Risk Management Perspective of the Impact of Agricultural Value Chain Disruption on Food Inflation in Nigeria

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Abstract: Despite agriculture's crucial role in the economy, value chain disruptions hinder growth and food security. This study investigates the impact of agricultural value chain disruptions on food inflation in Nigeria from a risk management perspective. Specifically, it analyzes the effects of factors like weather changes, conflict, and financial costs on both value chain disruptions and food inflation, using a mixed-methods approach and secondary data from key sources (e.g., Central Bank of Nigeria, National Bureau of Statistics), it employs quantitative techniques, such asValue at Risk and the Multinomial Endogenous Treatment Effects Model. The findings reveal that climatic change, conflict, disasters, and monetary policy significantly influence agricultural value chain disruptions and subsequent food inflation. Financial costs, in particular, were identified as a strong predictor of these disruptions. The study provides a comprehensive framework for policymakers, recommending targeted strategies such as enhancing financial accessibility, promoting sustainable practices, and improving infrastructure to mitigate risks, build agricultural resilience, and ensure Nigeria's food security and economic stability.

JEL Classification: E31, Q10, Q13, Q18.

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1. INTRODUCTION

The structure of an agricultural value chain is a complex network of interrelated activities that flow in different directions both forward and backward along with the various players responsible for transitioning products to satisfy the needs of all involved. This process necessitates managing relationships regarding quantity, quality, timing, and pricing among several key agents: input suppliers, producers focusing on quality and efficiency, and marketing channels facilitating the delivery of finished products to the end consumer.Porter's generic value chain model, presented in his seminal work "Competitive Advantage: Creating and Sustaining Superior Performance" (1985a, b), distinguishes between primary and secondary activities. Primary activities are directly associated with the creation or production of goods and services. In contrast, secondary activities are supportive, enhancing the overall effectiveness and efficiency of each contributor within the value chain, ultimately leading to comparative or competitive advantages over others (Pila et al. 2010; Lowitt et al. 2015).

An agricultural value chain illustrates the entire journey of agricultural products, from the initial raw materials all the way to the final consumer. This encompasses every activity involved in the production, processing, distribution, and consumption of these products. Various participants play vital roles in this process, including farmers, processors, traders, and retailers, each contributing to the product's lifecycle. Efforts to develop the agricultural value chain focus on finding effective ways to connect producers with agribusiness and integrate them into these chains. A common approach is contract farming, where farmers agree to supply a certain quantity of agricultural products to agribusiness firms, adhering to specific quality standards and delivery timelines. The pricing is typically negotiated upfront. Many agribusinesses also offer support to farmers by providing inputs, extension services, and logistics for transporting produce to their facilities. In many developing countries, including Nigeria, promoting market linkages is often based on the idea of "inclusive value chains." These are value chains that either already exist or are newly formed, with the capacity to include small-scale farmers. Agriculture is essential in Nigeria, where it engages about 36% of the workforce and makes a significant contribution to the nation's GDP. The primary objectives of the agricultural value chain include ensuring food security, achieving food sovereignty, and maintaining economic viability. However, the strategies implemented to achieve these goals can vary widely from one country to another. The value chain encompasses various interconnected stages input supply, production, processing, distribution, and marketing all of which play a crucial role in determining the efficiency and profitability of agricultural enterprises.

In February 2011, global food prices soared to unprecedented levels, climbing over 30 percent compared to the previous year, fueled by significant hikes in the costs of grains, cooking oils, and meat products (ADB, 2023). Although the recent surge in prices was primarily instigated by production deficits caused by adverse weather conditions, the underly-

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ing structural and cyclical issues that were present during the 2007–2008 food crisis remain relevant, particularly in the context of the robust recovery of numerous emerging markets from the global financial downturn.Inflation has become one of the most pressing and dynamic macroeconomic challenges facing economies globally. In Nigeria, it has sparked considerable conversation among families and in the media, as its impact increasingly affects daily life due to rising prices (Olatunji et al., 2010). Over the years, the consumer price index for food in Nigeria has made up a significant portion of the overall consumer price index. As Oppedahl (2009) pointed out, households in developing nations typically allocate more of their budgets to food compared to other expenses, making food price inflation a critical factor in the overall inflation landscape.

In the agriculture sector, where vulnerabilities to a wide range of risks such as weather changes, economic shifts, and market dynamics are prevalent, effective risk management becomes even more critical. By adopting strong risk management strategies, farmers can lessen negative impacts, boost productivity, and contribute to food security. The Food and Agriculture Organization (FAO, 2021b) highlights that establishing solid risk management frameworks enhances farmers' resilience, minimizes losses, and supports sustainable agricultural practices. The challenges faced in agriculture are complex, with both the likelihood and severity of risks influenced by various critical factors. By implementing risk management techniques, stakeholders can proactively identify, assess, respond to, and mitigate these risks, effectively reducing their likelihood and impact. It also serves as an early warning tool, enabling better preparation and response planning for risk events.In Nigeria, there are numerous hurdles that hinder effective agricultural risk management. These include limited access to financial services, a lack of insurance options, inadequate infrastructure, and insufficient knowledge about available risk management tools. Furthermore, the impacts of climate change are becoming ever more evident, worsening the risks faced by agricultural production (Adger *et al*., 2018). Addressing these issues calls for a thorough assessment of current risk management strategies and their overall effectiveness. The relationship between the agricultural value chain and food inflation is significant. When the value chain operates inefficiently, it can drive up food prices and worsen inflation. Conversely, as food prices rise, there’s often a push towards adopting more efficient and sustainable farming practices. A well-functioning agricultural value chain is essential for ensuring food security and maintaining economic stability. In Nigeria, food production ideally should be abundant enough that fluctuations in demand or supply have little impact on food prices, which would help stabilize the overall price level. It’s reasonable to anticipate that improvements in agricultural productivity can lead to lower food prices, thereby reducing overall inflation rates (Benfica, Boughton, Mouzinho and Uaiene, 2017; Salik & Aras, 2020). It's concerning that, despite the country's vast agricultural resources, food prices continue to rise alongside a high inflation rate.

From a risk management standpoint, the agricultural value chain encounters numerous challenges that could potentially contribute to food inflation. These challenges encompass production risks such as adverse weather conditions, pests, and diseases market risks like price fluctuations and limited access to financing, as well as logistical risks related to transportation and storage. To effectively address these challenges, it's essential to implement risk management strategies like diversification, insurance, and strategic storage. These approaches are vital for reducing risks and helping to stabilize food prices. Concerns regarding agricultural productivity and food prices should not be taken lightly, especially considering their role in sustaining food inflation and the overall rise in the country’s price levels. For example, from 1981 to 2021, food prices saw a significant increase from an index of 48 in 1981 to 129 by 2021. During this same time frame, inflation remained troublingly high, hitting double digits 71% of the time over 40 years. Research by Benfica, Boughton, Mouzinho, and Uaiene (2017) indicates that between 2008 and 2011, before the surge in food prices, there were notable rises in agricultural productivity and participation intensity. This period also showed modest productivity gains across all crop categories. These changes were driven by global transformations in the agricultural sector, making shifts in food product prices and the rising cost of inputs within the national context particularly significant (Njegovan & Simin, 2020).

This situation might be a key factor influencing the current inflation in Nigeria, which exceeded 15% in 2021. The World Bank noted that April 2021 experienced the highest year-on-year inflation rate in four years, reaching 18.2%. Notably, food prices accounted for more than 60% of this inflation increase. The years 2020 and 2021 marked the steepest rise in food-price inflation in nearly twenty years for Nigeria. As a result, it has become essential to explore the relationship between agricultural value chain disruption and food inflation in Nigeria, particularly from a risk management standpoint. A crucial question arises: How have agricultural value chain disruption influenced fluctuations in food inflation in Nigeria, considering the aspects of risk management.

2. LITERATURE REVIEW

The theoretical framework for this study on agricultural value chain disruption and food inflation in Nigeria integrates several established economic and risk management theories. The framework is built on Michael Porter's Generic Value Chain Model which distinguishes between primary and supporting activities, is used to understand the entire agricultural value chain process, from the sourcing of raw materials to the final consumer. The primary activities in this context are inbound logistics, operations, outbound logistics, marketing and sales, and service, while supporting activities include procurement, technology development, human resource management, and infrastructure. The model helps to identify where disruptions can occur and how they impact the chain's efficiency. Secondly, Risk Management Theoryis essential for the study's focus on a risk management perspective. It involves identifying, analyzing, and addressing potential risks that could affect the agricultural value chain. The study uses this theory to understand how various risks, such as adverse weather, economic shifts, and market dynamics, can impact the sector. The Value Chain Risk Assessment (VCRA) Modelexplicitly uses the VCRA model to understand how different risks interact within the agricultural value chain and their cumulative effects on food inflation. This model helps to identify and prioritize risks, enabling the development of effective mitigation strategies. In addition, the Input-Output Model (IOM)was utilized to illustrate the interdependencies between different agricultural sectors and their contributions to the economy. By depicting how the output of one industry becomes an input for another, the model helps to assess the broader economic effects of agricultural disruptions, such as price volatility and shifts in crop yields, on other sectors and, ultimately, on food inflation; and lastly, Value at Risk (VaR) Measure is a quantitative tool used to analyze the potential risks associated with food inflation over time. The study employs this measure to visualize the historical pattern of food inflation risk and to inform strategic planning and proactive measures to stabilize food prices.

A thorough literature review covering the years 2010–2020 is presented thematically by Kaur (2023). It offers a thorough examination of the ways in which monetary policy regimes are reacting to the inflation of food. It talks about the elements that contribute to food inflation and how financial market efficiency helps spread policies. Additionally, it describes how rising food prices worsen food insecurity and how wealthy nations shield their farmers with input subsidies, so indirectly fueling the increase in food costs worldwide. Additionally, it makes the case that stationarity and mean-reversion to inflation rates can be facilitated by a strong monetary policy credibility. The problems central banks confront in measuring inflation are then covered, including supply-side restraints ranging from high farm-to-fork markups to cartelization and hoarding, as well as conflicts of choice in various inflation measures. The question of whether to target headline or core inflation is addressed in the section that follows. It then gives a brief overview of how different developed and developing nations manage their monetary policies while implementing fiscal policies. It demonstrates how the level of fiscal intervention should be determined based on each nation's unique threshold while accounting for the percentage of the population that is Ricardian and non-Ricardian.

