clearer understanding of both the persistent trends in sentiment and the cyclical variations driven by temporary events.

The Hamilton Filter Decomposition has emerged as a robust tool for time series analysis, particularly in isolating trends and cyclical components from noisy financial data. Empirical studies have shown its effectiveness in extracting long-term trends and capturing short-term fluctuations in various economic and financial contexts. For instance, **Kim & Nelson (1999)** demonstrated the utility of the Hamilton Filter in analyzing business cycle fluctuations in the United States, where it proved effective in distinguishing cyclical economic activity from long-term growth trends. This distinction between cyclical and structural components is essential for analyzing investor sentiment, which, like economic activity, is shaped by both persistent factors and transient shocks. The study by **Franke et al. (2024)** further supports this, where they highlight the superiority of the Hamilton Filter over the Hodrick-Prescott (HP) Filter, particularly in contexts where avoiding end-point bias is crucial, such as when analyzing volatile data like financial markets or investor sentiment.

In the context of financial markets, including emerging markets like Nigeria, investor sentiment is significantly influenced by a combination of persistent factors (e.g., economic growth trends, political stability) and transient shocks (e.g., oil price fluctuations, geopolitical events). The Hamilton Filter is particularly well-suited for capturing these dual influences, as it can decompose sentiment into cyclical components driven by short-term shocks and trend components influenced by longer-term structural factors. This is crucial for understanding the sentiment dynamics in markets like Nigeria's, where investor mood often swings between periods of optimism driven by favorable economic conditions and pessimism triggered by external shocks, such as oil price fluctuations or political instability.

Empirical evidence suggests that simpler methods, like trading volume or volatility indices, are insufficient for capturing the nuanced fluctuations in investor sentiment. For instance, **Vatsa et al. (2024)** explored stock market cycles and macroeconomic dynamics, noting that traditional sentiment measures, such as trading volumes or volatility indices, often fail to account for the underlying cycles and long-term trends that drive market behavior. The Hamilton Filter offers a more sophisticated approach, allowing for a clearer understanding of the cyclical nature of investor sentiment. By isolating the cyclical components, the Hamilton Filter helps to identify periods of heightened optimism or pessimism, which are crucial for predicting market volatility and potential mispricing of assets. Moreover, studies such as those by **Islam (2024)** and **Bonaparte (2025)** highlight the importance of separating the long-term and short-term components of sentiment to avoid misleading conclusions. **Islam (2024)** decomposes consumer sentiment into cyclical and trend components, underscoring the relevance of capturing short-term fluctuations that can drive market dynamics, while **Bonaparte (2025)** emphasizes the need for methods that can effectively extract true sentiment from the noise, a capability that the Hamilton Filter excels at.

In the case of Nigeria, where investor sentiment is heavily influenced by both domestic economic factors and external shocks like oil price fluctuations, the Hamilton Filter provides an essential tool for accurately computing a sentiment index. The ability of the Hamilton Filter to separate structural changes (such as long-term economic trends) from cyclical fluctuations (like short-term market reactions to oil prices or elections) ensures that the sentiment index reflects both persistent factors and transient shocks. This distinction is critical for making more accurate predictions regarding market movements and identifying potential mispricing of assets, especially in a market prone to volatility and rapid sentiment shifts due to external influences. The empirical studies reviewed here, including those by **Kim & Nelson (1999)**, **Franke et al. (2024)**, and **Vatsa et al. (2024)**, support the use of the Hamilton Filter in the analysis of investor sentiment, particularly in volatile and shock-sensitive markets like Nigeria. The Hamilton Filter's ability to capture both long-term trends and short-term fluctuations in sentiment makes it an ideal method for understanding and forecasting market dynamics, providing a clearer picture of sentiment-induced price movements that simpler methods may miss. By distinguishing cyclical sentiment shifts from long-term trends, it offers a more accurate and comprehensive measure of investor sentiment, which is crucial for predicting stock market volatility and assessing potential market mispricing in response to both structural and transient factors.

