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RESEARCH ARTICLE

Asset Class Volatility and Output Gap in Africa: A Big Data Analysis

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Abstract: This study investigates the relationship between asset class volatility and the output gap in selected African countries – Nigeria, Ghana, Cameroon, and Côte d'Ivoire – using machine learning techniques on daily financial data from 2010 to 2022. Employing advanced computational models, including the Light Gradient Boosting Machine (LightGBM), the study achieves an *R*-squared of 0.68, demonstrating the effectiveness of big data analytics in economic research. The findings reveal that stock market volatility has the most significant impact on the output gap, followed by gold and crude oil, while Bitcoin exhibits the least influence. The study highlights the importance of stabilizing stock markets, leveraging gold as a financial hedge, managing crude oil price fluctuations, and regulating cryptocurrency markets to enhance macroeconomic stability. These insights provide valuable policy recommendations for mitigating financial volatility and ensuring sustainable economic growth in Africa. By integrating machine learning into economic research, the study offers a novel approach to understanding financial market dynamics and their implications for macroeconomic stability.

Keywords: asset class, output gap, machine learning, big data, Africa

1. Introduction

Different factors that are specific to each asset class and zone cause asset classes to change over time. When considering international investments, stakeholders must evaluate their capacity to manage risk, diversify their holdings over a range of assets, and keep up with market developments. Due to the progressive removal of trade barriers between nations, the global financial markets have become more integrated in the twenty-first century. This has made it easier for information about currencies, oil prices, and financial markets to be shared quickly. But the removal of these barriers has also left economies vulnerable to a variety of outside shocks, such as those brought on by global warming, the COVID-19 pandemic, gender equity, and technological advancements. These uncertainties have created distortions in economic growth, often pushing economies away from their expected growth trajectories and widening their output gaps. The output gap is a macroeconomic variable that deals with the calculation of the real and possible growth of an economic system from the real sector; it shows the movement of growth from the trend line, which is often called potential growth. The "output gap" represents the discrepancy between an economy's real growth and its highest potential growth, expressed as a percentage of its national income.

It should be noted that this gap can be positive or negative. A positive output gap means that the economy is above its potential growth, whereas a negative output gap means that actual output is below potential output. The output gap is an essential instrument for guiding macroeconomic policy. Furlanetto et al. [1] argue that in setting interest rates or fiscal policy management, the output gap plays a fundamental role. Though recent global shocks have made the earlier estimation of the potential gap less unique due to uncertainty, emphasis is always placed on labor, capital, and technology when calculating the output gap, neglecting financial and asset variables.

The output gap is primarily used to identify an economy's cyclical position, reflecting the different stages of recession and growth. According to Billmeier [2], the output gap serves as a broadly recognized sign of the economy's cyclical position and the extent of unused capacity. For a variety of analytical purposes, information on the cyclical position is crucial. First, changes in actual output as compared to potential output have definite ramifications for the economy's inflationary pressures. In this context, assessing the output gap is critical for discussing central banking policy, such as in the application of the inflation targeting or Taylor rule. Additionally, when calculating the "structural fiscal balance," which targets to assess the direction of fiscal policy, the economy's cyclical position, indicated by the magnitude and trend of the output gap, plays a key role. Furthermore, the extent of the output gap is crucial for evaluating economic output, as it assists in determining whether variations in real growth are due to regular variables (like a slowdown in commerce partner economies) or reflect a longer-term shift in potential growth. A proper estimation of the actual and potential output gap helps in the implementation of structural targets [3]. The idea of implementing a more structural approach to fiscal policy in Europe has gained more and more traction. The recently agreed European Union (EU) Fiscal Compact mandates that countries incorporate structural targets in their fiscal regulations, against which policy performance will be assessed. The assumption that both current and potential growth can be reliably assessed is essential for the realization of structural aims. Real-time projections of growth, both real and potential, frequently undergo

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substantial adjustments. Even after the budget year has ended, certain modifications could still be made. To determine the underlying economic trends, other methodologies are also used to quantify the unobservable potential growth. The most recent modifications to the EU's approach for calculating structural unemployment serve as an illustration of how these methods have been changing over time.

Emerging countries, such as Mexico, were faced with various phases of growth, which necessitated the government of Mexico to pay emphasis on the output gap. Faal [4] highlighted that since 1960, Mexico has gone through several distinct growth phases. During the years 1960–1979, the GDP achieved a mean annual growth rate of 6.5%, but between 1980 and 2003, this growth decelerated to 2.5%. Annual GDP growth decreased to less than 1% from 2001 to 2003 before recovering to 4.4% in 2004, after having averaged more than 5% from 1996 to 2000. Questions about the causes of Mexico's past GDP growth and its future consequences are raised by the changes in growth performance. This was corrected later by the study of the output gap in the economy of Mexico. African countries are mostly underdeveloped countries and bear different shocks from the Western economy. These shocks have a distinct impact on the growth of African nations, and investors and citizens are therefore forced to embark on different asset classes in order to protect the value of their wealth. These assets range from gold, stocks, oil prices, and currently the R-squared, which is recently rising as a valuable asset class. This leads to the fact that shocks in most African countries widen the output gap and, at the same time, distort the value of stocks, which causes a spontaneous reinvestment in other asset classes such as oil, gold, and bitcoin in the economy, and it further determines the value of wealth in the economy, which constitutes the consumption component, which is also a major component for the rate of movement of the output gap.

