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RESEARCH ARTICLE

# The Analysis of Climate Risk Impacts on Food Price Volatility: Moderating Role of Green Innovation Technology

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**Abstract:** The increasing temperature anomaly and greenhouse gas emission and other related climate-events have imposed serious threats to agricultural output, leading to volatility of commodity prices across the globe. This paper analyzes the asymmetry between climate risks, green innovation, and food price volatility in Nigeria. Time-series data were collected and analyzed using generalized autoregressive conditional heteroscedasticity in conjunction with non-linear autoregressive distributed lag modelspanning from 1990 to 2023. Data for the variables are generated from World Bank, World Development Indicators and Central Bank of Nigeria Statistical Bulletin online database. We regress climate risk measured by carbon emission ($CO_2$) and global average temperature anomaly on food price index and incorporate green innovation technology as a moderating variable while renewable energy consumption and population growth rate as control variables. To ascertain the asymmetric impacts, temperature anomaly and carbon emission ($CO_2$) were decomposed into positive (+ve) and negative (−ve) partial sums. We find that positive temperature (Temp+) and $CO_2$ shocks significantly increase food price volatility in the long and short terms. Conversely, negative shocks in $CO_2$ and temperature anomaly yield long-term volatility reduction, suggesting mitigation potentials. We also find that green innovation technology improves environmental quality and boost food production. The study recommends that the Nigerian government should encourage adoption of smart agricultural practices, build climate mitigation strategies that will improve environmental quality, and sustainable food production.

**Keywords:** climate change, environmental threats, agriculture, low-carbon economy, green technologies, resilience, sustainable development

## 1. Introduction

In the last few decades, global climate risks occasioned by rising global temperatures and carbon emissions and the need to adopt green technology as a mechanism for achieving low-carbon economy have attracted global discourse [1]. Climate risks are risks associated with climate change. Wang et al., [2] classified climate risk into two, namely, physical risk and transition risk. Physical risks are risks arising from extreme weather events, while transition risk refers to risks from transition from fossil fuel consumption greenhouses to low-carbon economy.

To lessen the dependence on fossil fuels, mining coal and burning wood that contribute to chlorofluorocarbons and greenhouse gasses (GHGs), green technologies are being encouraged to achieve a carbon-free economy all over the world. Green technologies have been adopted as adaptation and mitigation strategies in most emerging economies such as China and India. However, African countries, including Nigeria, are yet to benefit from such advanced mitigation strategies to achieve climate goals. Their vulnerability arises from factors, including low technological base, limited adaptive capacity, and weak institutional capacity [3, 4].

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Innovation in green technologies has become one of the important mechanisms for transitioning from fossil fuels to low-carbon economy [5, 6]. Technological innovation plays a very significant role by increasing agricultural productivity and reducing greenhouse gas emissions [4]. Adom et al. [3] identified five of such technology areas that include renewable, energy efficiency, carbon capture storage, and information and communication technologies (ICTs).

Many empirical works have suggested that a positive technological shock is critical in reducing carbon emission and increasing total factor productivity [7–11]. Green technological innovation helps enterprises in improving production efficiency and reducing production cost [11]. Technological innovations are specifically designed toward climate goal [10]. Adopting innovative green technology can reduce carbon emission and fosters a more resilient and sustainable economy [12].

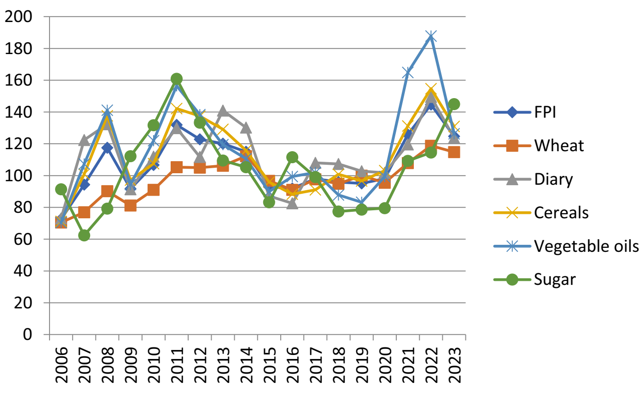
Indeed, climate change has been identified in most literature as important drivers of food price volatility through its impact on agricultural output. Rising food prices erode the purchasing power and real incomes of vulnerable populations especially those in sub-Saharan Africa [13]. Furthermore, high food prices have resulted in hunger, malnutrition, and food insecurity. According to Food and Agricultural Organization [14], over 25 million Nigerians have been pushed into hunger and food insecurity as a result of food price hike. Indeed, in 2023, roughly about 900 million people worldwide suffered food insecurity, with climate change being the driving force.

