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Modelling Dynamic Linkage between Climate Change and Food Inflation in Nigeria

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The study delves into the critical issue of climate change and its detrimental impact on various regions worldwide, including Nigeria. It emphasizes the urgent need for global efforts to mitigate these effects and advocates for measures to address human activities contributing to climate dynamics. Specifically, the study empirically examines the affiliation between climate change shocks and food price inflation in Nigeria using a Nonlinear Autoregressive Distributed Lag (NARDL) approach. The dataset covers the period from January 2011 to December 2022.The empirical findings reveal a robust cointegrating relationship between climate change shocks and food price inflation in Nigeria. Notably, climate change shocks significantly contributed to rising food prices within the study period. Furthermore, the Error Correction Term (ECT), estimated at 52 percent, indicates that food price inflation adjusts by 52 percent in the current month to counteract the initial shock experienced in the previous month. The Dynamic Multiplier graph, along with a 95

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percent confidence interval, demonstrates that the explanatory variables exert substantial influence on food price inflation in Nigeria during the study period. Considering these findings, the study recommends that Nigeria should transit from traditional agricultural practices to Climate-Smart Agriculture to address future needs and climate-related challenges. Additionally, the government and stakeholders should implement alternative practices such as irrigation and the replenishment of shrinking water bodies in the Sudan and Sahel savannah regions.

Keywords: Food price inflation, climate change, unit root, NARDL; Nigeria.

JEL Classification: E51, E52, G21.

1. INTRODUCTION

Climate change refers to long-term alterations in the Earth's average weather patterns and climate system. It encompasses various shifts in temperature, precipitation, wind patterns, and other climate-related factors that occur over extended periods, typically decades to millions of years. This change could be anthropogenic (human induced) or biogeographical [1]. The reality of climate change and its increasingly frequent and dire consequences pose significant threats to human populations across various regions globally. These adverse outcomes have spurred global concerns and concerted efforts to mitigate the effects, along with advocacy for measures to curb human activities contributing to climate change must be activated. Extensive evidence underscores the role of climate change in exacerbating food crises in specific regions and sparking security concerns due to conflicts arising from competition over limited agricultural resources.

Reports by the Food and Agricultural Organization (FAO) in 2017, 2018, and 2019 titled "The State of Food Security and Nutrition in the World" have identified climate change, national economic conditions, and conflict as the primary drivers of global food crises [2]. Nigeria, situated in sub-Saharan Africa, is recognized as one of the countries vulnerable to the impacts of shifting climate patterns [3]. Several researchers, including [4-6], have observed that recurrent environmental disasters in various parts of Nigeria have compounded challenges in food production and led to increased human suffering over the past decade. For instance, in 2012, Nigeria faced severe flooding, an event unprecedented in the country for the preceding four decades. This event resulted in significant human casualties, substantial crop and livestock losses, and the widespread displacement of people [7]. Notably, the changes in environmental conditions driven by climate change impact Nigeria's six distinct vegetative zones to varying degrees [8].

In the semi-arid Sudan and arid Sahel Savannah regions, a noticeable reduction in rainfall has resulted in drought and the expansion of desertification. Both the Northern and Southern Guinea savannah belts have experienced shifts in rainfall patterns, leading to delayed rains and extended dry season. Coastal areas have also seen significant flooding during the rainy season, as documented by [9]. In the Rain Forest zone, the effects of climate change include a delayed onset of rainfall, prolonged dry seasons, heatwaves, and coastal flooding. In contrast, the Mangrove Swamp regions have experienced increased flooding in areas that are typically dry, and the persistent rise in sea levels poses a significant threat to farming activities. Additionally, rising water temperatures have had adverse effects on fishing, as highlighted by [10].

Numerous studies have demonstrated the adverse impacts of extreme climatic conditions, such as desertification, heavy rainfall, and flooding, on food production. This is supported by research conducted by [11-13]. These researchers have identified climate change as a subtle yet significant factor contributing to the current food security and human security crises in Nigeria. The persistent decrease in rainfall in northern Nigeria has made these areas increasingly unsuitable for both crop cultivation and livestock farming, putting a strain on natural resources, as observed by [14].

In separate publications [15] and the [16] have both highlighted the looming peril of climate change to the sustainable production of food in Nigeria. [17] underscored the fact that Nigeria is facing the pervasive impacts of climate change, which have now become an everyday reality. These impacts are growing in intensity and leading to a heightened frequency of environmental challenges such as floods, droughts, extreme temperature, and other extreme weather events. These disruptions are significantly affecting agricultural activities in the country. In a similar vein, [18] pointed out that the livelihoods of approximately 15 million pastoralists in northern Nigeria are under severe threat. This threat arises from reduced access to water sources and shortages of pasture, both of which can be directly attributed to the effects of climate change.

The study conducted by [19] has also shed light on the worsening food insecurity situation in Nigeria. This is particularly pronounced in regions that were already vulnerable to hunger and malnutrition. The study further emphasized that climate variability and extreme weather events are poised to present even greater challenges to food security in the future. They highlighted the concerning trend of consistently rising food prices in certain parts of Nigeria, which could render essential food items unaffordable for individuals with low incomes.

Fasona et al. [20] observed that growing aridity in the Sahel and Sudan savannah regions had rendered significant expanses of land unsuitable for agriculture, leading to food security crisis in densely populated areas. They further predicted consequences of climate change results to a steady increase in the number of malnourished children in Nigeria. [21] analyzed the links between climatic factors like rainfall, temperature, and relative humidity using time series data spanning from 1975 to 2010. Their research uncovered a close connection between climatic conditions and agricultural output, both in the short and long term. These findings are consistent with the conclusions reached by other researchers who have conducted similar investigations. Additionally, several empirical studies have highlighted the adverse impact of climatic variability on agricultural productivity, as demonstrated by [22]. A study by [23] examined how declining water supplies, rising temperatures, and rising CO2 emissions affect food production. Their findings, which concur with the work of many other researchers, highlighted a strong link between changing climatic conditions and poor crop performance. Notably, the production stage of the food supply chain is primarily impacted by climate change, with effects cascading throughout the entire supply chain.

