Analyzing the Evolving Relationships among Climate Change, Insecurity, and Food Price Inflation in Nigeria: NARDL Approach

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ABSTRACT

The dynamics, scale, and direction of mediating relationships between climate change shocks, Insecurity and food price inflation has recently caught the attention of researchers and has become a subject of intense debate. Yet, studies differ on the type, scale, and evidence of the relationship between climate change shock, insecurity, and food price inflation. Thus, this study empirically investigates the affiliation between insecurity, climate change shocks and food price inflation in Nigeria. To achieve this objective, we adopted both Linear and Nonlinear Autoregressive Distributed Lag approach of cointegration analysis, with time series data spanning 2011M1-2022M12. The results show very strong evidence of a cointegrating relationships between insecurity, climate change shock and food price inflation in Nigeria. Both the ARDL and NARDL bound tests show that the variables of interest have symmetric and asymmetric long run relationships. We found that insecurity and climate change shock are significant determinant of heightened food prices in Nigeria within the study period. The Dynamic Multiplier graph with its accompanying 95 percent confidence interval for statistical inferences indicate that explanatory variables exert significant influence on the food price inflation in Nigeria. This study, therefore, recommends policy interventions to support households adversely impacted by insecurity in the affected zones. Also, the Nigerian state is encouraged to transit from traditional agricultural system to Climate-Smart Agriculture to meet future needs and climate related challenges.

Key words: Nigeria, Food Price Inflation, Insecurity, Climate Change, ARDL, NARDL.

INTRODUCTION

Significant strides have been recorded in the aftermath of the first Millennium Development Goal (MDG) aimed at eradicating global extreme poverty. However, concerns regarding food and nutrition security persist, especially in low-income countries in the Global South. Countries in Africa, such as Nigeria, South Sudan, Ethiopia, Libya, Burkina Faso, and Burundi, grapple with ongoing conflicts, civil unrest, and political instability, hindering substantial progress in sustainable development. Notably, a staggering 381.4 million out of 650.3 million chronically undernourished people in 2021 were from conflict-ridden countries, often exacerbated by climate-related shocks (Food and Agriculture Organization (FAO 2021), International Fund for Agricultural Development, United Nations Children's Fund, World Food Programme, and World Health Organization, (2021).

Additionally, according to FAO et al. (2017, 2021), three-quarters of children under the age of five who have stunted growth live in war-torn areas. Disruptions stemming from political instability, natural disasters, pandemics, and conflicts have profound adverse effects on social, economic, and human development (Von Einsiedel et al., 2017; Schillinger et al., 2020; Qayyum, Anjum, and Sabir 2021; Menton et al. 2021; Hamoodi 2021; Okunlola and Okafor 2020; George, Adelaja, and Awokuse 2021). The Sustainable Development Goals of the United Nations are also hampered by these disruptions, particularly those related to "No poverty (goal 1)," "Zero hunger (goal 2)," "Good health and well-being (goal 3)," "Responsible consumption and production (goal 12)," and "Peace, justice, and strong institutions (goal 16)." Research has indicated that armed conflicts, such as those involving the Fulani ethnic militia in countries like Nigeria, have significantly negative impacts on farm outputs, harvested areas, cattle holdings, and overall agricultural production (George, Adelaja, and Awokuse 2021).

The debate surrounding the link between insecurity, climate change shocks, and food price inflation has been fervent in the literature (FAO et al., 2022; Hendriks, et al., 2022; Day & Caus, 2020). This has led to global concern regarding access to food and the nutritional value of staple foods, particularly following the 2008-2009 food crisis and the subsequent global economic turmoil, which affected frontier economies like Nigeria. Nigeria faces the adverse impacts of climate change, posing significant challenges to various sectors of its economy, including agriculture, water resources, and infrastructure. Irregular rainfall patterns, prolonged droughts, increased flooding, and rising temperatures have resulted in reduced agricultural productivity, water scarcity, and environmental degradation (FAO et al., 2017). These effects worsen food insecurity and contribute to surging food prices, endangering the livelihoods of millions of Nigerians (Kralovec, 2020).

Additionally, Nigeria contends with multiple security challenges, including insurgency, terrorism, communal conflicts, and criminal activities. These security threats have far-reaching socio-economic consequences, including displacement, loss of life, crop failures, reduced yields, and livestock losses (George et al., 2021). In regions affected by insecurity, farming activities are disrupted, leading to reduced agricultural output, loss of livelihoods, and increased food insecurity. Conflict and violence also impede the efficient distribution of food, exacerbating issues related to food availability and affordability. The combination of climate change impacts and insecurity has contributed to significant food price inflation in Nigeria. Reduced agricultural productivity, disrupted supply chains, and increased production costs have resulted in decreased food supply and heightened demand, leading to higher food prices. The consequences of rising food prices disproportionately affect vulnerable populations, pushing them deeper into poverty, limiting their access to adequate and nutritious food, and exacerbating existing inequalities. Statistics reveal that around 48% of Nigeria's population lives below the poverty line (World Bank, 2020; World Poverty Clock, 2020). Consequently, comprehending the nature of these interconnected problems is paramount for crafting effective strategies and policies to mitigate their effects and ensure a sustainable future for Nigeria.

It's important to note that Nigeria is a suitable case study due to the culmination of these adverse impacts. The combination of climate change impacts and insecurity has contributed to significant food price inflation in Nigeria. Reduced agricultural productivity, disrupted supply chains, and increased production costs have led to decreased food supply and increased demand, resulting in higher food prices. Rising food prices disproportionately affect vulnerable populations, pushing them deeper into poverty, limiting their access to adequate and nutritious food, and exacerbating existing inequalities. These interconnected issues pose a threat to the well-being, stability, and development of the nation. Statistics show that around 48% of Nigeria's population lives below the poverty line (World Bank, 2020; World Poverty Clock, 2020. Therefore, understanding the nature of these problems is crucial for formulating effective strategies and policies to mitigate their impacts and ensure a sustainable future for Nigeria. Due to all these negative impacts, Nigeria is a suitable specimen to use as a case study.

The research aims to analyze the intricate relationships between climate change, insecurity, and food price

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inflation. It will also explore the scale of these phenomena as a key factor in their interactions. Additionally, the study will investigate how climate, insecurity, and food prices may exhibit both linear and non-linear relationships. A notable aspect to consider is the localized nature of these instabilities: local Nigerian markets are often insulated from global price fluctuations, various forms of insecurity are highly localized, and climate and environmental changes are predominantly experienced and adapted to at the local level. Factors such as disruption of supply chains, government interventions, pests and diseases outbreaks, reduced crop yield, subsistence farming, local varieties preference among other factors can influence the extent to which the local market is insulated from global price fluctuations. However, it's essential to note that while these factors can provide some insulation, they do not make the local market completely immune to global price fluctuations. Nigeria is part of the global economy and is affected by international factors like global food prices, exchange rates, and trade policies.

Following this introductory section, Chapter Two will delve into the background, while Chapter Three will provide a comprehensive review of the theoretical and empirical literature. Chapter Four will focus on the estimation and discussion of results. Finally, Chapter Five will summarize the findings, draw conclusions, and provide recommendations for addressing these critical issues in Nigeria.

METHODOLOGY

Model Specification

Following a theoretical exploration of eco violence, which examines the connection between environmental scarcities of essential renewable resources like cropland, fresh water, forests, and violent rebellions, insurrections, and ethnic clashes, the affiliation between insecurity, climate change shocks, and food price inflation in Nigeria is well clarified. The eco-violence theory is appropriate to analytically capture and explain the complex relationship between climate change, insecurity, and food price inflation in Nigeria, particularly in the context of shocks caused by climate change and herder-farmer conflicts in the country's northern and southern regions. The choice of the NARDL approach stemmed from the fact that the traditional linear regression models assume a linear relationship between the dependent and independent variables. However, many economic relationships exhibit non-linear behaviors, such as threshold effects, asymmetry, and non-monotonicity. The relationships between food inflation, climate change, and insecurity in Nigeria are likely to be complex and nonlinear. For example, extreme weather events caused by climate change could lead to both higher food prices and increased insecurity, but the relationship between these variables may not be straightforward. A NARDL model can capture these nonlinear relationships more effectively than a linear model.

Consequently, our model follows the following format in consistent with the theoretical framework of the study:

$$FPI = (RAIN, TEM, INS, INSC.) \qquad (1)$$

From the equation (1), FPI is the dependent variable while Rain and Tem (proxy for climate change) and Ins. and Insec. (Farmers herders' clashes (FH) and Bokoharam) represent explanatory variables. Thus, Equation (1) indicates that FPI is influenced by climate change and insecurity.