In their analysis, Afesorgbor and Lim (2023) discovered that the COVID-19 pandemic had a significant impact on food security by causing supply chains to be disrupted by border closures. Our research focuses on South Asia and uses monthly panel data from 2018–2021 to analyze the relationship between COVID-19, agri-food trade, and inflation. Our results show that the epidemic significantly increased food prices in the area. However, this influence was mitigated by the strong correlation between COVID-19 and the agri-food trade. This emphasizes how important trade policies were in reducing food inflation during the South Asian epidemic.

Valdes, (2023) did an exploratory study that examined the factors impacting the recent increase of food prices in Latin America. Concerns about the inflation of food prices have been greatly increased since the outbreak began. Significant disruptions in local and global value chains have resulted from the rapid succession of quarantines, mobility limitations, and uncertainty. In addition, the conflict between Russia and Ukraine has made the already dire inflationary scenario worse by causing more disruptions and disruptions to agribusiness value chains. This article analyzes the effects of the SARS-CoV-2 outbreak and the ensuing conflict between Ukraine and Russia on the inflation of food prices in Latin America using empirical research. Additionally, it evaluates the policies that nations have put in place and projects future developments in this area. Concerns about the region's inadequate supply chains and susceptibility to food security have been raised by regional food inflation processes. The connection between these activities and the economy's total price level must be taken into account. According to the data, food costs have increased more sharply than those of the rest of the economy, indicating a price spike in comparison to other consumer items. This has had a direct effect on food producers and final consumers.

According to Obiora *et al*. (2023), food security is a major worldwide issue that is especially important in emerging nations like Nigeria. Individual health, cognitive growth, and the creation of human capital all depend on having adequate access to wholesome food. In a larger sense, food security is essential to social stability, rural development, and poverty alleviation. Food security has been negatively impacted by inflation's effect on food costs, especially for Nigerian rural farming households. Nigeria, a large African country, faces food insecurity in the face of recent high prices. Their study used a thorough literature analysis to analyze the relationship between inflation and food security in Nigeria. The research examined the various ways that inflation affects food security, with a particular emphasis on how it affects food prices, purchasing power, production, distribution, and household consumption habits in Nigeria. The study emphasized how rising food prices due to inflation reduce consumer purchasing power, particularly for those with low incomes, leading to poor nutrition and health problems. Low agricultural productivity, extreme weather patterns, exchange rates, transportation and distribution, government policies, insurgency, energy crises, the Russian-Ukrainian War, market competition, and hoarding are some of the exacerbating factors that this study identified in relation to inflation-induced food security issues. In order to mitigate the impact of inflation on food security, the study's conclusion recommended a range of comprehensive policy measures, including stabilizing inflation rates, boosting agricultural productivity, bolstering safety nets, increasing infrastructure, and fortifying governance and policy execution. To fully understand and solve the complex interactions between inflation and food security in Nigeria, it is imperative to prioritize interdisciplinary approaches integrating economics, agriculture, nutrition, and other relevant sectors.

According to Yusuf and Oyegoke (2021), food inflation has a significant potential because of its relationship to the socioeconomic crises and the need for food. The true impact of the COVID-19 outbreak and the federal government's ensuing lockdown on food inflation has not yet been established, though. Weekly Covid-19 incidence statistics (obtained from NCDC), weekly food inflation data, average weekly exchange (BDC) rates, and crude oil prices (obtained from NBS) are all analyzed in their study using the ARDL analytical method. Nigeria should expand local agricultural production and value addition to raw products to boost the food supply at a competitive level and minimize imports, according to the study's conclusion that the exchange rate is the real source of food inflation in the country. Like the price of crude oil, the COVID-19 coefficient is marginally negative (-0.000096) but not statistically significant.

Ismaya and Anugrah (2018) look into what causes Indonesia's food inflation. We demonstrate that both forward-looking and backward-looking expectations have a significant influence on food inflation using quarterly data (2008: Q1 to 2017: Q4) and a GMM estimator. Furthermore, we demonstrate the great significance of the factors that influence the general inflation of food prices, including demand level (M1/consumption), infrastructure, food imports, farm sector finance, food production, agriculture sector output, and seasonal events (Eid Mubarak). Expectations for the future and the past, the price of domestic oil, and the degree of demand have all contributed to the high cost of food, whereas variables related to general food price inflation have caused the price of food to decline.

In addition to the natural trend, food prices have been increasingly volatile lately (Roache, 2009), which worries producers and consumers about food price inflation. This contributes to the popularity of food inflation as a research topic. The factors that contribute to food inflation have been the subject of extensive research. Most people agree that the primary cause of price instability is a supply shock (Subervie, 2008). According to Kornher & Kalkuhl (2013), domestic food prices are greatly impacted by output and inventories, which represent the supply side. Additionally, Durevall, Loening, and Ayalew Birru (2013) provide this evidence. They demonstrate how food production influences food inflation in the near term, leading to significant departures from long-term price trends. Food output and food price inflation are negatively correlated in both studies. Another element that could affect food inflation from the supply side is food imports. The stock level and imports have a tendency to stabilize prices. According to Miranda & Glauber (1995), in areas with a persistent supply-demand imbalance, asymmetry between trade (import) and storage results, and imports are primarily driven by the structural supply-demand imbalance. In this case, imports will significantly impact storage activity, whereas storage has minimal impact on imports. Additional research on imports and inflation in food prices can be found in the works of Kornher & Kalkuhl (2013), Joiya & Shahzad (2013), and Abdullah (2023). These studies demonstrate that imports have a statistically significant positive impact on the inflation of food prices. In general, a country's features (such as its closed economy or importer-exporter status) determine how important production, stocks, and imports are. GDP is another possible contributor to the inflation of food prices. Inflation and GDP have a complicated relationship. According to empirical research, there can be a positive, negative, or neutral relationship between GDP and inflation (Olamide, Ogujiuba, & Maredza, (2022)). In Pakistan, there is a negative correlation between GDP and the inflation of food prices, according to other research like Adnan and Ali (2014) and Rehman & Khan (2015). However, when Joiya and Shahzad (2013) examine the factors that contribute to high food prices, they discover that one of the key factors influencing food price inflation is GDP. Inflation of food prices may also be caused by infrastructure. According to Fielding (2008), one of the statistically significant causes of inflation is infrastructure. Better transportation and communication infrastructure, as measured by road length, literacy, and language homogeneity, is linked to decreased inflation volatility, according to his analysis of 96 individual product data from 37 Nigerian states. According to a different study by Timmer (2000), price stability, economic growth, and poverty reduction are all directly impacted by increases in agricultural productivity that are sparked by government spending on rural infrastructure, irrigation, agricultural research and extension, and suitable price incentives (Ismaya & Anugrah, 2018).

3. METHODOLOGY

The source of data is secondary data, sourced from (i) the Central Bank of Nigeria (CBN), National Bureau of Statistics (NBS), Foods and Agricultural Organization (FAO), and The World Bank. The variables of interest to the study include the following: *Agricultural production* (yields of selected crops and livestock commodities); *Climatic change* (temperature, humidity, CO_2 emission, and precipitation); *Conflict and Insecurity* (conflict indices, insecurity measures); *Disaster* (Community preparedness indices); *Economic growth* (Real GDP growth rate); *Financial cost* (Maximum lending); *Monetary policy* (CBN interest rates, money supply); *Food inflation rate*; and *Agricultural value chain disruption*.The information was collected from the World Bank, the Foods and Agricultural Organization (FAO), the National Bureau of Statistics (NBS), and the Central Bank of Nigeria (CBN) publications that were already in existence for the years 1990–2004.

The approach is quantitative in character. Regression analysis and econometric modeling are employed as quantitative methods to examine the connection between food inflation and disruptions in the agricultural value chain (Olufemi-Phillips, Ofodile, Toromade, Igwe, & Adewale, (2024). Descriptive statistics and statistical models, including the multiple regression model and the value at risk (VAR) model, are used to analyze the data. The regression model estimates several key statistics, including the multiple correlation coefficient (R), the co-efficient of multiple determination (R^2), Durbin-Watson statistics, the ANOVA test, the confidence interval, part and partial correlation, multicollinearity statistics, serial (auto) correlation, tolerance statistics, and collinearity statistics.

Naturally, more of the variation in the response variable can be explained if we include more components in our model that are helpful in explaining the response variable. As a result, improved models for predicting the response variable can be created using multiple regression analysis. The ability to incorporate very general functional form correlations is another benefit of multiple regression analysis. Only one function of a single explanatory variable may be included in the equation for the basic regression model. A lot more flexibility is possible with the multiple regression model, hence, the Multinomial Endogenous Treatment Effects Model (METM).

In the population, the multiple linear regression model can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + \varepsilon \quad (1)$$

In this case, β_0 represents the intercept, β_1 the parameter linked to x_1, β_2 the parameter linked to x_2, and so forth. There are k+1 (unknown) population parameters in equation (1) because there are k independent variables and an intercept. The slope parameters are the parameters ($\beta_1, \beta_2, \ldots, \beta_k$) that are not the intercept (β_0). The error term or disturbance is represented by the variable ε. It includes variables that impact y besides $x_1, x_2, \ldots, x_k$. ε contains all of the components that we are unable to incorporate in our model, regardless of how many exogenous variables we include.

It is simple to express the fundamental premise of the multiple regression model as a conditional expectation: The formula:

$$E(\varepsilon | x_1, x_2, \ldots, x_k) = 0 \quad (2)$$

All of the components in the unobserved error term must, at the very least, be uncorrelated with the exogenous variables in order for equation (2) to work. Additionally, it indicates that the functional relationships between the response and exogenous factors have been appropriately taken into consideration. Equation (2) fails if there is an issue that makes ε correlated with any of the exogenous variables. Ordinary least square (OLS) is unbiased, according to equation (2), and will determine the bias that results from leaving out a crucial variable from the equation.

We look for estimates $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$ in order to achieve the ordinary least square estimate in the equation:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \cdots + \hat{\beta}_k x_k \quad (3)$$

To minimize the sum of squared residuals, k+1 of the OLS estimates is selected:

$$\sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_2 - \cdots - \hat{\beta}_k x_{ik})^2 \quad (4)$$

Multivariate calculus can be used to address the minimization problem.