The fishery sector, as emphasized by [24] study, is vulnerable to the impacts of climate variability. The study pointed out that the fishery sector in regions relying on natural water resources has been particularly affected by climate change-induced drought. [25] further observed that the decreasing water resources in Nigeria's Lake Chad region, a consequence of climate change, have severely disrupted the once-prosperous fishing activities in that area. This disruption has severed the supply chain of fish originating from the region, resulting in job losses for numerous fishermen. Furthermore, [26] highlighted the dire consequences of climate change on aquatic life. Increasing water temperatures, driven by climate change, deplete oxygen levels in water, disrupt fish habitats, and may lead to fish mortality, reduced productivity, or contamination with harmful bacteria. Researchers widely agree that the advancing desertification contributes to the loss of water bodies and aquatic fauna [27,28,29].

The objective of this research is to empirically investigate the affiliation between the climate change shock and food price inflation in Nigeria. To accomplish this goal, we employ a nonlinear autoregressive distributed lag (NARDL) approach using dataset from January 2011 to December 2022. This strategy was chosen because, as previous research [30,31] has shown, many macroeconomic relationships inherently exhibit nonlinearity, which justifies a nonlinear analysis. According to earlier studies [32,33,34], nonlinear models are also advantageous because they provide a more concise and reliable representation of the data, delivering a better fit with unbiased estimators and smaller residual errors. Additionally, the NARDL method accommodates asymmetry, allowing for transitions between short-term and long-term effects. This study makes a significant contribution to existing knowledge by not only examining the extent to which climate change impacts food price inflation but also by discerning the distinct and relative effects of climate change on food inflation through a nonlinear analysis. Importantly, it advocates for the implementation of appropriate policy measures, particularly in the context of a vulnerable economy like Nigeria, based on the findings.

Following this introductory section, Chapter Two will provide methodology, while Chapter three covers the estimation and discussion of results, and finally, Chapter four will summarize the findings, draw conclusions, and offer policy recommendations.

2. METHODOLOGY

2.1 Model Specification

The processes of most macro variables, including those associated with climate change, are well-documented in the literature [35,36,37]. This is because most macro variables exhibit non-linear characteristics. Therefore, when specifying the explanatory variables for our model, we adhered to the methodology described by [38,39].

We start by defining the general partial sums that are centered on zero and denoted by the symbols x+t and x_t. We distinguished between positive and negative changes in the growth rate of the dependent variable. This strategy is essential because imposing long-run symmetry in situations where the relationship is inherently non-linear can make it harder to determine whether a long-term relationship is stable. In our analysis, such a constraint might produce fictitious dynamic responses.

Furthermore, it is essential to accurately capture asymmetries in the data. Doing so enables us to uncover potential variations in how economic agents respond to positive and negative shocks. Consequently, we arrange and specify our model in the following format:

$$FPI = (RAINF, TEM,) \quad (1)$$

From the equation (1), FPI is the dependent variable while Rainf and Tem (proxy for climate change) represent explanatory variables. Thus, Equation (1) indicates that FPI is influenced by climate change.

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 [40,41,42] and Trade Openness Trade, calculated as Import + Export/ GDP is a traditional measure of trade liberalization or openness [43-50]. Nigeria's open economy warrants the inclusion of trade openness, and [51] have similarly claimed that 38% of the countries with open economy policies experienced currency appreciation and inflationary pressure.

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

$$InFPI = (InRAINF, InTEM, InOPEN, InPMS) \quad (2)$$

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:

$$(\boldsymbol{InFPI_t}) = \emptyset_0 + (\boldsymbol{In\emptyset_1 RAINF_t}) + (\boldsymbol{In\emptyset_2 OPEN_t}) + (\boldsymbol{In\emptyset_3 PMS_t}) + \boldsymbol{In\emptyset_4 TEM_t} + \boldsymbol{\varepsilon_t} \quad (3)$$

Where FPI is the log of food price inflation (as the dependent variable), OPEN is the log of trade openness; PMS is the log of premium motor Spirit (proxy for transportation cost); RAINF signifies average log of rainfall (proxy for climate change) and TEM represents mean log of temperature (proxy for climate change).

In line with [52], the nonlinear ARDL is subjected to the bounds test of the Autoregressive Distributed Lag (ARDL), and the Pesaran critical values are equally suitable and used to determine cointegration. To investigate the asymmetric positive and negative reactions of Food Price Inflation (FPI) to Climate Change shocks, Non-Linear Autoregressive Distributed Lag (NARDL) is used.

Thus, the general ARDL model for the study is specified thus:

$$\Delta LFPI_{it} = a_{oit} + \sum_{i=o}^{k} \emptyset_{1it}\, \Delta LRAINF_{it} + \sum_{i=o}^{k} \emptyset_{2it} \Delta LTEM_{it} + \sum_{i=0}^{K} \emptyset_{3it}\, \Delta LOPEN_{it} + \sum_{i=o}^{k} \emptyset_{4it}\, \Delta LPMS_{it} + \gamma_{1it} + \gamma_{1it}\, LFPI_{1it} + \gamma_{2it}\, LRAINF_{it} + \gamma_{3it}\, LTEM_{it} + \gamma_{4it} LOPEN_{it} + \gamma_{5it} LPMS_{it} + \mu_{it} \quad (4)$$

Where, (ΔFPI and LFPI) are the dependent variables in first differences and levels, and (ΔRAINF, ΔTEM, ΔOPEN and ΔPMS, and LRAINF, LTEM and LPMS, LOPEN) are the independent variables in the model in first difference and levels. Indeed, the a_{oit} is the intercept, $\emptyset_{1it \ldots \emptyset_{4it}} \ldots \gamma_{1it} \ldots . \gamma_{5it}$ are the parameters of variables and μ_{it} is the error term of the model.

