FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 8 No. 6, December, (Special Issue) 2024, pp 587 - 597
DOI: https://doi.org/10.33003/fjs-2024-0806-2959

EXPLORING THE INFLATIONARY AND ECONOMIC EFFECT OF THE ABSENCE OF COINS IN TRADE (PMS) TRANSACTIONS IN NIGERIA: A DATA-DRIVEN APPROACH

***[1]Yakubu Musa, [1]Ahmed Audu and [2]Sani Yahaya**

[1]Department of Statistics, Usmanu Danfodiyo University, Sokoto
[2]Department of Banking and Finance, Federal University, Dutse, Jigawa

*Corresponding authors' email: arimaym@gmail.com

ABSTRACT

Coins are still widely used in financial transactions in various countries, including Nigeria, despite their economic importance. However, in Nigeria, people often do not realize how their attitudes and tastes toward coins' rejection contribute to inflation. This study employed the ARIMA model, the autoregressive (VAR) model, and the random forest machine learning method to analyze the impact of differentials from pump premium motor spirit (PMS) price changes on economic uncertainty and the inflation rate. The ARIMA model forecast showed that the absence of coins increases inflation for ahead periods. The impulse response from the VAR model shows a significant positive effect of the variables that can cause a significant response from the economic policy uncertainty, though with a zero value at the end period. The forecast variance error decomposition of the VAR model shows that the NPP variable, SPP variable, and ZPP variable increasingly contributed to the variations of economic uncertainty, more specifically in the long term. The machine learning method revealed that the ZPP and NPP variables have more importance and contribution in estimating economic uncertainty among study variables in Nigeria, with a small contribution from the SPP variable using the random forest method. The mean square error and node impurity increased the most when the ZPP variable was randomly permuted. The study emphasizes the adverse effect of coins' rejection or absence in the economy and argues that a coin's return can have a significant positive impact on the Nigerian economy by reducing inflation and facilitating financial inclusion.

Keywords: MAX Model, VAR Model, Random Forest, Coins, Nigeria

INTRODUCTION

Getting exact change has become wishful thinking for many clients who participate in one trade transaction or the other due to the unavailability of coins and/or its rejection in day-to-day enterprises in Nigeria. This problem extends its influence on the economy as it fosters inflation and excessive earnings to others. Without including coins, the history of money cannot be considered comprehensive.

Coins have been a means of trade since the third stage of the construction of money, which was preceded by the second and first phases of commodities and barter, respectively (Sa'id, Yahaya, and Garba, 2022). Coins are often employed as a kind of legal money and mostly in the shape of tiny, flat, and round bits of metal or plastic. They are mass-produced in a mint in order to streamline commerce, and their weight is standardized (Orji, 2017). It is vital to remember that most nations in the world still employ coins for most of their regular economic transactions, particularly in little commerce, which is the cornerstone of economic progress.

Despite their rejection and/or disappearance in Nigeria, which may partially be related to public illiteracy and the government's refusal to enforce their usage, coins are still in use and are widely accepted for transactions in industrialized, developing, and underdeveloped nations. Three outstanding examples are the United States, the United Kingdom, and France. Others include South Africa, Malaysia, and India. Additionally, nations like Ghana and Niger utilize it. Both notes and coins may be found in use in these nations, however each has a specific dominance ratio, thus in certain regions notes are more extensively used than coins, while in some others the opposite is the case (Sa'id, Yahaya, and Garba, 2022). Some of these nations required the use of coinage in particular venues, including rail and bus terminals, movie theaters, post offices, phone booths, retail malls, and hotels (Alao, 2019).

However, Nigeria generally uses notes for transactions while entirely neglecting coins, which gave rise to queries by concerned citizens about why things are different in Nigeria, taking awareness of the great benefits that coins and their usage provided to an economy. On July 18, 2023, the Nigerian National Petroleum Company Limited (NNPCL) published the freshly revised pump pricing of petrol across the country after the withdrawal of the subsidy on the product. It was claimed frequently that persons at the top of the social scale preferred to conduct business in US dollars, which may have had an influence on the routine commercial dealings of ordinary Nigerians. Prices are rounded owing to a lack of coins and other smaller denominations. As an instance, products that might have been sold for N8 would rather be N10. Reason: A person who may have dropped N10 for such an item will not receive a N2 adjustment. People overpay for items and services as a consequence, which is a condition known as inflation (Bolarinwa, 2015).

The aforementioned position is in agreement with Awa (2016), who argues that coins are crucial in any economy as they make transactions easier and less likely to be approximated to the closest currency note. Reporting by Awa (2016) highlighted that because the customer must collect his or her balance, coins break down huge monetary quantities into smaller ones, inhibiting excessive inflation of prices for goods. He proceeded by noting that the seemingly little sum that people typically neglect has been added to the final price, which is why product expenses are so exorbitant. This is made worse by the fact that some sellers would not supply consumers such a modest quantity and some buyers would not request it. He pointed out that even when consumers request their balance, it is not always available, prompting them to either leave it or buy something they didn't plan to in order to make up the difference.

Orji (2017) makes the point in his study that the advantages of phasing out coins do not exceed the advantages of keeping them in use and that the reasons put out in support of this stance are grossly inappropriate as a foundation for action. He noted that the removal of coinage will have far-reaching implications.

Nigerians have stated why smaller denominations are problematic, despite the need of doing so for cutting inflation and stabilizing the economy. These include its exorbitant cost and weak purchasing power. According to Okoro (2022), an economist from the University of Port Harcourt observed that Nigerians have the inappropriate mentality toward utilizing lesser denominations of cash, particularly coins. Even though you may still observe individuals utilizing coins when you travel outside of Nigeria. Therefore, it is a matter of attitude because sometimes when you offer coins or even N10 to some people, they are unwilling to collect them, which has a negative impact on prices since, according to economic theory, it is difficult to bring down the costs of products and services once they have increased.

According to Saidu, Yahaya, and Garba (2022), one of these occasions when things are not functioning as intended is the unwillingness to employ money in ordinary transactions. The negative consequences that coin removal will have on the economy make it alarming. The economic repercussions of doing away with coins in the Nigerian economy were carefully studied in their study. Data were obtained and processed during the study process from primary sources. Based on the data, the paper reaches the conclusion that the progressive disappearance of coinage in Nigeria had a major detrimental influence on the economy. Reintroducing coins will avoid rounding up prices and the "no change syndrome," among other difficulties, which will minimize the risk of inflation and consumer extortion.