Figure 1 shows the global trend analysis of food commodity prices, including cereals, dairy products, wheat, vegetable oils, and sugar. The global prices of most of these food products have increased significantly between 2007 and 2008 reaching its peak at the second quarter of 2008 and begin to decline. The FPI rose sharply from 89.6 in 2002 to 201.4 in 2008 and jump to 209.8 in 2013 [14]. The various global commodity prices including, wheat, cereals, diary, vegetable oils, and sugar have shown persistent increase over the sample period. In 2007, global food prices collapsed as a result of global financial crisis and recession and spike again since 2010 and remained high up till moment. The most driving forces of global food commodity price volatility include global population growth, increase in biofuel production and consumption, oil price shocks, extreme weather events, depreciation of naira to a dollar, speculation, low food stocks, and policy measures [15–17].

There are uniquely some research gaps that the current study aims to bridge. A good amount of research has explored climate risk and commodity price volatility across the world [18–23]. Several studies, including Alexandridis et al. [24], find that weather events negatively affect crop yield which further limit food availability and exacerbate food price volatility. Previous studies have focused mainly on developed and emerging economies with already established substantive mitigation strategies [21–23, 25]. However, few studies consider differential impacts and the moderating role of technological shocks in Nigeria. The only work that is closely related to our study was that of Xu and et al. [11] who modeled the moderating role of innovation in green technology, yet their studies were restricted to China. So, existing studies [26, 36] have applied linear regression models, which may lead to inaccurate policy recommendations. In addition, previous studies have failed to conduct sensitivity analysis to determine the possibility of food prices being sensitive to climate shocks. This study fills literature gap by exploring the complex relationship between climate risk, food price volatility, and technology innovations using non-linear autoregressive distributed lag (NARDL) and GARCH models.

Our study contributes significantly to a wide spectrum of knowledge in the following ways. First, from the methodological point of view, this study employs an asymmetric modeling approach (NARDL) combined with volatility modeling (GARCH), which is more robust than traditional linear regressions often used in prior studies. Second, by focusing on Nigeria, where literature is scarce compared to China/India, provides a potentially important case study. Third, we examine the vital research gap in the literature by introducing green technology as a moderating variable, which could enrich policy debates. Fourth, by focusing on Nigeria, a climate vulnerable, with limited adaptive capacity, gives the study potential policy significance and originality.

**Figure 1**
**Global food price volatility (2006–2023)**




Source: World Bank database.

This paper primarily investigates the asymmetry between climate risks (measured by global average temperature anomalies and $CO_2$emissions), green innovations, and price volatility in Nigeria. Our tested hypothesis is that climate risk and green innovation do not significantly mitigate price volatility. To achieve this target, we have used the generalized autoregressive conditional heteroscedasticity (for volatility modeling) and NARDL approach (for asymmetric and long-run dynamics), using yearly dataset that spans from 1990 to 2023.

## 2. Literature Review

Adnan and Billah [27] employed symmetric and asymmetric techniques to examine the impact of technological innovations on environmental quality in Qatar using time-series data from 2012 to 2000. They found that positive and negative shocks of patent application have a significant effect on carbon emission. Lybbert and Sumner [13] also find that climate change negatively affect volatility of selected commodities. Pei et al. [28] find that renewable energy sources mitigate climate change through the reduction of carbon emission, supporting submissions by Maino and Emrullahu [29].

Elias and Kazeem [30] explored climate change impacts on volatility of food prices in Nigeria using GARCH-MIDAS. They find that climate change do not affect price fluctuations in Nigeria. Adesete et al. [31] employed a Generalized Method of Moments (GMM) approach to analyze the correlates between greenhouse gas emissions and food security in 30 SSA countries (2000–2009). Their findings agree with Nam [32]. Similarly, Adom et al. [3] discovered that climate change has led to increased temperatures (causing heat waves) and altered rainfall patterns (resulting in floods and droughts), thereby disrupting agricultural production and undermine food security in South Africa. Alexandridis et al. [24] further emphasize that extreme weather events affect food crops, ultimately limiting food availability.