In addition, studies have noted that certain controlled variables also influence food price inflation. Such variables are Premium Motor Spirit (PMS) proxy for the cost of transportation (Ogunbodede et al, 2010; Eregha et al., 2016; Orlu, 2017) and Trade Openness Trade, calculated as Import + Export/ GDP is a traditional measure of trade liberalization or openness (Evans, 2007; Cooke, 2010; Zakaria, 2010; Jafari Samimi et al., 2011; Mukhtar, 2010; Wynne and Kersting, 2007; Hanif and Batool, 2006; Romer, 1993).

Nigeria's open economy warrants the inclusion of trade openness, and Lee et al. (2021) have similarly claimed that 38% of the economies with open economy policies experienced currency appreciation and inflationary pressure. The inclusion of other forms of insecurity (INSc) proxy by Boko haram terrorist group into the model is for robust check.

With the controlled variables, the equation (1) with log, can be rewritten as:

InFPI = (InRAINF, InTEM, InINS, InINSc, IN OPEN, InPMS) (2)

Expressing equation (2) in a linear form and including the constant term, the stochastic error term and the logarithm form of the model, equation two is transformed to become:

$$(\boldsymbol{InFPI_t}) = \boldsymbol{\emptyset_0} + (\boldsymbol{In\delta_1 INS}) + (\boldsymbol{In\emptyset_2 OPEN_t}) + (\boldsymbol{In\emptyset_3 PMS_t}) + (\boldsymbol{In\emptyset_4 RAINF_t} + \boldsymbol{In\emptyset_5 INSc_t}) + \boldsymbol{In\emptyset_6 TEM_t} + \boldsymbol{\varepsilon_t} \quad (3)$$

Where FPI is the log of food price inflation (as the dependent variable), INS. is the log of insecurity (FH); INSc is the log of other insecurity concerns in Nigeria (Proxy by Bokoharam). OPEN is the log of trade openness; PMS is the log of premium motor Spirit (proxy for transportation cost); RAIN signifies average log of rainfall (proxy for climate change) and TEM represents mean log of temperature (proxy for climate change).

The Autoregressive Distributed Lag (ARDL) is adopted and is in the form of Unrestricted Error Correction Model (UECM) to decompose the total effect of a variable into its short and long-run components, and Non-Linear Autoregressive Distributed Lag (NARDL). The NARDL is applied to examine the asymmetric negative and positive responses of Food Price Inflation (FPI) to Insecurity and Climate Change shocks and to analyze the asymmetric short, long relationships between Food Price Inflation, Insecurity and Climate Change in Nigeria.

The general ARDL model which measures and capture the objective of the study is specified thus:

$$\begin{aligned}\Delta LFPI_{it} = a_{oit} &+ \sum_{i=o}^{k} \emptyset_{1it}\, \Delta LINS_{it} + \sum_{i=o}^{k} \emptyset_{2it}\, \Delta LRAINF_{it} \sum_{i=o}^{k} \emptyset_{3it} \Delta LTEM_{it} + \sum_{i=0}^{K} \emptyset_{4it}\, \Delta LOPEN_{it} \\ &+ \sum_{i=o}^{k} \emptyset_{5it}\ \Delta LPMS_{it} + \sum_{i=o}^{k} \emptyset_{6it}\, \Delta LINSc_{it} + \gamma_{1it}\, LFPI_{1it} + \gamma_{2it}\, LINS_{it} + \gamma_{3it}\, LRAINF_{it} \\ &+ \gamma_{4it}\, LTEM_{it} + \gamma_{5it} LOPEN_{it} + \gamma_{6it} LPMS_{it} + \gamma_{7it}\, LINSc_{it} \\ &+ \mu_{it} \qquad (4)\end{aligned}$$

Where, (ΔFPI and LFPI) are the dependent variables in first differences and levels, and (ΔINS,ΔRAINF, ΔINSc, ΔTEM, ΔOPEN and ΔPMS, and LINS,LRAINF, LINSc, LTEM and LPMS, LOPEN) are the independent variables in the model in first difference and levels. Indeed, the a_{oit} is the intercept, $\emptyset_{1it \ldots \emptyset_{5it}} \ldots \gamma_{1it} \ \ldots . \gamma_{7it}$ are the parameters of variables and μ_{it} is the error term of the model.

Additionally, by extending the ARDL method of Pesaran and Shin (1999) and Pesaran, Shin, and Smith (2001) in equation 4, we created a parametric dynamic model for combined long-run and short-run asymmetries; as a result, the nonlinear form of the ARDL model is specified as follows:

$$\Delta FPI_{it} = a_{oit} + \sum_{i=o}^{k} \emptyset_i^+ \Delta LINS_{t-1}^{+} + \emptyset_i^- \Delta LINS_{t-1}^{-}$$
$$+ \sum_{i=o}^{k} \emptyset_i^+ \Delta LTEM_{t-1}^{+} + \emptyset_i^- \Delta LTEM_{t-1}^{-} \sum_{i=0}^{K} \emptyset_i^+ \Delta LOPEN_{t-1}^{+} + \emptyset_i^- \Delta LOPEN_{t-1}^{-}$$
$$+ \sum_{i=o}^{k} \emptyset_i^+ \Delta LPMS_{t-1}^{+} \emptyset_i^- \Delta LPMS_{t-1}^{-} + \sum_{i=o}^{k} \emptyset_i^+ \Delta LRAINF_{t-1}^{+} \emptyset_i^- \Delta LRAINF_{t-1}^{-}$$
$$+ \sum_{i=o}^{k} \emptyset_i^+ \Delta INSc_{t-1}^{+} \emptyset_i^- \Delta INSc_{t-1}^{-} + \gamma_{1it} LFPIit + \gamma_i^{+} LINS_{t-1}^{+} + \gamma_i^{-} LINS_{t-1}^{-}$$
$$+ \gamma_i^{+} LTEM_{t-1}^{+} + \gamma_i^{-} LTEM_{t-1}^{-} + \gamma_i^{+} LOPEN_{t-1}^{+} + \gamma_i^{-} LOPEN_{t-1}^{-}$$
$$+ \gamma_i^{+} LPMS_{t-1}^{+} + \gamma_i^{-} LPMS_{t-1}^{-} + \gamma_i^{+} LINSc_{t-1}^{+}$$
$$+ \gamma_i^{-} LINSc_{t-1}^{-} + \gamma_i^{+} LRAINF_{t-1}^{+} + \gamma_i^{-} LRAINF_{t-1}^{-} + \mu_{1it} \quad (\mathbf{5})$$

Where, (ΔFPI and LFPI) are the dependent variables in first differences and levels, and ($\Delta INS_{t-1}^{+}, LINS_{t-1}^{-}, \Delta TEM_{t-1}^{+}, LTEM_{t-1}^{-}, \Delta OPEN_{t-1}^{+}, LOPEN_{t-1}^{-}, \Delta LPMS_{t-1}^{+} LPMS_{t-1}, \Delta INSc_{t-1}^{+}, LINSc_{t-1}^{-}, \Delta RAINF_{t-1}^{+}, LRAINF_{t-1}^{-}$)

are the positive and negative asymmetries, and the independent variables in the model in levels and first-difference. Then, the a_{oit} is the intercept, while $\emptyset_i^+ \ldots \emptyset_i^- \ldots . \gamma_i^{+} \ldots \gamma_i^{-}$ are the positive and negative parameters of asymmetries, and μ_{1it} is the error term of the model.

Stability Test

To prevent spurious outcome, any model should go through a stability verification check, according to Brown, Durbin, and Evans (1975). They recommended using both the cumulative sum (CUSUM) and cumulative sum of square (CUSUMSQ) on the recursive regression residual. The plots must fall within the 5% critical bounds of significance to accept the model's stability. In the CUSUM and CUSUMSQ analysis, both use the cumulative sum of recursive residual as their foundation. The first set of n observations, which is updated recursively and plotted against the breakpoints, serves as the foundation for this model.

Diagnostic Test

It is anticipated that the study will run diagnostic tests on the model to determine whether serial correlation and a heteroscedasticity test are present. The presence of serial correlation is the null hypothesis for the serial correlation test, whereas the model's heteroscedasticity is the null hypothesis for the heteroscedasticity test. If the null hypothesis fails in both tests, the model is likely well-specified, does not have serial correlation issues, and is determined to be homoscedastic.

ESTIMATION AND DISCUSSION OF FINDINGS

Descriptive Analysis

The descriptive portion of the analysis, which deals with the behaviors of the variables prior to estimation, is covered in this section. The observation of data is crucial to economic modelling. It aids in overcoming the problem of erroneous regression brought on by outliers and an abnormal data distribution.