Let the least squares function be defined as

$$L = \sum_{i=1}^{n} \mu_i^2 = \sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_2 - \cdots - \hat{\beta}_k x_{ik})^2 \quad (5)$$

The least square estimate must satisfy

$$\frac{\partial L}{\partial \beta_0} = -2 \sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_2 - \cdots - \hat{\beta}_k x_{ik}) = 0 \quad (6)$$

and

$$\frac{\partial L}{\partial \beta_j} = -2 \sum_{i=1}^{n} x_{ij} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_2 - \cdots - \hat{\beta}_k x_{ik}) = 0 \quad (7)$$

j = 1, 2, …, k

This leads to $k+1$ linear equations in $k+1$ unknowns $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$.

$$\sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \cdots - \hat{\beta}_k x_{ik}) = 0$$

$$\sum_{i=1}^{n} x_{i1} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \cdots - \hat{\beta}_k x_{ik}) = 0$$

$$\sum_{i=1}^{n} x_{i2} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \cdots - \hat{\beta}_k x_{ik}) = 0$$

$$\vdots$$

$$\vdots$$

$$\sum_{i=1}^{n} x_{ik} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \cdots - \hat{\beta}_k x_{ik}) = 0$$

(8)

The OLS first order conditions (F.O.C.) are a common term for these. The method of moments can be used to derive the OLS first order conditions, just like with the simple regression model: under equation (2), $E(\varepsilon) = 0 \; and \; E(x_j \varepsilon) = 0$, where $j = 1, 2, \ldots, k$. These population moment' sample counterparts are represented by the equations in equation (8).

The least squares normal equations are

$$n\hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1} + \hat{\beta}_2 \sum_{i=1}^{n} x_{i2} + \cdots + \hat{\beta}_k \sum_{i=1}^{n} x_{ik} = \sum_{i=1}^{n} y_i$$

$$\hat{\beta}_0 \sum_{i=1}^{n} x_{i1} + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1}^2 + \hat{\beta}_2 \sum_{i=1}^{n} x_{i1} x_{i2} + \cdots + \hat{\beta}_k \sum_{i=1}^{n} x_{i1} x_{ik} = \sum_{i=1}^{n} x_{i1} y_i$$

$$\vdots$$

$$\vdots$$

$$\hat{\beta}_0 \sum_{i=1}^{n} x_{ik} + \hat{\beta}_1 \sum_{i=1}^{n} x_{ik} x_{i1} + \hat{\beta}_2 \sum_{i=1}^{n} x_{ik} x_{i2} + \cdots + \hat{\beta}_k \sum_{i=1}^{n} x_{ik}^2 = \sum_{i=1}^{n} x_{ik} y_i$$

(9)

The regression coefficients' least squares estimators are the answers to the normal equations in equation (9).

Writing equation (3) in terms of changes,

$$\Delta\hat{y} = \hat{\beta}_1 \Delta x_1 + \hat{\beta}_2 \Delta x_2 + \cdots + \hat{\beta}_k \Delta x_k \quad (10)$$

The coefficient on x_1 measures the change in $\hat{y}$ due to a one-unit increase in x_1, holding all other independent variables fixed. That is,

$$\Delta\hat{y} = \hat{\beta}_1 \Delta x_1, \quad (11)$$

holding $x_2, x_3, \ldots, x_k$ fixed. Thus, we have controlled for the variables $x_2, x_3, \ldots, x_k$ when estimating the effect of x_1 on y. The other coefficients have a similar interpretation.

After obtaining the OLS regression line, equation (3), we can obtain a fitted or predicted value for each observation. For observation i , the fitted value is simply

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} \ldots + \hat{\beta}_k x_{ik}, \quad (12)$$

which is just the predicted value obtained by plugging the values of the exogenous variables for observation i into equation (3).

The anticipated value, $\hat{y}_i$, will typically not match the actual value, y_i, for any observation *i*. The average squared prediction error, which provides no information about the prediction error for any given observation, is minimized using OLS. Similar to the case of simple regression, the residual for observation *i* is defined as

$$\hat{\varepsilon}_i = y_i - \hat{y}_i. \tag{13}$$

There is a residual for each observation. If $\hat{\varepsilon}_i > 0$, then $\hat{y}_i$ is below y_i, which means that, for this observation, y_i is underpredicted. If $\hat{\varepsilon}_{i_i} < 0$, then $y_i < \hat{y}_i$, and y_i is overpredicted.

Some significant characteristics of the OLS fitted values and residuals are direct extensions from the single variable case:

i. The sample average of the residuals is zero and so $\bar{y} = \hat{\bar{y}}$.

ii. The sample covariance between each independent variable and the OLS residuals is zero. Consequently, the sample covariance between the OLS fitted values and the OLS residuals is zero.

iii. The point $(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_k, \bar{y})$ is always on the OLS regression line: $\bar{y}_i = \hat{\beta}_0 + \hat{\beta}_1\bar{x}_1 + \hat{\beta}_2\bar{x}_2 \ldots + \hat{\beta}_k\bar{x}_k$.

Property (3.1) immediately leads to property (3.3). The first two properties are immediate results of the set of equations used to obtain the OLS estimates: the first equation in equation (3.8) states that the sum of the residuals is zero, and the remaining equations are of the form $\sum_{i=1}^{n} x_{ij}\,\hat{\varepsilon}_i = 0$, which implies that each independent variable has zero sample covariance with $\hat{\varepsilon}_i$.

In order to separate the entire sum of squares into components resulting from regression and residuals, the regression equation is estimated as follows:

$$\text{SST} = \text{SSR} + \text{SSE} \tag{14}$$

Where

$$SST = \sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{15}$$

$$SSE = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 \tag{16}$$

$$SSR = \sum_{i=1}^{n} \varepsilon_i^2 \tag{17}$$

Stated differently, the sum of the total variations in $\{\hat{y}_i\}$ and $\{\hat{\varepsilon}_i\}$ is the total variation in $\{y_i\}$.

Assuming the entire variance in *y* is nonzero, as is the case unless y_i is constant in the sample, we can divide equation (14) by *SST* to get

$$\frac{SSR}{SST} + \frac{SSE}{SST} = 1 \tag{18}$$

Similar to the case of simple regression, the R-squared is defined as

$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} \tag{19}$$

and it can be understood as the percentage of the sample variation in y_i that the OLS regression line explains. The explanatory strength of the regression is characterized by its R – square value, obtained from the sums of square term. R^2 is a number between 0 and 1 by definition.

It is also possible to demonstrate that R^2 is equivalent to the squared correlation coefficient between the fitted values $\hat{y}_i$ and the actual y_i. That is,

$$R^2 = \frac{[\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{y})]^2}{[\sum_{i=1}^{n}(y_i - \bar{y})^2][\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2]} \tag{20}$$

The relative sizes of the sums of squares terms show how well the regression fits the calibration data; if the regression is perfect, all residuals are zero (SSE is zero), and R^2 is 1; if the regression is a complete failure, the sum of squares of residuals equals the total sum of squares; no variance is accounted for by regression, and R^2 is zero. But just as correlation does not imply causation, so does a high R^2 in regression.

An Analysis of Variance (ANOVA) table is frequently used to describe sums of squares and associated data.

Table 1. ANOVA.

Source of Variation	**Df**	**SS**	**MS**
Regression	*K*	*SSR*	$MSR = \frac{SSR}{k}$
Residual	n – k – 1	SSE	$MSE = \frac{SSE}{(n-k-1)}$
Total	n – 1	SST	$MST = \frac{SST}{(n-1)}$

Note: SS = sum of squares term; DF = degrees of freedom for SS term; MS = mean square terms

By dividing the sum of squares terms by the degree of freedom, the mean square terms are calculated. The variance of the regression residuals is estimated sample-wise by the residual mean square (MSE). The population value of the error term is commonly stated as σ_e^2 whereas the sample estimate is given by

$$S_e^2 = MSE \tag{21}$$

The statistical significance of the regression equation is estimated by the F-ratio, also known as the overall F, which is calculated from the mean square terms in the ANOVA table. The F-ratio can be found using

$$F = \frac{MSR}{MSE} \tag{22}$$

The F-ratio has an advantage over R^2 since it accounts for the degrees of freedom, which are influenced by the sample size and the number of predictors in the model. If the sample size is small in relation to the number of predictors in the model, a model with a high R^2 may still not be statistically significant. The F-ratio evaluates the significance of the association by taking into account the number of predictors and sample size.

The Value at Risk (VaR) is a risk assessment and management method that statistically calculates the probability of a particular loss happening statistically. VaR stands as one of the most used measures for risk assessment and management. In risk management, the goals are to identify and understand risk exposures, measure that risk, and then take the necessary action. VaR stands for Value at Risk, a statistic that shows a normal distribution of past losses. Often used on an investment portfolio, the computation provides a confidence interval about the likelihood of exceeding a particular loss threshold.

The most common parametric VaR measure is specified as:

$$VaR(\alpha,t) = \mu + \sigma * Zscore \quad (23)$$

Where VaR(α, t) is the value-at-risk at time *t* with confidence level α, μ is the expected return of portfolio, σ is the standard deviation of portfolio returns, and Zscore is a value from the standard normal distribution table, corresponding to the chosen confidence level. An investment portfolio's mean, or expected value, and standard deviation are first determined using the parametric technique. It employs probability theory to calculate the maximum loss for a portfolio by examining the price fluctuations of investments during a look-back time.

4. MODEL SPECIFICATION

The models for this study are based on the theoretical framework above as adopted in the study carried out by Debela et al. (2021). Thus, to empirically examine the impact of agricultural value chain disruptions on food inflation in Nigeria from a risk management perspective the following Multinomial Endogenous Treatment Effects (Regression) Models and Value at Risk (VaR) measure are utilized.

Model I: Contribution of the Study Disruptors to AVCD

The model is specified as below:

AVCD = *f* (CC, CI, DS, FC, MP) (24)

Where AVCD = Agricultural value chain disruptions *Endogenous variable*

CC = Climatic change

CI = Conflict and insecurity

DS = Disaster

FC = Financial cost

MP = Monetary policy

Climate change [CC] – Temperature, Humidity, CO_2 emission, Precipitation.

Conflict and insecurity [CI] – National terrorism index.