Additionally, we created a parametric dynamic model for combined long-run and short-run asymmetries by extending the ARDL method of [53] and Pesaran, [54] in equation 4. As a result, the nonlinear form of the ARDL model is defined as follows:

$$\begin{aligned}
&\Delta FPI_{it} = \\
&a_{oit} + \textstyle\sum_{i=o}^{k} \emptyset_i^{+} \,\Delta LRAINF_{t-1}^{+} + \\
&\emptyset_i^{-} \Delta LRAINF_{t-1}^{-} \textstyle\sum_{i=o}^{k} \emptyset_i^{+} \Delta LTEM_{t-1}^{+} + \emptyset_i^{-} \Delta LTEM_{t-1}^{-} \textstyle\sum_{i=0}^{K} \emptyset_i^{+} \,\Delta LOPEN_{t-1}^{+} + \\
&\emptyset_i^{-} \Delta LOPEN_{t-1}^{-} \textstyle\sum_{i=o}^{k} \emptyset_i^{+} \Delta LPMS_{t-1}^{+} \,\emptyset_i^{-} \Delta LPMS_{t-1}^{-} + \gamma_{1it}\, LFPIit + \gamma_i^{+} LRAINF_{t-1}^{+} + \\
&\gamma_i^{-}\, LRAINF_{t-1}^{-} + \gamma_i^{+} LTEM_{t-1}^{+} + \gamma_i^{-} LTEM_{t-1}^{-} + \gamma_i^{+} LOPEN_{t-1}^{+} + \gamma_i^{-} LOPEN_{t-1}^{-} + \\
&\gamma_i^{+} LPMS_{t-1}^{+} + \gamma_i^{-} LPMS_{t-1}^{-} + \mu_{1it} \qquad (5)
\end{aligned}$$

Where, (ΔFPI and LFPI) are the dependent variables in first differences and levels, and (ΔRAINF $_{t-1}^{+}$, $LRAINF_{t-1}^{-}$, ΔTEM $_{t-1}^{+}$, $LTEM_{t-1}^{-}$, ΔOPEN $_{t-1}^{+}$, $LOPEN_{t-1}^{-}$, $\Delta LPMS_{t-1}^{+}$ $LPMS_{t-1}^{-}$) 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.

2.2 Stability and Diagnostic Tests

In line with the guidelines proposed by [55], it is essential to conduct a stability verification check for any model to prevent the emergence of misleading or erroneous outcomes. Their recommendation involves employing both the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) methods on the residuals of a recursive regression. To deem the model stable, it is crucial that the plots generated through these methods consistently remain within a 5% significance boundary. These plots are constructed using the initial set of n observations, which are subsequently updated in a recursive fashion and then graphed against specified breakpoints. The stability assessment relies on the cumulative sum of recursive residuals, and the CUSUMSQ process follows a similar procedure.

The study is also expected to carry out diagnostic tests on the model where the presence of serial correlation and heteroscedasticity test would be evaluated. In serial correlation test, the null hypothesis is that there is presence of serial correlation, while the null hypothesis in heteroscedasticity test is that the model is heteroscedastic. If the null hypothesis is rejected in both tests, it indicates a well specified model, does not suffer from serial correlation problem and that the model is adjudged homoscedastic.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

This section discusses the descriptive part of the analysis, involving behaviours of the variables before estimation. Observing data plays a pivotal role in economic modelling as it serves as a crucial tool for mitigating challenges such as spurious regression arising from outliers and non-normal data distribution.

Table 1. Summary Statistics

	FPI	PMS	RAINF	TEM	OPEN
Mean	17.21	26.53	32.9	15.69	50.28
Median	11.67	14.52	31.5	27.48	49.78
Maximum	10.13	17.01	30.1	20.77	40.55
Minimum	8.80	62.1	35.8	27.23	10.26
Std. Dev.	2.35	32.55	71.2	0.58	10.89
Skewness	0.61	-0.07	3.5	2.57	0.30
Kurtosis	3.02	4.83	27.9	10.16	2.04
Jarque-Bera	12.52	9.27	40.8	46.04	6.74
Probability	0.00	0.03	0.0	0.00	0.02
Sum	10.35	18.35	53.5	39.88	52.40

Sum Sq. Dev.	15.04	13.32	11.1	18.80	40.50
Observations	144	144	144	144	144

Source: Authors' Computation

From the Table 1, the summary statistics of the raw data indicate that after applying the natural logarithm transformation of all the variables, they became normally distributed, as suggested by the Jarque-Bera probability values being greater than 0.05. This normality is also evident in kurtosis and skewness of the variables. Two of the variables have kurtosis values less than 3, indicating that they fall within the range of normal distribution (neither too peaked nor too flat). However, it's worth noting that most variables exhibit positive skewness, except for PMS that is negatively skewed. Furthermore, the close affinity between the mean and median values across different variables provides strong evidence of normal data distribution, as it reduces bias in the variance of our model. This closeness between mean and median values also suggests that our population sample is sufficiently large. Additionally, the maximum and minimum values of the variables do not show sign of being outliers, as they are still within a reasonable range relative to the observations of their respective variables. The use of the natural logarithm transformation, as advised by [56] and [57], was essential to guaranteeing interpretable results and valid regression output.

3.2 Graphical Analysis

To obtain an initial visual overview of the parameters, it's essential to conduct graphical analysis. In the context of time series analysis, this process is commonly known as the "eyeball test." The graphical plots provide an early insight into the characteristics and patterns exhibited by the parameters being studied.

In the preliminary analysis, Fig. 1 illustrates graphical representations of the variables under examination. These graphical plots, including scatter plots, box plots, pie charts, line charts, histograms, and more, hold significant importance in empirical research. They serve as a valuable tool for providing interested readers with an overview and deeper understanding of the dataset in question. Graphical representations effectively convey large sets of numerical data and are essential for highlighting patterns, trends, and relationships among variables over a specific timeframe. Upon examining the graphical representations in Fig. 1, it becomes evident that the parameters exhibit trends and varying levels of volatility. These findings indicate the need for further testing to determine their stationarity status.