Affoh et al. [33] studied climate change and food security among 25 SSA (sub-Saharan African) countries spanning 1985–2018. The results revealed temperature anomaly negatively influenced food security. These results confirm studies by Gadédjisso-Tossou et al. [34]. Bele et al. [35] conducted a study on vulnerability to climate change by communities in forest zone of Cameroon and reported that the regions were adversely affected by climate-related events. Ullah et al. [8] found that technological advancement improves environmental quality through the reduction of carbon emission. These findings also support studies by [9, 10, 7, 23, 36]. Similarly, Adebayo and Kirikkaleli [10] explored the relationship between $CO_2$, technological advancements, and renewable energy in Japan using wavelet statistical approach that spans the years 1990 to 2015. They find that technological advancement increases C02 emissions in Japan. A study by Mensah et al. [37] confirms that green innovation helps in reducing carbon emissions. Erdoğan et al. [38] in a study of G20 countries find that innovation reduces emissions in industrial sector. On the contrary, Du et al. [39] discovered that green innovations do not reduce carbon emission for economies with a minimum threshold level of income.

## 3. Materials and Methods

### 3.1. Data sources

To empirically estimate the asymmetries between climate risk and food price fluctuations, we use yearly data covering the period 1990 to 2023. The rationale for this timeframe was contingent on the fact that the period coincides with the onset of significant global warming observed in Nigeria since the early 1990s. Our dependent variable is food price index (FPI). Data on food price index (FPI) and technological innovation (TI), measured by R&D (Research and Development) expenditures, are obtained from WDI (World Bank's World Development Indicators) database [40]. Data on climate risk measured by global average temperature anomalies and carbon emission ($CO_2$) are sourced from the World Bank's Climate Change Knowledge Portal, renewable energy is obtained from US energy information Administration, while data on population growth rate are retrieved from online database of the CBN Statistical Bulletin [41].

### 3.2. Econometric technique and model specification

We employ GARCH and NARDL framework to analyze the data. For this study, we consider NARDL model appropriate due to the following reasons. First, this approach is suitable for addressing nonlinear correlations among economic variables. Second, this approach can better handle variables that have mixed integration order 1(0), or 1(1), provided they are not integrated at second order 1(2) [42, 43]. Our data exhibit this characteristic. Additionally, to account for volatility clustering, we have opted for GARCH model, which has been widely used in measuring volatility in most empirical literature [44]. We start by presenting the general framework of GARCH (1, 1) model as follows.

$$r_t = X^1 \varphi_t + \mu_t \tag{1}$$

$$\sigma^2{}_t = \varphi_0 + \varphi_1 \sum_{j=1}^{p} \varphi_k + \beta_{X_{t-1}} \tag{2}$$

Equation (2) is respecified as follows:

$$\sigma^2{}_t = \varphi_0 + \alpha_1 e_{t-1} + \beta X_{t-1} \tag{3}$$

where $r_t$ *denotesfoodprice* volatility series, $w_t\tilde{}\ N(0, \sigma_t^2)$

$$\sigma^2{}_t = \omega\alpha_o + \alpha_1 \mu_{t-1}^2 + \beta X_{t-1} \tag{4}$$

From Eq. (4), $\sigma^2{}_{t-1}$ represents the *GARCH* term; $\mu_{t-1}^2$ denotes the ARCH term; $\omega and\sigma^2{}_t$ represent the conditional mean and variance of food price returns, and $X_{t-1}$ denotes the lagged conditional variance. Thus, volatility persistence is captured by $\alpha + \beta$, and covariance stationarity requires that $(\alpha + \beta < 1)$.

Like Salisu and Oloko [45, 11], we utilize temperature anomaly and $CO_2$ as proxy for climate risk and R&D expenditure as a measure of green technology innovation. Thus, we express the equation as follows.

$$Fpindex_t = \varphi_0 + \varphi_1 \sum_{j=1}^{p} \text{CLIMR}_t + Z_t, +X_t, +\mu \tag{5}$$

where *Fpindex* is the explained variable, representing food price index at time *t*, CLIMR is the main explanatory variable, representing climate risk, $Z_t$ represents the moderating variable (green technology innovation); $X_t$ is a vector denoting control variables including population growth (POP) and renewable energy consumption (RENW), while μ represents the random disturbance term.