Disaster [DS] – Disaster risk index

Financial cost [FC] – Maximum lending

Monetary policy [MP] – Central bank interest rates, Money supply

The linear form of equation (3.24) is:

$$AVCD = \gamma_0 + \gamma_1(CC) + \gamma_2(CI) + \gamma_3(DS) + \gamma_4(FC) + \gamma_5(MP) + \upsilon \quad (25)$$

Where γ_0: Intercept term explaining AVCD when the exogenous variables are equal to zero; $\gamma 1 - \gamma_5$: Coefficients for the corresponding exogenous factors that describe how they contribute to the disruptions in the agricultural value chain; υ: Error term.

Model II: Impact of AVCD on Food Inflation

The model is specified as below:

FI = *f* (AVCD, AP, CC, CI, EG, MP) (26)

Where FI = Food inflation → *Endogenous variable*

AVCD = Agricultural value chain disruptions

AP = Agricultural production

CC = Climatic change

CI = Conflict and insecurity

EG = Economic growth

MP = Monetary policy

Agricultural production [AP] – Crop yields, livestock production

Economic growth [EG] – Real GDP rate

The linear form of equation (3.26) is:

$$FI = \beta_0 + \beta_1(AVCD) + \beta_2(AP) + \beta_3(CC) + \beta_4(CI) + \beta_5(EG) + \beta_6(MP) + \varepsilon \quad (27)$$

Where β_0: Intercept term explaining food inflation rate when the exogenous variables are equal to zero; $\beta_1 - \beta_6$: coefficients for the corresponding exogenous factors that describe how they affect food inflation; ε: Error term.

Model III: VaR Measure

The VaR measure can be specified as:

$$VaR(\alpha,t) = \mu_{FI} + \sigma * 1.65 \quad (28)$$

Where: VaR(α, t) = Value-at-Risk at time *t* with 95% confidence level.

μ_{FI} = Expected food inflation rate

σ: price volatility

Similarly, this study incorporates Agricultural Value Chain Disruptions (AVCD) into the VaR measure:

$$VaR(\alpha,t) = \mu_{FI} + (\sigma * 1.65) + (\beta * AVCD) \quad (29)$$

Where β is the coefficient representing the impact of AVCD on FI.

Table 2. Descriptive Statistics.

-		FI	CC	CI	DS	FC	MP	AP	EG	AVCD
N	Valid	35	35	35	35	35	35	35	35	35
	Missing	0	0	0	0	0	0	0	0	0
Mean		19.10	26.76	6.45	6.58	24.84	14.28	9496.36	4.63	.65
Std. Error of Mean		2.83	.07	.12	.12	.74	.75	349.70	.56	.03
Median		14.67	26.78	6.37	6.68	23.79	13.50	10193.60	4.19	.68
Mode		.32[a]	26.52[a]	5.40[a]	5.39[a]	18.70[a]	13.50	5779.50[a]	3.40	.39[a]
Std. Deviation		16.72	.42	.73	.72	4.36	4.44	2068.83	3.34	.16
Variance		279.48	.17	.54	.52	19.00	19.68	4280050.08	11.16	.024
Skewness		2.03	-.73	.42	-.12	.44	1.055	-.66	1.193	-.237
Std. Error of Skewness		.40	.40	.40	.40	.40	.40	.40	.40	.40
Kurtosis		4.15	.66	-1.01	-1.26	-.46	2.38	-.90	1.93	-1.25
Std. Error of Kurtosis		.78	.78	.78	.78	.78	.78	.78	.78	.78
Range		76.44	1.89	2.47	2.46	17.73	21.50	6436.00	15.25	.48
Minimum		.32	25.59	5.40	5.39	18.36	6.00	5779.50	.08	.39
Maximum		76.76	27.48	7.87	7.85	36.09	27.50	12215.50	15.33	.87
Percentiles	10	3.77	26.19	5.54	5.63	19.17	9.65	5943.02	.72	.40
	50	14.67	26.78	6.37	6.68	23.79	13.50	10193.60	4.19	.68
	90	49.92	27.20	7.58	7.48	30.58	19.45	11832.96	9.18	.85
a. Multiple modes exist. The smallest value is shown										

Source: Author's computation 2025.

5. RESULTS AND DISCUSSION

5.1. Descriptive Statistics

With a sample size of 35 for all variables, the table provides insights into their central tendency, dispersion, and distribution. For instance, the mean food inflation rate is 19.10%, with a significant standard deviation of 16.72%, indicating high volatility in food prices over the period. Agricultural production has a mean of 9496.36, with a standard deviation of 2068.83, suggesting variability in agricultural output.The mean for agricultural value chain disruptions is 0.65 with a standard deviation of 0.16, indicating that disruptions are a consistent, albeit somewhat variable, factor. The high standard deviation for food inflation points to significant fluctuations in food prices, which directly impacts the purchasing power of average Nigerians and contributes to food insecurity. The variability in agricultural production also highlights the vulnerability of Nigeria's food supply to various factors, emphasizing the need for robust agricultural policies to ensure stability.

5.2. METM (regression) Analysis: Model I: Exogenous variables on AVCD

Table **3** below presents a line plot illustrating the trends of Agricultural Value Chain Disruptions (AVCD) and its exogenous variables (Climatic Change, Conflict & Insecurity, Disaster, Financial Cost, and Monetary Policy) over time. This plot allows for a visual assessment of how these factors co-move or influence each other. For instance, one might observe periods where spikes in financial cost or monetary policy align with increases in agricultural value chain disruptions. The implication for Nigeria is that such plots can help identify potential causal relationships or strong correlations between these factors, informing policy interventions. For example, if financial cost consistently precedes or coincides with AVCD, it suggests that addressing financial accessibility and affordability within the agricultural sector could mitigate disruptions.

Fig. (**1**) above presents a line plot illustrating the trends of Agricultural Value Chain Disruptions (AVCD) and its exogenous variables (Climatic Change, Conflict & Insecurity, Disaster, Financial Cost, and Monetary Policy) over time. This plot allows for a visual assessment of how these factors co-move or influence each other. For instance, one might observe periods where spikes in financial cost or monetary policy align with increases in agricultural value chain disruptions. The implication for Nigeria is that such plots can help identify potential causal relationships or strong correlations between these factors, informing policy interventions. For example, if financial cost consistently precedes or coincides

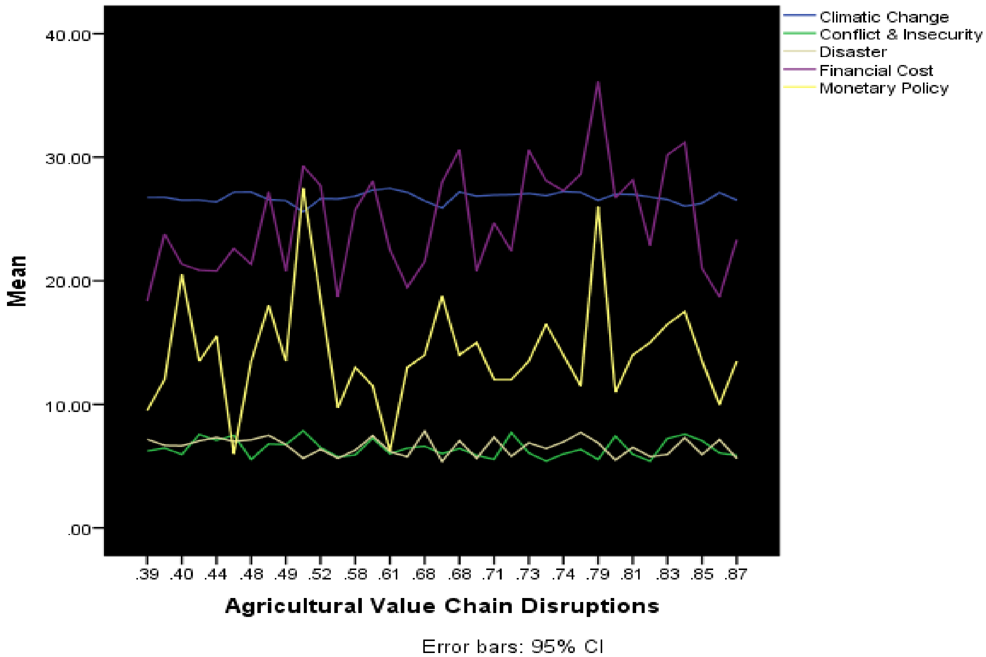


Fig. (1). Line plot for AVCD in the presence of the study's exogenous variables; **Source:** Researcher's computation (2025).

Table 3. Model Summary (Goodness-of-fit & Seria Auto Correlation test).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.557[a]	.310	.191	.14025	2.212
a. Predictors: (Constant), Monetary Policy, Conflict & Insecurity, Disaster, Financial Cost, Climatic Change;					
b. Dependent Variable: Agricultural Value Chain Disruptions					

Table 4. ANOVA (*F – Test*).

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.257	5	.051	2.610	.046[b]
	Residual	.570	29	.020		
	Total	.827	34			
a. Dependent Variable: Agricultural Value Chain Disruptions;						
b. Predictors: (Constant), Monetary Policy, Conflict & Insecurity, Disaster, Financial Cost, Climatic Change						

with AVCD, it suggests that addressing financial accessibility and affordability within the agricultural sector could mitigate disruptions.

Model I: Table 3 provides the model summary for Model I, which examines Agricultural Value Chain Disruptions (AVCD) as a function of Climatic Change (CC), Conflict & Insecurity (CI), Disaster (DS), Financial Cost (FC), and Monetary Policy (MP). The R-value of 0.557 indicates a moderate positive correlation between the predictor variables and AVCD. The R-squared value of 0.310 suggests that approximately 31% of the variance in agricultural value chain disruptions can be explained by the exogenous variables in Model I. The Adjusted R-squared of 0.191 accounts for the number of predictors, indicating that the model explains roughly 19.1% of the variance in AVCD after accounting for degrees of freedom. The Durbin-Watson statistic of 2.212 is used to check for serial autocorrelation in the residuals. A value close to 2 indicates no significant serial autocorrelation, suggesting that the residuals are independent. For Nigeria, an R-squared of 0.310 implies that while climatic change, conflict, disaster, financial cost, and monetary policy contribute to AVCD, it also highlights the complexity of agricultural disruptions in Nigeria and the need for a multifaceted approach to risk management.