Although those who advocated against using coins claimed that their low purchasing power, bulk, and high cost of production were the reasons for their rejection or elimination, their opponents insisted that using them would, among other things, lower the high rate of inflation, unemployment, and poverty. They said that it would moderate the nation's crime and security rates. In light of all of this, it is felt that this study is both rational and timely.

The advantages of coinage cannot be emphasized. Since coins were originally introduced as one of the country's currencies in 1973, they have been present in all economic activities and are often used to pay for items and services. But suddenly it faded and became not visible in Nigeria today. Its importance has been felt in the economy and would continue to be (Adekunle, 2017). This is so that it can fit both lower market prices and denominations while also being a part of all everyday major and little transactions (Azuka, 2020).

Against this background, this research analyzed the sources of coins' influence on economic policy uncertainty activities and how it impacts the rate of inflation in the context of more dynamic pump prices in Nigeria.

MATERIALS AND METHODS

The approach adopted for this investigation is designed according to quantitative methodology.

Quantitative methodologies emphasize objective measurements and the statistical, mathematical, or numerical analysis of data acquired through polls, questionnaires, and surveys, or by altering pre-existing statistical data using computational techniques (Babbie, 2010).

Data structure and study area

This study utilized a mix of three data categories to assess the impact of coin absence on company transactions, particularly the average retail price customers pay for Premium Motor Spirit (petrol). The data are categorized into:

i. Headline Inflation (HIF): Headline inflation is a raw number that represents changes in the consumer price index (CPI) throughout the whole economy.
ii. Economic Policy Uncertainty (EPU): Economic Policy Uncertainty is an indicator built based on media stories on policy uncertainty from key newspapers. It counts the number of newspaper stories containing the phrases uncertain or uncertainty, economic or economy, and one or more policy-relevanat terms.
iii. Differential from monthly average retail price paid by customers for petrol/premium motor Spirit. Computational methodologies based on information available on petrol/premium motor spirit consumption figures, 2016, were employed.

Let p_1 : Total Monthly Average Consumption per litre

p_2: Average monthly pump petrol price per litre

p_3: Differential from p_2 to nearest 5 Naira Note or 10 Naira Note (Example if the average price per litre is 593 then $p_3 = 2$, also if the price is 477.5 then $p_2 = 2.5$ in such order)

p_4: $p_3 \times p_1$ is the data used.

Also, the following representation were made as follows:

NPP: Differential from monthly average retail pump petrol price paid by consumers in Nigeria

SPP: Differential from monthly average retail pump petrol price paid by consumers in Sokoto

state. KPP: Differential from monthly average retail pump petrol price paid by consumers in Kebbi

state. ZPP: Differential from monthly average retail pump petrol price paid by consumers in Zamfara State.

The data for the monthly average petrol/premium motor spirit price per liter was acquired from the National Bureau of Statistics for various years. The data collection was undertaken at sample outlets dispersed throughout 774 local government areas in all the 36 states and the FCT, Abuja. The data was acquired from approximately 10,000 respondents stationed in the outlets. The estimates were produced using the weights generated from household expenditure on fuel and the actual prices households bought the petrol (National Bureau of Statistics (NBS), 2024).

The aim was to identify the economic uncertainty and possibly inflation impacting consumers/customers linked with the lack of coinage in business/trade transactions in Nigeria and notably also in far northern states of Sokoto, Kebbi, and Zamfara.

Methods

Three distinct models were fitted on the data. The first two models are standard statistical models: ARIMAX and VAR, while the other model is a machine learning model—Random Forest (RF). The best model was selected using the RMSE performance metrics. For the machine learning model Random Forest (RF), the data were separated into two groups, namely the training and test sets. The training set is 80% of the data, while the remaining 20% is for the test set. The training set is used to estimate the parameters of the model, while the test set is used to validate the model and to know the performance of the model on the fresh dataset.

Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model developed by Box and Jenkins (1976) is a combination of the Autoregressive (AR) model and the Moving Average (MA) model on a stationary data. It is denoted as ARIMA (p, d, q) where ‘‘d’’ is the number of times the data is differenced to make it stationary, and an ARMA model, which includes moving an average (MA) process and autoregressive (AR) model. As express in Yakubu and Stephen (2020) the ARIMA (p, d, q) model of a time series data Y_t is given as:

$\phi(L)(1-L)^d Y_t = \mu + \theta(L)\varepsilon_t$ (1)

Where $\phi(L)$ is the characteristic polynomial of order ‘p’ for the autoregressive component of the model. $\theta(L)$ is the characteristic polynomial of order ‘q’ for the moving average component of the model. $(1-L)^d$ is the differencing of order ‘d’ of the data. Y_t is the observed value at time t , ε_t is the random error. The suggested model is compared to models with parameters close to it in order to identify a better model using the Akaike Information Criterion (AIC).

Based on the ARIMA model, ARIMAX model can take the impact of covariates into account by adding the covariate to the right hand of the ARIMA model equation. The equation of ARIMAX model is presented as follows:

$\phi(L)(1-L)^d Y_t = \mu + \theta(L)X_t + \theta(L)\varepsilon_t$ (2)

Autoregressive (VAR) Model

The study uses a standard VAR model to estimate the impact of differential costs on the nearest N5 and N10 in terms of percentage inflation and economic uncertainty in Nigeria. Sims's ground-breaking work from 1980 introduced unrestricted vector autoregression (VAR), which lets all the variables in the system interact and feedback on each other. It also seems to be very good at forecasting and policy analysis compared to large-scale macro-econometric models. As expressed in Yakubu and Jibrin (2013), the process can be presented as:

$Y_t = \mu + \phi Z_t + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t$ (3)

where Y_t is the set of k time series variables $Y_t = (Y_{1t}, Y_{2t}, \ldots, Y_{kt})'$, $A_i^{'}$sare $(k \times k)$ coefficient matrices, μ is the vector of deterministic terms , Z_t is the vector of non-stochastic variables such as economic intervention and seasonal dummies and $u_t = (u_{1t}, u_{2t}, \ldots, u_{kt})'$ is an unobservable error term. The equation (3) model is suitable for variables with stochastic trends and not for cointegration relations.