The functional representation of the Nonlinear ARDL is estimated below:

$$Fpindex = f(Temp^+ Temp^-, CO_2^+ \, CO_2^-, TI, Pop, Renw) \tag{6}$$

Econometrically, the model in Eq. (6) is modified as follows.

$$\begin{aligned} Fpindex = \lambda_0 + \lambda_1\, Temp^+ + \lambda_2 Temp^- + \lambda_2\, CO_2^+ + CO_2^- \\ + \lambda_3\, Ti + \lambda_4 Pop + \lambda_5 Renw + \mu \end{aligned} \tag{7}$$

Following Shin *et al.* [46], Eq. (7) is transformed into NARDL model specified below:

$$\begin{aligned} &\Delta Fpindex_t \\ &\equiv \lambda_0 + \lambda_1 Fpindex_{t-1} + \Delta\lambda_2 Temp_{t-1}^+ + \Delta\lambda_3 Temp_{t-1}^- \\ &\quad + \Delta\lambda_4 C02_{t-1}^+ + \Delta\lambda_5 C02_{t-1}^- + \Delta\lambda_6 Ti + \Delta\lambda_9 Pop \\ &\quad + \lambda_8 \text{R}enw + \sum_t^q \lambda_1 Fpi + \sum_t^q \lambda_2 Temp + \sum_t^q \lambda_3 C02 \\ &\quad + \sum_i^t \lambda_4 Ti + \sum_t^q \lambda_5 Pop + \sum_t^q \lambda_6 \text{R}enw + \varepsilon_t \end{aligned} \tag{8}$$

Model capturing the moderating role of innovation is specified as follows:

$$\begin{aligned} &\Delta Fpindex_t \\ &\equiv \lambda_0 + \lambda_1 Fpindex_t + \Delta\lambda_2 Temp^+ + \Delta\lambda_3 Temp^- + \Delta\lambda_4 C02^+ \\ &\quad + \Delta\lambda_5 C02^- + \Delta\lambda_6 Ti + \Delta\lambda_7 (Temp^* \, Ti) + \Delta\lambda_8 (CO2^* \, Ti) \\ &\quad + \Delta\lambda_9 Pop + \lambda_{10} \text{R}enw + \sum\nolimits_i^q \lambda_1 Fpi + \sum_i^r \lambda_2 Temp \\ &\quad + \sum\nolimits_i^s \lambda_3 C02 + \sum\nolimits_i^s \lambda_4 (C02^* \, Ti) + \sum\nolimits_i^s \lambda_5 (CO2^* \, Ti) \\ &\quad + \sum_i^t \lambda_6 Ti + \sum\nolimits_i^u \lambda_7 Pop + \sum\nolimits_i^v \lambda_8 \text{R}enw + \theta ECM + \varepsilon_t \end{aligned} \tag{9}$$

In Eq. (8), *Fpindex* is the food price index, *Temp* represents global temperature anomalies (degrees °C), $CO_2$ refers to carbon emission (metric tons per capita), *TI* is technological innovations(Ti) (measured by the ratio of Research and Development (R&D) expenditure to GDP), *Pop* is population growth rate, *Renw* represents renewable energy consumption, $\lambda_0$ denotes constant intercept, ($\lambda_1 - \lambda_6$) are the coefficients, *p, q, r, s* denotes the optimal lag length, and $\mu_t$ is the stochastic error term.

To explore the asymmetries, like [45, 46], we decompose the variables into positive and negative partial sums. The partial sums of temperature shocks ($Temp^+$ and $Temp^-$) are represented as follows:

$$Temp^+ = \sum_{i=0}^{q} \Delta Temp^+ = \sum_{i=0}^{q} \max(\Delta Temp_i, 0) \tag{10}$$

$$Temp^- = \sum_{i=0}^{q} \Delta Temp^- = \sum_{i=0}^{q} \max(\Delta Temp_{2i}, 0) \tag{11}$$

While $CO_2$ shocks ($C02^+$ and $C02^-$) is displayed below.

$$C02^+ = \sum_{i=0}^{r} \Delta C02^+ = \sum_{i=0}^{q} \max(\Delta C02_i, 0) \tag{12}$$

$$C02^- = \sum_{i=0}^{n} \Delta C02^- = \sum_{i=0}^{q} \max(\Delta C02_{2i}, 0) \tag{13}$$

## 4. Results

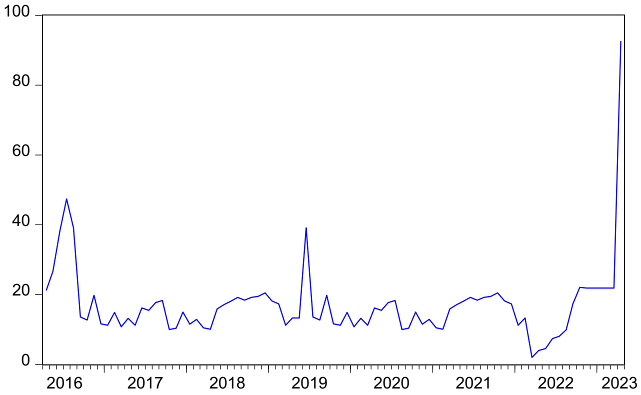
### 4.1. Volatility test and descriptive statistic