3.3 Unit Root Test

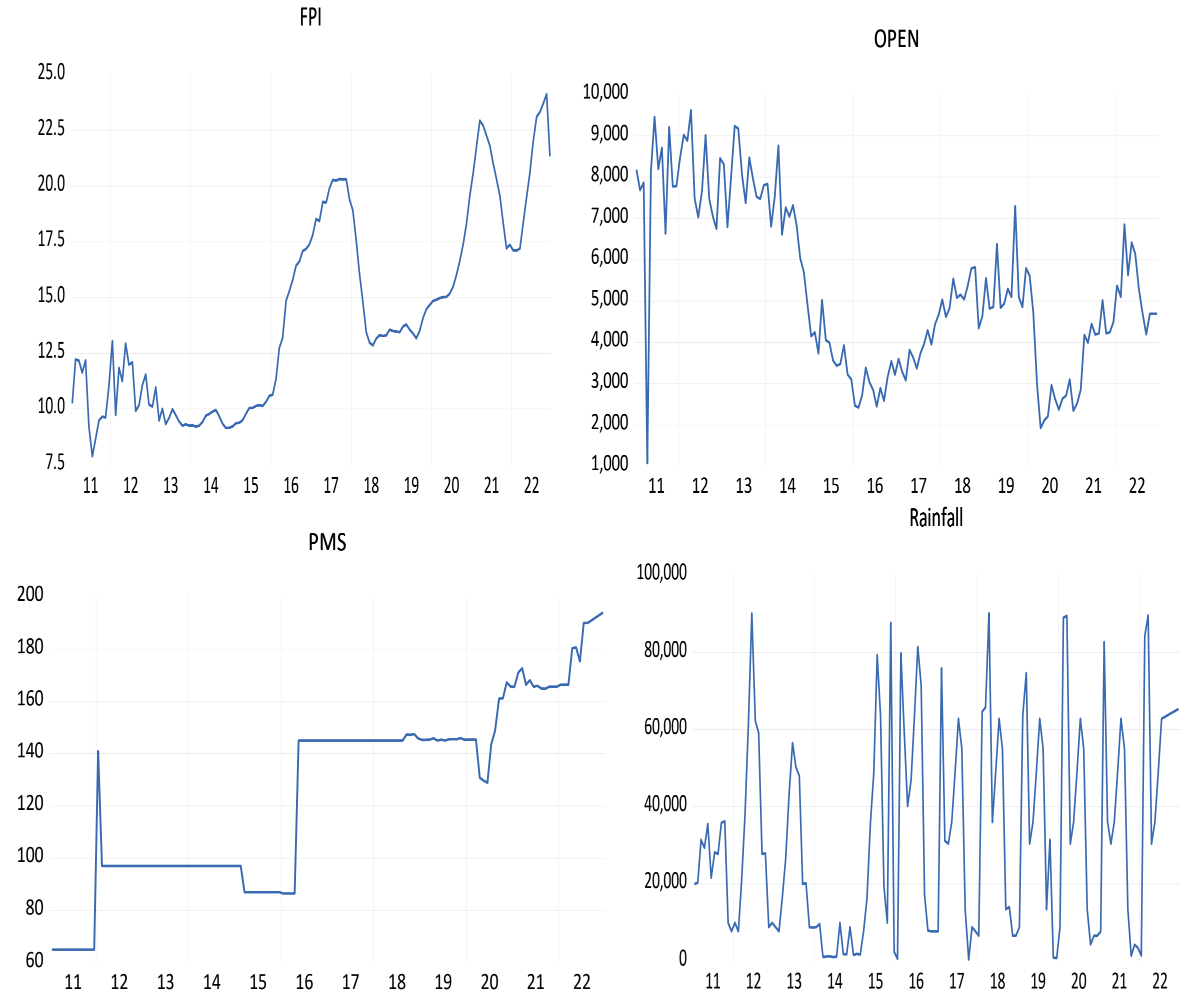
Before embarking on co-integration analysis, it's crucial to ensure that each variable involved is stationary. Neglecting this step can lead to spurious findings in regression analysis, as emphasized by [58]. One fundamental requirement in the bounds testing approach is that no individual variable should exhibit I(2) integration order, although a mixture of I(1) or I(0), or a combination of I(I) and I(0) integration orders, is acceptable. Table 2 display the results of these tests at both the levels and first differences using the Dickey Fuller-Generalized Least Square (DF-GLS) and Phillips-Perron (PP) methods.

The Schwarz Information Criterion (SIC) for optimum lag order and Newey-West bandwidth were used to test the Dickey Fuller-Generalized Least Square (DF-GLS) and Phillip-Perron (PP). The unit root property of the parameters was 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 2 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 NARDL analysis. This is to ascertain the existence of asymmetric long-run relationships or otherwise of the parameters, negative and positive reactions, and shocks of the variables, as well as the Wald test to further validate the cointegration status of the parameters.

3.4 Nonlinear ARDL Analysis

The results in Table 3 provide evidence for a dynamic nonlinear relationship between food inflation and climate change in Nigeria. According to the estimated results, both positive and negative shocks of the variables are statistically significant.

The result in Table 3 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. Specifically, a 1% positive shock in rainfall will cause an increase of about 0.026 per cent in food price inflation. A 1per cent negative shock 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 as captured in the result show that both positive and negative shock of variability in rainfall 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. Numerous studies have confirmed that extreme climatic conditions such as desertification, heavy rainfall, and flooding have detrimental effects on food production [59,60,61]. The continual decline in rainfall levels in parts of northern Nigeria has made these areas increasingly unsuitable for crop and livestock farming using natural resources [62]. Moreover, persistent flooding along the coastlines and in the southernmost regions of Nigeria has resulted in crop damage, loss of soil fertility, soil toxicity, and disruption of the soil ecosystem [63]. Both the World Bank and the Food and Agricultural Organization have issued warnings through their publications that climate change would continue to pose significant threat to sustainable food production in Nigeria [64,65]. These findings do not align with the conclusions of [66], who suggested that average rainfall may not have a long-term impact, and favourable weather conditions with higher rainfall in the preceding period may lead to improved harvests and lower food prices in the current period.



