Communication in Physical Sciences, 2023, 10(2): 034-046

Application of Factor Analysis in the Modelling of Inflation Rate in Nigeria

Chisimkwuo John, *Promise Izuchukwu Okoroafor, Chinenye Theresa Amobi

***Received:* 09 July 2023/Accepted 28 November 2023/Published 28 November 2023**

Abstract: *Inflation is a sustained increase in the general price level of goods and services in an economy over some time. The measure of inflation is the inflation rate, the annualized percentage change in the general price index usually the consumer price index over time. This study examines the application of factor analysis on the Nigeria inflation rate, The specific objectives of the study are: to describe the covariance relationship among the headline, core and non-core inflation rates in Nigeria. The headline inflation is the "all items" inflation, the core inflation is the "all items less farm produce" and "all items less farm produce and energy" inflation while the non-core inflation is the "food" inflation. To analyze the data generated for the study, the principal component and maximum likelihood method of factor analysis were employed. The findings of the study show that for the different kinds of inflation in Nigeria, there exists some covariance relationship amongst the months of the years and three underlying factors were discovered to be responsible for these relationships which are known as the early. .month factor, the middle month factor and the late month factor.*

Keywords*: Factor analysis, Nigerian Inflation Rate, Principal Component Analysis, All Items Less Farm Produce, Food Inflation, All Items Inflation.*

Chisimkwuo John
Department of Statistics, Michael Okpara University of Agriculture, Umudike.
Email:john.chisimkwuo@mouau.edu.ng
Orcid id: **0000-0001-9312-3779**

Okoroafor Promise Izuchukwu
Department of Epidemiology and Medical Statistics Ibadan, Ibadan.
Email: okoroaforizuchukwu@gmail.com
Orcid id: 0009-0009-5037-8777

Amobi Chinenye Theresa
Department of Statistics, Michael Okpara University of Agriculture, Umudike.
Email: amobichinenye25@gmail.com
Orcid id: 0000-0002-4704-3644

1.0 Introduction

Inflation refers to the ongoing increase in the overall prices of goods and services within an economy. The technical definition of the inflation rate involves measuring the percentage change in the general price level of goods and services over a specific period. This is a significant concern for all parties involved. Interestingly, even without any external economic disruptions, inflation tends to persist and continue into successive periods. Starting from the 1970s, Nigeria has experienced periods of elevated and unstable inflation rates. According to Masha's findings in 2000, the country's episodes of high inflation during this time were primarily influenced by the expansion of the money supply and various structural attributes of the economy. These attributes encompassed factors like weather conditions, wage hikes, production patterns, currency devaluation, and alterations in trade terms. Adenekan *et al.*(2004), highlighted that by the years 1988 and 1989, inflation had surged to over 50 percent in

Nigeria. Dimensionality reduction is a technique that can be applied to understand macro-level a given data data. It reduces the number of features of our dataset such that we are left with only the important parts. Nicholas *et al*.(2016), performed factor analysis on resident assessment and faculty evaluation tools. Despite the complexity of these tools, they provided very little discrimination between characteristics. The authors performed factor analysis on the individual items instrument and faculty evaluation collected from 2006 to 2012. The factor analysis of the resident assessment tool revealed that one component was responsible for 96.6% of the variance, the component encompassed each question from the assessment form and could also be termed overall residence competency. They then concluded that three components accounted for 90% to 97% of the observed variance in their analysis. Wenhua *et al*.(2014) demonstrated how the bootstrap method could be conducted in exploratory factor analysis (EFA) with a syntax written in SPSS. The data obtained from the Texas childhood obesity prevention policy Evaluation Project (T-COPPE project) were used for illustration. A 5 step procedure to conduct bootstrap factor analysis (BFA) was introduced, (1) conduct principal component analysis (2) create the target matrix (3) resample with replacement (4) conduct EFA and procreates rotation (5) calculate BFA results. The result of the illustrated BFA example indicated that 15 variables from this study were stable across the samples and they concluded that the bootstrap method when applied in EFA for health-related research is a particularly powerful internal replicability analysis.

Knoke *et al.*(2000), applied factor analysis to data from a population of active duty Seabees in response to the factor analysis conducted by (Haley et al.,1997). The study population was drawn from US Navy construction-battalion personnel (Seabees) who were on active duty in 1990 and remained on active duty in 1994 when the study was conducted. The instrument contained 98 symptom questions. Among the 524 Gulf war veterans and 925 non-deployed Seabees, Knoke *et al*.(2000) performed three-factor analyses, the first on the deployed Seabees, the second on the non-deployed Seabees and the third on both. The three-factor analysis accounted for 80%, 89% and 93% of the total variance and each extracted five factors. The authors also conducted a discriminate analysis to test the ability of the factors to discriminate between Gulf War deployed and non-deployed veterans. They concluded that there was no evidence of a unique spectrum of neurological injury.