Before presenting the NARDL results, we first evaluate the GARCH (1, 1) model results, a formal test of volatility. We applied the GARCH (1, 1) (Table 1). We calculate log-returns of food price volatility (f*vr*) (Figure 2), and the volatility returns series is then tested for stationarity using ADF and PP test (Table 3). The results indicate that the coefficient of the ARCH term ($\alpha$ = 0.00043) and GARCH term ($\beta$ = 52904.03) are significant at 5% level (Table 1). The mean and variance equations are correctly signed, and there is no autocorrelation issue as demonstrated by the Q and $Q^2$statistic. The LM test demonstrates nonsignificance of the observed R-squared coefficient, suggesting the null hypothesis of no ARCH effect.

The reported descriptive statistics (Table 2) indicate that the standard deviation statistic values are relatively higher for all the variables, showcasing a high degree of volatility for food prices. The Jarque-Bera (J-B) statistics are greater than their Kurtosis values, demonstrating evidence of this normalcy. The closely related values of the mean and median are an additional proof of normal distribution. In addition, stationarity test shows that the series FPINDEX, $CO_2$, POP, and RENW are stationary at first difference, TEMP and INNOV at level, portraying mixed levels of integration (Table 3). Given varying order of integrations in this instance, and none is integrated of order 1(2), further lend support for using nonlinear ARDL bounds test (Table 4).

To empirically assess the existence of possible co-integration, we used nonlinear ARDL bounds test (Table 4). The findings reveal that $F$-calculated exceed the critical values at 5% ($F -$ statistic $=$ 4.616500 $>$ 3.38), demonstrating asymmetric association among the selected variables. The estimation results further provide empirical support for the chosen asymmetric, NARDL model for this study.

**Figure 2**
**Conditional variance of food returns volatility series**




### 4.2. Discussion

To empirically assess the impacts of climate risk on food price volatility, we employed nonlinear ARDL approach (Table A1) and generalized autoregressive conditional heteroscedasticity (Table 1). The short-run asymmetrical outcomes are displayed in Table A1. We discovered positive shocks in temperature and carbon emission (CO2) significantly increase food price volatility, highlighting climate mitigation actions. Conversely, negative shocks in CO2 emission and temperature anomalies decrease food price volatility, showcasing mitigation potentials. This finding corresponds to the submissions of Gupta and Pierdzioch [22] and Wang *et al.* [25]. Our analysis further shows that innovation shock significantly induces food price volatility, supporting findings by Isa and Muse [47].

Also, population growth (POP) was found from our estimation is 12.57%. Meaning that when the population increases, the demand for food items would increase, leading to sharp increases in price. This finding supports studies by Subramanian [48], the finding also indicates that shocks in renewable energy consumption lead to food price increase of about 5.095279. This means that an increase in renewable energy consumption also increases food

**Table 1**
**Results of GARCH (1, 1)**

| Variables | Coefficient | Std. Error | z-Values | Prob. |
|---|---|---|---|---|
| | | **Mean Equation** | | |
| C*** | −11.26576 | 3.340351 | 3.372626 | 0.0007 |
| *vfpr*(−1)*** | 0.123808 | 0.038702 | 3.198994 | 0.0014 |
| | | **Variance Equation** | | |
| C* | 0.831771 | 0.346734 | 2.398878 | 0.0164 |
| ARCH* | 0.000433 | 0.000153 | 2.820455 | 0.0048 |
| GARCH(−1)** | 52904.03 | 8359.987 | 6.328244 | 0.0000 |
| | | **Diagnostic Test** | | |
| ARCH-LM | | | | |
| Obs. R^2 | 0.085791 | | | 0.6986 |
| O & $Q^2$ *Statistic* | 0.529400 | | | Not Sig |

Asterisks *, ** and *** signify 10%, 5% and 1% statistical significance.