Volatility in asset classes poses chains of risks and challenges for investors trying to invest in Nigeria. Some of the problems linked to volatility in asset classes in Nigeria are market uncertainty due to high volatility and complications for investors in terms of the ability to forecast and strategize their investments. Price fluctuations caused by volatility can lead to potential losses on investments if they are not carefully managed. Volatile asset classes are associated with a higher risk of capital loss. During periods of market instability, investors experience a drastic fall in their investments, particularly if they need to sell all their assets during a downturn.

Nigeria's financial markets may have limited risk management tools available to investors. For example, the availability of options, futures, and other derivative products may be relatively limited, making it challenging to hedge against volatility effectively. Limited options for diversification can exacerbate the impact of volatility on investment portfolios. If investors have limited access to a variety of asset classes or sectors, they may be more susceptible to the risks associated with a particular asset class's volatility. Nigeria's investment environment can be shaped due to shifts in regulations and political factors.

Market stability can be undermined by regulatory changes and administrative shifts, affecting asset liquidity and price discovery. In Ghana, the stock exchange experiences significant fluctuations due to economic conditions and market sentiment. Currency volatility impacts investment values, especially for international investors. Interest rate changes affect fixed-income investments, while commodity price swings influence the mining, agriculture, and energy sectors. Urban real estate faces volatility from demand shifts and policy changes. Regulatory uncertainty and political transitions further impact Ghana's investment climate. Cameroon faces similar asset class fluctuations.

Here are some potential problems associated with volatility in Cameroon's asset classes: Cameroon's stock market, known as the Douala Stock Exchange (DSX), can experience volatility. Factors such as economic conditions, corporate performance, investor sentiment, and global market trends can influence stock prices. Rapid price fluctuations can make it challenging for investors to accurately time their trades and assess the true value of stocks. Cameroon's currency, the Central African CFA franc (XAF), can be subject to volatility against major global currencies. Fluctuations in exchange rates can impact the value of investments, especially for foreign investors or those with exposure to foreign markets. Changes in currency values can affect returns and introduce additional uncertainty. Cameroon's interest rates can be volatile, which can impact fixed-income investments such as government bonds and corporate debt. Changes in interest rates can affect bond prices inversely, leading to potential capital losses or gains for investors. Higher interest rates and market fluctuations can hinder investors' ability to make accurate predictions and manage risks associated with fixed-income investments. Cameroon is rich in natural resources, including oil, gas, timber, and agricultural commodities. The prices of these commodities can fluctuate significantly due to global supply and demand dynamics, geopolitical events, and factors specific to each commodity. This volatility in commodity prices can affect investment performance in sectors such as energy, mining, agriculture, and forestry. The real estate market in Cameroon, especially in urban centers like Douala and Yaoundé, can experience fluctuations. Property prices can be affected by factors such as shifts in demand, economic factors, and government policies. Real estate investors may encounter difficulties in accurately predicting market trends and managing risks related to property investments. Additionally, Cameroon's investment climate can be impacted by regulatory changes, political instability, and policy uncertainty. Abrupt regulatory shifts, government changes, or geopolitical events can create further volatility and uncertainty in the market, affecting investment returns and investor confidence.

Ivory Coast, also known as Côte d'Ivoire, can experience volatility in its asset classes. Here are some possible issues linked to volatility in Ivory Coast's asset classes: the country has a stock exchange called the Bourse Régionale des Valeurs Mobilières (BRVM). Like other stock markets, it can experience volatility influenced by factors such as economic conditions, corporate performance, investor sentiment, and global market trends. Rapid price fluctuations can make it challenging for investors to time their trades and assess the true value of stocks accurately. Currency risk is a concern in the Ivory Coast, where the West African CFA franc (XOF) is the official currency, shared with several other nations in the West African Economic and Monetary Union. Fluctuations in exchange rates between the XOF and major global currencies can impact the value of investments, especially for foreign investors or those with exposure to foreign markets. Changes in currency values can affect returns and introduce additional uncertainty. Interest rates in the Ivory Coast can be subject to volatility, which can impact fixed-income investments such as government bonds and corporate debt. Fluctuations in interest rates can result in changes in bond prices, which may lead to capital gains or losses for investors. Higher interest rate instability can create challenges for investors in making accurate predictions and managing risks associated with fixed-income investments. Ivory Coast is a major producer and exporter of commodities such as cocoa, coffee, palm oil, and rubber.

Prices of these commodities can be volatile due to universal demand and supply forces, weather circumstances, geopolitical happenings, and commodity-specific factors. Volatility in commodity prices can impact the performance of investments in sectors like agriculture and mining. The real estate market in the Ivory Coast, particularly in major cities like Abidjan, can experience volatility. Changes in demand, economic conditions, and government policies can affect asset prices. Investors in real estate may face challenges in accurately forecasting market trends and managing risks associated with property investments. Ivory Coast's investment climate can be influenced by regulatory changes, political instability, and uncertainty in policies. Abrupt regulatory alterations, government transitions, or geopolitical events can create further volatility and unpredictability in the market, affecting investment returns and investor confidence.