Hassan *et al*.(2012), conducted a study using factor analysis to identify new factors influencing students' learning styles among university students. They collected data from 189 respondents through survey questionnaires and employed descriptive statistics, factor analysis, and the Kruskal-Wallis test for analysis. The results revealed seven factors impacting learning styles: changes in students' attitudes before and after class, strategies to understand lectures, lecture importance, class size and condition, efforts beyond class, classroom convenience and significance of lecture listening. Gender differences were observed in the factor related to efforts outside class, while years of study affected students' attitudes before and after class. Science and non-science students differed in their learning styles, with non-science students emphasizing practical application and science students finding satisfaction in class conditions. Adam *et al*.(2018), presented the development and validation of a new couples communication satisfaction scale (CCSS). The CCSS observes each partner`s level of satisfaction with various aspects of their communication. An exploratory factor analysis revealed five factors that addressed their communication presence, their own emotional experience, their partner`s responsiveness, their partner's contribution and communication characteristics. A confirmatory factor analysis was conducted to validate the five-factor structure, findings revealed high levels of reliability in the sample and across genders. Measuring a couple's communication satisfaction may help provide a more complete picture of a couple's communication processes.

Okeke *et al*.(2017), researched the academic performance of pupils in primary school. Variation in the analyzed performance and the factors causing the variation were studied using factor analysis, the data used was secondary data collected from Federal University Wukari staff school and it was on the terminal examination scores of the pupils in seven selected subjects over one selected academic session. From both the rotated and unrotated factor analysis results, we observed a fair relationship between the mathematical and less mathematical subjects though they present the major variation in the pupils' performance to be in the less mathematical subjects like English Language, Verbal Aptitude, Social Studies Creative Art and Religious Studies. Also, the analysis presented three factors (gender, age and environment) to be the cause of the variation in the pupil`s performance in primary school.

Jamal (2015) aimed to examine motivations to use social media in a sample of university students. Grounded in the theory of Uses and Gratification, the current research sought to delineate user motivations with exploratory factor analysis. To reach the study goals, the researcher used a cross-sectional survey methodology in which a questionnaire was distributed to 1327 undergraduate students with their consent. The analysis of the data revealed that almost all respondents used social media. Based on factor analysis results, their motivations for doing so are entertainment, information seeking, personal utility and convenience. These factors were positively related to the user experience, time spent, and level of satisfaction with social media. In this study, we employ factor analysis, a statistical method guided by fundamental principles. Factor analysis hinges on the concept of latent variables influencing observed variables. The strength and direction of these influences are captured by factor loadings. The technique distinguishes between common and unique variance, aiming to extract underlying factors that explain correlations in the data. Eigenvalues and eigenvectors play a crucial role, with eigenvalues representing explained variance and eigenvectors indicating factor directions. Rotation methods enhance interpretability, and communality measures the proportion of variance explained by factors. Factor scores provide a means to interpret and compare observations based on their factor-related characteristics. These principles collectively guide our exploration, revealing latent structures and patterns within the dataset.

2. 0 Methodology

2.1 Method of data analysis

The observable random vector X, with p component, has mean μ and variance matrix ∑ The factor model postulates that X is linearly dependent upon a few unobservable random variables F1, F2, …, Fm called common factors, and p additional sources of variation $\varepsilon_1\varepsilon_1,\ldots,\varepsilon_p$, called errors or, sometimes, specific factors. In particular, the factor analysis model is

$$X_1 - \mu_1 = \ell_{11}F_1 + \ell_{12}F_2 + \ldots + \ell_{1m}F_m + \varepsilon_1$$

$$X_2 - \mu_{21} = \ell_{21}F_1 + \ell_{22}F_2 + \ldots + \ell_{2m}F_m + \varepsilon_2 \quad (1)$$

$X_p - \mu_p = \ell_{p1}F_1 + \ell_{p2}F_2 + \ldots + \ell_{pm}F_m + \varepsilon_p$

Or in matrix notation,

$$\underset{(\mathbf{pX1})}{\mathbf{X} - \boldsymbol{\mu}} = \underset{(\mathbf{pXm})}{\mathbf{L}} \; \underset{(\mathbf{mX1})}{\mathbf{F}} + \underset{(\mathbf{pX1})}{\boldsymbol{\varepsilon}} \qquad (2)$$

The coefficient ε_i is called the loading of the ith variable on the jth factor, so the matrix L is the matrix of factor loadings. Note that the ith specific ε_i is associated only with the ith response X_i. The p deviation

$X_1 - \mu_1,\ X_2 - \mu_2, \ldots, \rightleftarrows X_p - \mu_p$

are expressed in terms of p + m random variables $F_1, F_2, \ldots, F_m, \varepsilon_2, \ldots, \varepsilon_p$ which are unobservable. This distinguishes the factor model of (2) from the multivariate regression model in which the independent variables (whose positive is occupied by F in 2) can be observed. With so many unobservable quantities, a direct verification of the factor model from observations on $X_1,\ X_2 \ldots, \rightleftarrows X_p$ is hopeless. However, with some additional assumptions about the random vectors F_1 *and* ε, the model in (2) implies certain covariance relationships, which can be checked.