Table **4** presents the ANOVA results for Model I, which assesses the overall statistical significance of the regression model in explaining Agricultural Value Chain Disruptions (AVCD). The F-statistic of 2.610 with a significance (Sig.) value of 0.046 indicates that the model is statistically significant at the 5% level ($p < 0.05$). This means that at least one

Table 5a. Model Coefficients *(t – Test)*.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	1.923	2.704		.711	.483
	Climatic Change [CC]	-.034	.097	-.090	-.348	.731
	Conflict & Insecurity [CI]	-.041	.037	-.192	-1.118	.273
	Disaster [DS]	-.069	.035	-.317	-1.975	.058
	Financial Cost [FC]	.022	.007	.606	2.964	.006
	Monetary Policy [MP]	-.014	.010	-.399	-1.397	.173

a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD]

Table 5b. Multicollinearity (Part & Partial Correlation test).

Model		95.0% Confidence Interval for B		Correlations		
		Lower Bound	Upper Bound	Zero-order	Partial	Part
1	(Constant)	-3.607	7.452			
	Climatic Change [CC]	-.231	.164	.093	-.064	-.054
	Conflict & Insecurity [CI]	-.115	.034	-.158	-.203	-.172
	Disaster [DS]	-.140	.002	-.237	-.344	-.305
	Financial Cost [FC]	.007	.037	.365	.482	.457
	Monetary Policy [MP]	-.035	.007	.021	-.251	-.215

a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD].

of the independent variables (Climatic Change, Conflict & Insecurity, Disaster, Financial Cost, or Monetary Policy) has a statistically significant effect on Agricultural Value Chain Disruptions. The low p-value of 0.046 implies that the chosen set of variables collectively contributes to explaining the disruptions in Nigeria's agricultural value chain. This finding is crucial for policymakers in Nigeria, as it validates the importance of considering these factors when formulating strategies to mitigate agricultural value chain disruptions and improve food security.

Table **5** displays the coefficients for each independent variable in Model I, along with their standard errors, standardized coefficients (Beta), t-statistics, and significance values. These values reveal the individual contribution and statistical significance of each variable to Agricultural Value Chain Disruptions (AVCD). For instance, Financial Cost (FC) has a positive and statistically significant coefficient (B = 0.022, t = 2.964, Sig. = 0.006), indicating that an increase in financial cost leads to an increase in agricultural value chain disruptions. Disaster (DS) has a negative coefficient (-0.069) and a p-value of 0.058, which is marginally significant at the 10% level, suggesting that greater disaster preparedness (as implied by higher community preparedness indices for disaster) may reduce disruptions. Climatic Change, Conflict & Insecurity, and Monetary Policy are not individually statistically significant at conventional levels in this model. The significant positive impact of financial cost on AVCD has strong implications for Nigeria; it suggests that high lending rates and other financial burdens can impede agricultural activities and disrupt the value chain. This calls for policies aimed at providing affordable credit and financial support to farmers and agricultural businesses in Nigeria.

Table **6** presents the part and partial correlation coefficients for Model I, which help in assessing the unique contribution of each predictor to the variance in the dependent variable (AVCD) after accounting for the effects of other predictors. For example, Financial Cost (FC) has the highest partial correlation (0.482) and part correlation (0.457), indicating its strong unique contribution to explaining AVCD, even after controlling for other variables. This reinforces the finding from Table 5 about the significant role of financial cost. From a Nigerian perspective, these correlations further emphasize that financial barriers are a substantial and independent factor contributing to agricultural value chain disruptions. Policies addressing access to affordable finance would likely have a direct and substantial impact on mitigating these disruptions.

Table **6** displays the multicollinearity statistics, specifically Tolerance and Variance Inflation Factor (VIF), for the independent variables in Model I. Tolerance values range from 0 to 1, with values closer to 1 indicating less multicollinearity, while VIF values greater than 10 typically suggest a significant multicollinearity issue.

Table 6. Multicollinearity *(Tolerance & VIF test)*.

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Climatic Change [CC]	.359	2.787
	Conflict & Insecurity [CI]	.809	1.235
	Disaster [DS]	.922	1.084
	Financial Cost [FC]	.568	1.761
	Monetary Policy [MP]	.291	3.436

a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD]

Table 7a: Collinearity Diagnostic *(Eigenvalue test)*.[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Climatic Change [CC]	Conflict & Insecurity [CI]
1	1	5.891	1.000	.00	.00	.00
	2	.075	8.865	.00	.00	.01
	3	.017	18.693	.00	.00	.08
	4	.011	23.168	.00	.00	.44
	5	.006	31.105	.00	.00	.25
	6	4.019E-005	382.836	1.00	1.00	.22

a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD].

Table 7b: Collinearity Diagnostic *(Eigenvalue test)*[b]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				Disaster [DS]	Financial Cost [FC]	Monetary Policy [MP]
1	1	5.891	1.000	5.891	1.000	5.891
	2	.075	8.865	.075	8.865	.075
	3	.017	18.693	.017	18.693	.017
	4	.011	23.168	.011	23.168	.011
	5	.006	31.105	.006	31.105	.006
	6	4.019E-005	382.836	4.019E-005	382.836	4.019E-005

a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD].

In this table, all Tolerance values are above 0.291, and all VIF values are below 3.436. For instance, Monetary Policy has the lowest Tolerance (0.291) and highest VIF (3.436), suggesting some degree of correlation with other predictors, but still well within acceptable limits (VIF < 10). This indicates that multicollinearity is not a significant problem in Model I. For Nigeria, this is a positive finding as it means that the individual effects of the independent variables on agricultural value chain disruptions can be reliably interpreted without being overly confounded by their interrelationships.

Tables **7a** and **7b** present the Eigenvalue test, another diagnostic for multicollinearity. The Eigenvalues indicate the variance of the components, and a low eigenvalue associated with a high condition index (above 15 or 30) and high variance proportions for two or more variables would suggest multicollinearity. The condition index for dimension 6 is 382.836, which is very high, indicating a strong multicollinearity issue within the dataset for Model I. Looking at the variance proportions, for dimension 6, "Constant," "Climatic Change [CC]," and "Monetary Policy [MP]" all have vari-

Table 8. Coefficient Correlation & Covariance Matrix.

Model			MP	CI	DS	FS	CC
1	Correlations	MP	1.000	.326	.012	-.644	.758
		CI	.326	1.000	-.098	-.210	.434
		DS	.012	-.098	1.000	-.103	-.161
		FS	-.644	-.210	-.103	1.000	-.418
		CC	.758	.434	-.161	-.418	1.000
	Covariances	MP	.000	.000	4.233E-006	-4.737E-005	.001
		CI	.000	.001	.000	-5.601E-005	.002
		DS	4.233E-006	.000	.001	-2.626E-005	-.001
		FS	-4.737E-005	-5.601E-005	-2.626E-005	5.360E-005	.000
		CC	.001	.002	-.001	.000	.009
a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD]							

Table 9. Residual Statistics.

-	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.4760	.7795	.6455	.08689	35
Residual	-.25759	.33219	.00000	.12953	35
Std. Predicted Value	-1.951	1.542	.000	1.000	35
Std. Residual	-1.837	2.369	.000	.924	35

a. Dependent Variable: Agricultural Value Chain Disruptions [AVCD]

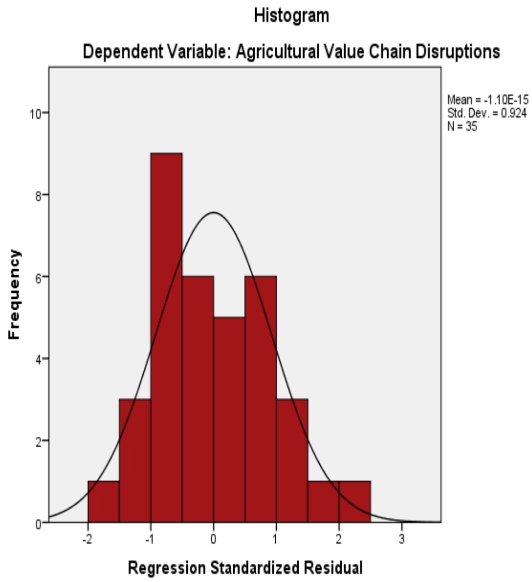
ance proportions of 1.00 or close to it, and "Conflict & Insecurity [CI]" also has a high variance proportion of 0.22.

This indicates a strong linear relationship among these variables, especially between Constant, Climatic Change, and Monetary Policy, potentially impacting the reliability of their individual coefficient estimates. While Table **4.6** suggested acceptable VIFs, the Eigenvalue test reveals a more severe multicollinearity issue. This implies that in Nigeria's context, there are strong interdependencies among factors like climate change and monetary policy, which can complicate efforts to isolate their individual impacts on agricultural value chain disruptions. Researchers and policymakers should be cautious when interpreting the individual coefficients of these highly correlated variables and consider alternative modeling approaches or data collection strategies.

Table **8** provides the correlation and covariance matrix for the coefficients of the independent variables in Model I. The correlation matrix shows the pairwise linear relationships between the predictors. For example, there's a strong positive correlation between Monetary Policy (MP) and Climatic Change (CC) (0.758), and a strong negative correlation between MP and Financial Cost (FC) (-0.644). These correlations support the findings from the multicollinearity diagnostics, suggesting that certain predictor variables move together. The covariance matrix shows the extent to which these variables vary together. The high correlation between Monetary Policy and Climatic Change suggests that a change in one might coincide with a change in the other, which is a significant consideration for Nigerian policymakers. For instance, if monetary policy responses to economic conditions indirectly influence or are influenced by climate-related events, this interdependency needs to be understood to formulate effective and holistic policies for the agricultural sector.

Table **9** presents the residual statistics for Model I. Residuals are the differences between the observed and predicted values of the dependent variable (AVCD). The mean of the residuals is 0.00000, which is expected in a well-fitted regression model, indicating that the model does not systematically overpredict or underpredict AVCD. The standard deviation of the residuals (0.12953) indicates the typical size of the error in prediction. The minimum and maximum residual values provide the range of prediction errors. The standard residual values, which range from -1.837 to 2.369, suggest that most errors are within approximately two standard deviations, which is generally acceptable. For Nigeria, these statistics indicate that the model for agricultural value chain disruptions, despite some multicollinearity concerns, provides a reasonably unbiased prediction of disruptions, meaning that the model is generally accurate in its average predictions.