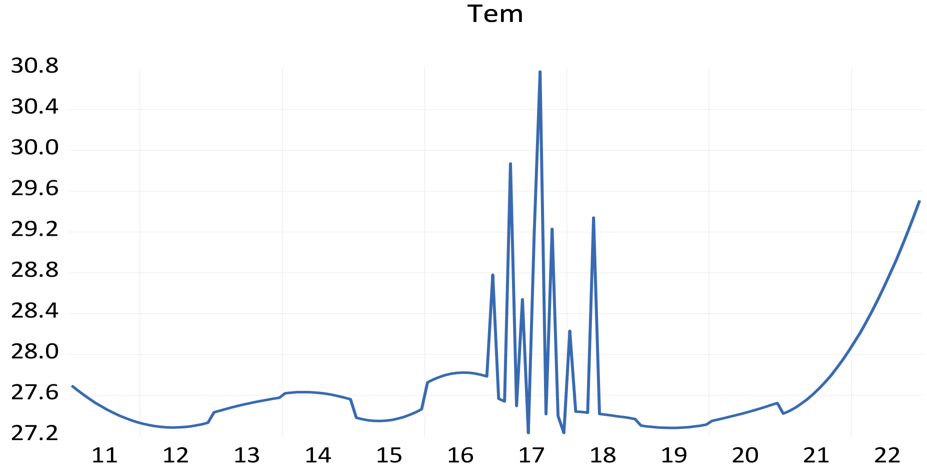


Fig. 1. Trend Analysis of the Variables

Source: Authors' Computation

Table 2. NARDL PP and DF-GLS test for unit roots

Variables	Phillips-Parron		Remarks	ADF-GLS (1st Difference)		Remarks
	Levels	1st Difference	Order of Integration	Levels	1st Difference	Order of Integration
InFPI	-1.231749	-10.81644***	1(1)	-1.393710	-3.36598***	1(1)
InTEM.	-2.653902	-7.008321***	1(1)	-0.057923	-2.728692*	I(1)
InRAIN	-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: Authors' 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*

Table 3. 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
$OPEN^+$	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

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

Source: Author's Computation

The results also suggest that both negative and positive shocks in the mean temperature are statistically significant, but the negative shock exert more impact than the positive effect. Specifically, 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 the variability in rainfall and temperature demonstrate significant impact on food price inflation in the long run. it shows that the climatic variables impact crop production, thereby affected food prices. In this instance, there are statistically significant asymmetric effects, large positive influences are stemming from temperature increases to food price inflation. In the case of rainfall, the effects are on both directions but more on the negative side. The results show that both rainfall and temperature which are variables of climate change are important to agricultural produce. The conclusions about the relationship between food prices and climate change shocks are consistent with studies done by numerous academics, including those by [67-70]. The studies collectively indicate that climate change leads to a sustained increase in food price inflation over time.

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 contagious effect on the prices of goods and services. High food prices are attributable not only to the increase in the cost of producing the food in the farm, but the cost of moving the food from the farm or the sub-urban processing plants to where most of the food is consumed by non-farmers. This aspect also affects the overall food prices in the market. This finding is in line with [71-74] who found significant positive relationship between food prices and PMS. However, the studies of [75,76, 77] showed that pump price variability did not affect food prices.

The findings regarding trade openness indicate that a 1 percent increase in trade openness tends to result in a 0.25 percent rise in food price inflation, while a 1 percent decrease in trade openness leads to a 0.047 percent increase in food price inflation. These results align with the research of [78], who also observed a positive relationship between a country's economic openness and inflation in Pakistan. Additionally, research by [79-82] has demonstrated that trade openness can cause inflationary pressures, particularly in countries that rely heavily on imports like Nigeria. In contrast, these findings contradict those of studies by [83-87], which hypothesized a negative relationship between trade openness and inflation. Furthermore, the outcomes affirm the significant influence of external factors on inflation and how they transmit their effects to domestic factors, particularly in processed food and core items, ultimately impacting headline inflation. Therefore, any factors or events that induce changes in either food or core inflation, or both, will have consequences for headline inflation. These findings corroborate the assertion made by [88] that Nigeria experiences imported inflation to some extent. In recent times, the mounting pressure on Nigeria's food index can be attributed to increased food imports, exacerbated by factors like the Russia-Ukraine war and domestic considerations.

The results of the NARDL bounds test, which are shown in Table 4, confirmed that the variables have a co-integrating relationship. The F-statistic must be higher than the 5% critical values of both the lower and upper critical bounds for there to be a long-term relationship between the variables. The F-statistic in this instance is 6.5422, exceeding the lower and upper bounds of 2.25 and 3.35, respectively. This demonstrates the asymmetric long-run relationships between the variables (RAIN, TEM, OPEN, PMS) and food price inflation.

The climate change variables in the short run 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 in the short run. Also in the short run, the PMS (Proxy for transport cost) show that 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 also rise the food price inflation by -0.007 per cent per month.

Table 4. Asymmetric bound test for the existence of a long-run relationship (NARD)

MODELS	K	F-Statistic	Lower Bound Critical Value 5%	Upper Bound Critical Value 5 %
$InFPI = f(\,InOPEN, InPMS, InRAINF, InTEM)$	3	6.5422	2.25****	3.35****

*Note *, **, *** and **** represent 10, 5, 2.5 and 1% level of significance, respectively.*
Source: Author's Computation

Table 5. Short run asymmetric autoregressive distributive lag model (NARDL) analysis

Variables	Coefficient	Std. Error	t-Statistic	Pro.
FPI(-1)	0.413	0.070	5.855	0.000
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
CointEq (-1) *	-0.522	0.036	-14.428	0.000

*Notes: ***, ** and * indicates statistical significance level at 1%, 5% and 10% level respectively*
Source: Author's Computation
R- Squared =0.988   Adjusted R-Squared = 0.984
F-Statistic = 225.183   Probability (F-Stat) = 0.0000
Durbin -Waston Statistic: 1.9

Upon establishing the presence of cointegration between the variables of interest, we estimated and obtained the short run/ECM results, which are reported in Table 5. The result suggests that the coefficient of the lagged error correction term (ECT (-1) carries a negative sign and is statistically significant at 1 per cent significant level. First, it is in line with a priori expectation, thus confirming a stable and robust asymmetric long-run relationship between food price inflation and climate change. Second, the value (- 0.522) implies that about 52 per cent of the short run's disequilibrium arising from the previous month's shocks (positive and negative) in the food price inflation are corrected within the current month to the tune of about 52 per cent.

