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Food Price Volatility and Regional Inequality in Nigeria: Implications for Market Integration and Food Security Policy.

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Abstract

Rapid food price inflation and volatility have become a major socioeconomic challenge in Nigeria, with uneven impacts across food commodities and geopolitical regions. However, national food inflation figures often mask substantial heterogeneity in price dynamics, limiting the effectiveness of policy responses. This study investigates the spatio-temporal dynamics of food prices in Nigeria, with the objectives of quantifying short- and long-term inflation patterns, assessing regional price disparities and market integration, and identifying vulnerability-relevant food commodities subject to compounded price pressure. The analysis uses officially reported retail food price data from the National Bureau of Statistics (NBS), Nigeria, covering 42 major food commodities and prices across six geopolitical zones for April 2024, March 2025, and April 2025. Methodologically, the study combines month-on-month (MoM) and year-on-year (YoY) inflation measures, spatial dispersion indices, ANOVA and Kruskal–Wallis tests of zonal price differences, multivariate techniques (principal component analysis and k-means clustering), and a composite Food Price Pressure Index (FPPI). Results show that while MoM inflation was modest on average (mean = 0.10%; SD = 4.63%), YoY inflation was substantial and widespread (mean = 58.45%; SD = 26.43%). Several staples and protein-rich foods experienced exceptionally high YoY inflation, including unripe plantain (123.1%), ripe plantain (103.9%), yam tuber (98.2%), and tilapia fresh fish (94.0%). Significant regional price disparities persist, with spatial coefficients of variation exceeding 0.30 for onions and sweet potatoes, indicating incomplete market integration. Multivariate analysis reveals three distinct commodity regimes—high-volatility protein foods, spatially segmented perishables, and high-inflation staples. The FPPI identifies plantain, yam, onions, and fish products as the most vulnerability-relevant commodities, combining high inflation, volatility, and spatial price dispersion. The findings demonstrate that food price pressure in Nigeria is commodity- and region-specific rather than uniform. The study provides data-driven evidence to support targeted food price monitoring, regional market integration, and vulnerability-focused food security policies.

Keywords: Food price inflation; Spatial price dispersion; Food price volatility.

1. Introduction

Food price instability has emerged as one of the most pressing socioeconomic challenges facing low- and middle-income countries (Dardeer & Shaheen, 2025), with direct consequences for household welfare, nutrition, and social stability (Negi, 2022). Recurrent surges in food prices affecting staples such as rice, maize, yam, plantain, and fish, have translated into rising food insecurity and declining purchasing power, particularly among urban poor and rural net-consuming households in Nigeria (Aye et al., 2025). Recent episodes of sharp price escalation, compounded by exchange-rate volatility, climate-induced supply shocks, and distribution bottlenecks, have made food affordability a daily concern for millions of Nigerians (Akinyemi et al., 2025). Understanding the dynamics of food price movements is therefore not only an economic issue but a critical development and policy priority.

This study focuses on the spatio-temporal dynamics of food prices in Nigeria, examining how prices evolve over time and vary across the country's six geopolitical zones. Using officially reported retail price data for major food commodities, the analysis quantifies short-term and long-term price changes, evaluates regional price dispersion, and identifies commodities subject to sustained inflation and instability. The study integrates temporal inflation measures, spatial dispersion metrics, and multivariate classification techniques to provide a comprehensive assessment of food price behavior across commodities and regions.

The need for such analysis is urgent. Aggregate food inflation figures often mask substantial heterogeneity across food items and locations, leading to policy responses that are insufficiently targeted. In Nigeria, where food expenditures account for a large share of household budgets, uneven price transmission across regions can exacerbate inequality and heighten vulnerability. Persistent regional price gaps and volatility undermine market integration, weaken the effectiveness of national stabilization efforts, and increase the risk of localized food stress, particularly during economic or climatic shocks.