Table 3.1 Descriptive test

	FPI	INSECURITY	INSECURITYc	PMS	RAINFALL	TEM	OPEN
Mean	14.21	78.71	47.09	25.51	37.9	27.69	53.28
Median	13.42	80.69	48.51	14.52	31.5	27.48	49.78
Maximum	24.13	15.38	10.09	19.01	30.1	30.77	96.55
Minimum	7.88	10.98	27.24	65.1	35.8	27.23	10.26
Std. Dev.	4.33	41.25	33.71	35.55	74.2	0.58	20.89
Skewness	0.52	0.15	0.14	-0.07	3.5	2.57	0.30
Kurtosis	2.08	1.73	1.9	1.83	27.9	10.16	2.04
Jarque-Bera	11.52	9.26	7.49	8.27	40.8	46.04	7.74
Probability	0.00	0.78	0.02	0.03	0.0	0.00	0.02
Sum	20.35	11.3	39.81	18.35	53.5	39.88	76.40
Sum Sq. Dev.	26.04	30.43	25.81	18.32	16.1	48.80	60.50
Observations	144	144	144	144	144	144	144

Source: Author's Computation 2023

Table 3.1 provides a summary of the raw data for the model after applying the natural logarithm transformation to all variables, a technique recommended by Wooldridge (2018) to achieve a normal distribution of the data. The Jarque-Bera probability values, which are notably greater than the 0.05 significance level (approaching zero), indicate that the variables have indeed achieved a state of normal distribution. This characteristic is also evident in the kurtosis and skewness measurements of the variables.

Most variables exhibit a kurtosis value of less than three (3), which suggests that they fall within the normal distribution range – not too peaked and not too flat. It is noteworthy that most variables display positive skewness, except for PMS. Furthermore, the close alignment between the mean and median values across different variables provides strong evidence for the normal distribution of the data, as noted by Holmes, Illowsky, and Dean (2017).

The similarity between the mean and median values also supports the assertion that our sample size is sufficiently large, minimizing bias in the variance of our model. Additionally, the maximum and minimum values do not qualify as outliers, as they remain within a close range of the respective variable being observed. To ensure interpretable and valid regression results, it is crucial to emphasize that this study employed natural logarithm-transformed data, as recommended by Ogun (2021) and Wooldridge (2018).

Graphical Analysis

The graphical analysis is required to provide a preliminary visual preview of all the parameters intended for evaluation. In time series, this is known as an eyeball test. Early information about the behavior of the parameters under investigation is provided by the graphical plot below.

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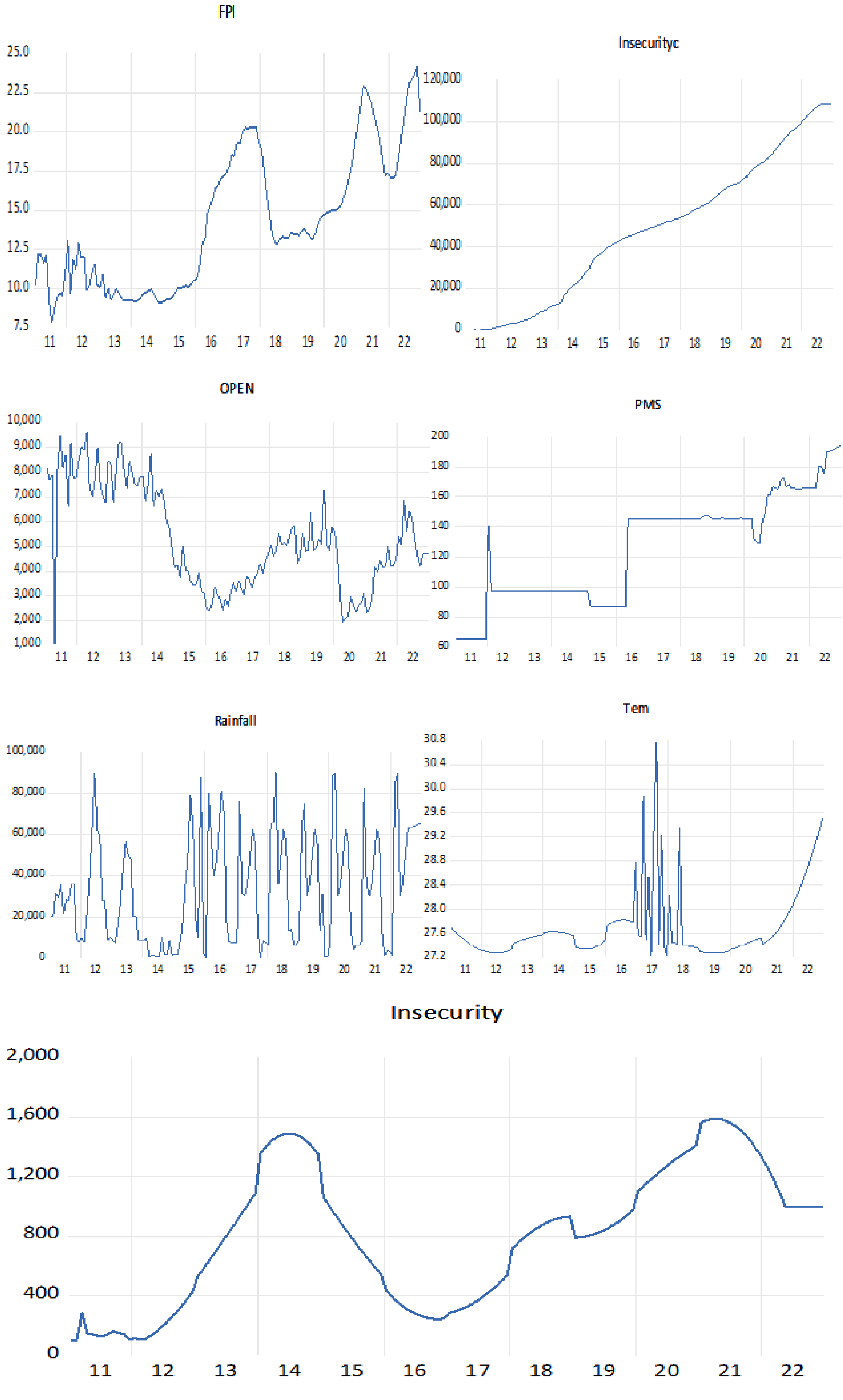
Figure 3.1: Trend Analysis of the Variables



Source: Author's Computation 2023

Figure 3.1 shows graphical plots for the variables under observation for the pretesting analysis. In empirical research, graphic plots like scatter plots, box plots, pie charts, line charts, histograms, and others are crucial. It gives an interested reader a summary, or better yet, an understanding and insight into the relevant data. Substantial amounts of numerical data can be displayed and summarized using this method, and it is essential for highlighting patterns, trends, and the relationships between various variables over a predetermined time frame. The variables' graphical representations in figure 3.1 above demonstrate that the parameters exhibit trend and differing degrees of volatility, necessitating additional testing to determine their stationarity.

Unit Root Test

Before performing a cointegration analysis, it is crucial to verify that each variable is stationary. If the data set is not stationary, the regression analysis may produce spurious results (Gujarati & Porter, 1999). No single indicator must be I (2) according to the bounds testing approach; however, mixtures of 1(1), 1(0), or mixture of 1(1) and I(0) integration orders are acceptable. The results of these tests using Dickey Fuller-Generalized Least Square (DF-GLS) and Phillip-Perron (PP) are shown in Tables 3.2 at both levels and the first difference.

Table 3.2: NARDL PP and DF-GLS Test for Unit Roots

Variables	Phillips-Parron		Remarks	ADF-GLS (1^{St} Difference)		Remarks
	Levels	1^{st} Difference	Order of Integration	Levels	1^{st} Difference	Order of Integration
InFPI	-1.231749	-10.81644***	1(1)	-1.393710	-3.36598***	1(1)
InINS	-0.193107	-12.05465***	1(1)	-2.389895	-4.05388***	I(1)
InINSc	-1.488828	-5.476220***	1(1)	-0.399162	-3.548029**	1(1)
InTEM.	-2.653902	-7.008321***	1(1)	-0.057923	-2.728692*	I(1)
InRAINF	-9.90826 ***	-1.07614	1(0)	-9.103576***	-1.046858	I(0)
InOPEN	-4.209180***	-2.31589***	1(0)	-4.311894***	-1.1349***	1(0)
InPMS	-1.176867	-16.23418***	1(1)	-0.143379	-7.75669***	1(1)

Source: Author's Computation

Note:

1) Truncation lag for DF-GLS is based on the Schwert criterion

2) Truncation lag for Phillips-Perron is based on the Newey-West bandwidth

3) *, ** and *** denote 1%, 5% and 10% significant levels, respectively

The Schwarz Information Criterion (SIC) for optimum lag order and Newey-West bandwidth were used to evaluate the Dickey Fuller–Generalized Least Square (**DF-GLS)** and Phillip-Perron (**PP)**. The unit root property of the parameters of the model were examined with the inclusion of intercepts component in the test equations at both levels and first difference. The tests signify that the variables have a mixed integration order, like I(1) and I(0) respectively. The estimated figures of most of the parameters contained in the **Table 3.2** above demonstrates that the coefficients are stationary at first difference, at 5% significant level and integrated at order 1(1) except Rainfall and Trade Openness variables which are stationary at levels for both tests. The mixture status of the stationarity of the estimated variables is a justification for the adoption of symmetric (ARDL) and asymmetric (NARDL) analysis to ascertain the existence of both symmetric and asymmetric long-run relationships or otherwise of the parameters, negative and positive shocks of the variables, as well as the Wald test to validate the cointegration status of the parameters.