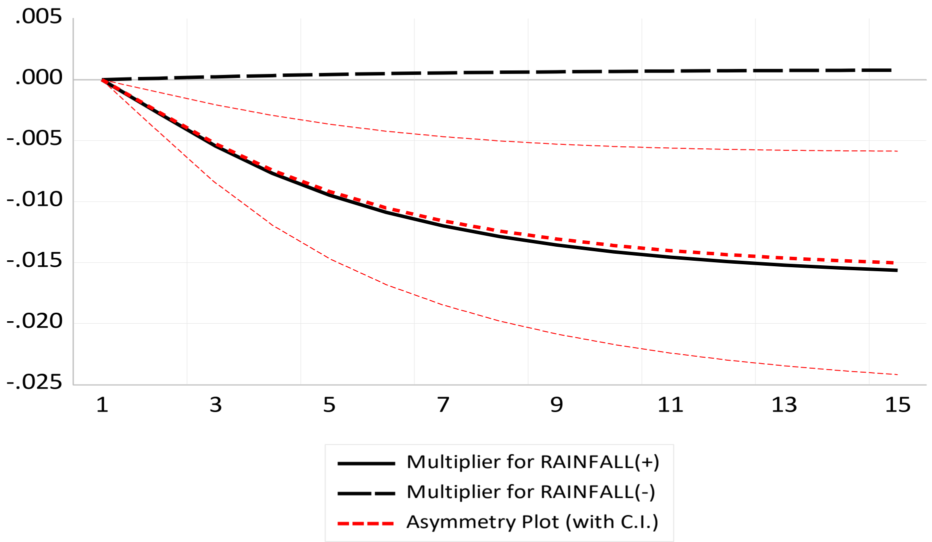
The Wald test is used to determine whether there is asymmetric impact in both the long and short runs. The outcome implies a strong cointegration or asymmetric long-run relationship between food price inflation and climate change in Nigeria. The result of the Wald test for cointegration test in Table 6 indicates that the null hypothesis of insignificant variables is rejected as the value (425.8133) of the calculated F-statistic for the Nonlinear ARDL model is greater than the upper bound critical value (5.135) at a 1% significance level. This further implies that the null hypothesis that the explanatory variables do not significantly impact on the dependent variable is rejected and we, therefore, conclude based on the F statistic value that climate change, PMS and trade openness have significant impact on food price inflation in Nigeria.

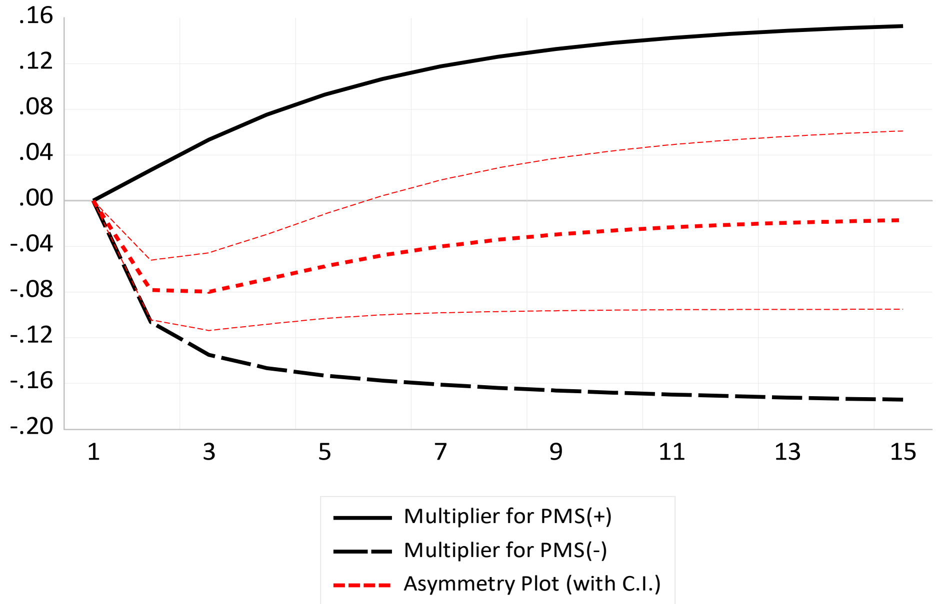
Fig. 2 illustrates the asymmetric cumulative dynamic multiplier in response to various factors such as food price inflation, climate change, trade openness, and PMS (Price of Motor Spirit). These factors exhibit both positive and negative unitary shocks, and these shocks align with the adjustments in the dependent variable. The dynamic multipliers depicted in these figures capture the impact of these positive and negative trends. The figures above provide estimates from the best-fit NARDL model for these dynamic multipliers. The solid black line represents the response of the dependent variable (FPI) to positive shocks, while the dotted black line shows the response to negative shocks in the independent variables (climate change variables, OPEN, and PMS). These lines include breaks to highlight the modulated pattern.