Random Forest (RF) Model

Random Forest (RF) is a machine learning approach. Random forest is an ensemble learning approach applied for classification and regression, which acts by creating numerous decision trees. The output is the mode of the classes (classification) or average prediction (regression) of the individual trees (Ho, 1998). The RF model frequently comprises numerous decision trees. Each decision tree is generated using a bootstrap sample of the original dataset (Breiman, 1996). Consequently, the RF is largely applied for regression and statistical classification. Random Forest in regression tasks is dependent entirely upon three user-specified parameters: the quantity of trees (ntree) in the ensemble, the minimal amount of data points in each terminal node (nodesize), and the number of features analyzed at each node (mtry). This study employs RF to estimate economic uncertainty in the absence of coinage in household transactions. To build an optimum RF prediction model, many ntree and mtry values were investigated. Nwosu et al. (2021) present a complete explication of random forest techniques. When splitting a node, random forest hunts for the largest feature from a random group of features.

Variable Importance

The idea of variable significance can be complicated, since it may depend on interactions with other variables. The random forest technique determines a variable's relevance by examining how much prediction error rises when out-of-bag (OOB) data for that variable is permuted while others stay constant. These computations are conducted for each tree as the forest is constructed.

The increase in mean square error (%IncMSE) and the rise in node impurity (%IncNodePurity) were used to evaluate the variable importance. They reflect the growth in mean square error and impurity, respectively, when a variable is randomly permuted. A variable that is less significant will not effect the %IncMSE and %IncNodePurity much when it is randomly permuted.

RESULTS AND DISCUSSION

The results of the three models: ARIMA, VAR, and RF are discussed.

Table 1: Stationary/Unit root test

Variable	Augmented Dickey–Fuller test (ADF)		
	t-statistics	**Prob.**	**Decision**
HIF	-0.030928	0.9529	I(1) Not Stationary
EPU	-5.064977	0..0000	I(0) Stationary
NPP	-8.293612	0.0000	I(0) Stationary
SPP	-9.548185	0.0000	I(0) Stationary
KPP	-10.58660	0.0000	I(0) Stationary
ZPP	-7.907711	0.0000	I(0) Stationary
Test Critical values	1% level	-3.492523	
	5% level	-2.888669	
	10% level	-2.581313	

The Augmented Dickey-Fuller unit root test was used to test the presence of a unit root in the data. The data shows a unit root for the inflation rate and stationarity for the rest of the variables. The inflation rate data became stationary after the first differencing.

The ARIMA model

The plot of the data set of the headline inflation (HIF) is provided in Figure 1. The data reveals non-stationarity, and this was validated by the Augmented Dickey–Fuller test [P-value (0.9529) larger than 0.05]. The data were differenced and checked for stationarity. The data became stagnant after the initial differencing. Taking the influence of covariates into account by adding the covariate to the right-hand side of the ARIMA model equation, the variables EPU, NPP, SPP, KPP, and ZPP were also evaluated for stationarity, and they are stationary at the level given in Table 1.

Different orders of the ARIMAX model were estimated and compared; the best-fitted model for the data and its variables was chosen to be regression with ARIMA(1,1,0)(2,0,0)[12] errors, as it had the least AIC as shown in Table 2. The residuals from the ARIMA(1,1,0)(2,0,0)[12] errors exhibited no trend, as demonstrated in the time series plot of the residual in Figure 2. The delays of the residuals break up all inside the threshold limit in the ACF plot, and the residuals are normally distributed. The residuals are white noise as they satisfied all the criteria for the residuals of the ARIMA model.

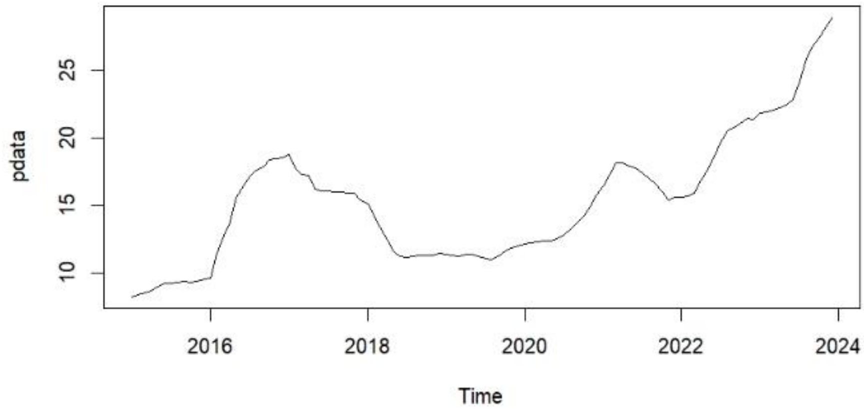

Figure 1: Time series plot of HIF

Table 2: Model Selection

Models	AICc
Regression with ARIMA(2,1,2)(1,0,1)[12]	errors : Inf
Regression with ARIMA(0,1,0)	errors : Inf
Regression with ARIMA(1,1,0)(1,0,0)[12]	errors : 89.27128
Regression with ARIMA(0,1,1)(0,0,1)[12]	errors : 109.6278
Regression with ARIMA(0,1,0)	errors : 188.5309
Regression with ARIMA(1,1,0)	errors : 92.63778
Regression with ARIMA(1,1,0)(2,0,0)[12]	errors : 80.87201
Regression with ARIMA(1,1,0)(2,0,1)[12]	errors : 83.32802
Regression with ARIMA(1,1,0)(1,0,1)[12]	errors : Inf
Regression with ARIMA(0,1,0)(2,0,0)[12]	errors : Inf
ARIMA(2,1,0)(2,0,0)[12]	with drift : Inf
Regression with ARIMA(1,1,1)(2,0,0)[12]	errors : 82.67512
Regression with ARIMA(0,1,1)(2,0,0)[12]	errors : 106.4525
ARIMA(2,1,1)(2,0,0)[12]	with drift : Inf
Regression with ARIMA(1,1,0)(2,0,0)[12]	errors : Inf