We assume that

$$E(F) = 0, \rightleftarrows \quad \underset{(mX1)}{Cov(F) = E(FF)} = \underset{(mXm)}{I}$$

$$\underset{(pX1)}{E(\mathcal{E}) = 0, \rightleftarrows \quad Cov((\varepsilon) = E(\varepsilon\varepsilon)} = \underset{(pXp)}{\psi} = \begin{bmatrix} \psi_1 & 0 & \ldots & 0 \\ 0 & \psi_2 & \ldots & 0 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ 0 & 0 & \ldots & \psi_p \end{bmatrix} \qquad (3)$$

And that F and $\mathcal{E}$ are independent, so

$$Cov(\varepsilon, F) = E(\varepsilon F') = \underset{(pXm)}{0}$$

These assumptions and the relation in 3 constitute the orthogonal; factor model

2.2 Orthogonal factor model in common factors

$$\underset{(\mathbf{pX1})}{\mathbf{x}} = \underset{(\mathbf{pX1})}{\boldsymbol{\mu}} + \underset{(\mathbf{pXm})}{\mathbf{l}} \; \underset{(\mathbf{mX1})}{\mathbf{f}} + \underset{(\mathbf{pX1})}{\boldsymbol{\varepsilon}} \qquad (4)$$

Where μ_i is the mean of variable I, ε_i is the ith specific factor, f_j is the jth common factor, and ℓ_{ij} is the loading of the ith variable on the jth factor.

The unobservable random vectors **f** and $\boldsymbol{\varepsilon}$ satisfy the following conditions:

f and $\boldsymbol{\varepsilon}$ are independent

E(f)=0, Cov (f)=1

$E(\boldsymbol{\varepsilon}) = 0,\ Cov(\boldsymbol{\varepsilon}) = \psi$ is a diagonal matrix

The orthogonal factor model implies a covariance structure for X. From the model in (4)

$(X - \mu)\ (X - \mu)' = (Lf + \varepsilon)\ (Lf + \varepsilon)'$

$= (Lf + \varepsilon)\ \left((Lf) + \varepsilon'\right)'$

$= Lf(Lf)' + \ \varepsilon(Lf)' + Lf\varepsilon' + \varepsilon\varepsilon'$

so that

$= LE(ff'(L' + E(\varepsilon f')L' + LE(f\varepsilon') + E(\varepsilon\varepsilon')$

$= LL' + \psi$

According to (3) Also by independence

$Cov(\varepsilon, f) = E(\varepsilon, f') = 0$

Also, by the model in (4),

$$(X-\mu)f' = (Lf+\varepsilon)f' = Lff' + \varepsilon f'.$$

$$Cov(X,f) = E(X-\mu)f' = LE(ff') + E(\varepsilon f') = L.$$

2.3 Covariance structure for the orthogonal factor model

1. $Cov(X) = LL' + \psi$

or

$$Var(X_i) = \ell_{ij}^2 + \ldots \ell_{im}^2 + \psi_1 \qquad (5)$$

$$Cov(X_i, X_k) = \ell_{i1}\ell_{k1} + \ldots + \ell_{im}\ell_{km}$$

2. *Cov (X,F)=L*

or

$$Cov(X_i, F_j)) = \ell_{ij}$$

The model $X-\mu = LF+\varepsilon$ is linear in the common factors. If the p responses X are, related to underlying factors, but the relationship id nonlinear, such as in

$$X_1 - \mu_1 = \ell_{11}F_1F_3 + \varepsilon_1 X_2 - \varepsilon_1, X_2 - \mu_2 = \ell_{21}F_2F_3 + \varepsilon_2$$

and so forth, then the covariance structure

$LL' + \psi$ given by (5) may not be adequate. The very important assumption of linearity is inherent in the formulation of the traditional factor model. That portion of the variance of the ith variable contributed by the m common factors is called the ith communality. That portion of Var(Xi) = σ_{ii} due to the commonality by h_i^2, we see from (5) that

$$\frac{\sigma_{ii}}{Var(X_i)} = \frac{\ell_{i1}^2 + \ell_{i2}^2 + \ldots + \ell_{im}^2}{communality} + \frac{\psi_i}{specific\ var\ i\ ance}$$

or

$$h_i^2 = \ell_{i1}^2 + \ell_{i2}^2 + \ldots \ell_{1m}^2 \qquad (6)$$

and

$$\sigma_{ii} = h_i^2 + \psi_i, \quad i = 1,2,\ldots,p = \ell_{i1}^2 + \ell_{i2}^2 + \ldots \ell_{1m}^2$$

The ith communality is the sum of the square of the loadings of the variable on the m common factors.

2.4 Principal component analysis

Principal Component Analysis (PCA) is a data reduction technique that transforms high-dimensional data into a smaller set of components while retaining most of the information. It aims to reduce redundancy and multi-colinearity in data. PCA considers total data variance, generates factor loadings to express relationships between variables and factors, and seeks to find interpretable dimensions that explain the maximum variance, although these dimensions may not always be readily interpretable. It differs from factor analysis, as PCA is primarily a descriptive model of the data, while factor analysis is a structural model. Key terms in PCA include common variance, specific variance, communality, and factor loadings.