Table 6. NARDL wald test for long run asymmetric

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

*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.*
Source: Authors' Computation





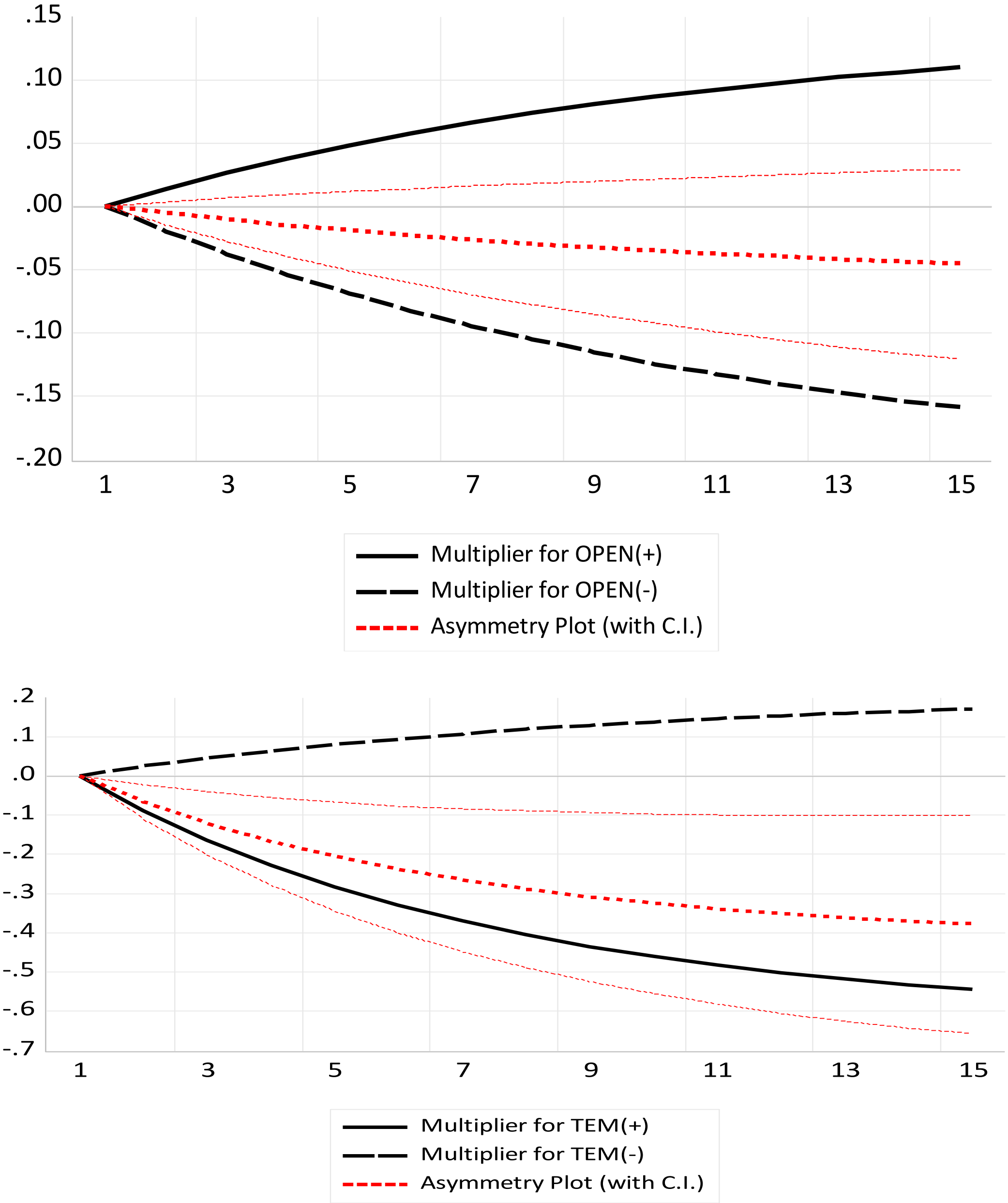


Fig. 2. NARDL Dynamic multiplier effect of independent variables

Source: Authors' Computation

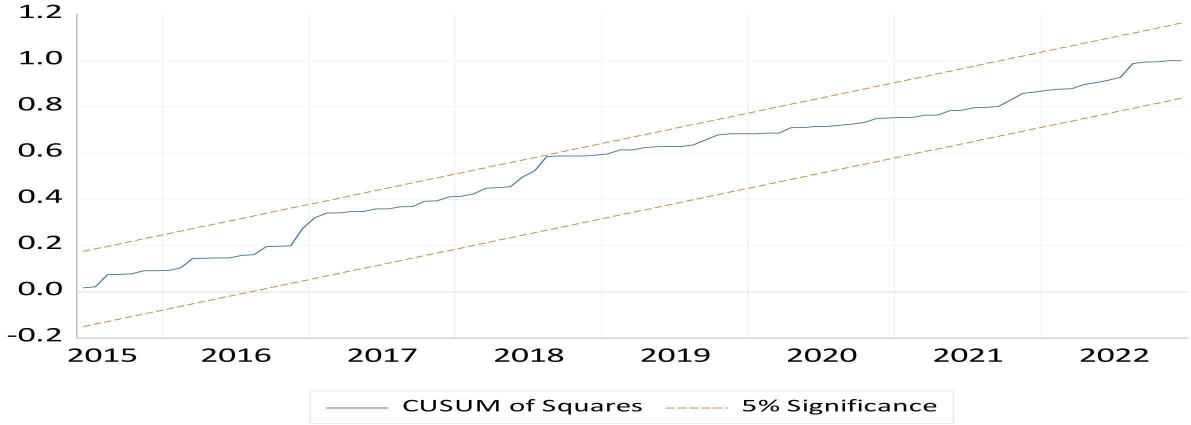
The red dotted line in the figures represents the asymmetric aspect, indicating how the dynamic multipliers change in response to shocks in each of the explanatory variables. This line helps illustrate the variations in dynamic multipliers associated with different shocks, i.e. ($wq+ - wq2$ $-$). The presented curve offers a comprehensive view, encompassing both lower and upper bands within a 95 percent confidence interval. This framework serves to provide a statistically robust assessment of asymmetry across various horizons defined by "q". When the zero line aligns with the midpoint between the two bands, it signifies that the examined explanatory variable holds no significant asymmetric effects. (Refer to the solid black line in the graphs in Fig. 2 for representation of shocks.).

The black short, dashed line illustrates the impact of a negative shift in CLIMATE CHANGE, OPEN, and PMS. Meanwhile, the red short, dashed line portrays the asymmetry curve, which elucidates the disparity between positive and negative alterations in the explanatory variables.