3. Methodology

This study focuses on using the Hamilton Filter Decomposition method to compute an investor sentiment index for Nigeria. The process involves applying the Hamilton Filter to the Nigerian All Share Index (ASI) to decompose the data into two components: the trend component and the cyclical component. The cyclical component—which reflects the short-term fluctuations in market sentiments interpreted as the investor sentiment index. The cyclical fluctuations represent the daily shifts in investor sentiment, capturing both optimism (positive cyclical components) and pessimism (negative cyclical components), which can influence stock market performance. This methodology offers several advantages over simpler techniques, as it is particularly effective in non-stationary time series data like stock prices and avoids common issues like end-point bias that may affect other methods, such as the Hodrick-Prescott (HP) filter.

Data Collection and Source

The data used in this study is sourced from Bloomberg, which provides the daily closing values of the Nigerian All Share Index (ASI) from January 2009 to November 2024. The ASI serves as a comprehensive indicator of the Nigerian stock market, reflecting the collective movement of stocks listed on the Nigerian Stock Exchange. The ASI data provides insights into the overall performance of the market and, by extension, investor sentiment, as it captures investor behavior in response to various domestic and global shocks.

The data was preprocessed by converting the raw ASI data into daily returns. This was done using the following formula:

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

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.

Computation of the Investor Sentiment

The Hamilton Filter is applied to the daily returns of the ASI to decompose the time series into two components: the trend and cyclical components. This decomposition is crucial for isolating the underlying sentiment that drives market behavior. The trend component represents the long-term movements in market sentiment, influenced by persistent economic factors such as economic growth, long-term policy shifts, or major structural changes in the economy. On the other hand, the cyclical component reflects short-term fluctuations in sentiment caused by temporary factors, such as market reactions to news events, oil price changes, or geopolitical events. These cyclical movements correspond to investor optimism (bullish sentiment) and pessimism (bearish sentiment), which drive market volatility.

The Hamilton Filter works by applying a state-space model, where the observed data (the daily returns of the ASI) is separated into a trend and cyclical component. The filter works iteratively, recursively estimating both components over time while minimizing end-point bias, which is a limitation in other methods like the HP filter. The cyclical component of sentiment, as extracted by the Hamilton Filter, captures fluctuations in investor mood, which are essential for understanding periods of optimism or pessimism in the market. The Hamilton Filter method is expressed as:

$$y_t = \tau_t + \epsilon_t \qquad (2)$$

$$\tau_t = \tau_{t-1} + \mu_t \qquad (3)$$

$$\mu_t = \rho\mu_{t-1} + \eta_t \qquad (4)$$

Where; y_t is the observed time series of returns (daily ASI returns), τ_t is the trend component (long-term sentiment), μ_t is the cyclical component (short-term sentiment fluctuations), ρ is the persistence parameter, η_t represents the innovation or error term at time, t.

The cyclical component (μ_t) that emerges from this decomposition is considered as the investor sentiment index. Positive values of μ_t indicate optimism in the market, associated with upward movements in stock prices, while negative values of μ_t suggest pessimism, which typically aligns with downward price movements.

The cyclical component represents short-term sentiment shifts, making it a crucial measure for understanding market reactions to both domestic and global events, such as political instability, global oil price fluctuations, and other external shocks.

Investor Sentiment Index Construction

Once the cyclical component is extracted, the study followed the example of Joseph et al. (2024) to constructs the investor sentiment index by normalizing the cyclical residuals using the min-max normalization approach. This method rescales the cyclical component to a range of 0 to 1, where the minimum value of the cyclical component corresponds to 0, and the maximum value corresponds to 1. The resulting sentiment index reflects periods of bullish sentiment (positive cyclical component) and bearish sentiment (negative cyclical component), with positive values indicating optimism in the market and negative values signifying pessimism. This index can be used to track the evolution of investor sentiment over time, offering valuable insights into market psychology and its influence on stock market performance.