Best model: Regression with ARIMA(1,1,0)(2,0,0)[12] errors

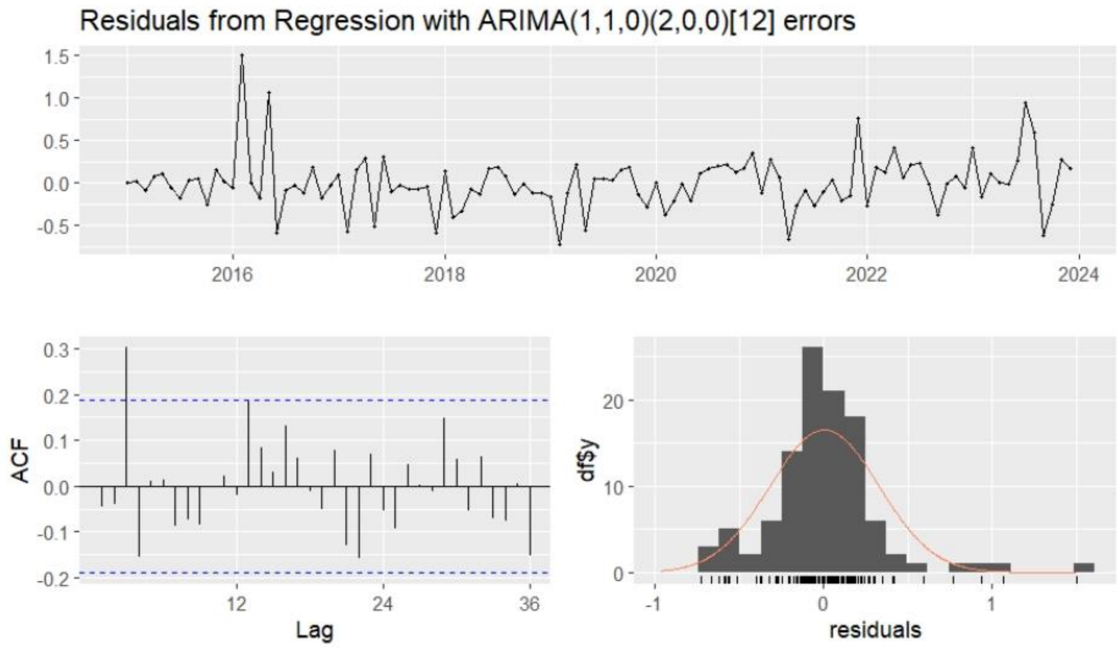

Figure 2: Residuals Checking

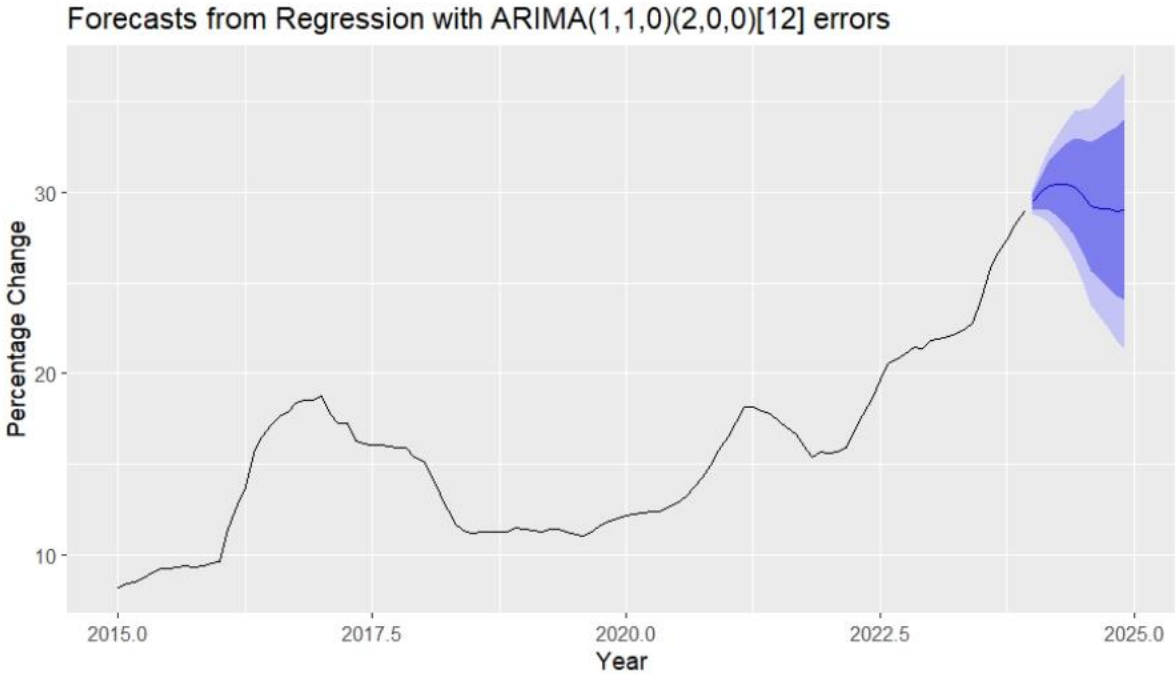

Figure 3: Forecast of ARIMA(1,1,0)(2,0,0)[12] model with covariates

As shown in Figure 3, the impact of covariates cannot be ignored; the forecast of the ARIMA(1,1,0)(2,0,0)[12] model with covariates shows an increase in the inflation for ahead periods. These show that the differential from average PMS prices in the absence of coins increases inflation as demonstrated.

VAR Model Specification

Before utilizing the data in the estimate of VAR, we need to know the time series characteristics of all the variables. Accordingly, a sequence of unit root tests, such as the Augmented Dickey-Fuller, is used to identify the order of integration for each series. As indicated in Table 1, the series are all stationary except inflation (HIF), and taking the difference of the variable makes it stationary.

A significant need in the estimate of a VAR system, either in its unrestricted or restricted Vector Error Correction (VEC) forms, is the choosing of an ideal lag duration. Lag length selection is critical for VAR specification since choosing too few delays results in mis-specification, while choosing too many lags results in excessive loss of degrees of freedom. To avoid this, lag lengths are selected using statistical tests, which include the modified Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn information criterion (HQ), and also examination of the roots of the characteristic polynomial to verify if the VAR is stable.

Table 3 showed the evidence based on the VAR Lag Order Selection Criteria, whereas Figure 4 provides the inverse roots of the AR characteristic polynomial linked with the different lag orders indicated by the selection criteria. Most of the numerous criteria applied recommend the adoption of one lag for the VAR specification; the inverse roots of the AR characteristic are inside the unit circle (Figure 4), therefore VAR with one lag meets the stability criterion and may be used for further analysis. Also, as seen in Table 4, the residuals of the VAR(1) model are uncorrelated.