Model Estimation

Table 3.3: Short Run Symmetric Autoregressive Distributive Lag Model (ARDL) Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
FPI(-1)	0.624	0.025	24.47	0.000
INS	0.004	0.032	1.266	0.328
INSc	0.212	0.176	1.204	0.653
OPEN	0.171	0.086	1.982	0.049
PMS	0.026	0.006	4.285	0.000
TEM	-0.044	0.007	-6.229	0.000
RAIN	0.024	0.008	2.953	0.003
C	0.014	0.006	2.337	0.021
CointEq(-1)*	-0.735	0.028	-5.344	0.000

Notes: ***, ** and * indicates statistical significance level at 1%, 5% and 10% level respectively

R- Squared =0.988   Adjusted R-Squared = 0.976

F-Statistic = 460.44   Probability (F-Stat) = 0.0000

Durbin -Waston Statistic: 2.1

As contained in table 3.3 above, the short run symmetric result of ARDL show that the overall significance of the model is demonstrated by the F-Statistic value of **460.44**, which is way above the rule of thumb, put at two (2). The R-Squared of 0.988 indicate that the variations in the model between the dependent and the explanatory parameters is explained to the tune of about 99%, meaning that the model is fit and well specified. It also shows that it does not suffer from serial correlation problem with DW Statistic value of 2.1. In the short run, all the estimated coefficients are statistically different from zero and complied with expected signs except insecurity, though positive but not significant. The results show that a 1 per cent increase in the Farmers herder's clashes will increase food inflation by 0.004 per cent in the short run. Similarly, food price inflation will go up by 0.212 per cent if other forms of insecurity increase by 1 per cent in the short run. The impact of climate change shock on food price inflation is significantly obvious in the short run as both variables proxy for climate change (Tem and Rain) are statistically significant. While a 1 per cent increase in Rain will increase food price inflation by 0.024 per cent, the result also show that food price inflation will reduce by -0.044 if Tem increases by 1 per cent. On the controlled variables, result show that both PMS and OPEN are statistically significant and positive. A 1 per cent increase in the petroleum motor spirit (proxy for cost of transportation) tend to increase food price inflation by 0.026 per cent. Similarly, Trade openness also affect food price inflation in Nigeria as a 1 per cent increase in trade openness will attract 17 per cent rise in the food price inflation basket in the short run.

The findings also reveal that the error correction term (ECT) is not only negative but statistical significance. Its absolute value falls within the range of zero to one, in line with the principles of error correction. This suggests a long-term convergence between food price inflation, climate change, and insecurity. In other words, if an external shock is introduced into the model in the preceding month, it will gradually converge over time. However, the coefficient for the error correction term (ECT) is estimated at -0.735, which translates to 74%. This indicates that the food price inflation's adjustment speed, following an initial shock from the previous month, will correct and converge by about 74% in the current month eventually.

Table 3.4: Long Run Symmetric Autoregressive Distributive Lag Model (ARDL) Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INS	0.175	0.075	2.352	0.021
INSc	0.031	0.014	2.223	0.028
OPEN	0.025	0.007	3.810	0.000
PMS	0.047	0.008	6.193	0.000
TEM	0.122	0.139	0.882	0.380
RAIN	0.028	0.008	3.372	0.001
C	-0.217	0.105	-2.057	0.042

Notes: ***, ** and * indicates statistical significance level at 1%, 5% and 10% level respectively

In the long-run, we observe that all estimated variables are statistically significant and comply appropriately with the expected signs. The results suggest that a 1 per cent increase in the level of insecurity (farmer herder's clashes) will increase food price inflation by about 18 per cent, while a 1 per cent rise in boko haram will also raise the food price inflation by 0.031 per cent. Our findings are in line with the results of extant studies showing that violent conflicts reduce agricultural production and food security which will in turn increase food prices (Arias, Ibá˜nez, and Zambrano, 2019; Brück, d'Errico, and Pietrelli,2019; George, Adelaja, and Weatherspoon 2020; George, Adelaja, and Awokuse 2021; Adelaja and George 2019).

The findings from the long-term analysis also indicate that a 1 percent rise in the average temperature (used as a proxy for climate change) is projected to lead to a 12 percent increase in food price inflation. Furthermore, there is an observed trend where food price inflation rises by 0.028 percent for every 1 percent increase in rainfall levels in the country. These findings are consistent with earlier studies conducted by organizations like the Food and Agriculture Organization of the United Nations in (FAO 2019) , Hendrix and Haggard (2015), Kreidenweis et al. (2016), and Stevanovi et al. (2016), all of which came to the same conclusion that climate change has a long-term effect on raising food prices.

Similarly, the results of the controlled variables are statistically significant and positive, suggesting that food price component of the inflation basket tend to rise by 0.047 per cent with a 1 per cent increase in the PMS (Proxy for transportation cost). This follows the studies done by (Ogunbodede et al, 2010; Eregha et al., 2016; Orlu, 2017) on the positive relationship between food prices and cost of transportation in Nigeria. Similarly, a 1 per cent increase in Trade Openness (OPEN) tend to increase food price inflation by 0.025 overall. This result is consistent with the following studies Thomas, 2012; Neeraj et. al., 2014; Taufeeq et. al., 2016; and Zakaria, 2010) who found positive relationships between inflation and openness. Meanwhile, there are other studies that have found negative relationships between inflation and trade openness (Joshi and Acharya, 2010; Samimi et al., 2012).

ARDL Bound Test

As previously mentioned, the ARDL model approach is used to estimate the long-term relationship between the variables in two stages. The bounds test is used in the first stage to determine whether a long-run relationship exists. The upper bound critical values at 5% or 10% must be greater than the bounds test F-statistic. This result is presented in table 3.5 below:

Table 3.5: Symmetric Bound Test

MODELS	**K**	**F-Statistic**	**Lower Bound Critical Value 5%**	**Upper Bound Critical Value 5 %**
InFPI=f(lnINS,lnINSc,InOPEN,InPMS,InRAIN,TEM)	4	6.2546	2.39****	3.38****

Note *, **, *** and **** represent 10, 5, 2.5 and 1% level of significance respectively.

The table 3.5 above shows that the result affirms that the F-statistic critical values (6.2546%) as observed above is higher when compared with the (Pasarant et al, 2001) critical value at the lower and upper bounds (1%, 5%, and 10% respectively). Based on the results, we found convincing evidence of cointegration between climate change (rainfall and temperature) insecurity (Farmers' herders clashes, Bok haram) and food price inflation. The result submit that the targeted variables (climate change and insecurity) have contributed positively to the rising food price inflation in Nigeria within the study period. The implication is that the contribution of these variables can never be overemphasized, apart from being symmetric in nature, it has also shown over the years to have significant impact on the rising cost of the food components in the inflation basket in the country.

Nonlinear ARDL Analysis

The Nonlinear Autoregressive Distributed Lag (NARDL) approach is utilized when dealing with variables that may have different order of integration characteristics, including being integrated of order 1(0)) or 1(1)), or a combination of both. This method effectively addresses issues related to endogeneity and serial correlation, while also accommodating potential asymmetry in the explanatory variables in line with the studies of Foye, Adedeji, and Babatunde (2020) and Pesaran and Shin (1999).

If a long-run relationship between the variables in each model is present, it can be determined using the NARDL bounds test methodology. In Nusair's work (2016), the advantages and implications of using NARDL are extensively covered and documented.

According to the findings in table 3.6, there is a dynamic nonlinear relationship between insecurity, climate change, and rising food prices. The estimated result demonstrates that over the long run, all of the variable shocks both positive and negative are statistically different from zero.