Accompanying this curve is a 95 percent confidence interval that facilitates statistical inference. Importantly, the zero lines fall within the upper and lower bounds of the 95 percent confidence interval, indicating that the asymmetric impact of the explanatory variables is statistically significant at a 5 percent significance level. The significant asymmetry curve provides evidence that shocks in Rainfall, Tem, OPEN, and PMS yield positive long-term effects, substantiating their positive influence on the dependent variable. Overall, the dynamic movement of the red short, dashed line, representing the asymmetry curve and its associated 95 percent confidence interval, underscores the substantial influence of explanatory variables on food price inflation in Nigeria during the study period.

3.5 Post Estimation Diagnostics

Table 7 provides an overview of the stability and diagnostic tests in our NARDL analysis. These tests evaluate the reliability and validity of our results. The serial correlation (Breusch-Godfrey) test and the stability tests (Cusum and Cusum of squares) are the main diagnostic and stability procedures. Our model's results are statistically significant and reliable because the probability values for the results of the serial correlation test are greater than 0.05. This demonstrates that our findings are valid. Additionally, the blue rays fall within the bootstrap area at a 95 percent confidence interval in accordance with the Cusum and Cusum of squares principles. The results suggest that our model is stable and not prone to large deviations.



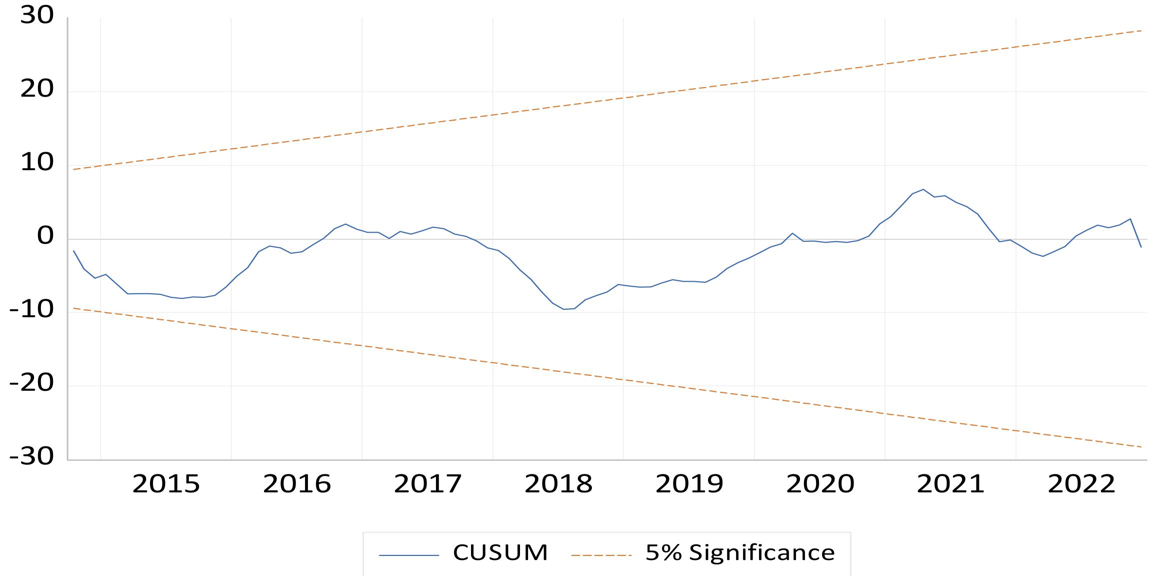


Fig. 3. CUSUM of square and CUSUM SUM graphs

Source: Authors' Computation

Table 7 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: Authors' Computation

Furthermore, the heteroscedasticity test (Breusch-Pagan-Godfrey) ensures that our model's variance remains constant. This is crucial because any variation in our variance could lead to bias of standard errors and inference, potentially invalidating the significance of our results. However, the diagnostic test results indicate that the disturbance errors in our model exhibit homoscedasticity, with a constant variance at a significance level of 0.05.

In summary, the diagnostic test results for our analyses demonstrate that the residuals in our model are free from serial correlation, heteroscedasticity, or model misspecification errors. This strengthens the credibility of our research findings.

4. CONCLUSION AND POLICY RECOMMENDATIONS

The broad objective of this study is to investigate the affiliation between climate change shocks and food price inflation in Nigeria with monthly time series data spanning 2011M1 to 2022M12. To accomplish this goal, the study used a Non-Linear Autoregressive Distributed Lag (NARDL) and performed a unit root test to determine the stationarity of the variables. The method is used to look at the asymmetrical short- and long-term relationships between Food Price Inflation and Climate Change in Nigeria, as well as the asymmetrical negative and positive responses of Food Price Inflation (FPI) 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 carried out some post estimation analysis, including stability, diagnostic and normality tests.

Based on the results, we found very strong evidence for asymmetric cointegration relationship between climate change and food price inflation in Nigeria within the period under study. This is confirmed by the empirical results of bound tests of 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 shocks are major threat to food production and have contributed significantly to the hike in food prices across Nigeria.

The NARDL analysis of climate change's positive and negative shocks reveals its pivotal role as a driver of food price inflation in Nigeria. The results underscore the substantial and statistically significant impact of climate change, signifying its significant influence on food price inflation. This outcome carries profound implications, highlighting the distressing challenges posed by climate change to the socioeconomic well-being of the Nigerian population and their access to food and nutritional security.

This research demonstrates that climate change exerts a substantial and adverse influence on both the agricultural and food sectors. The disruptions caused by climate change shocks have severely affected the usual patterns of food production and distribution. Consequently, these disruptions have led to a shortfall in the supply of food, contributing to a sustained upward trajectory in food prices.

In summary, the NARDL findings emphasize that climate change is a critical factor exacerbating food price inflation in Nigeria, and its adverse effects have far-reaching consequences, including food and nutritional insecurity and disruptions in the agricultural and food sectors.

The results also suggest 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:

i. 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 study recommends that Nigeria should transit from traditional agricultural practices to Climate-Smart Agriculture to address future needs and climate-related challenges.
ii. Additionally, the government and stakeholders should implement alternative practices such as irrigation and the replenishment of shrinking water bodies in the Sudan and Sahel savannah regions. These measures are aim to reinvigorate farmers' engagement in productive activities and help mitigate the adverse effects of climate change on food prices and availability in Nigeria.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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