Table 3: Lag order selection

Included observations: 103

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-8667.382	NA	5.58e+65	168.4152	168.5687*	168.4773
1	-8587.080	149.6885*	2.37e+65*	167.5550*	168.6293	167.9901*
2	-8565.439	37.81984	3.15e+65	167.8338	169.8290	168.6419
3	-8546.719	30.53338	4.48e+65	168.1693	171.0854	169.3504
4	-8517.872	43.69073	5.32e+65	168.3082	172.1452	169.8623

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

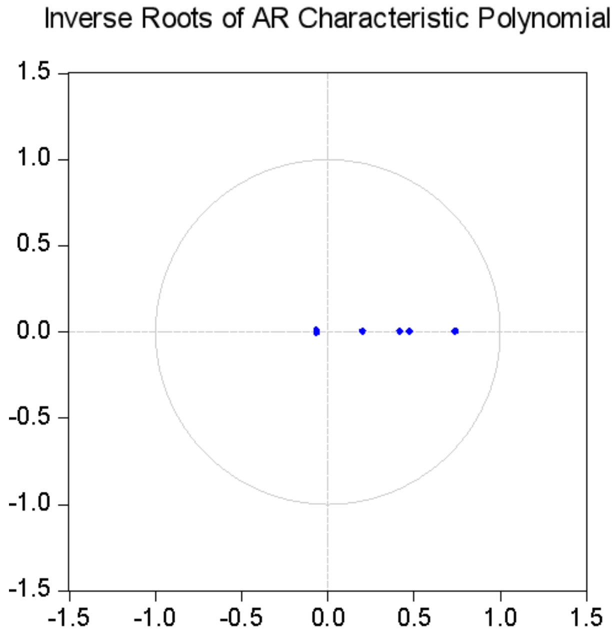

Figure 4: Inverse roots of AR characteristics polynomial

Table 4: VAR Residual Serial Correlation LM Test

Included observations: 106

Lags	**LM-Stat**	**Prob**
1	38.45562	0.3589
2	36.66477	0.4379

Probs from chi-square with 36 df.

Impulse Response Functions

Impulse Response Functions (IRFs) are one of the major instruments of the VAR approach for investigating the interaction between the variables in this research. They reflect how individual variables respond to shocks from other variables in the system. When graphically displayed, the IRFs give a visual depiction of the behavior of variables in response to shocks. A value of 0 means that the EPU, NPP, SPP, KPP, and ZPP shocks have no effect on the inflation variable, and the variables continue on the same path they would have followed. A positive or negative value signifies that the shock would lead the variable to be above or below its typical path, as the case may be. The response projection period is ten years to enable us to capture both the long-term and short-term reactions.

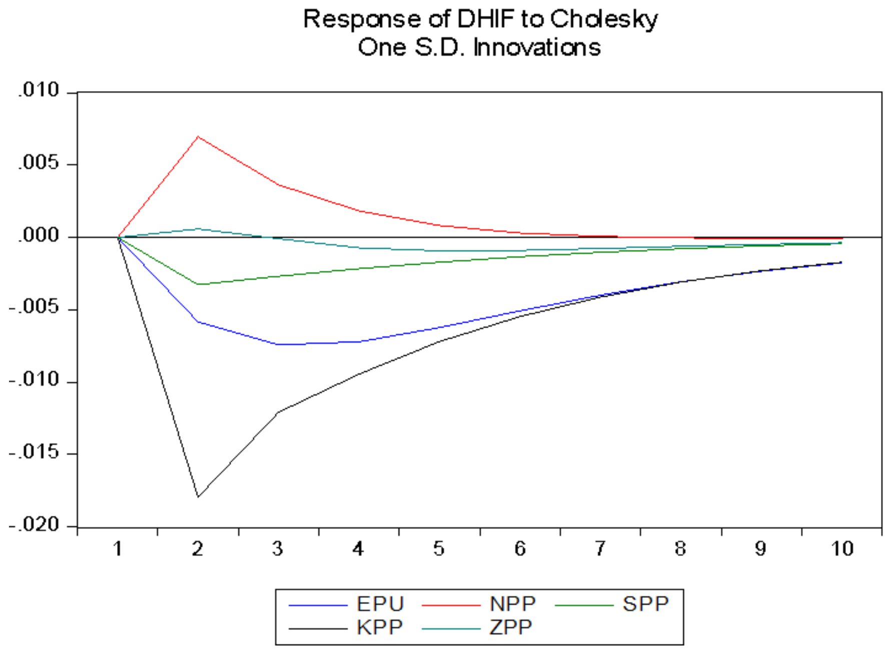

Figure 5: Response of DHIF to Cholesky

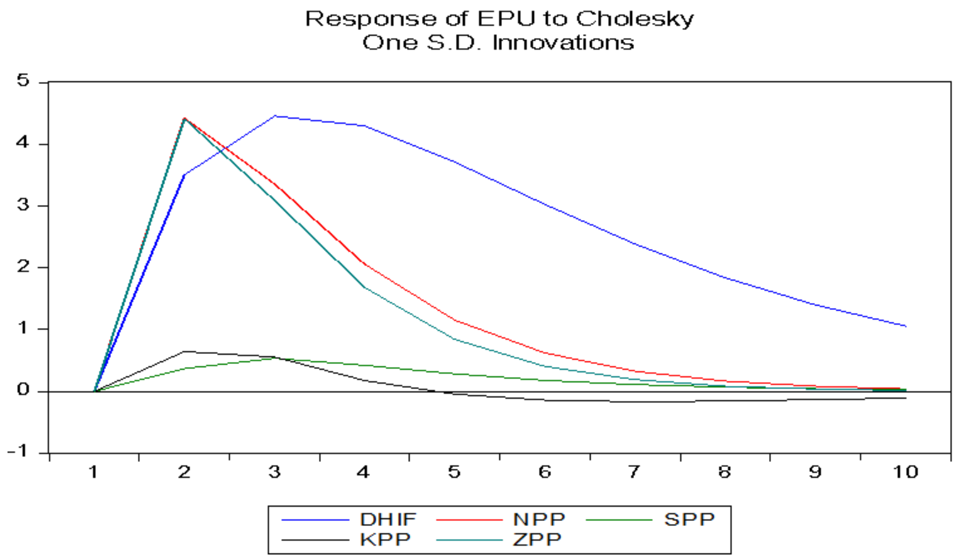

Figure 6: Response of EPU to Cholesky

Figure 5 depicts the reaction of inflation to economic policy uncertainty and average differential PMS price shocks. Although it starts around value zero, the inflation reacted considerably and positively in the short term for NPP shocks and ZPP with modest magnitude. The impact of EPU, SPP, and KPP is negative, with larger negative impacts from the disparity in Zamfara prices and a value of zero in the long term. The impulse response from Figure 6 demonstrates a strong positive influence of the factors that might generate a major response from the economic policy uncertainty; however, there is a zero value at the end period.