Fig. (**2**) displays residual plots for Model I. These plots are used to visually check for heteroscedasticity (non-constant variance of errors) and linearity, which are im-



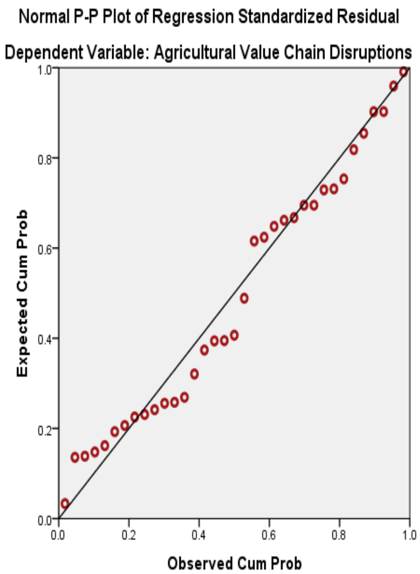


Fig. (2). Residual plots; **Source:** Researcher's study analysis (2025),

portant assumptions of linear regression. A healthy residual plot shows a random scatter of points around zero, with no discernible pattern. Any clear patterns (e.g., a fanning-out or curved shape) would suggest a violation of these assumptions, potentially impacting the validity of the regression results. The visual inspection of Fig. (**3**) would help determine if the model for agricultural value chain disruptions is appropriate for the data. If there are patterns, it implies that the linear model might not fully capture the relationships in Nigeria's agricultural value chain, potentially necessitating a different functional form or transformation of variables.

Model II: Exogenous variables on Food Inflation

The table below lists the variables included in Model II, which aims to explain Food Inflation (FI). The table confirms that all requested variables, namely Agricultural Value Chain Disruptions (AVCD), Agricultural Production (AP), Climatic Change (CC), Conflict & Insecurity (CI), Economic Growth (EG), and Monetary Policy (MP), were entered into the model using the "Enter" method. This means that the model for food inflation in Nigeria considers a comprehensive set of factors that are hypothesized to influence food prices, providing a broad framework for analysis.

Variables in the Model Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Monetary Policy, Agricultural Value Chain Disruptions, Economic Growth, Conflict & Insecurity, Agricultural Production, Climatic Change[b]	.	Enter

a. Dependent Variable: Food Inflation,
b. All requested variables entered.

Fig. (**3**) (note: the document labels two figures as 4.4, with the second one also serving as residual plots) depicts a line plot illustrating the trends of Food Inflation (FI) alongside its exogenous variables (Agricultural Value Chain Disruptions, Agricultural Production, Climatic Change, Conflict & Insecurity, Economic Growth, and Monetary Policy). This visual representation helps in identifying potential co-movements or lagged relationships between food inflation and the various influencing factors over the study period. For Nigeria, observing these trends can reveal periods where, for example, a decline in agricultural production or an increase in conflict and insecurity aligns with spikes in food inflation, offering immediate visual evidence of their interplay. This information is valuable for understanding the dynamics of food price volatility and for anticipating future inflationary pressures in the Nigerian context.

Table 10. Model Summary (Goodness-of-fit & Seria Auto Correlation test).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.625[a]	.390	.259	14.38694	1.010

a. Predictors: (Constant), Monetary Policy, Agricultural Value Chain Disruptions, Economic Growth, Conflict & Insecurity, Agricultural Production, Climatic Change
b. Dependent Variable: Food Inflation

Table **10** presents the model summary for Model II, which investigates the factors influencing Food Inflation (FI). The R-value of 0.625 indicates a stronger positive correlation between the predictors and food inflation compared to Model I. The R-squared value of 0.390 suggests that approximately 39% of the variance in food inflation can be explained by the included exogenous variables. The Adjusted R-squared of 0.259 indicates that about 25.9% of the variance in food inflation is explained by the model after adjusting for the number of predictors. The Durbin-Watson statis-

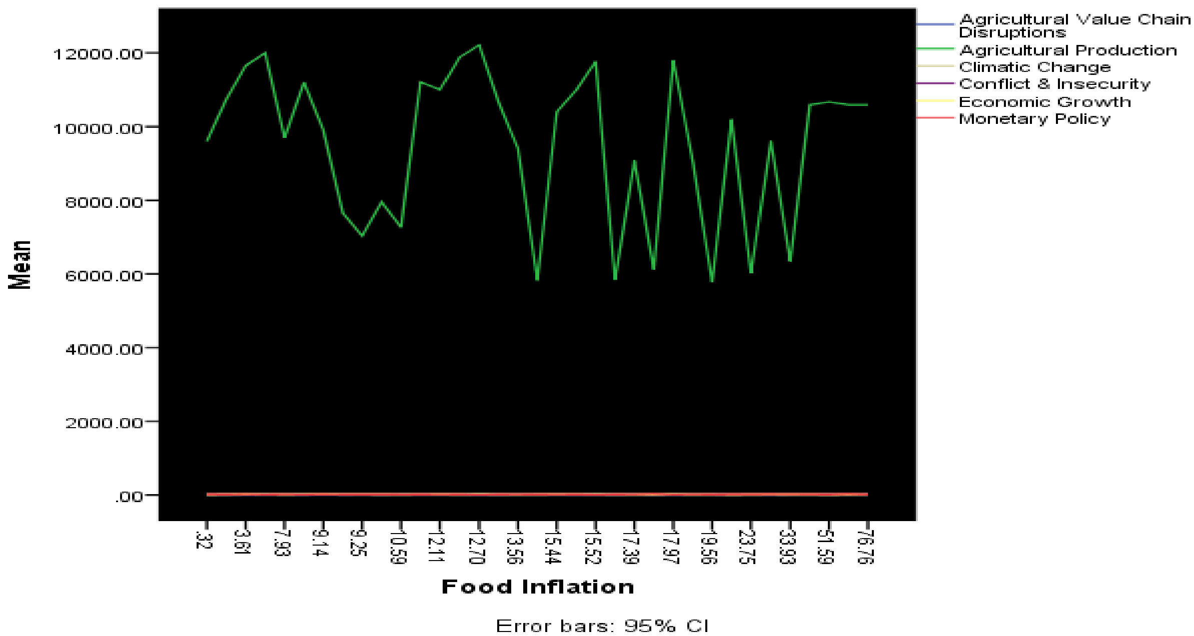


Fig. (3). Line plot for Inflation in the presence of the study's exogenous variables, **Source:** Researcher's study analysis (2025).

tic of 1.010 is considerably lower than 2, suggesting the presence of positive serial autocorrelation in the residuals. This implies that the errors in the food inflation model are not independent, which could affect the efficiency of the coefficient estimates. For Nigeria, an R-squared of 0.390 indicates that while the chosen variables have a significant explanatory power over food inflation, a substantial portion of food price variability remains unexplained by the model, suggesting other influential factors at play. The presence of serial autocorrelation implies that the model's assumptions might be violated, and this needs to be addressed for more reliable policy inferences in Nigeria.

Table 11. ANOVA (*F – Test*).

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3706.679	6	617.780	2.985	.022[b]
	Residual	5795.552	28	206.984		
	Total	9502.230	34			

a. Dependent Variable: Food Inflation.
b. Predictors: (Constant), Monetary Policy, Agricultural Value Chain Disruptions, Economic Growth, Conflict & Insecurity, Agricultural Production, Climatic Change.

Table **11** shows the ANOVA results for Model II, testing the overall statistical significance of the regression model for Food Inflation (FI). The F-statistic is 2.985 with a significance (Sig.) value of 0.022, which is statistically significant at the 5% level ($p < 0.05$). This indicates that the overall model is significant, meaning that at least one of the independent variables (Agricultural Value Chain Disruptions, Agricultural Production, Climatic Change, Conflict & Insecurity, Economic Growth, or Monetary Policy) has a statistically significant impact on food inflation. This finding is vital for Nigeria as it statistically confirms that the collective influence of these factors significantly contributes to food price fluctuations, thereby providing a basis for developing comprehensive policies to manage food inflation.

Table 12. Model Coefficients *(t – Test)*.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	408.157	259.408		1.573	.127
	Agricultural Value Chain Disruptions [AVCD]	31.197	16.129	.291	1.934	.063
	Agricultural Production [AP]	.002	.001	.206	1.252	.221
	Climatic Change [CC]	-15.733	8.950	-.391	-1.758	.090
	Conflict & Insecurity [CI]	.389	3.667	.017	.106	.916
	Economic Growth [EG]	-1.927	.796	-.385	-2.420	.022
	Monetary Policy [MP]	.167	.823	.044	.202	.841

a. Dependent Variable: Food Inflation [FI]

Table **12** presents the coefficients for each independent variable in Model II, along with their t-statistics and significance values. This table reveals the individual impact of each factor on Food Inflation (FI). Notably, Agricultural Value Chain Disruptions (AVCD) has a positive coefficient of 31.197 and is marginally significant (Sig. = 0.063), suggest-

Table 13. Multicollinearity (Part & Partial Correlation test).

Model		95.0% Confidence Interval for B		Correlations		
		Lower Bound	Upper Bound	Zero-order	Partial	Part
1	(Constant)	-123.216	939.531			
	Agricultural Value Chain Disruptions [AVCD]	-1.842	64.236	.234	.343	.285
	Agricultural Production [AP]	-.001	.004	.016	.230	.185
	Climatic Change [CC]	-34.065	2.600	-.427	-.315	-.259
	Conflict & Insecurity [CI]	-7.123	7.900	.082	.020	.016
	Economic Growth [EG]	-3.558	-.296	-.353	-.416	-.357
	Monetary Policy [MP]	-1.520	1.853	.328	.038	.030

a. Dependent Variable: Food Inflation [FI]

Table 14. Multicollinearity *(Tolerance & VIF test).*

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Agricultural Value Chain Disruptions [AVCD]	.962	1.040
	Agricultural Production [AP]	.805	1.242
	Climatic Change [CC]	.440	2.270
	Conflict & Insecurity [CI]	.844	1.185
	Economic Growth [EG]	.860	1.162
	Monetary Policy [MP]	.456	2.191

a. Dependent Variable: Food Inflation [FI]

ing that disruptions in the agricultural value chain contribute to higher food inflation. Economic Growth (EG) has a negative and statistically significant coefficient (-1.927, Sig. = 0.022), implying that higher economic growth is associated with lower food inflation. Climatic Change (CC) also has a negative coefficient (-15.733) and is marginally significant (Sig. = 0.090), suggesting that some aspects of climatic change might be associated with lower food inflation, which could warrant further investigation. The positive coefficient for Agricultural Value Chain Disruptions, even if marginally significant, is a critical insight for Nigeria, reinforcing the direct link between disruptions in food supply chains and increasing food prices. This underscores the necessity of investing in infrastructure, logistics, and risk management strategies to stabilize food supply and curb inflation. The significant negative impact of economic growth on food inflation suggests that sustainable economic policies can indirectly contribute to food price stability in Nigeria.