2.5 Exploratory factor analysis (Maximum Likelihood Estimation)

Factor analysis is a statistical technique used to uncover relationships among multiple variables. It can be used either exploratorily to find underlying structures or confirmatory to test predefined hypotheses about these structures. Exploratory factor analysis requires only the presence of correlations between variables, while confirmatory factor analysis involves testing the actual data structure against expected ones. The maximum likelihood method in factor analysis offers advantages such as assessing model fit, testing the significance of factor loadings, calculating inter-factor correlations, and determining confidence intervals for these parameters.

2.6 Factor rotation

After extracting factors in factor analysis, interpreting and naming these components based solely on factor loadings can be challenging. The primary criterion in principal component analysis is that the first factor accounts for the most variance, making it likely that most variables have high loadings on this factor and small loadings on others, complicating interpretation.

Factor rotation offers a solution to this challenge by altering the pattern of factor loadings, and improving interpretation. Imagine factors as axes in a graph where original variables load, and by rotating these axes, it's possible to create clusters of variables that load optimally.

Two types of factor rotation exist: orthogonal and oblique. This study employs the "Varimax" rotation, which falls under orthogonal rotation. The choice between the two depends on whether there's a theoretical basis for factors to be related or independent and how variables cluster on the factors before rotation.

2.7 Factor interpretation

Factor loadings are numerical values that indicate the strength and direction of a factor on a measured variable. Factor loadings indicate how strongly the factor influences the measured variable, to label the factors in the model, researchers examine the factor pattern to see which items load highly on which factors and then determine what those items have in common. Whatever the items have in common will indicate the meaning of the factor.

3.0 Data Illustration

The data used in this work as presented in Appendix I include all item inflation, food, all items less farm produce, all items less farm produce and energy data obtained from the CBN Statistical database from the period of 2003-2022.

3.1 Data Analysis

The scatter plot matrices show that there exists a correlation among the variables, further study and analysis will show whether there exists an underlying construct responsible for these correlations.

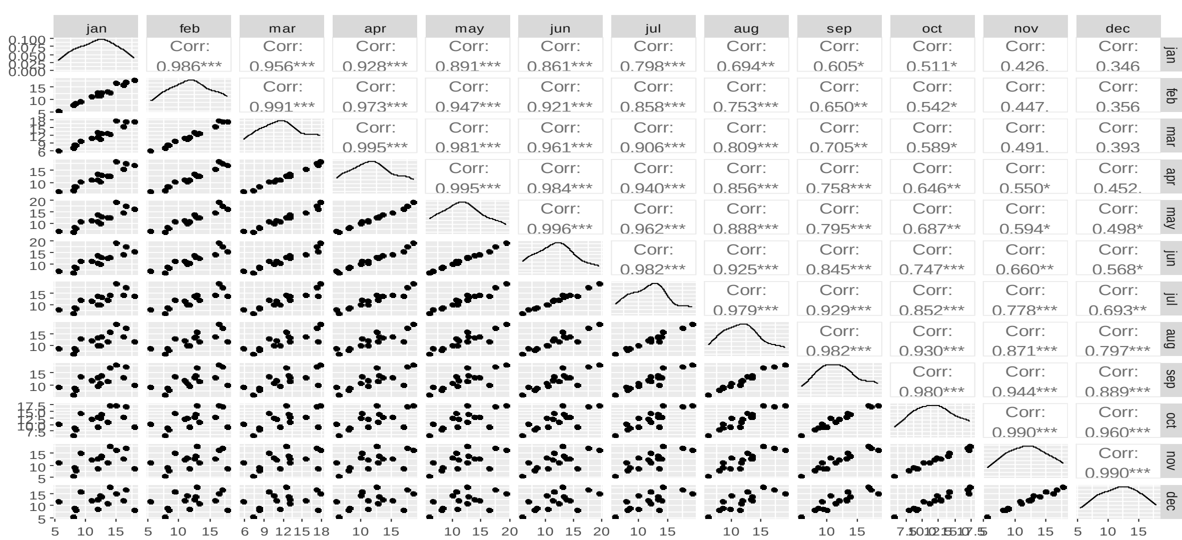

Fig. 1: Scatterplot matrix of the variables of the "all items" inflation.