To the best of our knowledge, existing studies on food prices in Nigeria have largely focused on national averages or single commodities, with limited attention to the combined effects of temporal inflation, spatial price segmentation, and commodity-specific vulnerability. There remains a clear gap in identifying which food commodities exert the greatest pressure on households due to the interaction of sustained inflation, volatility, and regional price disparities. Accordingly, this study addresses the following questions: (i) How do food prices in Nigeria evolve over short- and long-term horizons? (ii) To what extent do food prices differ across geopolitical zones, indicating market integration or segmentation? and (iii) Which commodities represent the highest vulnerability risk due to compounded price pressures?

This study advances food price analysis by integrating spatio-temporal inflation metrics with multivariate classification and a composite Food Price Pressure Index, enabling systematic identification of vulnerability-relevant commodities. Empirically, it provides commodity- and region-specific evidence on food price behavior in Nigeria, offering insights beyond aggregate inflation measures. From a policy perspective, the findings support more targeted food price monitoring and intervention strategies by highlighting where and for which commodities price pressures are most severe.

2. Material and methods

2.1 Study Area

Nigeria as Africa's most populous country, located in West Africa between latitudes approximately 4°–14° N and longitudes 2°–15° E (Dike et al., 2020). Nigeria exhibits substantial geographic, climatic, and socioeconomic heterogeneity, making it a suitable case for examining spatial and temporal food price dynamics. The country is administratively divided into 36 states and the Federal Capital Territory (FCT) and is commonly grouped into six geopolitical zones, North Central, North East, North West, South East, South South, and South West, which form the spatial framework for this analysis (Adaviruku, 2025).

Nigeria's geopolitical zones differ markedly in terms of agroecological conditions, production structures, market access, and consumption patterns (Chiaka et al., 2022). The northern zones are characterized by extensive cereal and livestock production, higher exposure to climatic variability, and longer market supply chains, whereas the southern zones are dominated by root crops, horticulture, fisheries, and greater dependence on interregional food flows. These structural differences have direct implications for food price formation, spatial price transmission, and market integration. Nigeria's food markets are further shaped by infrastructure quality, storage capacity, and security conditions, which vary substantially across regions. Such spatial heterogeneity affects transaction costs and arbitrage efficiency, contributing to persistent regional price differentials for key food commodities. The geopolitical zoning framework adopted in this study provides a policy-relevant spatial unit that aligns with national statistical reporting and development planning, enabling meaningful interpretation of regional food price disparities.