**Table 2**
**Descriptive Statistics**

| TEST-STATISTIC | VARIABLES | | | | | |
|---|---|---|---|---|---|---|
| | *FPINDEX* | *TEMP* | $CO_2$ | *INNOV* | *POP* | *RENW* |
| Mean | 6475.690 | 144.1941 | 18.86976 | 18.43272 | 10.68325 | 35.97143 |
| Median | 5521.460 | 129.3600 | 17.79500 | 13.00697 | 10.24658 | 36.05871 |
| Std. Dev. | 3924.327 | 111.0562 | 3.851427 | 15.99273 | 3.484340 | 9.309363 |
| Skewness | 0.204688 | 0.692677 | 1.186910 | 2.190104 | 0.693440 | –0.104189 |
| Kurtosis | 1.290192 | 2.578238 | 5.216859 | 6.822219 | 2.996572 | 2.469138 |
| Jarque-Bera | 4.250168 | 2.883494 | 14.50555 | 46.46892 | 2.644743 | 0.447199 |
| Probability | 0.119423 | 0.236514 | 0.000708 | 0.000000 | 0.266503 | 0.799635 |

**Table 3**
**Unit root test**

| Variables | Levels | | First Diff | | |
|---|---|---|---|---|---|
| | ADF | PP | ADF | PP | Remark |
| FPINDEX | –2.356*** | –2.233 | –7.234 | –6.273*** | 1(1) |
| TEMP | –5.366* | –4.235* | NA | NA | 1(0) |
| $Co_2$ | –1.523*** | –0.215 | –4.253 | –5.462*** | 1(1) |
| INNOV | –5.494** | –4.256** | NA | NA | 1(0) |
| POP | –2.138* | –0.243 | –5.023 | –6.326* | 1(1) |
| RENW | –2.923** | –2.142 | –7.024 | –4.528** | 1(1) |

**Note**: Asterisks *, ** and *** stand for 10%, 5% and 1% significance levels respectively, NA signifies not applicable.

**Table 4**
**NARDL bounds test**

| Model *(F(FPINDEX/ $TEMP^-$ POS, $CO_2{}^-$ POS, INNOV, POP, RENW))**** | *F-Value* 4.616500 | Upper Bound 1(1) | Lower Bound 1(0) |
|---|---|---|---|
| **Critical Values (%)** | | | |
| 10 | | 3.00 | 2.08 |
| 5 | | 3.38 | 2.39 |
| 1 | | 4.15 | 3.06 |

prices. The implication of this result is that if there is an increase in biofuel consumption, producers also increase the supply by diverting large quantities of cropland from food and feed crops production to biofuel production leading to trade-off. The diversion, all things being equal, results in a decrease in the supply of food crops and animal feeds, consistent with findings by Adebayo and Kirikkaleli [10]. The estimated error correction term (ecm) was significant, indicating high speed of adjustment to equilibrium after a temporary shock.

Table A2 demonstrates long-term asymmetric analysis. In the long run, positive shocks in temperature (TEMP) and CO2 emission increase food price volatility, suggesting urgent mitigation action. Conversely, negative shocks in temperature (TEMP) and CO2 decrease food price volatility, indicating climate mitigation's potentiality. This result was confirmed by studies of Minot, [49, 11]. The result also indicates that innovation plays a moderating role on food price volatility, but the coefficient is not significant, suggesting the need to invest in green technology to promote green production of food so as to prevent food price hike. This is in line with the conclusion of Sharma and Narayan [50]. In effect, a 1% change in green innovation technology (INNOV) will reduce food price increase by approximately 1.74%. Additionally, RENW has a positive and insignificant impact on food price volatility. The $R^2$ of 0.818588 in Table A2 showcases high explanatory power. Also, the $F$-value is significant, showcasing strong forecasting prowess.

## 4.3. Robust check

To ascertain robustness of our model's outcomes, we conducted heteroskedasticity, serial correlation, and the Ramsey test (Table 6).

The results displayed in Table 5 reveal no obvious cases of autocorrelation and heteroskedasticity in the model. In addition, the

**Table 5**
**Results of diagnostic test**

| Tests | $F$-calculated | Decision Rule |
|---|---|---|
| **A. Serial Correlation** | 0.636658 (0.5319$^{\rho}$) | No serial correlation |
| **B. Heteroskedasticity** | 1.378836 (0.2495$^{\rho}$) | No heteroskedasticity |
| **C. Ramsey** | 1.162244 (0.2845$^{\rho}$) | Model well specified |
| **D. Normality** | 1.406130 (0.2357$^{\rho}$) | Residuals normally distributed |
| **E. Endogeneity** | 0.374762(0.5404$^{\rho}$) | No endogeneity issue |

$^{\rho}$*indicates F-Statistic Probability and the values in parenthesis signify the probability values.*

value of the Ramsey test is insignificant proving that the model is correctly specified. The outcome of our analysis further confirms that the NARDL model is reliable, consistent, and robust for concise and comprehensive policy intervention. To address the potential endogeneity between food prices and climate variables, we carried out the test. The results displayed in Table 5 proved that there was no endogeneity problem.