Fig 2

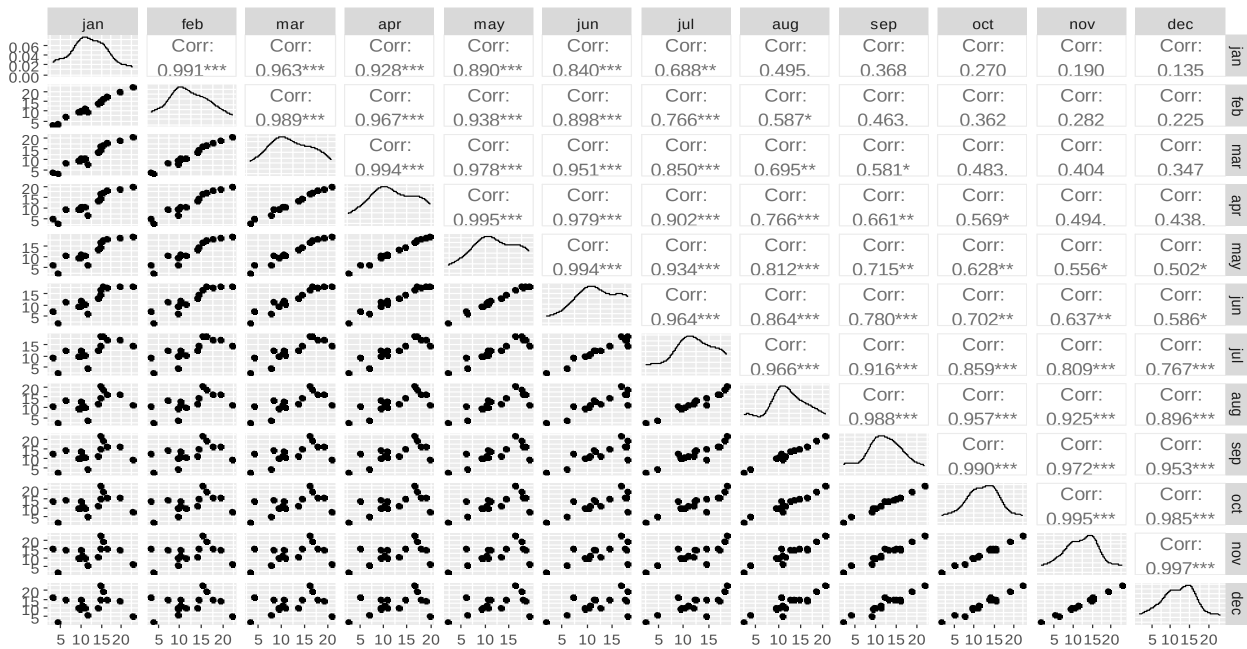

Fig. 2: Scatterplot matrix of the variables of the "food" inflation.