The connection between the volatility of asset classes and the output gap is mainly indirect and functions through several transmission channels within the economy. The output gap represents the disparity between an economy's actual output and its potential output and is commonly utilized to assess the general health and achievement of the economy. Asset class volatility pertains to the extent of fluctuation or variability in the prices of various fiscal assets, including stocks, bonds, and commodities. The prices of these assets are capable of being affected by various factors, including market sentiment, market conditions, interest rates, as well as investor expectations. For example, in wealth effects, increased asset class volatility can affect household wealth. A significant decline in the prices of financial assets can result in a reduction in the value of individual investment portfolios. This can reduce consumer confidence and discretionary spending, which, in turn, can dampen economic activity and contribute to a larger output gap. Also, in investment and financing decisions, high asset class volatility can create uncertainty and affect investment decisions by both businesses and individuals. Businesses may delay or reduce investment plans if they perceive greater risk in the market. This can lead to a decrease in capital expenditures, lower productivity, and a wider output gap. Similarly, individuals may postpone major purchases or reduce borrowing, affecting consumption and overall economic growth.

Studying market volatility's economic impact reveals how financial fluctuations affect broader economic stability. When markets experience significant volatility, economic activities can be disrupted, affecting investor confidence and potentially triggering crises. Understanding these connections helps identify business vulnerabilities. This research uniquely examines how volatility in diverse assets (stocks, gold, oil, and Bitcoin) relates to economic output gaps in selected African economies. Each asset responds differently to economic conditions – gold serving as a safe haven, stocks fluctuating with earnings, and Bitcoin representing emerging digital assets. The inverse correlations between certain assets provide insights into diversification strategies. The focus on African countries with similar economic characteristics and commodity exposure offers a valuable perspective on financial dynamics in emerging markets.

These countries likely represent a group with similarities in economic structure, reliance on resource exports, and vulnerability to external shocks. This selection helps capture regional dynamics while allowing for cross-country comparisons. Understanding the connection between asset class fluctuations and the output gap can aid in analyzing business cycle dynamics. For instance, high asset class volatility during economic expansions may indicate an increased risk of a downturn or recession. This section is followed by the literature review, which is Section 2, and then the research methodology, which contains different machine learning methodologies (Section 3). Section 4 presents the results of each machine learning model. Section 5 contains the conclusions, and Section 6 outlines the policy recommendations.

2. Literature Review

Studies have investigated the nexus of asset classes and output in Africa. We will review some empirical literature such as that by Ezenduka and Joseph [5], who examined the link between Nigeria's stock market performance and economic growth from 1985 to 2018 using data from the Securities and Exchange Commission and the Central Bank of Nigeria. Their analysis included ordinary least squares (OLS) regression and co-integration tests, revealing long-run relationships between economic expansion, money supply, credit to the private sector, market capitalization ratio, number of listed securities, and turnover ratio. The results indicated a strong correlation between market capitalization, the number of listed securities, and economic output.

Chukwuka and Nzotta [6] studied the effect of Nigeria's stock market on manufacturing output from 1981 to 2018, using data from the Central Bank of Nigeria's Statistical Bulletin. They analyzed the relationship between manufacturing output and independent variables such as market capitalization, new issues, transaction volume, and equity stock. Utilizing unit root tests, cryptocurrency techniques, and an error correction model, they found that the stock market significantly influences the performance of the manufacturing sector, as confirmed by OLS analysis. Akinmade et al. [7] conducted a statistical analysis of stock market manipulation on the Nigerian Stock Exchange and its economic effects, examining 186 manipulation cases from 2002 to 2016.

Stock market manipulation harms efficiency and drives away legitimate traders, negatively affecting economic outcomes. In Nigeria, stock market factors account for 73% of industrial growth variations [8], suggesting market enhancement could support industrial development. Ghana shows significant economic benefits from stock market growth, strongly linked to monetary policy [9]. Establishing a stock exchange in the Gambia could potentially mobilize funds and boost investment, addressing the country's low savings rate and inadequate financial intermediaries [10].

Appiah et al. [11] analyzed the effects of crude oil consumption and oil prices on Ghana's economic growth from 1980 to 2016, utilizing data from the World Development Indicator and Energy Information Administration. Their findings revealed a positive long-term correlation between oil prices and economic growth, while crude oil consumption had an inverse relationship over time. The study recommended that the government diversify the economy to mitigate potential oil price shocks. Adabor and Buabeng [12] focused on the asymmetric effects of oil and gas resource rents on Ghana's growth from 2010 to 2019. Using a Nonlinear Autoregressive Distributed Lag (NARDL) model, they found that oil resource rents positively impacted growth, supporting the resource blessing theory, whereas gas rents negatively affected growth, aligning with the resource curse theory. Their findings suggest that short-term policies should favor oil firms, while long-term strategies should aim to develop both sectors. Adabor et al. [13] investigated the causal relationship between oil resource rents and economic growth in Ghana from 2011 to 2020. They employed various models and concluded that a 1% increase in oil resource rents resulted in a 0.84% rise in economic growth. Oil price drops significantly impact Nigeria's economic growth more than other price changes [14]. In Cameroon, kerosene and LPG consumption maintains equilibrium with economic factors, with LPG offering better growth benefits [15]. Rising oil prices substantially boost Cameroon's GDP in both short- and long-term periods [16]. While Cameroon shows a long-term relationship between GDP and revenues, non-oil revenue negatively impacts growth, though both revenue types provide positive short-term benefits [17]. Empirical literatures on asset class volatility and output gap, are few, literatures such as Umeokwobi and Ocheni [18] analyzed the nexus of cryptocurrency and output gap in Nigeria using a decision tree. They found that bitcoin reduces the output gap in Nigeria. It was clear that no study has analyzed asset class volatility and the output gap in Africa; we therefore make use of machine learning employing the Python programming language because the dataset is big data, classified under long-tail data. Some empirical literatures have been done using big data in various fields of study, such as Qing et al. [19], Dagestani and Qing [20], and Cheng et al. [21].