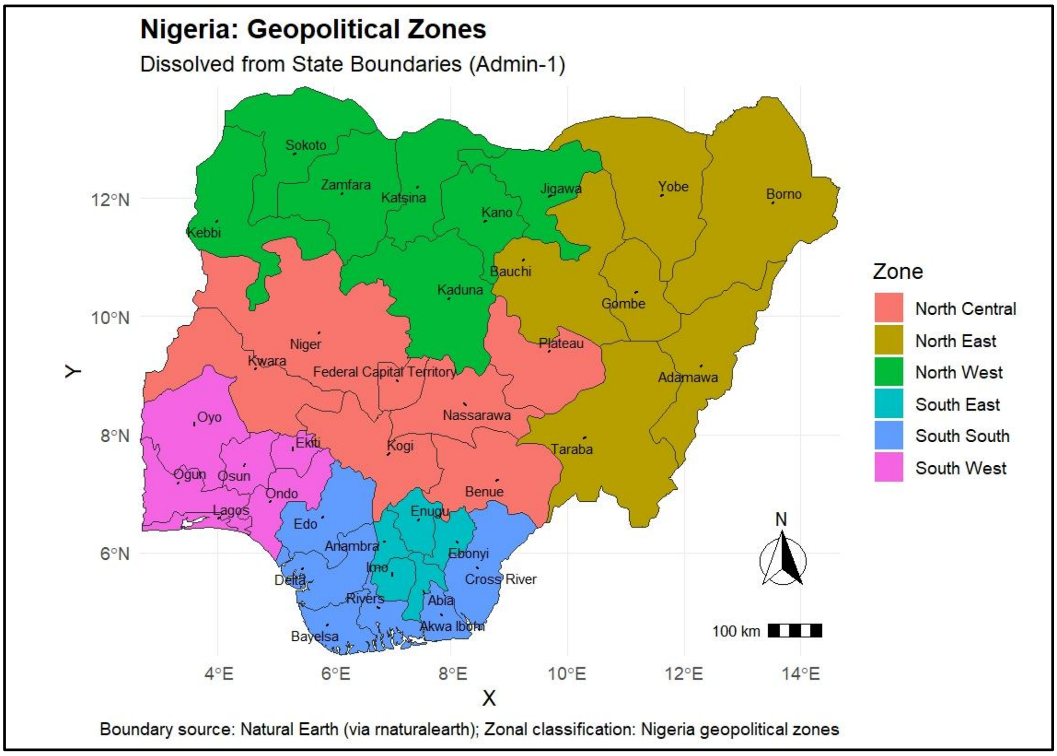

Figure 1. Study area showing Nigeria's six geopolitical zones (North Central, North East, North West, South East, South South, and South West), delineated from state-level administrative boundaries and used as the spatial framework for analyzing regional food price dynamics.

2.2 Data Sources and Pre-Processing

This study employs officially reported retail food price data for Nigeria obtained from the National Bureau of Statistics (NBS) Microdata Portal (https://microdata.nigerianstat.gov.ng/) (*Data Catalog*, 2025). The analysis is based on two harmonized datasets: (i) national average retail prices for selected food commodities observed in April 2024, March 2025, and April 2025, and (ii) April 2025 zonal price observations across Nigeria's six geopoliticalolitical zones, North Central, North East, North West, South East, South South, and South West. All datasets were processed and analysed using R statistical software (version ≥ 4.3). Price values were standardized by removing non-numeric characters (e.g., thousand separators) and converted to numeric format. Commodity names were normalized to ensure consistent matching across datasets. Only valid, non-zero price observations were retained for inflation and spatial dispersion analyses to avoid undefined ratios and ensure robustness of computed indicators.

2.3 Measurement of Spatio-Temporal Price Dynamics

2.3.1 Month-on-Month (MoM) Inflation

Short-term price dynamics were quantified using month-on-month (MoM) inflation, computed as the percentage change between March 2025 and April 2025 prices for each commodity (Graf, 2020), Eq (1):

$$\mathrm{MoM}_i = \frac{P_{i,\mathrm{Apr2025}} - P_{i,\mathrm{Mar2025}}}{P_{i,\mathrm{Mar2025}}} \times 100 \qquad (1)$$

where $P_{i,t}$ denotes the average national price of commodity i at time t.

2.3.2 Year-on-Year (YoY) Inflation

Longer-term inflationary pressure was assessed using year-on-year (YoY) inflation, defined as Eq (2):

$$\mathrm{YoY}_i = \frac{P_{i,\mathrm{Apr2025}} - P_{i,\mathrm{Apr2024}}}{P_{i,\mathrm{Apr2024}}} \times 100 \qquad (2)$$

YoY inflation reflects cumulative structural price changes and persistent cost pressures over a 12-month horizon (Deaton & Muellbauer, 1980).

2.4 Regional Price Disparities and Market Integration

2.4.1 Spatial Price Dispersion Across Geopolitical Zones

Regional price disparities were assessed using April 2025 food prices across Nigeria's six geopolitical zones. Spatial dispersion for each commodity was quantified using the coefficient of variation (CV), Eq (3):

$$\mathrm{CV}_i^{\mathrm{zone}} = \frac{\sigma_i^{\mathrm{zone}}}{\mu_i^{\mathrm{zone}}} \qquad (3)$$

where σ_i^{zone} and μ_i^{zone} denote the standard deviation and mean of zonal prices for commodity i, respectively. Higher CV values indicate stronger spatial price segmentation and weaker market integration. Zonal price distributions were examined using boxplots and density plots to visually compare price levels and dispersion across regions (Porter, 2009).