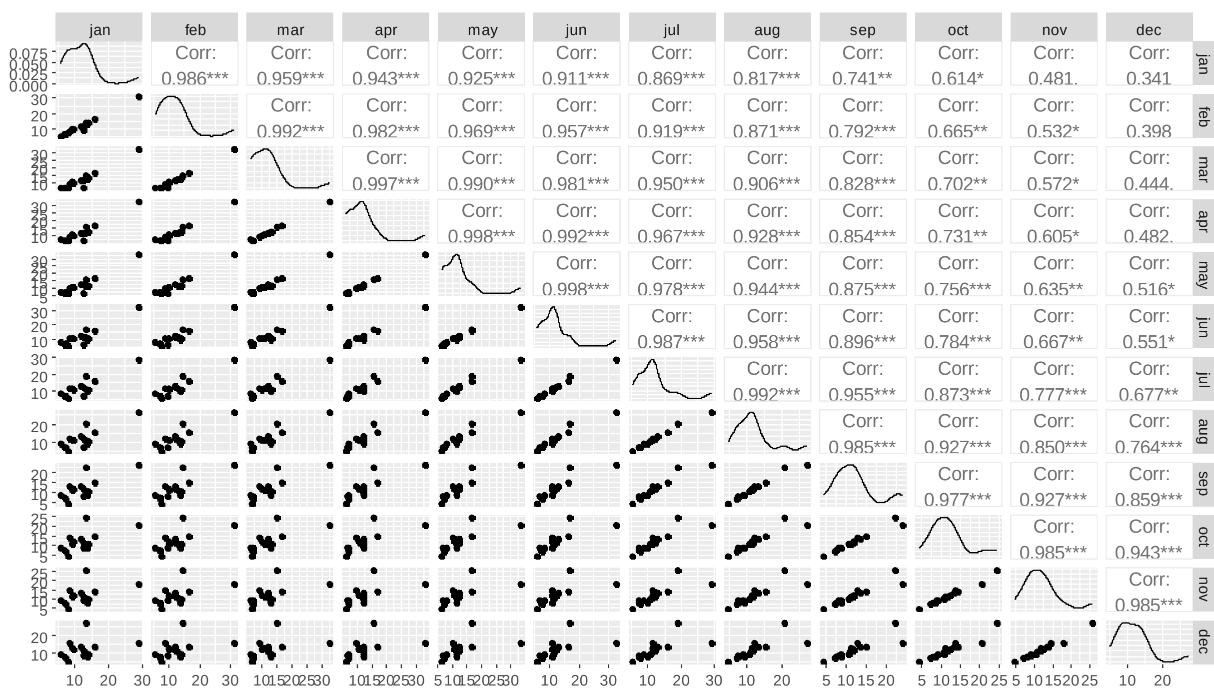

Fig. 3: Scatterplot matrix of the all items less farm produce inflation

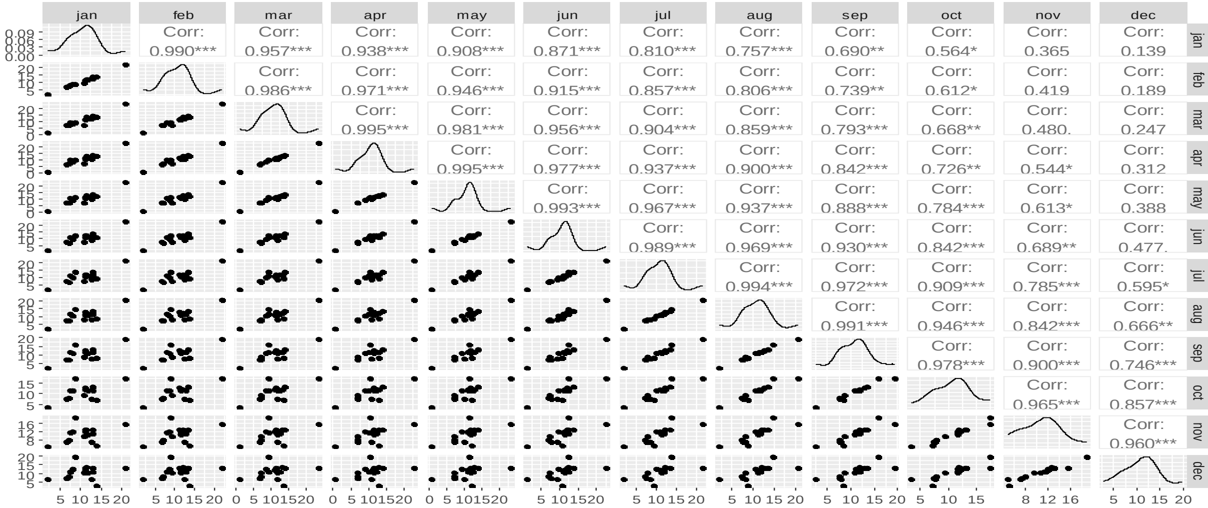

Fig. 4: Scatterplot matrix of the all items less farm produce and energy inflation.

Fig. 5, shows a scree plot for a situation with 12 components/factors, an elbow occurs in the plot at about I =3, this simply means that the eigenvalues after that are relatively small and about the same size. This means that without further evidence three factors/ principal components effectively summarize the total variance.

The result of the analysis displayed in Table 1 shows clearly that using both estimation methods, the variables January, February, March, and April define Factor 1 (high loadings on Factor 1, small or negligible loadings on other factors) while variables September., October., November. and December. define Factor 2 and lastly, variables May, June, July, August define Factor 3.

Result of Factor Analysis on All Items less Farm Produce Inflation

The result of the analysis displayed in Table 2 shows clearly that using both estimation methods, the variables Jan, Feb, March, and April define Factor 1(high loadings on Factor 1, small or negligible loadings on other factors) while variables September., October., November. and December. define Factor 2 and lastly, variables May, June, July, August define Factor 3.

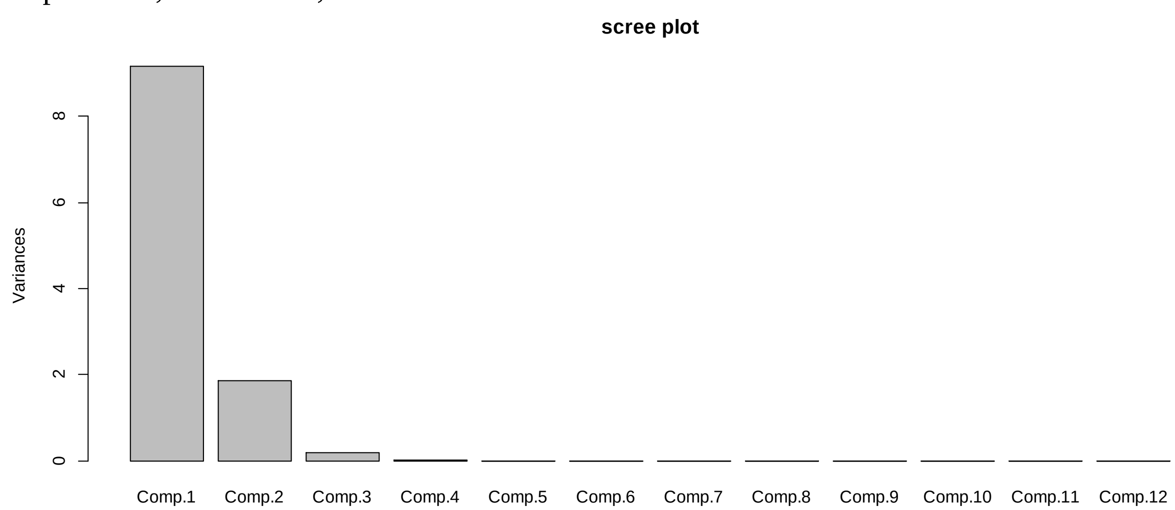

Fig. 5: Screeplot of the all items inflation

The result of the analysis displayed in Table 3 shows clearly that using both estimation methods, the variables January, February, and March define Factor 1(high loadings on Factor 1, small or negligible loadings on other factors) while variables November. and December. define Factor 2 and lastly, variables April, May, June, July, August, September and October define Factor 3.