4. Result and Discussion

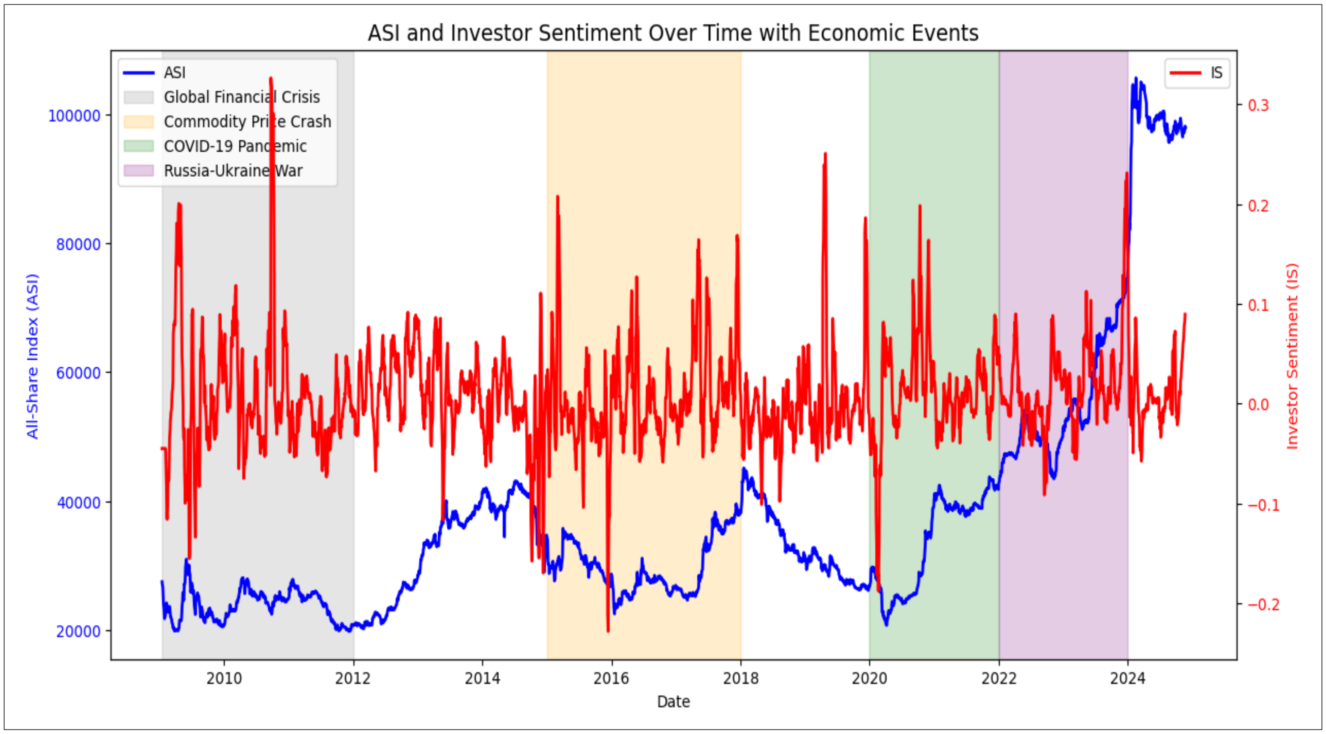
The Investor Sentiment Index (IS) has been constructed using the cyclical component of the Nigeria All Share Index (ASI). This cyclical component represents short-term fluctuations in investor sentiment, capturing periods of market optimism and pessimism that can significantly affect stock market movements. By normalizing the data to a range of 0 to 1 using the min-max normalization approach, we gain a clear representation of how sentiment evolves over time.

The cyclical fluctuations captured by the Investor Sentiment Index provide valuable insights into the level of market volatility. In periods of heightened optimism (bullish sentiment), the market tends to experience upward price movements, reflecting an increase in stock purchases. Conversely, during periods of pessimism (bearish sentiment), the market witness declines in stock prices, often due to mass selloffs as investors react to perceived risks or unfavorable conditions. In Nigeria, which is an emerging market with high sensitivity to both domestic and international events, the Investor Sentiment Index serves as a barometer for predicting market volatility. When sentiment is overly optimistic, it could lead to overvaluation of stocks, creating potential bubbles. Conversely, when sentiment turns negative, it can lead to undervaluation, causing market inefficiencies.

To make sense of the computed Investor Sentiment computed, the study plots the IS alongside the Nigeria All Share Index to estimate the relationship. The estimated Investor Sentiment for Nigeria between 2009 and 2024 is presented in Figure 1 alongside the All-share Index. The data as revealed in Figure 1 revealed that for most period of observation, the ASI (blue line) and IS (red line) move in broadly consistent directions—when the market experiences gradual upswings, sentiment tends to be relatively positive, and when the market trends downward, sentiment often declines. However, the relationship is not one-to-one; at times, investor sentiment exhibits more pronounced short-term fluctuations than the ASI itself.