2.4.2 Temporal Normalization for Inter-Commodity Comparison

To facilitate comparison of price trajectories across commodities with different price scales, a base-index normalization was applied using April 2024 as the reference period (index = 100), Eq (4):

$$\mathrm{BaseIndex}_{i,t} = \frac{P_{i,t}}{P_{i,\mathrm{Apr2024}}} \times 100 \qquad (4)$$

This transformation highlights relative price growth dynamics and enables direct comparison of inflation acceleration and deceleration across commodities (Providence et al., 2022).

2.4.3 Statistical Assessment of Zonal Price Differences

To formally test whether food prices differ systematically across geopolitical zones, an analysis of variance (ANOVA) was conducted on log-transformed prices (Sthle & Wold, 1989), Eq (5):

$$\ln\,(P_{i,z}) = \alpha + \beta_z + \varepsilon_{i,z} \qquad (5)$$

where β_z captures zone-specific effects. Log transformation improves normality and reduces heteroskedasticity. Given potential distributional violations, a complementary Kruskal–Wallis (KW) non-parametric test was applied to raw prices to provide a robust, rank-based assessment of zonal differences.

At the commodity level, separate ANOVA and KW tests were conducted. To control for multiple testing, p-values were adjusted using the Benjamini–Hochberg false discovery rate (FDR) procedure, Eq (6):

$$p_i^{\mathrm{adj}} = \mathrm{BH}(p_i) \qquad (6)$$

2.4.4 Identification of Spatially Segmented Commodity Markets

Commodities were classified as spatially segmented if they satisfied both:

- High spatial dispersion ($\mathrm{CV}_i^{\mathrm{zone}} \geq 0.15$), and
- Statistically significant zonal price differences ($p_{\mathrm{KW}}^{\mathrm{adj}} < 0.05$).

This combined economic statistical criterion ensures robust identification of commodities exhibiting persistent regional price segmentation (Alexandr Cherkashin & Myadzelets, 2022).

2.4.5 Heatmap Visualization and Hierarchical Clustering

To examine multi-commodity spatial price patterns, a commodity × zone price matrix was constructed using April 2025 prices. Prices were log-transformed using $\log(1+P)$and standardized within commodities, Eq (7):

$$Z_{i,z} = \frac{X_{i,z} - \bar{X}_i}{s_i} \qquad (7)$$

where $\bar{X}_i$and $s_i$represent the mean and standard deviation of log-prices for commodity $i$across zones.

Hierarchical clustering was applied using Ward's minimum variance method (Ward.D2) with Euclidean distance, Eq (8):

$$d_{ij} = \sqrt{\sum_z (Z_{i,z} - Z_{j,z})^2} \qquad (8)$$

Heatmaps and dendrograms were jointly used to identify clusters of commodities with similar spatial pricing structures, providing insight into regional co-movement, market integration, and fragmentation patterns (Hertel, 2018).

2.5 Vulnerability-Relevant Commodity Groups and Food Price Pressure

2.5.1 Spatial Price Structure and Multivariate Representation

To examine spatial price structures across commodities, a commodity × zone price matrix was constructed using April 2025 prices. Prices were first log-transformed to stabilize variance and then standardized within commodities (Emediegwu & Rogna, 2024), Eq (9):

$$Z_{i,z} = \frac{X_{i,z} - \bar{X}_i}{s_i} \qquad (9)$$

where $X_{i,z}$denotes the log-transformed price of commodity $i$in zone z, and $\bar{X}_i$and $s_i$represent its mean and standard deviation across zones. This transformation enables direct comparison of spatial price profiles across commodities with different price scales (Wang et al., 2023).

Hierarchical clustering was applied to the standardized matrix using Ward's minimum variance method (Ward.D2) with Euclidean distance, Eq (10):

$$d_{ij} = \sqrt{\sum_z (Z_{i,z} - Z_{j,z})^2} \qquad (10)$$

This approach groups commodities exhibiting similar spatial pricing patterns, facilitating identification of market integration and segmentation regimes.