Table **13** shows the part and partial correlation coefficients for the variables in Model II. These correlations highlight the unique contribution of each predictor to food inflation after accounting for the influence of other variables. Economic Growth (EG) has the highest partial correlation (-0.416) and part correlation (-0.357), indicating its significant unique contribution to explaining food inflation. Agricultural Value Chain Disruptions (AVCD) also shows a notable partial correlation (0.343) and part correlation (0.285), reaffirming its distinct impact on food inflation. For Nigeria, these specific correlations can guide policy prioritization; addressing factors that uniquely and substantially influence food inflation, such as promoting stable economic growth and mitigating agricultural value chain disruptions, would be highly effective.

Table **14** presents the Tolerance and VIF statistics for Model II. All Tolerance values are above 0.440, and all VIF values are below 2.270. For example, Climatic Change has the lowest Tolerance (0.440) and highest VIF (2.270), indicating a moderate level of correlation with other predictors, but still well below the common threshold of 10. This suggests that multicollinearity is not a significant concern for Model II, meaning that the individual coefficients of the independent variables on food inflation can be interpreted with reasonable confidence. In the Nigerian context, this is a favorable finding as it implies that the estimated impacts of factors like agricultural value chain disruptions and economic growth on food inflation are distinct and not overly influenced by their interrelationships with other predictors within the model.

Table 15a. Collinearity Diagnostic *(Eigenvalue test)*.[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Agricultural Value Chain Disruptions [AVCD]	Agricultural Production [AP]
1	1	6.531	1.000	.00	.00	.00
	2	.308	4.604	.00	.00	.00
	3	.077	9.212	.00	.04	.07
	4	.051	11.315	.00	.72	.15
	5	.025	16.099	.00	.09	.66
	6	.007	30.058	.00	.14	.07
	7	4.754E-005	370.665	1.00	.00	.04

a. Dependent Variable: Food Inflation [FI].

Table 15b. Collinearity Diagnostic *(Eigenvalue test)*.[b]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				Climatic Change [CC]	Conflict & Insecurity [CI]	Economic Growth [EG]	Monetary Policy [MP]
1	1	6.531	1.000	.00	.00	.00	.00
	2	.308	4.604	.00	.00	.79	.01
	3	.077	9.212	.00	.00	.12	.37
	4	.051	11.315	.00	.01	.03	.00
	5	.025	16.099	.00	.12	.04	.08
	6	.007	30.058	.00	.70	.00	.01
	7	4.754E-005	370.665	1.00	.17	.00	.53

a. Dependent Variable: Food Inflation [FI].

Tables **15a** and **15b** display the Eigenvalue test results for Model II, another check for multicollinearity. Similar to Model I, a very high condition index (above 15 or 30) coupled with high variance proportions for multiple variables indicates multicollinearity. In Model II, Dimension 7 has a very high condition index of 370.665. The variance proportions for Dimension 7 show that "Constant," "Climatic Change [CC]," and "Monetary Policy [MP]" all have a variance proportion of 1.00 or close to it, and "Conflict & Insecurity [CI]" also has a high variance proportion. This again points to a significant multicollinearity issue, particularly among the constant, climatic change, and monetary policy variables. This implies that while the VIF values in Table **15** were acceptable, the Eigenvalue test identifies stronger linear dependencies among these variables within the broader dataset for Model II. For Nigeria, this means that the individual contributions of these highly correlated variables to food inflation may be difficult to disentangle precisely. Policymakers should exercise caution in attributing isolated effects and recognize the complex interplay of these factors when addressing food inflation in Nigeria.

Furthermore, Table **16** presents the coefficient correlation and covariance matrix for Model II. The correlation matrix indicates the pairwise linear relationships between the predictors of food inflation. For example, there is a strong positive correlation between Monetary Policy (MP) and Climatic Change (CC) (0.716). This strong correlation aligns with the multicollinearity identified in the Eigenvalue test. The covariance matrix quantifies how the coefficients of these variables vary together. The high correlation between Monetary Policy and Climatic Change suggests that in Nigeria, these two factors often move in tandem, which can influence the overall economic landscape and, consequently, food prices. This interconnectedness requires a coordinated policy approach, where monetary policy decisions might need to consider potential climatic impacts, and vice versa, to effectively manage food inflation in Nigeria.

Table **17** provides the residual statistics for Model II, which predicts Food Inflation (FI). Similar to Model I, the mean of the residuals is 0.00000, indicating that the model is unbiased in its predictions of food inflation on average. The standard deviation of the residuals is 13.05593, which represents the typical error in predicting food inflation. The range of residuals from -25.34499 to 36.33006 indicates the extent of prediction errors. The standardized residuals, ranging from -1.762 to 2.525, show that most errors fall within a reasonable range, though there might be a few larger outliers. These statistics suggest that the model, while not perfectly

Table 16. Coefficient Correlation & Covariance Matrix.

Model			Monetary Policy	Agricultural Value Chain Disruptions	Economic Growth	Conflict & Insecurity	Agricultural Production	Climatic Change
1	Correlations	MP	1.000	-.069	.011	.245	.261	.716
		AVCD	-.069	1.000	-.039	.116	.057	-.085
		EG	.011	-.039	1.000	-.036	-.344	-.057
		CI	.245	.116	-.036	1.000	.075	.366
		AP	.261	.057	-.344	.075	1.000	.172
		CC	.716	-.085	-.057	.366	.172	1.000
	Covariances	MP	.678	-.922	.007	.741	.000	5.275
		AVCD	-.922	260.145	-.496	6.878	.001	-12.238
		EG	.007	-.496	.634	-.106	.000	-.404
		CI	.741	6.878	-.106	13.447	.000	12.001
		AP	.000	.001	.000	.000	1.766E-006	.002
		CC	5.275	-12.238	-.404	12.001	.002	80.094

a. Dependent Variable: Food Inflation [FI]

Table 17. Residual Statistics.

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.1087	40.4299	19.1006	10.44126	35
Residual	-25.34499	36.33006	.00000	13.05593	35
Std. Predicted Value	-1.723	2.043	.000	1.000	35
Std. Residual	-1.762	2.525	.000	.907	35

a. Dependent Variable: Food Inflation [FI]

accurate, provides a good average fit for predicting food inflation in Nigeria. However, the Durbin-Watson statistic in Table 11 suggested positive serial autocorrelation, which implies that while the average error is zero, the errors themselves might not be randomly distributed over time, requiring further attention for more robust inferences.

Fig. (**5**) (the second instance of the figure, described as residual plots) displays the residual plots for Model II. These plots are crucial for visually assessing the assumptions of linear regression, specifically linearity and homoscedasticity. A random scatter of points around the zero line in the residual plot suggests that the linear model is appropriate and that the variance of the errors is constant across the range of predicted values. Any clear patterns or systematic deviations would indicate a violation of these assumptions, which could mean that the linear model is not the best fit for explaining food inflation in Nigeria, or that there might be unobserved factors influencing the relationship. For Nigeria, if patterns are observed, it suggests that the relationship between the independent variables and food inflation might be non-linear, or that there are other variables influencing the residuals that need to be accounted for to improve the model's accuracy and reliability for policy recommendations.

5.3. VaR Analysis

Table **18** presents the Value-at-Risk (VaR) measure for food inflation from 1990 to 2024. VaR is a statistical measure used to quantify the level of financial risk within a specified time frame and confidence level. In this context, it appears to be applied to food inflation, showing the expected maximum potential food inflation at a 95% confidence level. For example, in 1990, the food inflation was 3.61%, and the VaR was 62.84%, while in 1994, food inflation was 76.76% and VaR was 73.31%. The VaR percentages across the years generally remain high, indicating a persistent risk of high food inflation. This table provides a quantitative measure of the potential risk of food inflation in Nigeria, highlighting periods where the actual food inflation exceeded the VaR, or where the VaR itself was very high. This is highly signifi-

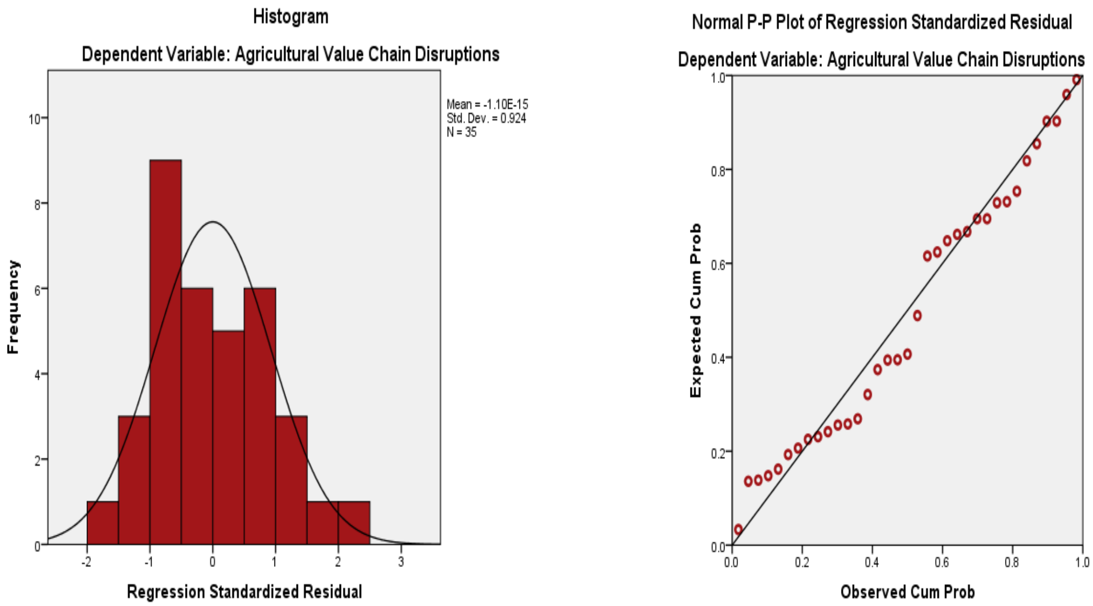


Fig. (5). Residual plots; **Source:** Researcher's study analysis (2025).