Forecast Error Variance Decomposition

Variance decompositions are shown in Tables 5 and 6, which assist in highlighting the primary routes of effect for particular variables. Each table, represents the contribution of other factors to the variance of each variable evaluated in turn. The figures for each variable show the percentage of variation of the variable investigated that was attributed to the individual variable during a 10-year period.

Table 5: Variance Decomposition

Period	S.E.	DHIF	EPU	NPP	SPP	KPP	ZPP
1	0.371098	98.87425	0.769302	0.001693	0.120079	0.230022	0.004651
2	0.465932	98.61503	0.651455	0.031353	0.095539	0.600785	0.005838
3	0.511392	98.59871	0.587538	0.033762	0.087470	0.686981	0.005542
4	0.535103	98.59812	0.551754	0.032973	0.083720	0.728330	0.005106
5	0.547844	98.59971	0.531877	0.032020	0.081734	0.749783	0.004877
6	0.554782	98.60090	0.520841	0.031369	0.080643	0.761466	0.004786
7	0.558584	98.60159	0.514718	0.030981	0.080035	0.767924	0.004755
8	0.560673	98.60197	0.511323	0.030759	0.079696	0.771509	0.004747
9	0.561824	98.60217	0.509442	0.030636	0.079506	0.773501	0.004746
10	0.562458	98.60228	0.508402	0.030567	0.079401	0.774605	0.004747

Cholesky Ordering: EPU NPP SPP KPP ZPP DHIF

Table 6: Variance Decomposition

Period	S.E.	DHIF	EPU	NPP	SPP	KPP	ZPP
1	0.371098	0.769302	94.21894	0.012619	4.745009	0.022978	0.231148
2	0.465932	3.648921	86.80862	3.042214	4.143370	0.074628	2.282244
3	0.511392	6.557115	82.27955	4.216297	3.806451	0.126108	3.014477
4	0.535103	8.883782	79.63144	4.551588	3.647742	0.134246	3.151199
5	0.547844	10.49552	78.05243	4.607937	3.566396	0.132656	3.145058
6	0.554782	11.51924	77.11353	4.594720	3.521617	0.130971	3.119925
7	0.558584	12.13642	76.56322	4.573430	3.496188	0.130363	3.100375
8	0.560673	12.49686	76.24562	4.557447	3.481664	0.130352	3.088053
9	0.561824	12.70319	76.06469	4.547368	3.473406	0.130528	3.080816
10	0.562458	12.81978	75.96264	4.541433	3.468745	0.130708	3.076689

Cholesky Ordering: DHIF NPP SPP KPP ZPP EPU

The objective here is to analyze the influence and prediction abilities of NPP, SPP, KPP, and ZPP on inflation and economic policy uncertainty. According to Table 5, inflation accounted for its current difference from its own inventions with roughly 99 percent. There was little additional fluctuation produced by KPP factors in subsequent times.

Table 6 demonstrated that economic policy uncertainty accounted for its contemporaneous variance from its own inventions with roughly 94 percent in the initial year. The inflation, NPP variable, SPP variable, and ZPP variable increasingly contributed to the changes of economic uncertainty, more especially in the long run.

The Random Forest Model

Importance of variable factors: The average decrease in mean precision (%IncMSE) and average reduction in node impurity (IncNodePurity) from the random forest regression technique and ranger approach were used to characterize the relevance of the explanatory factors. The average reduction in mean precision (%IncMSE) is the increase in error relative to the original error estimated by the random forest model after randomizing the values of the variables; the larger the value of %IncMSE, the greater the importance of the variable to the random forest regression; the average reduction in node impurity (IncNodePurity) indicates the degree of influence of a variable on the nodes of the decision tree; the larger the value of IncNodePurity, the more important it is. The bigger the value of IncNodePurity, the more significant it is.

Figures 8 and 10 indicate the degree of effect of the four chosen factors on the economic uncertainty forecasts in the random forest model, with the three most important influences being the ZPP variable, SPP variable, and NPP variable. The performance of the random forest (RF) models with varied numbers of explanatory variables was assessed to quantify the predictions' ability of the response variable. RMSE was utilized to pick the optimum model using the least value. The final number utilized for the model was mtry = 2.

The ZPP and NPP variables have higher values and contributions in predicting economic uncertainty among the research variables in Nigeria; however, there is a modest contribution from the SPP variable using the random forest approach. The mean square error (%IncMSE) and the node impurity (%IncNodePurity) rise the greatest when the ZPP variable is randomly permuted, as illustrated in Figures 7 & 8. The KPP variable did not impact the ''%IncMSE'' and ''%IncNodePurity'' substantially when they were randomly permuted.

The range technique was also utilized to evaluate the prediction performance of the explanatory factors to the response variable. The tuning parameter 'min.node.size' was maintained constant at a value of 5, and RMSE was utilized to find the best model using the least value. The final settings utilized for the model were mtry = 2, splitrule = extratrees, and min.node.size = 5. The application of the range technique demonstrated the SPP and ZPP variables had a larger contribution in assessing the economic policy uncertainty among study variables in Nigeria; however, there was less contribution from the NPP variable. The mean square error (%IncMSE) and the node impurity (%IncNodePurity) rise the greatest when the SPP variable is randomly permuted, as illustrated in Figures 9 & 10. The KPP variable did not impact the ''%IncMSE'' and ''%IncNodePurity'' substantially when they were randomly permuted.