To be explicit, Figure 1 revealed that investor sentiment typically becomes more volatile during period of crises (e.g., the Global Financial Crisis around 2008–2011, the COVID-19 pandemic around 2020–2021). In these periods, we saw higher volatility (either up or down) in sentiment, while the ASI reacts but sometimes with a lag. Conversely, in periods of recovery or boom, sentiment can surge and remain high, potentially overshooting market fundamentals. Again, during the 2015-2017 commodity price crash, the oil prices and other commodity prices fell, Nigeria's stock market faced renewed pressures, with the ASI losing ground. As in each case, after each major downturn, once the ASI showed signs of stabilization or modest growth, sentiment typically recovers sometimes very quickly, illustrating that investors become more optimistic as soon as they perceive a turning point. Moreover, during the he initial Covid-19 pandemic, there was a sharp drop in the ASI and a rapid dip in IS, followed by large swings in sentiment as uncertainty over lockdowns, stimulus measures, and vaccine developments unfolded. The ASI eventually recovered, but investor sentiment showed repeated spikes—investors were highly reactive to both positive (vaccine progress, stimulus) and negative (new variants, economic slowdowns) news.

Figure 1: The relationship between All-Share Index and the Investor Sentiment (IS)



In summary, investor sentiment is highly reactive and can act as a leading indicator during certain periods, especially during crises or major market shifts. While sentiment typically follows the ASI in a general direction, it can lead or lag the market during periods of instability or recovery. The correlation between the ASI and IS is not constant, varying depending on the market phase. During stable periods, the two indices tend to move in harmony, but in times of crisis, they may diverge, with sentiment responding more quickly to events than the ASI.

This dynamic suggests that investor sentiment can be a useful tool for forecasting market behavior in the short term, particularly when examining market reactions to external shocks. However, it should not be relied upon exclusively for long-term market predictions, as sentiment can sometimes overshoot market fundamentals, leading to mispricing or heightened volatility. Therefore, while the IS index offers valuable insights into market psychology, it is essential for investors and policymakers to combine it with other market indicators and economic data for a more comprehensive analysis of stock market performance in Nigeria.

5. Conclusion and Policy Implications

The Investor Sentiment (IS) index offers valuable insights into the dynamics of the Nigerian stock market, highlighting how market participants react to both internal and external factors. The analysis of sentiment over the period from 15/01/2009 to 21/11/2024 reveals a strong relationship between investor sentiment and market movements, with sentiment generally following the direction of the Nigerian All-Share Index (ASI). However, the correlation is not always perfect, particularly during periods of crisis or major shocks. During such times, investor sentiment exhibits greater volatility, reacting more swiftly to market events compared to the ASI itself. This is particularly evident during crises such as the Global Financial Crisis and the COVID-19 pandemic, where sentiment spikes or dips sharply in response to news, economic disruptions, and investor uncertainty.

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Moreover, the study demonstrates that investor sentiment often acts as a leading indicator during periods of crisis or recovery, showing early signs of market movements before the ASI fully adjusts. While sentiment can sometimes overshoot market fundamentals, it plays an important role in providing a timely reflection of market psychology and the emotional biases driving market behavior. This dynamic makes sentiment an essential tool for understanding market volatility and mispricing, especially in response to both external and domestic shocks.

Policy Implications

The findings from this study have several important policy implications for Nigeria's financial market:

Policymakers and regulators should be aware of the volatile nature of investor sentiment, particularly during periods of uncertainty. Given that sentiment can lead or lag stock market movements, understanding these fluctuations can help in anticipating periods of market instability. Regulatory bodies could use sentiment analysis to implement counter-cyclical measures, such as liquidity support or market intervention, to stabilize the market during periods of extreme sentiment, whether overly optimistic or pessimistic.

As sentiment often reacts faster than the market itself, it can be used as an early warning system to identify investor concerns or excessive optimism in response to government policies, geopolitical events, or macroeconomic changes. Policymakers should incorporate investor sentiment data into their decision-making processes to pre-emptively address potential market disruptions. For instance, during periods of heightened pessimism, government stimulus packages, or fiscal interventions could be introduced to boost investor confidence and prevent prolonged market downturns.