3. Methodology

Based on available data, the study shall utilize a daily secondary dataset for the period 2010 to 2022 for selected countries in Africa, which are Nigeria, Ghana, Cameroon, and Côte d'Ivoire. The dataset includes the output gap, which will be used to capture the volatility of output in Africa. Stock volatility, oil volatility, gold volatility, and Bitcoin volatility would represent asset class volatility. The output gap is obtained from the HP filter of output of African countries, which is extracted from World Bank database, and variables for bitcoin and stock are obtained from Bloomberg, while crude oil and gold are obtained from the Nigerian Central Bank, the Bank of Ghana, the Bank of Central African States, and BCEAO.

This work would adopt the linear models for big data to prevent overfitting such as the lasso, ridge, and elastic net regression. If we see that the prediction is not well explained by the predictors, then we apply the nonlinear models of big data such as the decision tree, the random forest, the gradient boosting regressor, and light gradient boosting. We would employ the hyperparameter optimization with light gradient boosting to examine the level of impact which the predictors can explain the predicted.

Og is the predictor that serves as a proxy for the output gap, and asi is one of the predictors that is used to proxy stock volatility in Africa. Gold is also one of the predictors that is used to proxy gold volatility in selected African countries. Brent is used to proxy crude oil volatility in selected African countries. Bitcoin, on the other hand, is used to proxy cryptocurrency volatility in selected African countries. The og was transformed into a daily frequency in order to be in the same frequency as the predictors as seen in Table 1.

To model volatility, this study employed Autoregressive Conditional Heteroscedastic (ARCH) developed by Engle [22], which is further extended by Bollerslev [23] to the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. It is commonly used in finance and econometrics to model and forecast volatility in time series data. The GARCH model allows for more flexibility in capturing the dynamics of volatility compared to the ARCH model. It can capture volatility clustering, leverage effects (asymmetric response to positive and negative shocks), and long-term persistence in volatility.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{0}$$

In a GARCH model, all variance equation parameters must be positive and typically below one. When these coefficients sum exactly to 1, this special case is called an Integrated GARCH (IGARCH) process.

$$\text{Og} = \text{predicted} = \text{y}, \text{asi} + \text{gold} + \text{brent} + \text{bitcoin} = \text{predictors} = \text{x} \tag{1}$$

Lasso regression applies a penalty based on coefficient absolute values, shrinking some completely to zero. This automatically selects variables, creating simpler models that retain only the most important predictors – especially valuable when dealing with many irrelevant variables.

$$Lasso = min\left\{1/2 \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \gamma \sum_{j=i}^{p} \setminus \beta_j \setminus \right\} \tag{2}$$

Ridge regression adds a penalty term proportional to the square of the magnitude of the coefficients (L_2 norm). It reduces large coefficients but does not shrink them to zero. It is useful for multicollinearity, as it stabilizes coefficient estimates. It works well when all predictors are important but may lack sparsity. The ridge could be estimated as:

$$Minimize = \sum\nolimits_{i=1}^{n} (y_i - y_i)^2 + \gamma \sum_{j=1}^{p} \beta_j^2 \tag{3}$$

Elastic net regression combines the penalties of both ridge L_2 and lasso L_1 regression. It handles high-dimensional data and multicollinearity. It performs variable selection like lasso while maintaining the regularization benefits of ridge, making it ideal when predictors are correlated and sparsity is needed.

$$Minimize = \sum\nolimits_{i=1}^{n} (y_i - y_i)^2 + \gamma_1 \sum\nolimits_{j=1}^{p} /\beta_j / + \gamma_2 \sum\nolimits_{j=1}^{p} \beta_j^2 \tag{4}$$

When the linear regression does not fully explain the analysis, we employ the decision tree regression analysis.

Table 1
Measures of variables

Variables	Proxy	Measurement
og	Output gap or Production gap	Transformed into daily frequency from GDP
asi	Stock returns	Daily stock returns
gold	Gold	Gold prices in USD returns
brent	Crude oil	Brent crude oil returns
bitcoin	cryptocurrency	Bitcoin prices in USD returns

The decision tree is a nonparametric supervised learning algorithm used to predict continuous target variables. It splits the data into subsets based on feature thresholds and calculates the mean (or another aggregation metric) of the target variable in each subset. The decision tree can be expressed as:

$$Minimize\ :\ \sum_{t=1}^{T} \sum_{i \in R_t} (y_i - y_{Rt})^2 \tag{5}$$

The random forest is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and control overfitting. It works by building several trees on random subsets of data and features and then averaging (regression) or taking the majority vote (classification) of their outputs.

$$Minimize\ :\ 1/N \sum_{i=1}^{N} (y_i - 1/T \sum_{t=1}^{T} f_t(x_i))^2 \tag{6}$$

Gradient boosting regressor is a powerful machine learning algorithm that builds an ensemble of weak learners (typically decision trees) sequentially. Each tree corrects the errors of the previous trees by minimizing a loss function using gradient descent. It is widely used for tasks like regression, ranking, and classification due to its accuracy and flexibility.

$$Minimize\ :\ \sum_{i=1}^{n} L(y_i, F(x_i)) \tag{7}$$

Tree-based gradient boosting effectively manages nonlinear patterns and datasets of various sizes, providing interpretable feature importance rankings and supporting multiple loss functions. LightGBM specifically offers faster, more efficient tree-based learning designed for large, high-dimensional datasets, outperforming traditional gradient boosting methods in speed and scalability.

$$Minimize\ :\ \sum_{i=1}^{n} L(y_i, F(x_i)) \tag{8}$$

Hyperparameter tuning is essential for optimizing LightGBM performance, finding the ideal parameter balance that maximizes results while preventing overfitting. The LightGBM regression model can be mathematically expressed in a specific form as:

$$Y = \sum_{m=1}^{M} \alpha_m T_m(X, \theta_m) \tag{9}$$

$T_m(x, \theta_m)$ is a decision tree m fitted to input x, θ_m parameters of the mth tree, and α_m is the learning rate controlling the contribution of each tree.