2.5.2 Measurement of Commodity-Level Price Volatility

Temporal price instability was quantified using three observation points (April 2024, March 2025, and April 2025). For each commodity i, the mean price, standard deviation, and coefficient of variation (CV) were computed as, Eq (11 to 13):

$$\mu_i^{3t} = \frac{1}{3}\sum_{t=1}^{3} P_{i,t} \qquad (11)$$

$$\sigma_i^{3t} = \sqrt{\frac{1}{2}\sum_{t=1}^{3}(P_{i,t} - \mu_i^{3t})^2} \qquad (12)$$

$$\mathrm{CV}_i^{3t} = \frac{\sigma_i^{3t}}{\mu_i^{3t}} \qquad (13)$$

where $P_{i,t}$ denotes the price of commodity i at time t. The CV provides a scale-independent indicator of relative price volatility.

Short-run instability was further captured using a rolling variance proxy based on consecutive price changes, Eq (14 - 15):

$$\Delta_{i,1} = P_{i,\mathrm{Mar2025}} - P_{i,\mathrm{Apr2024}}, \Delta_{i,2} = P_{i,\mathrm{Apr2025}} - P_{i,\mathrm{Mar2025}} \qquad (14)$$

$$\mathrm{RV}_i = \mathrm{Var}(\Delta_{i,1}, \Delta_{i,2}) \qquad (15)$$

This metric highlights commodities experiencing uneven or shock-like price adjustments.

2.5.3 Spatial Price Dispersion Across Geopolitical Zones

Spatial price dispersion was assessed using April 2025 zonal prices. For each commodity, the zonal coefficient of variation was calculated as, Eq (16):

$$\mathrm{CV}_i^{\mathrm{zone}} = \frac{\sigma_i^{\mathrm{zone}}}{\mu_i^{\mathrm{zone}}} \qquad (16)$$

where σ_i^{zone} and μ_i^{zone} denote the standard deviation and mean of zonal prices, respectively. Higher values indicate stronger spatial segmentation and weaker market integration.

2.5.4 Feature Integration and Dimensionality Reduction

All vulnerability-relevant indicators were consolidated into a unified feature vector for each commodity, Eq (17):

$$\mathbf{X}_i = \{\mathrm{YoY}_i, \mathrm{MoM}_i, \mathrm{CV}_i^{3t}, \mathrm{RV}_i, \mathrm{CV}_i^{\mathrm{zone}}\} \qquad (17)$$

Principal Component Analysis (PCA) was applied to the standardized feature matrix to reduce dimensionality and identify dominant drivers of food price pressure (Essoussi et al., 2025), Eq (18):

$$Z_{i,j} = \frac{X_{i,j} - \bar{X}_j}{s_j} \qquad (18)$$

The proportion of variance explained by each principal component was used to interpret the relative importance of inflation, volatility, and spatial dispersion.

2.5.5 Commodity Classification Using k-Means Clustering

Based on the standardized multivariate feature space, k-means clustering was employed to classify commodities into homogeneous vulnerability groups (Ikotun et al., 2022). The number of clusters was fixed at $k = 3$, representing distinct food price regimes. Each commodity was assigned to the cluster minimizing within-cluster Euclidean distance, Eq (19):

$$d_{ik} = \sqrt{\sum_j (Z_{i,j} - C_{k,j})^2} \qquad (19)$$

where $C_{k,j}$ denotes the centroid of cluster k along feature j.

2.5.6 Construction of the Food Price Pressure Index (FPPI)

To synthesize multiple dimensions of price stress into a single indicator, a Food Price Pressure Index (FPPI) was constructed as a weighted linear combination of standardized components, Eq (20):

$$\mathrm{FPPI}_i = 0.40\,Z(\mathrm{YoY}_i) + 0.15\,Z(\mathrm{MoM}_i) + 0.20\,Z(\mathrm{CV}_i^{3t}) + 0.10\,Z(\mathrm{RV}_i) + 0.15\,Z(\mathrm{CV}_i^{\mathrm{zone}}) \qquad (20)$$

Weights reflect the relative contribution of sustained inflation, short-term adjustment, temporal volatility, and spatial price dispersion. Higher FPPI values indicate commodities subject to compounded food price pressure and vulnerability.