Table 7: Summary of Split Training and Testing Data

Input	Parameter	Split Data		Target
		Trainng	Testing	
NPP	Y_1	80%	20%	NO
SPP	Y_2	80%	20%	NO
KPP	Y_3	80%	20%	NO
ZPP	Y_4	80%	20%	NO
EPU	Y_5	80%	20%	YES

Table 8: Model performance Evaluation of Random Forest method

Mtry	RMSE	R^2	MAE
2	0.2234510	0.1081285	0.1798555
3	0.2269349	0.1022910	0.1834742
4	0.2306223	0.1059591	0.1856882

Table 9: %IncMSE and IncNodePurity of Random Forest Method

Variables	%IncMSE	IncNodePurity
NPP	-2.0592649	0.8521887
SPP	-2.6221300	0.6083329
KPP	-3.8770278	0.6410444
ZPP	0.6364676	0.8715878

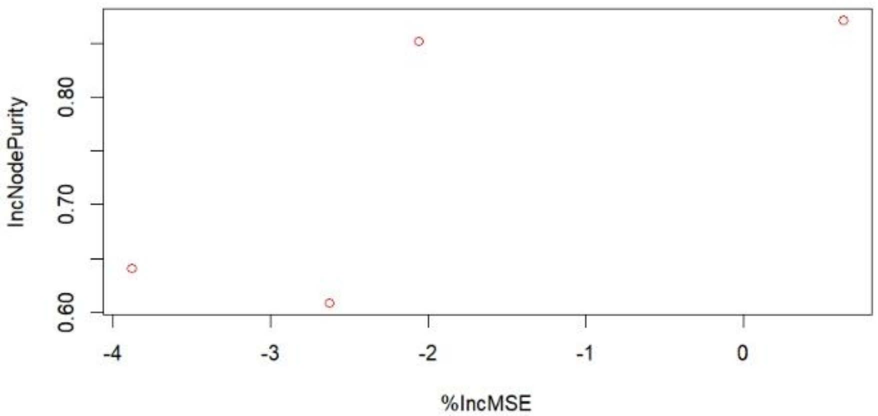

Figure 7: Plot %IncMSE and IncNodePurity of Random Forest Method

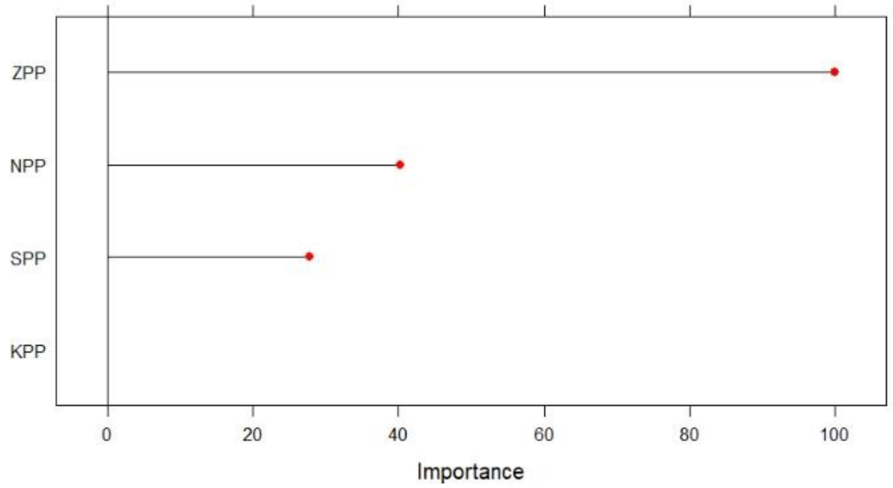

Figure 8: Importance ranking

Ranger method

Table 10: Model performance Evaluation of Ranger method

Mtry	splitrule	RMSE	R^2	MAE
2	variance	0.2149063	0.1098439	0.1746446
2	extratrees	0.2067563	0.1287471	0.1661616
3	variance	0.2173248	0.1029554	0.1772854
3	extratrees	0.2106877	0.1280672	0.1699827
4	variance	0.2185679	0.1104679	0.1782924
4	extratrees	0.2118196	0.1453722	0.1711703

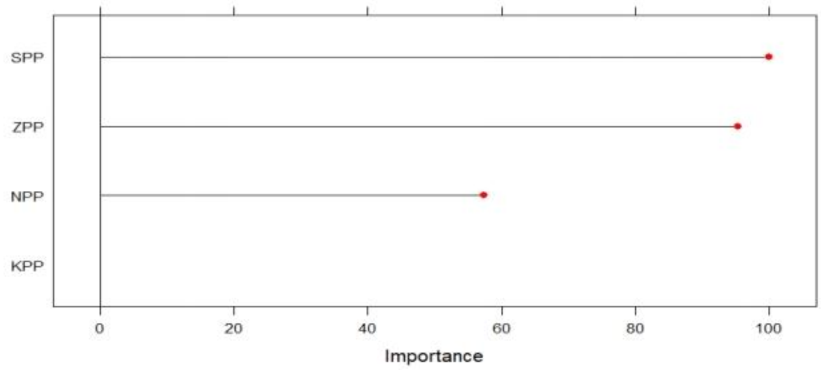

Figure 9: Importance ranking of Ranger method

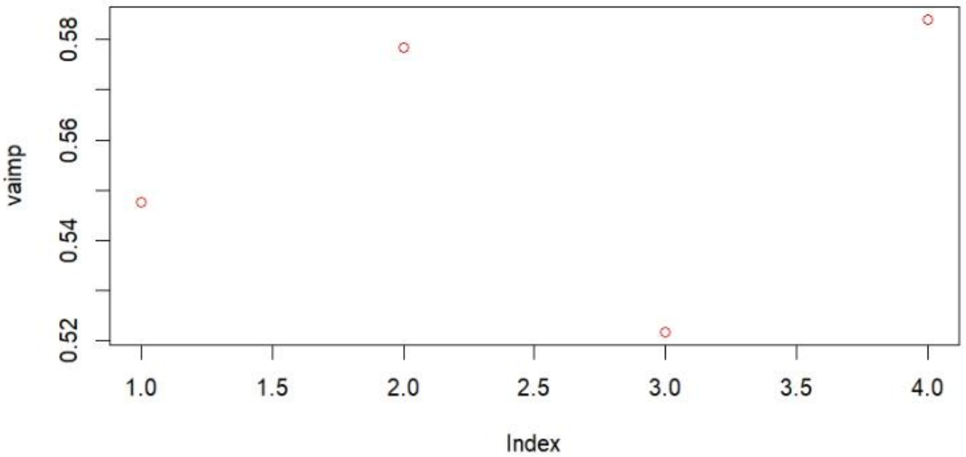

Figure 10: Plot of variable importance index

The usage of a random forest regression model is significant in discovering the prediction ability of explanatory factors to the response variables. Two strategies were employed: the random forest method and the ranger method. The random forest approach performs better for training set data than the ranger method with minimal RMSE. The Ranger technique fared better for test set data than the random forest method for the research variables.