4. Result

Descriptive statistics offer a way to capture the essence of data without drawing broader conclusions. Unlike inferential approaches that make predictions about larger populations, these methods focus entirely on understanding what's directly observable in the dataset. Central tendency measures form a key component of this toolkit. The mean calculates an average that represents the typical value, while the median identifies the central point when all values are arranged sequentially. The mode simply reveals which value appears most frequently. Together, these metrics provide analysts with a clear, straightforward understanding of their data's fundamental characteristics.

Gold shows price stability with low mean and deviation, in Table 2, serving as a safe haven during economic uncertainty. Oil's high volatility reflects global supply-demand shifts and geopolitics, creating fiscal challenges. Bitcoin combines high returns with substantial risk, requiring balanced regulation as adoption grows. The all share index (ASI) volatility indicates market fluctuations from domestic and global pressures, highlighting the need for stabilizing policies to maintain investor confidence.

4.1. ARCH test

The ARCH test in Table 3 checks for patterns in a time series where volatility clusters over time. It determines if past volatility helps predict future volatility, which is common in financial data. This statistical tool helps analysts identify when variance isn't constant, an important factor when modeling financial markets or other time-dependent data.

Table 3
ARCH test

Variables	Arch (1)Lm stat	P
asir	59.74	0.00
cruder	252.14	0.00
goldr	24.07	0.00
bitcoinr	237.39	0.00

ARCH test results show volatility clustering in all asset classes, with changing variance patterns over time rather than constant volatility. GARCH (1,1) modeling was applied to address these time-varying volatility patterns in the financial data.

4.2. GARCH volatility test

GARCH models capture and predict market volatility patterns, accounting for how periods of high and low-price swings tend to

Table 2
Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Gold	0.000093	0.000054	0	0.0005412
Brent	0.0005345	0.0008455	0	0.0100867
Bitcoin	0.0039876	0.0065525	0	0.083462
Asi	0.6158092	0.6158092	0	63.37355
Og	–548.4743	0.00000211	0.0000013	0.0000012

Table 4
GARCH test statistics

Variables	asir	cruder	goldr	bitcoinr
Past (–1)	0.23***	–0.01	–0.01	0.02
Residual	0.20***	0.10***	0.15***	0.11***
GARCH	0.69***	0.89***	0.60***	0.89***

Note: * represents 10% significance, ** represents 5% significance, while *** represents 1% significance.

cluster together in financial data. This approach helps analysts better understand changing risk levels across different market conditions.

Table 4 reveals that the volatility of All Share Index return (ASIR) is influenced by its past values, whereas cruder, goldr, and bitcoinr do not exhibit such dependence. The inclusion of the residual and GARCH terms indicates that the estimated values for ASIR and goldr are less than one, suggesting that their volatility persists throughout the series. In contrast, cruder and bitcoinr do not display persistent volatility, as their residual and GARCH estimates are approximately equal to one. This is still okay since their sum was not more than one.

4.3. Fisher's unit root test

The Fisher unit root test is a method used to determine whether a panel data series is non-stationary; that is, it contains a unit root. It is named after the statistician Ronald A. Fisher. This test combines p-values from individual unit root tests applied to each cross-section in the panel, providing an overall test for stationarity in the panel data. It is especially useful in panel data contexts where data are available across multiple entities (e.g., countries, companies) over multiple time periods. Asset class volatility and output gaps in Africa can differ significantly across countries. The Fisher test allows for cross-country heterogeneity, whereas the Augmented Dickey Fuller (ADF) test assumes a uniform structure, which may not hold across different economies.

The Fisher's unit root test in Table 5 shows that the output gap, gold prices, crude oil prices, Bitcoin prices, and stock indices are stationary at their levels, indicating stable long-term statistical properties. Stationarity in the output gap suggests mean-reverting economic cycles, while stationary gold and crude oil prices imply long-term predictability despite short-term fluctuations, benefiting investors and policymakers. Bitcoin's stationarity, despite its volatility, highlights long-term predictability important for investors and regulators. Stationary stock indices suggest mean-reverting market returns, aiding investment strategies and portfolio management.

Table 5
Fisher unit root test table

Variables	At level	AT first difference
Og	190.92***	
Lngold	103.26***	
Lnbrent	118.36***	
Lnbitcoin	134.46***	
Lnasi	225.35***	

Note: * represents 10% significance, ** represents 5% significance, while *** represents 1% significance.

Table 6
Linear models for big data

Model	MSE	R-squared
Ridge	4.99e+22	–0.00
Lasso	4.94e+22	–0.00
Elastic net regression	4.94e+22	–0.00

4.4. Ridge, lasso and elastic net regression

Ridge, lasso, and elastic net regression techniques are evaluated using mean squared error (MSE) and R^2 metrics. These measurements reveal each method's accuracy in fitting data and their flexibility in identifying underlying patterns within datasets.