Table 3.6: Long Run Asymmetric Autoregressive Distributive Lag Model (NARDL) Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.235	0.114	-2.062	0.042
INS^+	0.189	0.076	2.488	0.015
INS^-	-0.024	0.006	-3.786	0.000
$OPEN^+$	0.257	0.125	2.052	0.043
$OPEN^-$	-0.047	0.008	-6.159	0.00
PMS^+	0.206	0.107	1.923	0.057
PMS^-	-0.170	0.072	-2.356	0.020
$RAIN^+$	0.026	0.006	4.462	0.000
$RAIN^-$	-0.028	0.008	-3.307	0.001

TEM^{+}	0.017	0.009	1.967	0.052
TEM^{-}	-0.278	0.072	-3.855	0.000
$INSc^{+}$	0.103	0.014	7.357	0.003
$INSc^{-}$	-0.008	0.115	-0.070	0.944

Notes: ***, ** and * indicates statistical significance level at 1%, 5% and 10% level respectively

The result in table 3.6 shows that the increasing shock in rainfall is positive and statistically significant at 1%. Similarly, the decreasing shock in rainfall is also statistically significant and have negative effect on the price inflation. This means that a 1% increase in rainfall will cause an increase of about 0.026 per cent increase food price inflation. Importantly, the negative shock for rainfall will generate a huge rise in the food price inflation as a 1per cent increase in rainfall will increase the food price inflation by 0.028 per cent. The results suggest that a negative shock may exert significant negative impact on food price inflation than the positive shock. The impact of climate change through excessive and shortage of rainfall and heat as captured in the result show that both positive and negative shock of climate change variables affect food price inflation in Nigeria. This may not be unconnected with the fact that scarcity of water through inadequate rainfall and excess rainfall may affect crop production and cause more food scarcity thereby leading to hike in food items. Studies have confirmed that extreme climatic conditions such as desertification, heavy rainfall, and flooding have significantly detrimental impacts on food production (Tirado et al., 2010; Wossen et al., 2018; Uwazie, 2020). Similarly, the results also suggest that a 1 per cent increasing shock in mean temperature will result to 0.017 per cent increase in the food price inflation while a 1 per cent negative shock in mean temperature will also increase food price inflation by -0.278 per cent. The results suggest that rainfall and temperature demonstrate significant impact on food price inflation. Climate change causes long-term increases in food price inflation, according to studies by the Food and Agriculture Organization of the United Nations (2019), Hendrix and Haggard (2015), Kreidenweis et al. (2016), and Stevanovi et al. (2016). These findings are consistent with our results which show a clear relationship between food prices and climate change shocks in Nigeria.

In case of the insecurity variables, both the shocks from Boko haram and the farmer's herders' clashes are statistically significant as shown in the results. The results show that a 1 per cent positive shock in insecurity (FH) will raise food price inflation by 0.189 per cent while a 1 per cent negative shock in insecurity (FH) will reduce food price inflation by -0.024 per cent in the country. For robust check and to test the impact of other security concerns on food price inflation, we factored in the impact of Boko haram menace on food prices, the result proved to be significantly different from zero. Specifically, a 1 per cent positive shock in Boko haram in the country will lead to 0.103 per cent increase in food price inflation in the country. Similarly, a 1 per cent negative shock in Boko haram will increase food price inflation by about -0.008 per cent. Our findings harmonize with existing studies that demonstrate how violent conflicts diminish agricultural productivity, reduce food availability, and drive up food prices, as evidenced by the works of Arias, Ibáñez, and Zambrano (2019); Brück, d'Errico, and Pietrelli (2019); George, Adelaja, and Weatherspoon (2020); and George, Adelaja, and Awokuse (2021), as well as Adelaja and George (2019).

The control variables in the model including Trade Openness and PMS (Proxy for transportation cost) are statistically significant. For the PMS, a 1 per cent positive shock will increase food price inflation by 0.206 per cent while a 1 per cent negative shock will reduce food price inflation by -0.170 per cent. This is premised on the fact that the economy of Nigeria revolves around the petroleum industry and prices of petroleum products have had a contagious effect on the prices of goods and services. This finding is in line with Al-Maadid et al., 2017; Kumar et al ,2017; Gozgor and Kablamaci, 2014; Nazlioglu and Soytas (2012) who found significant positive relationship between food prices and PMS. However, the studies of (Siami-Namini and Hudson, 2017; Wang et al., 2014; Nazlioglu and Soytas, 2011) showed that pump price

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variability did not affect food prices.

The result for trade openness suggests that a I per cent increasing shock tend to raise the food price inflation by 0.25, while a 1 per cent negative shock tend to increase food price inflation by 0.047 per cent. This result is consistent with the findings of Kim et al., 2012; Alfaro, 2005; Kim and Beladi, 2005; and Zakaria, 2010) who established that trade openness causes inflationary pressure especially for import dependent countries like Nigeria. The results disagree with studies of (Sachsida et al., 2003; Romer, 1993; Gruben and McLeod, 2004; Muellbauer, 2007; and Kim et al., 2012) which postulated a negative relationship between trade openness and inflation. The result also confirmed the significant impact of external factors of inflation and their filtering effects on the domestic factors through processed food and core items on the headline inflation. Consequently, any factor and events that causes change to either food or core inflation and/or both will impact on headline inflation. These findings, therefore, confirmed Doguwa and Alade (2013) that there is element of imported inflation in Nigeria. Nigeria's food import has been piling more pressure on the food index in recent times, following the fallout of the Russia-Ukraine war and other domestic factors.

Table 3.7: Asymmetric Bound Test

Model	**k**	**F-Statistic**	**Lower Bound Critical Value 5%**	**Upper Bound Critical Value 5 %**
InFPI=f(lnINS,lnINSc,InOPEN,InPMS,InRAIN,TEM)	3	6.5422	2.25****	3.35****

Note *, **, *** and **** represent 10, 5, 2.5 and 1% level of significance, respectively.

Table 3.7 confirmed the presence of a co-integrating relationship among the variables using the NARDL bounds test. To establish a long-run relationship, it is essential for the F-statistic to exceed the 5 per cent critical values for both the lower and upper bounds. In this instance, the F-statistic stands at 6.5422, surpassing the lower bound of 2.25 and the upper bound of 3.35. This result indicates that the variables (INS, INSc, TEM, RAIN, OPEN, PMS) exhibit a long-run asymmetric relationship with food price inflation.

In the short run, all the variables in their positive and negative forms are statistically significant except the negative shocks in TEM. The outcome indicate that climate change, insecurity, and food price inflation exhibit a dynamic nonlinear relationship in Nigeria within the period under investigation.

Table 3.8: Short Run

Variables	Coefficient	Std. Error	t-Statistic	Pro.
FPI(-1)	0.413	0.070	5.855	0.000
INS+	0.027	0.006	4.313	0.000
INS-	-0.013	0.003	-3.724	0.003
PMS+	0.011	0.004	2.426	0.017
PMS-	-0.007	0.003	-2.608	0.010
OPEN+	0.027	0.006	4.364	0.000
OPEN-	-0.044	0.007	-6.054	0.000
RAIN+	0.413	0.070	5.855	0.000
RAIN-	0.027	0.006	4.313	0.000
TEM+	0.043	0.007	5.866	0.000

TEM-	0.172	0.108	1.591	0.114
(INSc+	0.007	0.003	2.608	0.010
(INSc-	-0.023	0.014	-2.491	0.014
CointEq(-1) *	-0.522	0.036	-14.428	0.000

Notes: ***, ** and * indicates statistical significance level at 1%, 5% and 10% level respectively

R- Squared =0.988 Adjusted R-Squared = 0.984

F-Statistic = 225.183 Probability (F-Stat) = 0.0000

Durbin -Waston Statistic: 1.9

The results show that positive shock to insecurity lead to increase in food price inflation, while negative shock increase the impact on prices. Specifically, a 1 per cent shock in insecurity (FH) will lead to about 0.027 per cent in the amount of food prices, while a 1 per cent negative shock will reduce food price inflation by -0.176 per cent. Similarly, a 1 per cent positive shock in Boko haram will increase food price inflation by 0.007 per cent while a negative shock will raise food price inflation by 0.011 per cent. The result show that the negative shock is greater than the positive shock. This means that food production may be cheaper in the face of a secured and conducive environment for farming and other agro allied chains of food production.

The climate change variables in the short run also exhibit similar trait with the long run variables. Both the amount of average rainfall and mean temperature are statistically different from zero and exhibit similar reaction in response to positive and negative shocks. As for rainfall, a 1 per cent positive shock results to 0.413 per cent increase in food price inflation while a 1 per cent negative shock led to about 0.027 per cent rise in the food prices in the market. This is quite understandable as both scarcity and excess rainfall may automatically affect food production and thereby lead to hike in food prices. Excess rainfall could lead to erosion, flooding (2012, 2015, 2018) which may affect crop yield and loss of farm produce. The mean temperature also shows similar trait as a 1 per cent positive shock indicate a rise in food price inflation by 0.043 per cent. The negative shock though positive, but not significant. The result suggests that a 1 per cent negative shock will result to a 0.172 per cent fall in food price inflation within the study period.