Table 11: RMSE

Method	**RMSE**	
	Trainset	**Testset**
RF	0.105571	0.140333
Ranger	0.134594	0.132576

Our results align with the conclusions of Awa (2016), Orji (2017), Okoro (2022), and Saidu, Yahaya, and Garba (2022). Awa (2016) emphasized that the necessity for customers to collect their balance results in coins fragmenting large monetary amounts into smaller denominations, hence preventing significant inflation of pricing for commodities. Orji (2017) observed that the elimination of coinage will have significant consequences. Nigerians have voiced apprehensions over lower denominations, despite their necessity for mitigating inflation and stabilizing the economy. These factors encompass its prohibitive price and diminished buying power. Okoro (2022) asserts that individuals often exhibit reluctance to accept coins or even N10, which adversely affects prices, as economic theory posits that it is challenging to reduce the costs of goods and services once they have escalated. Furthermore, Saidu, Yahaya, and Garba (2022) argued that the gradual elimination of coinage in Nigeria significantly harmed the economy. The reintroduction of coins will prevent price rounding and the "no change syndrome," among other issues, therefore reducing the likelihood of inflation and consumer exploitation.

CONCLUSION

In this study, we evaluated the forecast from ARIMAX model, the Impulse response and forecast variance decomposition of VAR model and the performance of machine learning model (Random Forest) in exploring the impact of absent of coins in trade (Pump PMS) transaction in Nigeria and specifically in North-western states of Sokoto, Kebbi and Zamfara. The conventional ARIMAX model illustrates that the influence of covariates cannot be disregarded; the forecast of the ARIMA(1,1,0)(2,0,0)[12] model with covariates reveals a rise in the inflation for forward periods. These illustrate that the disparity from average PMS prices in the absence of coinage causes inflation as demonstrated. The VAR model's impulse response function shows inflation's response to economic policy uncertainty and differential PMS price shocks. Inflation reacts positively in the short term for NPP shocks and ZPP, but negatively impacts EPU, SPP, and KPP, with larger negative impacts from Zamfara price disparity. The impulse response from Figure 6 shows a strong positive influence of factors generating a major response from economic policy uncertainty, but a zero value at the end period. The VAR model variance error decomposition analyzed the impact of NPP, SPP, KPP, and ZPP on inflation and economic policy uncertainty. Inflation accounted for 99% of the difference from inventions, while KPP factors showed minimal fluctuations. Economic policy uncertainty accounted for 94% of the variance in the initial year. The variables inflation, NPP, SPP, and ZPP contributed to economic uncertainty changes, especially in the long run. The study assessed the performance of random forest (RF) models with various explanatory variables to determine the predictability of the response variable. The optimum model was chosen using the least value, and the final number used was mtry = 2. The results showed that the ZPP and NPP variables had higher values and contributions to predicting economic uncertainty in Nigeria. However, the SPP variable had a modest contribution. The mean square error and node impurity increased the most when the ZPP variable was randomly permuted, while the KPP variable did not significantly impact these factors. The range technique was also used to evaluate the prediction performance of the explanatory factors to the response variable. The results showed that the SPP and ZPP variables had a larger contribution to assessing economic policy uncertainty in Nigeria, but less from the NPP variable.

REFERENCES

Adekunle, J. (2017). Review of Coins Production in Nigeria from pre-colonial Era till date

Alao, R. (2019). Extinction of Coins in Nigeria: A Course or Cause. A paper presented at the Launching of MSEs Grant and Soft Loan at Igboora, Oyo State, Nigeria.

Awa, O. (2016). Dearth of coins: How behaviour impacts inflation, the Guadiance newspaper, 27, June, 2016 https://guardian.ng/features/dearth-of-coins-how-behaviour-impacts-inflation/ accessed 8/6/2023

Azuka, L. (2020), The Economic Needs for the Reintroduction of Coins in Nigeria. A Lecture at the Annual Induction Programme at the Nigerian Institute of Management (Chartered) 4th -5th December 2020, Abuja Nigeria.

Babbie, Earl R. (2010). The Practice of Social Research. 12th ed. Belmont, CA: Wadsworth Cengage.

Bolarinwa M. (2015), Extinction of coin in Nigeria. https://www.linkedin.com/pulse/extinction-coins-nigeria-bolarinwa-mabawonku-ccna-mcib-acilrm

Box, G.E. and Jenkins, (1976). 'Time series Analysis' Forecasting and Controls, San Francisco, USA.

Breiman L. (1996). "Bagging Predictors", Machine Learning, vol. 24, pp. 123-140.

CBN (n.d.), History of Nigerian Currency https://www.cbn.gov.ng/currency/historycur.asp Accessed on 8/6/2023

Ho T. K. (1998). "The random subspace method for constructing decision forests," IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 8, pp. 832–844.

Nwosu, U. I., Obite, C. P., & Bartholomew, D. C. (2021). Modeling US Dollar and Nigerian Naira exchange rates during COVID-19 pandemic period: Identification of a high-performance model for new application. Journal of Mathematics and Statistics Studies, 2(1), 40-52.Available at: https://doi.org/10.32996/jmss.2021.2.1.5

Okoro, C. (2022) Reinforcing coin usage unlikely to counter price Inflation- Experts. https://businessday.ng/business-economy/article/reinforcing-coin-usage-unlikely-to-counter-price-inflation-experts/

National Bureau of Statistics (NBS) (2024). Premium Motor Spirit (Petrol) Price Watch Report.

Orji, E. T. (2017), Economic Consequences of Phase out of Coins in Nigeria. A term Paper Presented at Michael Okpara University of Agriculture Umudike, Nigeria.

Sa'idu, I., Yahaya, S and Garba, S.A (2022) Elimination of Coins in Nigeria: A Critical Assessment of its Implication on the Nigerian Economy. Journal of Economics and Finance (IOSR-JEF) e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 13, Issue 2

Sims, C. A. (1980). Macroeconomics and Reality. Econometrica, 48(1), 1-48.

Yakubu Musa and Jibrin A. Sanusi (2013). Analyzing the impact of Value Added Tax (VAT) on Economic Growth in Nigeria. Journal of Mathematical Theory and Modeling. Vol.3(14): 16-23