The Ridge, lasso, and elastic net models performed poorly with high MSE and extremely low R^2 values as shown in Table 6. These results indicate that the predictors lack significant influence on the outcome variable, making these regularization methods unsuitable for meaningful inference in this context. The models cannot accurately capture data patterns or provide reliable predictions, suggesting that alternative analytical approaches should be considered.

4.5. Decision tree regression

The decision tree regression model shows markedly different results compared to ridge, lasso, and elastic net approaches. As a nonparametric method, it can identify complex nonlinear patterns that linear regularization techniques miss. Its MSE and R^2 metrics demonstrate better performance with complicated data relationships that linear models struggle to represent accurately.

The results in Table 7 provide insights into the performance of the decision tree regression model applied to big data. The model yielded an MSE of 35,543 and a co-integration value of 0.28. These metrics suggest a mixed performance, which can be analyzed further. The MSE value of 35,543 indicates the average squared difference between the predicted and actual values. While this metric reflects the magnitude of errors in the predictions, its significance depends on the scale of the target variable. A high MSE, as seen here, could mean that the model's predictions are not highly accurate. However, the performance might still be reasonable for datasets with large variance or noise.

The R-squared value of 0.28 signifies that the decision tree regression model explains 28% of the variability in the target variable based on the predictors. Although this is better than random guessing, it implies that the model does not fully capture the complexity of the relationships in the data. This level of explanatory

Table 7
Decision tree regression for big data

Model	MSE	R-squared
Decision tree regression	35543	0.28

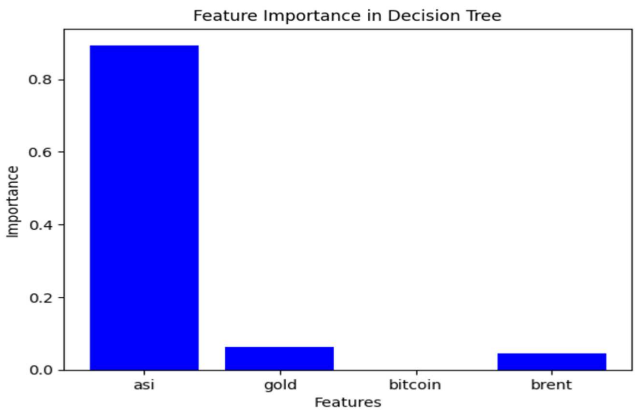
Table 8
Random forest regression for big data

Model	MSE	R-squared
Random Forest Regression	34196	0.30

power suggests that the decision tree was able to identify some patterns or relationships, but it might have been limited by factors such as overfitting, insufficient data preprocessing, or a need for feature engineering.

The decision tree regression reveals that stocks in Africa positively influence the output gap, as seen in Figure 1, suggesting that strong stock performance drives economic activity above its potential. Conversely, Bitcoin negatively impacts the output gap, indicating its speculative nature may hinder economic growth. Gold volatility has a stronger impact on the output gap than Brent crude, reflecting gold's sensitivity to economic uncertainty and its role as an R-squared asset. Since the R-squared is low, we would investigate the random forest regression.

Figure 1
Decision tree regression



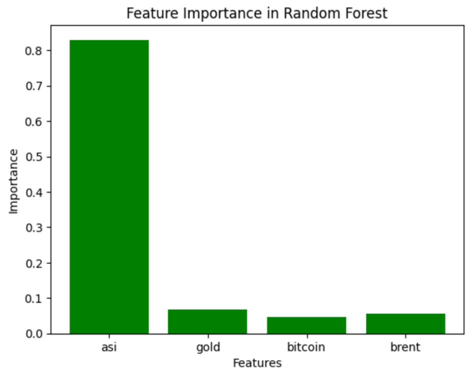
4.6. Random forest regression

Random forest regression outperforms other models through its ensemble method of combining multiple decision trees. This approach reduces overfitting while effectively identifying complex data patterns, resulting in more accurate and generalizable predictions.

Random forest regression achieved an MSE of 34,196 and R^2 of 0.30, showing moderate improvement over the decision tree model, as shown in Table 8. While explaining 30% of output gap variability represents progress, substantial unexplained variation remains due to data complexity or noise. The ensemble approach helps mitigate overfitting issues present in single decision trees.

The random forest results reveal that stock volatility has the most significant positive impact on the output gap in Figure 2, with a coefficient of approximately 0.8. This indicates that fluctuations in stock performance strongly drive economic activity above its potential, reflecting the critical role of stock markets in influencing economic dynamics. Gold volatility follows, though its impact is less pronounced, with a coefficient below 0.1, suggesting that while

Figure 2
Random forest



gold plays a role, its influence is more moderate compared to stocks. Brent crude also shows a slightly lower impact than gold, highlighting its relatively subdued effect on economic fluctuations. Bitcoin, while having a positive relationship with the output gap, exhibits the least influence, underscoring its limited role compared to the other asset classes. These results suggest that stock volatility is the primary driver among the assets analyzed, with others playing secondary but still positive roles.

4.7. Gradient boosting regression

Gradient boosting regression creates a strong predictive model by building a sequence of simple decision trees, with each new tree focusing on correcting errors made by previous trees. This approach effectively handles complex data patterns and nonlinear relationships that simpler models might miss.