Table 1: Result of factor analysis on food inflation

	Principal Component			**Maximum Likelihood**		
Variable	**Estimated rotated factor loadings**			**Estimated rotated factor loadings**		
	F_1	**F_2**	**F_3**	**F_1**	**F_2**	**F_3**
January	0.99	0.04	-	0.992		-
February	0.99	0.13	0.10	0.990	0.130	0.104
March	0.96	0.26	-	0.964	0.259	0.130
April	0.93	0.36	0.03	0.931	0.355	0.259
May	0.89	0.43	0.03	0.895	0.424	0.355
June	0.84	0.52	0.07	0.844	0.513	0.125
July	0.68	0.72	0.13	0.684	0.714	0.136
August	0.48	0.87	0.16	0.482	0.864	0.144
September	0.34	0.93	0.13	0.347	0.932	0.129
October	0.24	0.97	0.10	0.239	0.970	
November	0.15	0.99	0.06	0.155	0.987	
December	0.09	0.99	0.02		0.992	
			0.00			
			-			
			0.03			
Specific variances	0.51	0.48	0.01	0.515	0.473	0.008
Cumulative variance	0.51	0.99	1.00	0.515	0.989	0.997
	Principal Component			**Maximum Likelihood**		
Variable	**Estimated rotated factor loadings**			**Estimated rotated factor loadings**		
	F_1	**F_2**	**F_3**	**F_1**	**F_2**	**F_3**
January	0.99	0.04	-	0.992		-
February	0.99	0.13	0.10	0.990	0.130	0.104
March	0.96	0.26	-	0.964	0.259	0.130
April	0.93	0.36	0.03	0.931	0.355	0.259
May	0.89	0.43	0.03	0.895	0.424	0.355
June	0.84	0.52	0.07	0.844	0.513	0.125
July	0.68	0.72	0.13	0.684	0.714	0.136
August	0.48	0.87	0.16	0.482	0.864	0.144

September	0.34	0.93	0.13	0.347	0.932	0.129
October	0.24	0.97	0.10	0.239	0.970	
November	0.15	0.99	0.06	0.155	0.987	
December	0.09	0.99	0.02		0.992	
			0.00			
			-			
			0.03			
Specific variances	0.51	0.48	0.01	0.515	0.473	0.008
Cumulative variance	0.51	0.99	1.00	0.515	0.989	0.997

Table 2: **Result of factor analysis on all items less farm produce inflation.**

	Principal Component			**Maximum Likelihood**		
Variable	**Estimated rotated factor loadings**			**Estimated rotated factor loadings**		
	F_1	**F_2**	**F_3**	**F_1**	**F_2**	**F_3**
January	0.95	0.21	-	0.953	0.210	-
February	0.96	0.26	0.22	0.962	0.261	0.187
March	0.95	0.31	-	0.949	0.307	
April	0.93	0.35	0.07	0.932	0.348	
May	0.91	0.38	0.05	0.913	0.385	
June	0.89	0.43	0.09	0.891	0.426	0.131
July	0.81	0.56	0.11	0.813	0.565	0.152
August	0.74	0.66	0.12	0.735	0.666	0.135
September	0.62	0.78	0.11	0.618	0.781	0.127
October	0.45	0.89	0.10	0.450	0.891	
November	0.29	0.96	0.04	0.294	0.955	
December	0.15	0.99	0.00	0.147	0.985	
			-			
			0.01			
			0.02			
Specific variances	0.59	0.39	0.01	0.593	0.392	0.011
Cumulative variances	0.59	0.98	0.99	0.593	0.986	0.997

Table 3: Result of factor analysis on all items less farm produce and energy inflation

Variable	Principal Component Estimated rotated factor loadings			Maximum likelihood Estimated rotated factor loadings		
	F_1	F_2	F_3	F_1	F_2	F_3
January	0.98	0.12	-	0.976	0.127	-
February	0.98	0.17	0.16	0.982	0.175	0.120
March	0.97	0.24	-	0.966	0.235	
April	0.94	0.31	0.05	0.940	0.308	
May	0.90	0.39		0.903	0.388	0.134
June	0.86	0.48	0.08	0.855	0.480	0.178
July	0.77	0.60	0.07	0.774	0.601	0.192
August	0.71	0.67	0.07	0.709	0.677	0.193
September	0.62	0.76	0.05	0.624	0.761	0.192
October	0.47	0.87	0.03	0.473	0.872	0.162
November	0.26	0.96	0.00	0.257	0.963	0.102
December	0.02	0.99	-		0.995	
			0.01			
			-			
			0.03			
			0.01			
			0.03			
Specific variance	0.59	0.39	0.01	0.589	0.386	0.019
Cumulative variances	0.59	0.98	0.99	0.589	0.975	0.994

The result of the analysis displayed in Table 4 shows clearly that using both estimation methods, the variables January, February, and March define Factor 1(high loadings on Factor 1, small or negligible loadings on other factors) while variables October, November and December define Factor 2 and lastly, variables April, May, June, July, August and September define Factor 3.