### 4.4. Asymmetry test

In confirmation of asymmetry in the nonlinear ARDL model, Wald test was carried out. The results displayed in Table 6 confirmed the asymmetrical relationship among the variables.

**Table 6**
**Wald test**

| Test Statistic | Value | Df | Prob. Values |
|---|---|---|---|
| $F$-statistic | 63.21688 | (2, 24) | 0.0000 |
| Chi-square | 126.4338 | 2 | 0.0000 |

### 4.5. Stability test

Furthermore, we performed the NARDL stability test to ascertain whether our model is stable. The results from cumulative sum-of-squares (CUSUMsq) and cumulative-sum (CUSUM) displayed in Figure 3(a) and (b) proved that the model is stable.

### 4.6. Granger causality

As a further confirmation of our NARDL model's estimates, we applied Granger causality test (Table 7).

The results of Granger causality indicate that innovation shocks Granger causes $CO_2$, confirming that enhanced green technology innovation is crucial in reducing carbon emission. The finding corroborates with empirical results by Zang *et al.* [44], but disagrees with Du *et al.* [39]. Evidence of unidirectional causality was also established between $CO_2$ and RENW, meaning investments in renewable energy and technological innovation help in reducing carbon emissions in developing country like Nigeria. This finding agrees with submission by Ma *et al.* [9]. We also find INNOV granger causes FPINDEX, implying technological innovation shocks are critical in inducing food price volatility.

**Figure 3**
**(a) CUSUM and (b) CUSUM of squares**

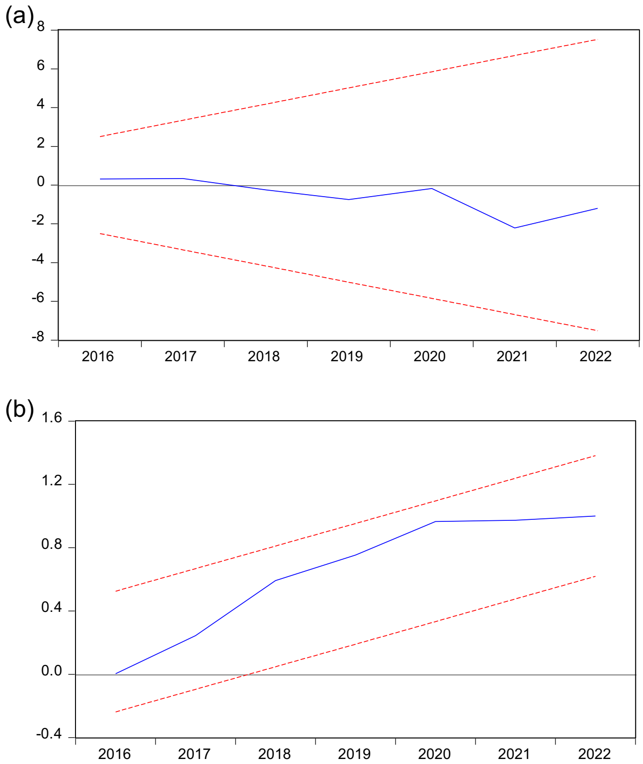



**Table 7**
**Granger causality test**

| Null Hypothesis: | $F$-Statistic | Prob. |
|---|---|---|
| *INNOV* does not Granger Cause $CO_2$ | 3.01978 | 0.0655 |
| $CO_2$ does not Granger Cause *INNOV* | 2.11615 | 0.1400 |
| *RENW* does not Granger Cause $CO_2$ | 10.4408 | 0.0004 |
| $CO_2$ does not Granger Cause *RENW* | 0.56036 | 0.5775 |
| *INNOV* does not Granger Cause *FPindex* | 2.88109 | 0.0734 |
| *FPindex* does not Granger Cause *INNOV* | 1.07521 | 0.3554 |

## 5. Conclusion and Policy Implications

This study examined the asymmetric and complex relationship between climate risk and price volatility in Nigeria. It considered the mediating role of green innovation technology in achieving the target of net zero $CO_2$ emissions. The study used the GARCH-NARDL model to analyze the asymmetry, using yearly data (1990–2023). Findings from nonlinear ARDL framework revealed that positive shocks of temperature anomaly and carbon emission ($CO_2$) yield a strong positive impact on food price volatility, suggesting the need to adopt climate mitigation strategies. Conversely, negative shocks in temperature anomaly and $CO_2$ dampen food price volatility, showcasing climate mitigation potentials, thus supporting many of the empirical studies [10, 11, 26].