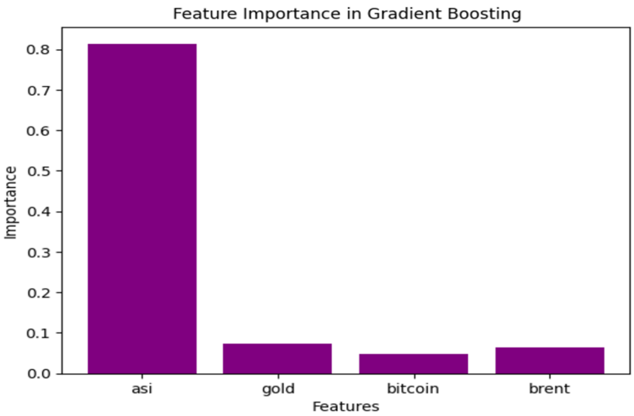
In Table 9, gradient boosting showed an R-squared of 0.44, which showed an improvement from the random forest that has an R-squared of 0.33.

Table 9
Gradient boosting regression for big data

Model	MSE	R-squared
Gradient boosting regression	27451	0.44

The gradient boosting regression results show that stock volatility in Africa in Figure 3 has the most significant positive impact on the output gap, indicating that fluctuations in the stock market strongly drive economic activity above its potential. Gold follows with a positive, though smaller, impact on the output gap, suggesting that gold's volatility also plays a role in influencing economic performance, albeit to a lesser extent. Brent crude oil has a similarly positive but relatively weaker impact than gold, reflecting its influence on economic dynamics, though not as strongly as stock volatility. Finally, Bitcoin, while also having a positive relationship with the output gap, has the least impact among the asset classes analyzed. These results emphasize that stock volatility is the primary driver of economic fluctuations, with gold, Brent, and Bitcoin contributing more modestly.

Figure 3
Gradient boosting regression



4.8. Light gradient boosting machine

LightGBM offers a faster, more efficient version of gradient boosting that builds decision trees in sequence to fix previous errors. Its optimized design handles large datasets more effectively than traditional gradient boosting approaches, making it particularly valuable for big data applications.

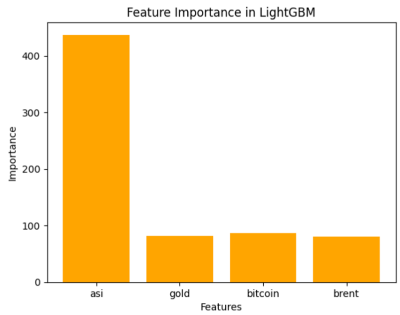
The Light Gradient Boosting Machine (LightGBM) model produced an MSE of 24,080 and a safe-haven value of 0.51, indicating strong performance, as shown in Table 10. The relatively low MSE suggests that the model's predictions are closer to the actual values, reflecting good accuracy. The *R*-squared value of 0.51 shows that the model explains 51% of the variation in the output gap, which is a significant improvement over the previous model. This demonstrates LightGBM's effectiveness in capturing complex relationships within the data, making it a powerful tool for big data regression tasks.

Table 10
Light gradient boosting machine for big data

Model	MSE	*R*-squared
Light Gradient Boosting Machine	24080	0.51

In Figure 4, the LightGBM results indicate that stock volatility has the strongest positive impact on the output gap, followed by Bitcoin volatility, which also shows a notable positive effect. This contrasts with the findings from other machine learning models, where Bitcoin's impact was less pronounced. Gold volatility comes next in terms of positive influence, with Brent crude showing the least impact. The discrepancy in Bitcoin's role could be due to the unique way LightGBM captures complex, nonlinear relationships in the data, allowing it to identify subtler patterns that other models might miss. This highlights the model's sensitivity to variations in Bitcoin's volatility and its potential influence on economic performance.

Figure 4
Light gradient boosting machine



4.9. Robustness check using hyperparameter optimization with LightGBM

Given that LightGBM produced the highest R^2 among the other machine learning models but contradicted some of their results, I conducted a robustness check by applying hyperparameter optimization to LightGBM. This process fine-tuned the model's parameters to improve its predictive performance and resolve any inconsistencies in the results. By optimizing hyperparameters, the model can be adjusted to better capture the underlying relationships in the data, potentially offering more reliable and consistent outcomes. This step helps verify whether the initial LightGBM results were robust or if further adjustments could align them with the findings from other models.