Table 18.VaR Measure.

Yr	FI	VaR (%)	Yr	FI	VaR (%)	Yr	FI	VaR (%)	Yr	FI	VaR (%)
1990	3.61	62.84	1995	51.59	61.93	2000	7.93	67.78	2005	15.51	66.94
1991	22.96	60.36	1996	12.72	59.21	2001	28.89	59.18	2006	3.88	73.77
1992	48.80	73.12	1997	12.25	73.81	2002	9.14	72.69	2007	8.23	58.73
1993	61.26	71.37	1998	3.13	61.62	2003	15.44	72.22	2008	17.97	63.94
1994	76.76	73.31	1999	.32	61.72	2004	12.11	68.69	2009	15.52	61.51

Yr	FI	VaR (%)	Yr	FI	VaR (%)	Yr	FI	VaR (%)
2010	12.70	65.87	2015	10.59	71.73	2020	19.56	70.55
2011	11.02	69.03	2016	17.39	69.78	2021	17.37	65.65
2012	10.20	58.84	2017	19.42	67.99	2022	23.75	69.48
2013	9.25	68.70	2018	13.56	71.93	2023	33.93	67.79
2014	9.15	64.87	2019	14.67	69.37	2024	17.94	62.63

cant for Nigeria, as it quantifies the potential severity of food price volatility, serving as a critical risk management tool for the government and policymakers. It can inform contingency planning and the allocation of resources to mitigate the impact of severe food price increases on the population.

Fig. (**6**) visually represents the VaR measure over time, illustrating the trend of Value-at-Risk for food inflation. This plot allows for a clearer visualization of how the potential risk of food inflation has evolved over the years in Nigeria. The plot would show the fluctuations in the VaR percentages, allowing for the identification of periods with exceptionally high or low perceived risk of food inflation. For Nigeria, this visual trend of VaR is invaluable for strategic planning and risk assessment. It enables policymakers to understand the historical pattern of food inflation risk and to anticipate future potential shocks, allowing for proactive measures to stabilize food prices and protect vulnerable populations.

6. IMPLICATIONS OF FINDING

The findings of this study offer a significant contribution to the understanding of the complex relationship between agricultural value chain disruptions and food inflation in Nigeria. Consistent with the abstract's claim and the quantitative results from the Value at Risk (VaR) and Multinomial Endogenous Treatment Effects (METE) models, the research

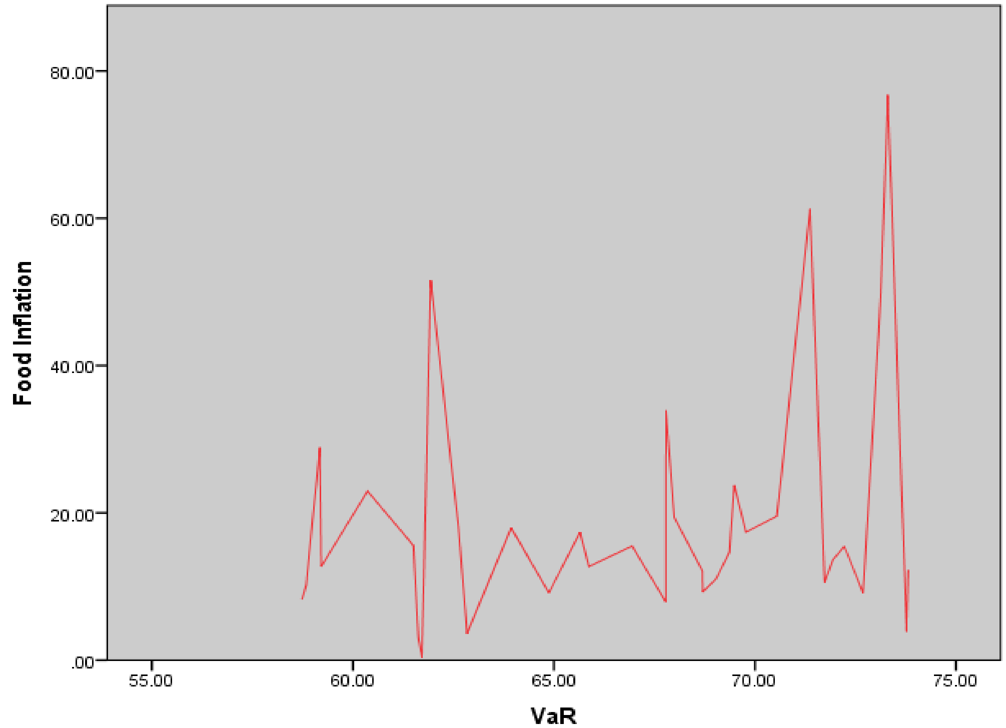


Fig. (6). VaR plot; **Source:** Researcher's study analysis (2025).

confirms that agricultural value chain disruptions (AVCD) are a positive and marginally significant driver of food inflation (FI) in the Nigerian context. This result aligns with the observations of Yusuf and Oyegoke (2021) and other global studies that have linked supply chain shocks, whether from pandemics (Afesorgbor & Lim, 2023) or other forms of disruption, to rising food prices. The research thus provides empirical support for the intuitive link between inefficiencies in the agricultural supply system and consumer price instability.

Furthermore, the study's two-tiered modeling approach provides nuanced insights into the factors influencing both AVCD and FI. The results for Model I reveal that climatic change, conflict and insecurity, disasters, financial costs, and monetary policy all have a statistically significant collective influence on agricultural value chain disruptions. The identification of financial costs as a strong predictor is a particularly critical finding, suggesting that the cost of capital, credit, and other financial services directly affects the resilience of the agricultural value chain. This resonates with the broader literature on financial inclusion and its impact on agricultural development and risk management (FAO, 2021b).

The analysis of Model II adds another layer of understanding, highlighting that while AVCD contributes to inflation, other variables also play a crucial role. The negative and statistically significant impact of economic growth (EG) on food inflation suggests that a robust, growing economy can act as a natural buffer against food price volatility, potentially by increasing consumer purchasing power or creating more stable market conditions. This supports the argument that comprehensive economic policies, not just sector-specific interventions, are vital for achieving food security and price stability. Additionally, the negative yet marginally significant coefficient for climatic change on food inflation warrants further investigation, as it may imply a complex, indirect relationship where the direct effects on inflation are absorbed or mediated by other factors in the model.A key methodological consideration, as highlighted in the Eigenvalue tests for both models, is the presence of significant multicollinearity among key variables, particularly between climatic change and monetary policy. This indicates a strong interdependence between these factors, making it challenging to isolate the individual effect of each variable. While this is a limitation of the current model, it is a crucial finding for Nigeria's policy environment. It suggests that a single-dimensional approach will be ineffective and underscores the need for a coordinated policy framework where monetary authorities, environmental agencies, and agricultural bodies collaborate to address interconnected challenges.

Furthermore, given the complex interplay of factors like climatic change and monetary policy, a siloed approach to managing food inflation is insufficient. Policymakers should pursue a coordinated strategy that integrates agricultural policies, financial regulations, and environmental management. For instance, the Central Bank of Nigeria's monetary policy decisions should consider their potential impact on financial costs within the agricultural sector, while environmental policies must be designed to enhance agricultural resilience.The positive link between AVCD and food inflation, coupled with the strong predictive power of financial costs, underscores the need for strategic, targeted investments. Public and private sector resources should be directed toward developing critical infrastructure such as improved road networks, storage facilities, and logistics that can reduce disruptions from the farm to the fork. Concurrently, efforts to enhance farmers' access to affordable credit, insurance, and other financial risk-management tools are paramount to mitigating the impact of financial costs and building a more resilient value chain. Also, the study provides a compelling case for adopting a comprehensive risk management framework in the agricultural sector. Beyond simply reacting to price shocks, stakeholders should focus on proactive measures such as crop diversification, climate-smart agricultural practices, and early warning systems for weather-related events and conflicts. These strategies, as mentioned in the literature (FAO, 2021b), are essential for minimizing losses and stabilizing prices.

CONCLUSION

The study's primary conclusion is a direct confirmation of the link between disruptions in the agricultural supply chain and rising food prices. It also provides a more detailed understanding of the factors at play, identifying that financial costs are a strong predictor of these disruptions.A crucial methodological finding is the presence of significant multicollinearity between key variables like climatic change and monetary policy. This leads to the conclusion that these factors are not independent but deeply interconnected. Therefore, a siloed, single-dimensional approach to policy will be ineffective.In essence, the study concludes that addressing food inflation requires a proactive, holistic, and coordinated policy framework that integrates agricultural, financial, and environmental strategies. It's a call for a shift from reactive measures to a comprehensive risk management approach.

RECOMMENDATIONS

The study suggests the following key policy recommendations for the Nigerian government and other relevant stakeholders:

The study found significant interdependence between climatic change and monetary policy. Therefore, it is crucial to move away from a siloed approach. Policymakers should create a collaborative framework where the Central Bank of Nigeria, the Ministry of Agriculture, and environmental agencies work together to formulate policies that address food inflation from multiple angles.

It also highlights that agricultural value chain disruptions are a significant driver of food inflation. To mitigate this, the government should direct public and private investment toward improving critical infrastructure, such as road networks, storage facilities, and logistics systems. This will help reduce post-harvest losses and ensure a smoother flow of food from farms to markets.

The study identified financial costs as a strong predictor of value chain disruptions. To address this, policies should focus on improving farmers' access to affordable credit, insurance, and other financial services. This will help them manage risks and invest in resilient agricultural practices.

Instead of just reacting to food price shocks, policymakers should encourage a shift toward a proactive risk management framework. This includes promoting climate-smart agricultural practices, crop diversification, and implementing early warning systems for natural disasters and conflicts that could disrupt the value chain.

The finding that economic growth has a negative impact on food inflation suggests that broad economic policies are also vital. By fostering overall economic growth, the government can help stabilize market conditions and increase consumer purchasing power, which can act as a buffer against food price volatility.

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