Our empirical evidence has policy implications, first, it provides insights to Nigeria governments and other developing countries to adopt and develop effective policies targeted at emission reductions to make economies more resilient. Second, there is need to adopt clean technologies to achieve sustainability of net-zero emissions. Modern technologies, including solar, hydropower, bioenergy, geothermal, and energy efficiency, can also contribute in achieving low-carbon economy.

As a limitation to this study, we examined the asymmetry between climate risk, price volatility, and green innovation using annual data. The time-series frequency (annual data) may limit volatility modeling power compared to quarterly/monthly data. Further research on this topic can be done using quarterly or monthly data to enrich the work.

## Ethical Statement

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

## Conflicts of Interest

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

## Data Availability Statement

The data that support this work are available upon reasonable request to the corresponding author.

## Author Contribution Statement

**Nuhu Musa:** Conceptualization, Methodology, Software, Validation, formal analysis, investigation, resources, data curation, writing—original draft, writing—review & editing, visualization, supervision, and project administration.

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## Appendix

**Table A1**
**Estimated Short-Run Non-linear ARDL Model Results (Dependent Variable: Food price index (FPINDEX))**

| Regressor | Coefficient | T-Statistic | Prob.* |
|---|---|---|---|
| D(FPINDEX(–1)) | 0.859980 | 16.64890 | 0.0000 |
| D(TEMP_NEG) | –12.44560 | –3.283545 | 0.0047 |
| D(TEMP_NEG(–1)) | –12.81129 | –3.034916 | 0.0068 |
| D(TEMP_POS) | 0.870244 | 4.823155 | 0.0001 |
| D(TEMP_POS(–1)) | 12.67809 | 3.341419 | 0.0041 |
| D($CO_2$_NEG) | –25.83239 | –1.987904 | 0.0642 |
| D($CO_2$_NEG(–1)) | –10.65526 | –2.582300 | 0.0170 |
| D($CO_2$_POS) | 37.42129 | 0.714507 | 0.4852 |
| D(INNOV) | –1.511682 | –0.110414 | 0.9129 |
| D(INNOV(–1)) | –5.513275 | –0.878612 | 0.3891 |
| D(POP) | 12.57916 | 2.944384 | 0.0083 |
| D(POP(–1)) | 71.30113 | 1.759293 | 0.0924 |
| D(RENW(1) | 11.47650 | 2.697988 | 0.0147 |
| D(RENW(–1)) | 15.80361 | 2.074136 | 0.0546 |
| CointEq(–1)* | –0.085764 | –14.30513 | 0.0000 |
| R-squared | 0.995061 | 28584.49 | |
| Adjusted R-squared | 0.990431 | 19677.98 | |
| S. of regression | 1924.897 | 18.26999 | |
| Sum squared resid | 59283653 | 19.00285 | |
| Log likelihood | –276.3198 | 18.51291 | |
| $F$-statistic | 214.9147 | 2.592557 | |
| Prob ($F$-statistic) | 0.000000 | | |

**Table A2**
**Estimated Long-Run Non-linear ARDL Model (Dependent Variable: Food price index(*FPINDEX))***

| Variable | Coefficient | t-Statistic | Prob.* |
|---|---|---|---|
| TEMP_POS | 0.931691 | 22.59218 | 0.0000 |
| TEMP_NEG | –10.65526 | –2.582300 | 0.0170 |
| $CO_2$_POS | 10.22119 | 2.431183 | 0.0237 |
| $CO_2$_NEG | –6.922739 | –0.242775 | 0.8104 |
| INNOV | –174.7034 | –1.398307 | 0.1730 |
| POP | 19.14494 | 4.728189 | 0.0001 |
| RENW | 71.30113 | 1.759293 | 0.0924 |
| C | 187.2239 | 0.260643 | 0.7968 |
| $R$-squared | 0.818588 | | |
| Adjusted $R$-squared | 0.786193 | | |
| D-W | 2.057411 | | |
| $F$-value | 3.530739 | | |
| Prob ($F$-statistic) | 0.000000 | | |