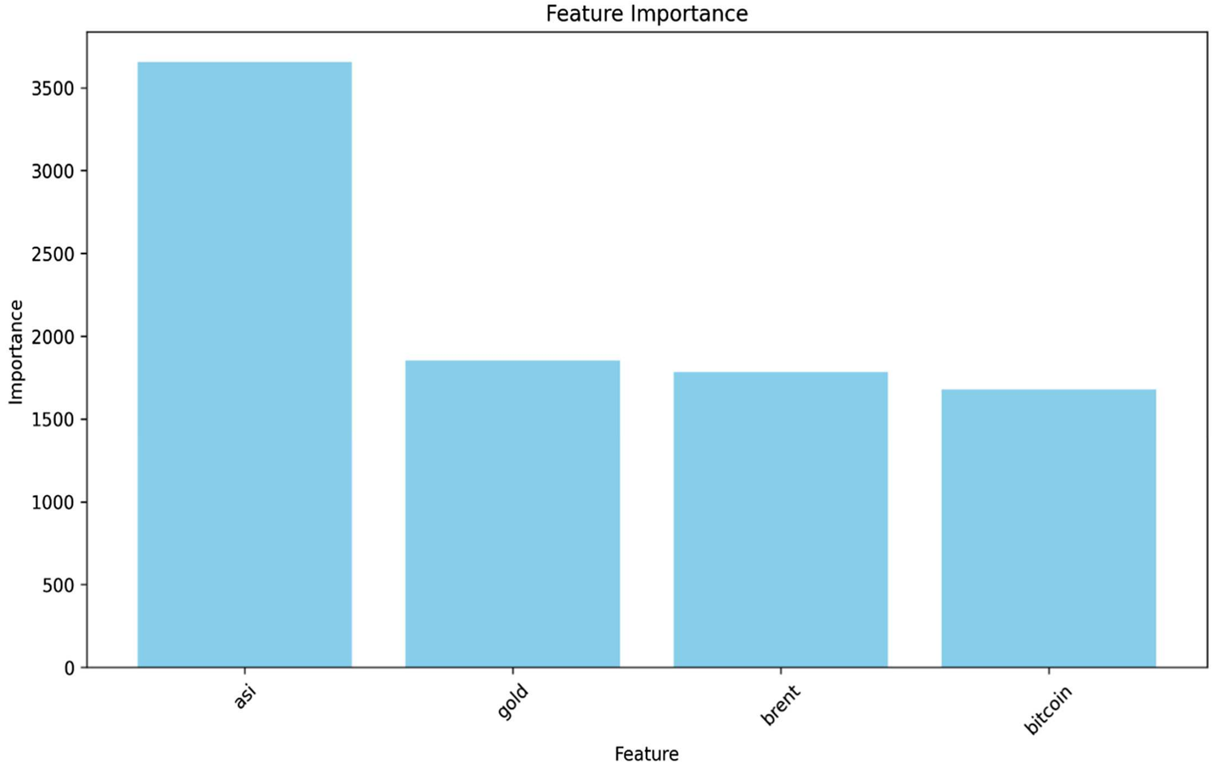
The optimized LightGBM model demonstrated remarkable improvement with an MSE of 1,559 and R^2 of 0.68, as shown in Table 11. These metrics show a dramatic reduction in prediction error and superior explanatory power for output gap variation. Hyperparameter tuning significantly enhanced the model's ability to identify complex data relationships, resulting in more accurate and dependable predictions compared to its initial configuration.

Table 11
Hyperparameter optimization with LightGBM using big data

Model	MSE	*R*-squared
Light Gradient Boosting Machine	1559	0.68

The robustness check using hyperparameter optimization on LightGBM in Figure 5 revealed a shift in the results, aligning more closely with the findings from other machine learning models. Stock volatility remained the strongest positive influence on the output gap, followed by gold volatility, which also had a positive impact. Crude oil volatility showed a similar positive effect on the output gap. However, Bitcoin volatility, which had previously been identified as having a stronger impact in the initial LightGBM model, was now found to have the least positive effect, consistent with the results from other models. This suggests that hyperparameter optimization helped refine the model, providing more consistent and reliable findings that are in line with the broader analysis across different machine learning techniques.

Figure 5
Robustness check using hyperparameter optimization



5. Conclusion

This study examined how asset volatility relates to economic output gaps in Nigeria, Ghana, Cameroon, and Côte d'Ivoire using machine learning to analyze daily data from 2010 to 2022. Key findings across multiple models showed stock market volatility as the strongest predictor of output gap variations, with a consistent positive relationship indicating its crucial role in economic performance. Gold volatility demonstrated a positive but moderate influence, reflecting its stabilizing function during uncertainty. Oil volatility showed similar but less pronounced effects than gold. Bitcoin had the least influence among assets studied, suggesting cryptocurrency's still-emerging role in African economies. Our methodological approach using various machine learning techniques provided robust insights, with ensemble methods like gradient boosting and LightGBM offering the most sophisticated analysis. The optimized LightGBM model achieved an R^2 of 0.68, representing strong explanatory power. This demonstrated the potential of advanced computational techniques in extracting meaningful economic insights from complex datasets. The use of big data analysis and python programming language in this analysis conforms with the work of Umeokwobi et al. [24], who showed that Brent, gold, and bitcoin had a positive impact on og, though the work contradicts based on that stocks was also positive based on the big data analysis and in Africa instead of Nigeria. The study highlights the critical role of stock market stability in driving economic growth, emphasizing the need for strong financial markets. Gold and crude oil serve as stabilizing assets, while Bitcoin remains a secondary driver of economic performance. These findings underscore the importance of policies that enhance market stability and integrate emerging assets, while also demonstrating the value of machine learning in economic analysis.

6. Policy Recommendations

Based on our findings, we recommend the following policy interventions for African economies:

1) Strengthen stock market fundamentals: Central banks should collaborate with market regulators to enhance transparency, enforce stronger oversight, and promote better corporate governance. These improvements will help reduce volatility while maximizing the stock market's positive influence on economic performance.
2) Leverage gold as an economic stabilizer: African governments should expand investment in the gold sector, build strategic reserves, and develop policies to enhance gold trading capabilities. Gold's consistent positive impact makes it valuable for economic stability during uncertain periods.
3) Reduce oil dependency: Oil-producing nations should prioritize economic diversification, channel oil revenues into sustainable development projects, and establish sovereign wealth funds to better manage price fluctuations and ensure long-term fiscal stability.
4) Develop thoughtful R-squared frameworks: Despite Bitcoin's currently limited impact, governments should create balanced regulations that protect consumers while encouraging responsible adoption of digital currencies as part of broader financial inclusion efforts.

5) Modernize economic analysis methods: Policymakers should invest in advanced analytical capabilities, including machine learning techniques, to improve economic monitoring and enable more responsive, data-driven policy decisions regarding asset volatility and output gaps.

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Disclaimer

This is the idea of the author and not the institution it represents.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest in this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Richard Umeokwobi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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