On the controlled variables, the result show that trade openness (OPEN) and premium motor spirit (PMS) proxy for cost of transportation are statistically different from zero. The result suggests that a 1 per cent positive shock in OPEN will result to 0.027 per cent increase in food price inflation, while a negative shock tend to increase food price inflation by 0.044 per cent. Also, the PMS (Proxy for transport cost) is statistically significant. A 1 per cent positive shock in PMS will lead to 0.011 per cent rise in food price inflation while a 1 per cent negative shock in PMS will reduce the food price inflation by -0.007 per cent per month.

After confirming the presence of cointegration among the variables of interest, we proceeded to estimate the short-term results, as presented in Table 3.8. The findings indicate that the coefficient associated with the lagged error correction term (ECT (-1)] is both negative and statistically significant at 1 percent level. This result aligns with our initial expectations and confirms the presence of a stable and robust asymmetric long-term relationship between food price inflation, climate change, and insecurity.

Furthermore, the calculated coefficient value of -0.522 implies that approximately 52 percent of the short-term disequilibrium resulting from shocks in food price inflation during the previous month (whether positive or negative) is corrected within the current month. In other words, about 52 percent of the deviations from the long-term equilibrium are rectified in the short run.

Wald Test Analysis

The Wald test is employed to investigate the existence of asymmetric effects in both the long and short terms. It assesses whether the null hypothesis of symmetry can be rejected in favour of the alternative hypothesis of asymmetry. The findings, as presented below, demonstrate the statistical significance of asymmetry in both the long- and short-term dynamics of food price inflation, climate change, and insecurity. This suggests that when analyzing the interplay between inflation, climate change, and insecurity in Nigeria, it is crucial to consider nonlinearity and asymmetry.

Table 3.9: NARDL Wald Test

Result of WARD Test for Asymmetric NARDL			
Test Statistics	Value	df	Prob.
F-statistic	425.8133***	(5, 135)	0.0000
Chi-square	2129.066	5	0.0000
Null Hypothesis: C(1)=0, C(2)=0, C(3)=0,C(4)=0, C(5)=0			
Null Hypothesis Summary			
Normalized Restriction (= 0)		**Value**	**Std. Error**
C(1)		0.842815	0.037751
C(2)		4.40432	2.55523
C(3)		0.09253	0.06216
C(4)		-0.00896	0.02783
C(5)		-0.00686	0.024302

Note: *, ** and *** represents significance level at 1%, 5% and 10%. $W_{LR}$and W_{SR}signify the Wald test for the null of long-run and short-run asymmetries for the given variables.

The findings suggest a robust cointegration or a distinctive long-term connection between food price inflation, climate change, and insecurity in Nigeria. The Wald test results presented in Table 3.9 are indicative of the rejection of the null hypothesis, which posits that the variables under consideration are not significant. This rejection is justified by the calculated F-statistic value (425.8133) for the Nonlinear ARDL model, surpassing the upper critical value threshold (5.135) at a 1% significance level. This outcome firmly supports the conclusion that the explanatory variables, insecurity, climate change, PMS , and trade openness, wield substantial influence on food price inflation in Nigeria.

NARDL Dynamic Multiplier Effect

The figures from 3.2 to 3.6 below illustrate the asymmetric cumulative dynamic multiplier effects of various factors on food price inflation. These factors include climate change, insecurity, trade openness (OPEN), and petroleum motor spirit (PMS). These multipliers reflect how food price inflation responds to both positive and negative shocks in each of these variables.

Figure 3.2: NARDL Dynamic Multiplier Effect of Temperature on Dependent Variable

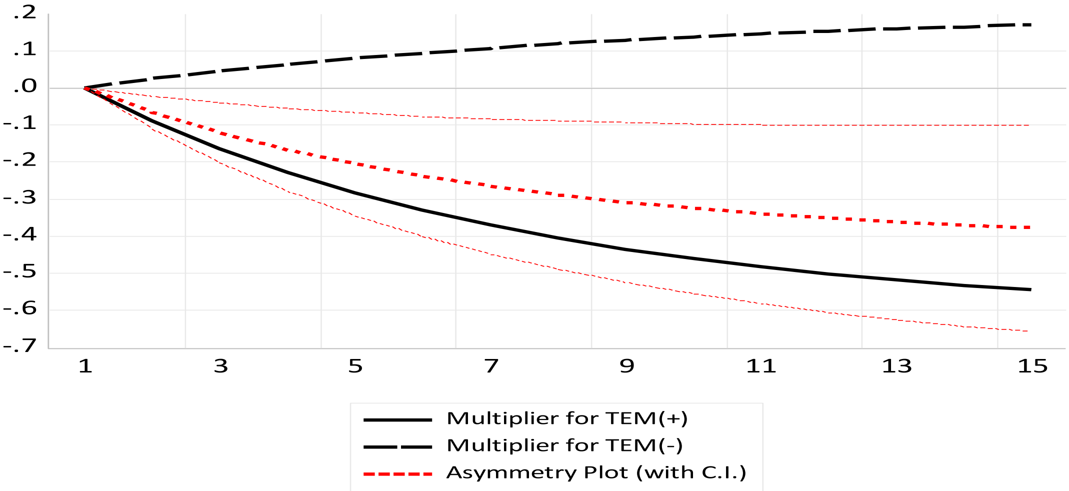


Figure 3.3: NARDL Dynamic Multiplier Effect of Rainfall on Dependent Variable

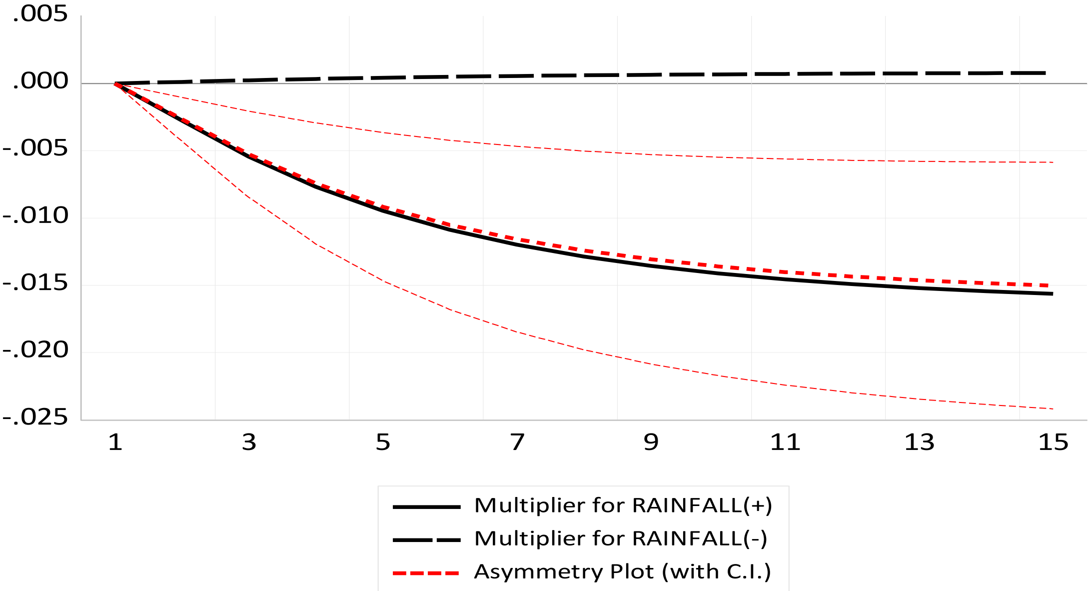


Figure 3.4: NARDL Dynamic Multiplier Effect of PMS on Dependent Variable

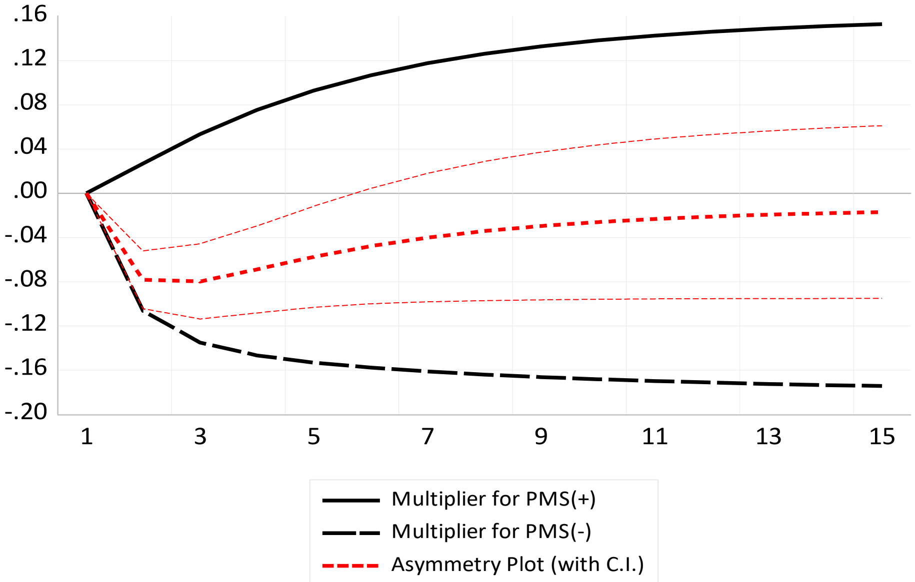


Figure 3.5: NARDL Dynamic Multiplier Effect of Trade Openness on Dependent Variable