Table 4: Result of factor analysis on all items inflation

Variable	Principal Component Estimated rotated factor loadings			Maximum likelihood Estimated rotated factor loadings		
	F_1	F_2	F_3	F_1	F_2	F_3
January	0.96	0.20	-	0.956	0.202	-
February	0.97	0.22	0.20	0.974	0.218	0.203
March	0.96	0.26	-	0.960	0.265	

April	0.93	0.33	0.04	0.931	0.332	
May	0.90	0.38	0.08	0.897	0.385	0.145
June	0.85	0.46	0.15	0.853	0.464	0.211
July	0.75	0.61	0.21	0.755	0.612	0.233
August	0.62	0.74	0.23	0.617	0.746	0.236
September	0.48	0.85	0.24	0.484	0.855	0.164
October	0.35	0.93	0.25	0.351	0.933	0.201
November	0.24	0.97	0.18	0.243	0.968	
December	0.15	0.98	0.07	0.144	0.980	
			0.01			
			-			
			0.06			
Specific variances	0.55	0.42	0.03	0.548	0.422	0.026
Cumulative variances	0.55	0.97	1.00	0.548	0.970	0.996

5.0 Conclusion

The study's findings reveal distinct underlying factors shaping inflation patterns throughout the year. These factors can be categorized into early-month, late-month, and middle-month influences. For food inflation, early months (Jan, Feb, March) exhibit one factor, late months (Sept, Oct, Nov, Dec) another, and middle months (May, June, July, August) a third. Similarly, all items less farm produce inflation follows a similar pattern. All items less farm produce and energy inflation share an early month factor, a late month factor involving Nov and Dec, and a middle month factor encompassing May to Oct. Lastly, all items inflation is characterized by an early month factor (Jan, Feb, March), a late month factor (Oct, Nov, Dec), and a middle month factor (May to Sept).The result of this study suggests that various types of inflation in Nigeria are influenced by covariance relationships among the months of the year, described by three factors: the early month factor, middle month factor, and late month factor. From previous findings, the central bank of Nigeria has been known to predict and measure the behavioural pattern of inflation on a quarterly or monthly basis, this study recommends that they calibrate and try applying this new multivariate approach for predicting the behavioral pattern of inflation in Nigeria to enhance in the planning for the nation's economic growth and inflation reduction.

6.0 References

Adam, C. J., Rebecca, I. J. & Morris, N. (2018). Development and Validation of the Couple Communication Satisfaction Scale. *American Journal of Family Therapy*, 46, 5, pp. 505- 524.

Adenekan, A.T. & Nwanna, G.A. (2004). Inflation dynamics in a developing economy: An error correction approach. *African Review of Money Finance and Banking, 2004*, pp. 77 –99. http://www.jstor.org/stable/23026294

Haley et al (1997). Exploratory and confirmatory factor analysis:

guidelines, issues, and alternatives. *Journal of Organizational Behaviour*, 18, 6, pp. 667-683.

Hassan, .S., Norlita, I., Wan, Y. W. J, Khadizah G, Kamsia . B, Darmesah . G & Asma, S.A.S (2012). Using factor analysis on survey study of factors affecting students learning styles. *International Journal of Applied Mathematics and Informatics*, 6, 1, pp. 33-40.

Jamal, A.M (2015). Motivations for Using Social Media. *International Journal of Psychological Studies*,7, 1 DOI:10.5539/ijps.v7n1p43

Knoke, J. D,, Smith, T. C., Gray, J. C., Kaiser, K. S, & Hawkworth A.W (2000). Factor Analysis of Self Reported Symptom: Does it Identify a Gulf War syndrome. American *Journal of Epidemiology*, 152, 4, pp. 379-388.

Masha, I. (2000): New Perspectives on Inflation in Nigeria.. *CBN Economic and Financial Review*, 38, 1, pp.34-56.

Nicholas. R, Rebecca. M & Steven J. K (2016). Utility of Factor Analysis in Optimization of Resident Assessment and Faculty Evaluation. *American Journal of Surgery*, 211, 6, pp. 1158-1163.

Okeke E. N, Okeke J. U, Yawe A, Anule J & Bello A (2017). Application of Factor Analysis on Academic Performance of Pupils. *American Journal of Applied Mathematics and Statistics*,5, 5, pp. 164-165.

Wenhua. L, Jingang. M, Lisako. E & Mckyer. J (2014). A Primer on Bootstrap Factor Analysis as Applied to Health Studies Research. *American journal of Health Education*., 45, 4 pp.199-204.

Compliance with Ethical Standards

Declarations

The authors declare that they have no conflict of interest.

Data availability

All data used in this study will be readily available to the public.

Consent for publication

Not Applicable

Availability of data and materials

The publisher has the right to make the data

Public.

Competing interests

The authors declared no conflict of interest.

Funding

There is no source of external funding

Authors' contributions

This paper is the outcome of collective endeavours by all authors. Involving participation in the literature review, analysis, interpretation of results, and manuscript writing.