The study highlights that sentiment is heavily influenced by external events and news. Therefore, government and regulatory bodies should develop effective communication strategies to mitigate extreme shifts in sentiment. Clear, transparent communication regarding economic policies, fiscal responses to crises, and market interventions can help reduce uncertainty, preventing the market from overreacting. Additionally, proactive communication about key economic indicators, such as oil price fluctuations, could help reduce the volatility of sentiment and, by extension, stock market reactions.

The study also suggests that investors' emotional biases play a significant role in driving market sentiment. Policymakers, financial regulators, and market participants should focus on investor education to encourage rational decision-making and mitigate the impact of herding behavior and panic selling. Providing education on market fundamentals and risk management strategies could help investors become more resilient to market fluctuations, improving the overall stability of the Nigerian stock market.

References

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance, 61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bonaparte, Y. (2025). A flexible framework to extract investors' distraction. Available at SSRN 5079473.

Bouri, E., Gabauer, D., & Gupta, R. (2021). Investor sentiment, stock market performance and the role of economic uncertainty: Evidence from the US. *International Review of Financial Analysis, 74*, 101634. https://doi.org/10.1016/j.irfa.2020.101634

Cuzzi, D., & Issler, J. V. Oil price predictability and risk premia based on market fundamentals.

Engelberg, J., & Parsons, C. A. (2011). The influence of weather on financial markets: The effect of temperature on the stock market. *Journal of Economic Behavior & Organization, 70*(1-2), 32–49. https://doi.org/10.1016/j.jebo.2008.06.003

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 25*(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Franke, R., Kukacka, J., & Sacht, S. (2024). Is the Hamilton regression filter really superior to Hodrick-Prescott detrending? Extended version. *Macroeconomic Dynamics*. Extended Version (June 30, 2023). https://doi.org/10.1017/S1365100519000702

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica, 57*(2), 357–384. https://doi.org/10.2307/1912559

Islam, A. (2024). Decomposition of consumer sentiment and the effects of its cyclical component. Available at SSRN 5043483.

Joseph, T., Awolaja, O., & Ajibola, O. (2024). Measuring Sub-Saharan Africa Economic Resilience to External Shocks: The role of Adaptive Policy Space. Applied Journal of Economics, Management and Social Sciences, 5(1), 1–28. https://doi.org/10.53790/ajmss.v5i1.91

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263–291. https://doi.org/10.2307/1914185

Kim, C.-J., & Nelson, C. R. (1999). Has the business cycle changed and why? In *Handbook of Macroeconomics* (Vol. 1, pp. 1101–1144). Elsevier. https://doi.org/10.1016/S1574-0048(99)10039-2

Kumar, A., & Lee, C. M. (2006). Retail investor sentiment and market anomalies. *Journal of Financial Markets, 9*(1), 1–34. https://doi.org/10.1016/j.finmar.2005.03.001

Lee, C. M., Shleifer, A., & Thaler, R. H. (2002). Investor sentiment and the closed-end fund puzzle. *Journal of Finance, 57*(5), 2077–2091. https://doi.org/10.1111/1540-6261.00498

Musa, D., Awolaja, O., Jerry, K., Okedina, I., Uduakobong, E. E., & Olayinka, I. (2022). Is the influence of oil price changes on oil and gas stock prices in Nigeria symmetric or asymmetric? *Cogent Economics & Finance, 10*(1), 2154311. https://doi.org/10.1080/23322039.2022.2154311

Shiller, R. J. (2000). *Irrational exuberance*. Princeton University Press.

Siemers, L. H. (2024). On the Hamilton-HP filter controversy: Evidence from German business cycles (No. 21-2024). *MAGKS Joint Discussion Paper Series in Economics*.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance, 62*(3), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x

Vatsa, P., Basnet, H. C., Mixon Jr, F. G., & Upadhyaya, K. P. (2024). Stock markets cycles and macroeconomic dynamics. *International Advances in Economic Research, 30*(3), 255-278.

Whaley, R. E. (2000). Derivatives on market volatility and the VIX index. *Journal of Derivatives, 7*(4), 6–23. https://doi.org/10.3905/jod.2000.319351

Yahya, F., & Lee, C. C. (2023). Disentangling the asymmetric effect of financialization on the green output gap. *Energy Economics, 125*, 106899. https://doi.org/10.1016/j.eneco.2023.106899