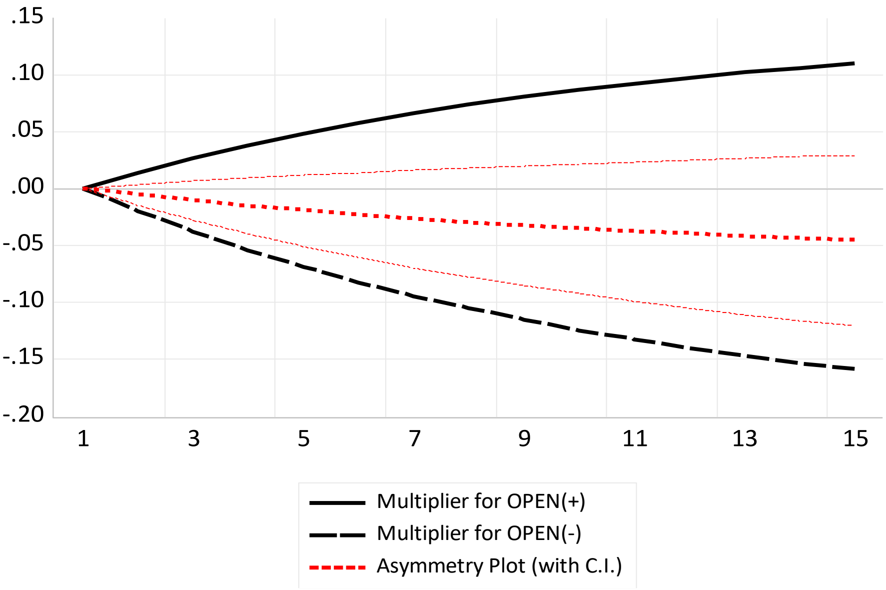


Figure 3.6 NARDL Dynamic Multiplier Effect of Insecurity on Dependent Variable

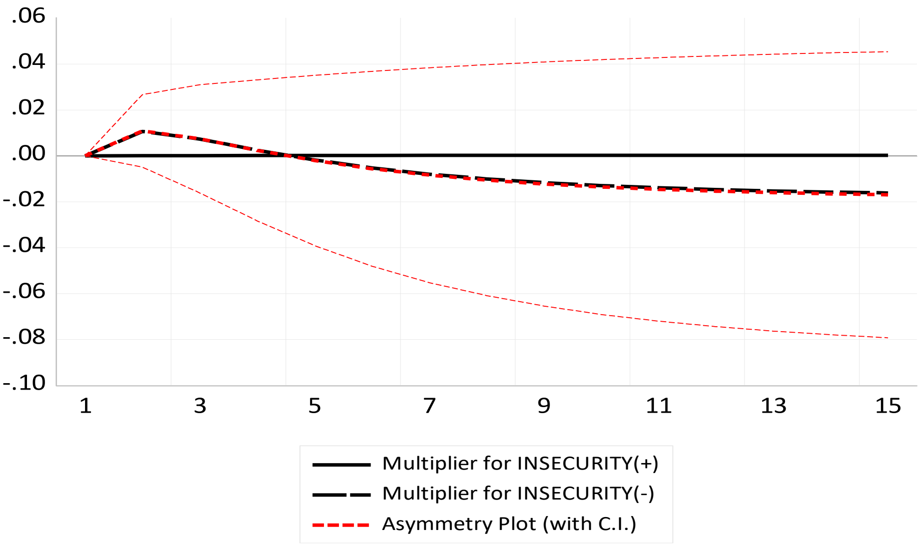
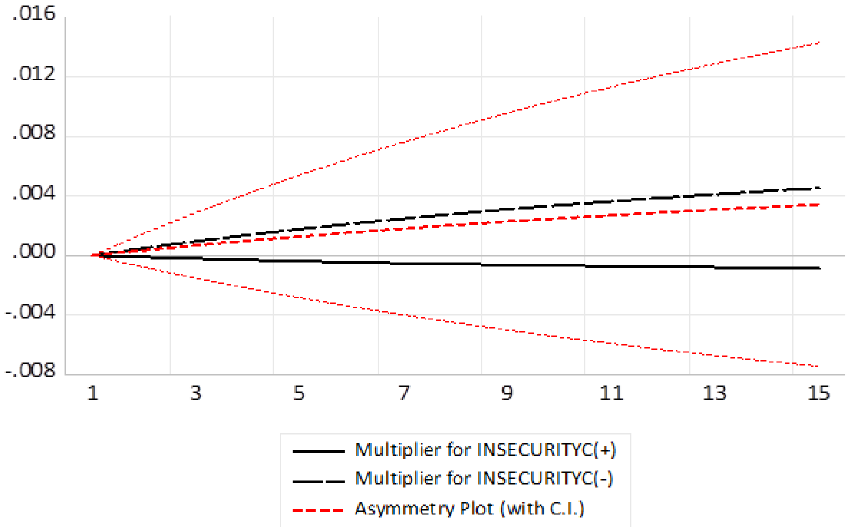


Figure 3.7: NARDL Dynamic Multiplier Effect of Insecurityc on Dependent Variable



In the graphs above, the solid black line representing the response to positive shocks and a dotted black line representing the response to negative shocks in the independent variables show how food price inflation adjusts over time following these shocks. The red dotted line represents the asymmetric effects, indicating the differences in dynamic multipliers between positive and negative shocks in each explanatory variable ($wq+ - wq-$). To ensure statistical reliability, these asymmetric effects are displayed along with 95 percent confidence intervals, shown as upper and lower bands. If the zero-line falls within these bands, it suggests that the explanatory variable's asymmetric effects are not statistically significant (as seen in figure 3.2 to 3.7, where the solid black line represents the shocks). The short, dashed black line represents the shock response to negative shifts in variables like insecurity (INS), climate change (CLIMATE CHANGE), trade openness (OPEN), and petroleum motor spirit (PMS). Meanwhile, the short, dashed red line corresponds to the asymmetry curve, showing the difference between positive and negative changes in these variables, with its associated 95 percent confidence interval for making statistical inferences. If the zero line lies within the upper and lower bands of the confidence interval, it indicates that the asymmetric effects of these explanatory variables are statistically significant at 5% level. This implies that shocks in insecurity, climate change, trade openness, and petroleum motor spirit have a lasting positive impact on food price inflation in Nigeria during the study period. Overall, the movement of the red short, dashed line (the asymmetry curve) and its associated confidence interval underscores the significant influence of these explanatory variables on food price inflation in Nigeria within the study period.

Post Estimation Diagnostics

Figure 3.8: CUSUM of Square

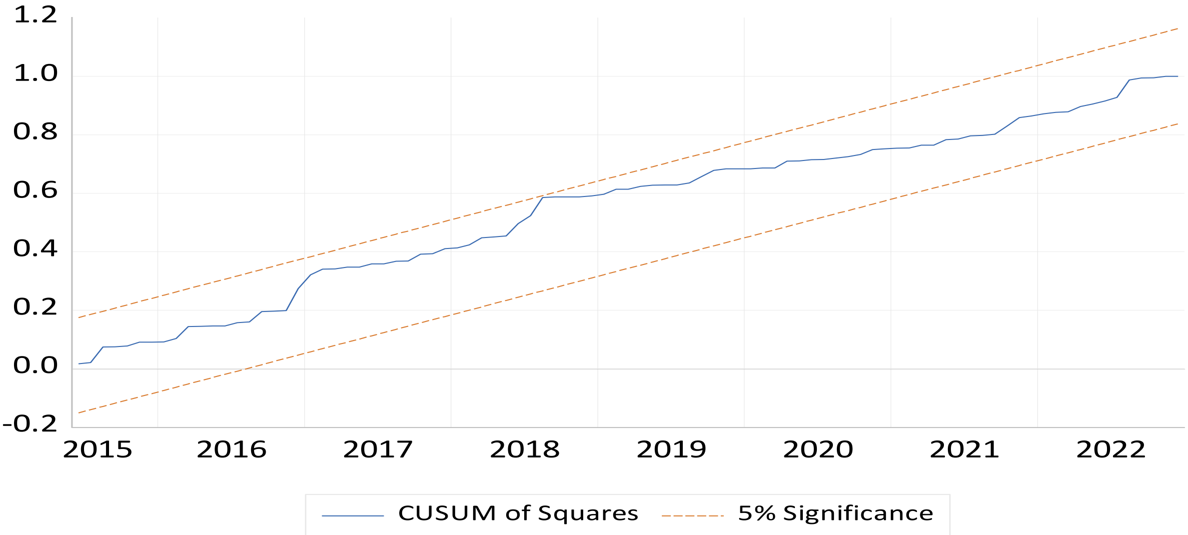


Figure 4.9: CUSUM SUM Graph

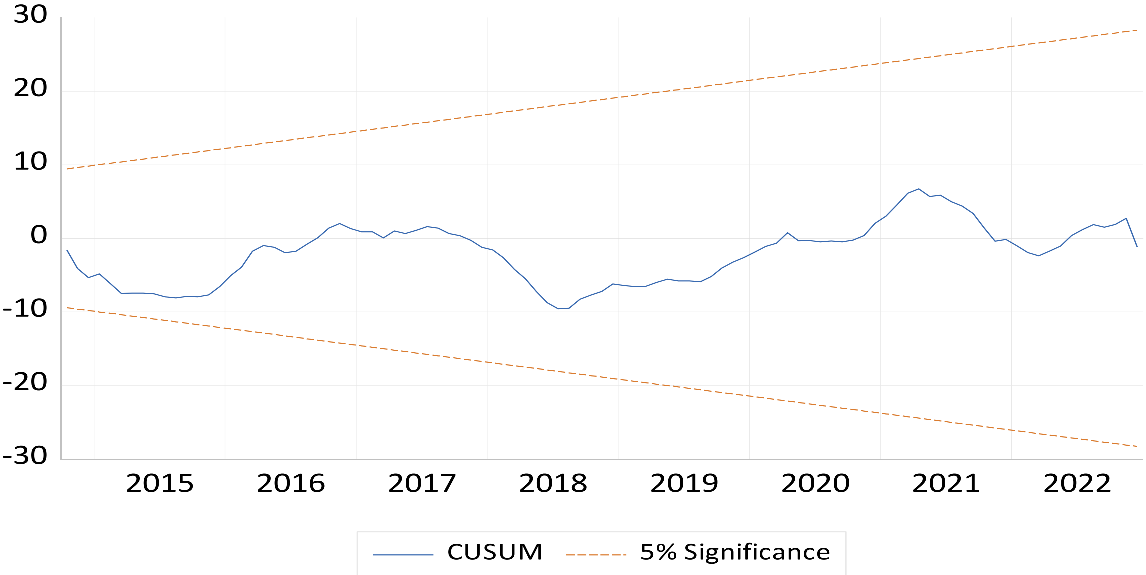


Table 3.10: Summary of Stability and Diagnostic Test

Stability Test	Stable	Unstable	**Diagnostic Test**	F-statistic	Prob. Value
CUSUM	Stable		Breusch-Godfrey Serial Correlation LM Test	1.288297	0.2798
CUSUM SQUARE	*Stable*		Breusch-Pagan Godfrey Heteroskedasticity Test	0.810608	0.7169

Source: Author's Computation

The lower right section of Table 3.10 above contains the results of the diagnostic tests used for the ARDL analysis. The serial correlation (Breusch-Godfrey) and stability (Cusum and Cusum of squares) tests serve as the main diagnostic tools for this analysis. The probability values linked to the serial correlation results for the model are greater than the 0.05 level of significance. This supports the accuracy and dependability of the findings. Furthermore, we see that the blue rays fall within the bootstrap area at a 95 percent confidence interval when looking at the Cusum and Cusum of squares results for the model. This suggests that the model is stable.

Additionally, the heteroscedasticity test (Breusch-Pagan-Godfrey) has been conducted to ensure that the variance of our model remains constant. It is essential for the variance to be constant because varying variance can distort the test of significance by introducing bias to standard errors and inference. The outcomes of this diagnostic test show that the model's variance is constant. Overall, the diagnostic test results show that the model's disturbance errors behave in a way known as homoscedasticity, which means they maintain a constant variance at a significant level of ≥ 0.05. This implies that the residuals from the analysis are free from issues such as serial correlation, heteroscedasticity, or model misspecification errors.

CONCLUSION AND POLICY RECOMMENDATIONS

The broad objective of this study is to investigate the affiliation between insecurity, climate change shocks and food price inflation in Nigeria with monthly time series data spanning 2011M1 to 2022M12. To achieve this broad objective, the study carried out unit root test to ascertain the stationarity of the variables, adopted Autoregressive Distributed Lag (ARDL) in the form of Unrestricted Error Correction Model (UECM) to decompose the total effect of a variable into its short and long-run components, and Non-Linear Autoregressive Distributed Lag (NARDL). The NARDL is applied to examine the asymmetric negative and positive responses of Food Price Inflation (FPI) to Insecurity and Climate Change shocks. The overall presence of asymmetric impact of the independent variables on the dependent variable in the long and short run was examined by the Wald test. The study also conducted some post estimation analysis, including stability and diagnostic tests.

Based on the results, we found very strong evidence for a symmetric and asymmetric cointegration relationship between climate change, insecurity, and food price inflation in Nigeria within the period under study. This is confirmed by the empirical results of bound tests of both the conventional ARDL and NARDL models. Our findings suggest that the ARDL results show that variables of interest are statistically significant at both short and long run which indicate that climate change and insecurity are major threat to food production and have contributed significantly to the hike in food prices across Nigeria.

The NARDL analysis highlights the substantial impact of both climate change and insecurity on food price inflation in Nigeria. It is evident that both factors, climate change and insecurity, play pivotal roles in driving up food prices. The findings clearly demonstrate the positive and statistically significant relationship between these phenomena and food price inflation during the study period. This outcome has far-reaching implications for the socioeconomic well-being of the Nigerian population and their ability to secure access to food and proper nutrition. The research underscores that climate change and insecurity represent formidable challenges, exacerbating the already precarious food security situation in the country.

The results also show that the coefficient of error correction term (ECT) of both ARDL and NARDL are estimated to be is estimated to be -0.735 (approximately 74%) and -0.522, respectively, meaning that the speed of error adjustment of food price inflation from the initial shock would be corrected and converge to the tune of about 74 per cent and 52 per cent, respectively, in the long run per month. The joint statistical significance of the variables was also affirmed via the Wald Test as the calculated F statistic is greater than the critical value at all levels of significance. The Dynamic Multiplier graph with its accompanying 95 percent confidence interval for statistical inferences indicate that explanatory variables exert significant influence on the food price inflation in Nigeria within the study period. Serial correlation, heteroscedasticity, or model misspecification errors do not affect the analyses' residuals. Additionally, the model's stability and goodness of fit are demonstrated by the results of the Cusum and Cusum squares.

Based on the empirical findings, the study recommends the following:

1. The empirical results indicate that climate change shock exert significant positive impact on food price inflation as variability in rainfall and temperature created heavy disruptions in the food chain (supply side), thereby creating demand gap, and then hike in food prices. Following this empirical finding, the Nigerian state should transit from traditional agricultural system to Climate-Smart Agriculture to meet future needs. Alternative practices such as the use of irrigation and recharging of shrinking water bodies in the Sudan and Sahel savannah regions should be carried out by government and other stakeholder to ensure that farmers are streamed back into productive activities.
2. In drought-prone areas, drought-resistant grass should be introduced and widely spread. This would lessen the pastoral north-south migration pattern, which has led to friction and conflicts between local farmers and herdsmen. Additionally, this action will ensure consistent crop production, human security throughout Nigeria, and the restoration of social order.
3. The positive relationship between insecurity and food price inflation has also been confirmed by our empirical revelation. As indicated in the results, insecurity menace of farmers herders' clashes and activities of Boko haram has continued to prevent farmers, especially in the northern parts and the middle belt of Nigeria from harvesting and processing their food crops. This factor has hampered livestock, crop production and increased cattle rustling, resulted in many casualties, displacement, and consequently high food prices (Ajibo et al., 2018; Awotokun et al., 2020; Ladan and Badaru, 2021). The outcomes require policy interventions from the new government to support households adversely impacted by insecurity. Such policies, for example, can include the provision of immediate safety nets, like food aid, to affected families, and planning post-conflict rehabilitation for both farmers and herders in regions severely affected by the conflicts.
4. The state should build modern (public) ranches with the best of technologies in the Sahel region, to discourage nomadic herding. However, to achieve this, the state should involve key Northern leaders like the Sultan of Sokoto, leaders of middle belt forum and the various Emirs on the need to imbibe ranching into their culture, considering the economic and security benefits it provides.

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