2.5.7 Commodity Ranking and Cluster-Level Interpretation

Commodities were ranked by FPPI to identify those exerting the greatest pressure on household food budgets. Cluster-level summary statistics—including mean YoY inflation, MoM change, temporal CV, and zonal CV—were computed to characterize vulnerability profiles across food price regimes.

3. Results

3.1 Spatio-Temporal Food Price Dynamics in Nigeria

3.1.1 Month-on-Month and Year-on-Year Price Changes Across Food Commodities

The mean MoM inflation rate was 0.10% (median = 0.67%; SD = 4.63%), reflecting limited short-run price adjustment across most items (Figure 2).

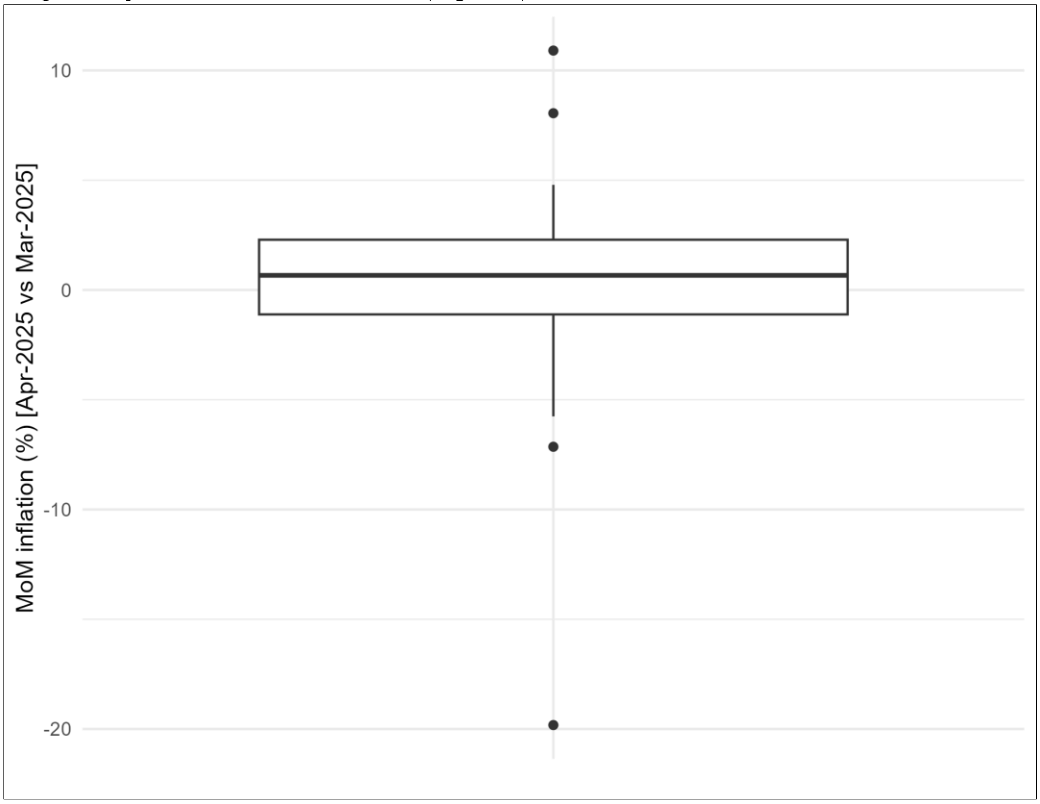

Figure 2. Boxplot of month-on-month (MoM) inflation rates, illustrating limited short-term variability relative to annual inflation.

In contrast, YoY inflation averaged 58.45% (median = 56.34%; SD = 26.43%), highlighting substantial annual price escalation.

Several staple and protein-rich commodities recorded exceptionally high YoY inflation, led by unripe plantain (123.1%), ripe plantain (103.9%), yam tuber (98.2%), and tilapia fresh fish (94.0%), indicating sustained upward pressure in nutritionally critical food groups (Figure 3).

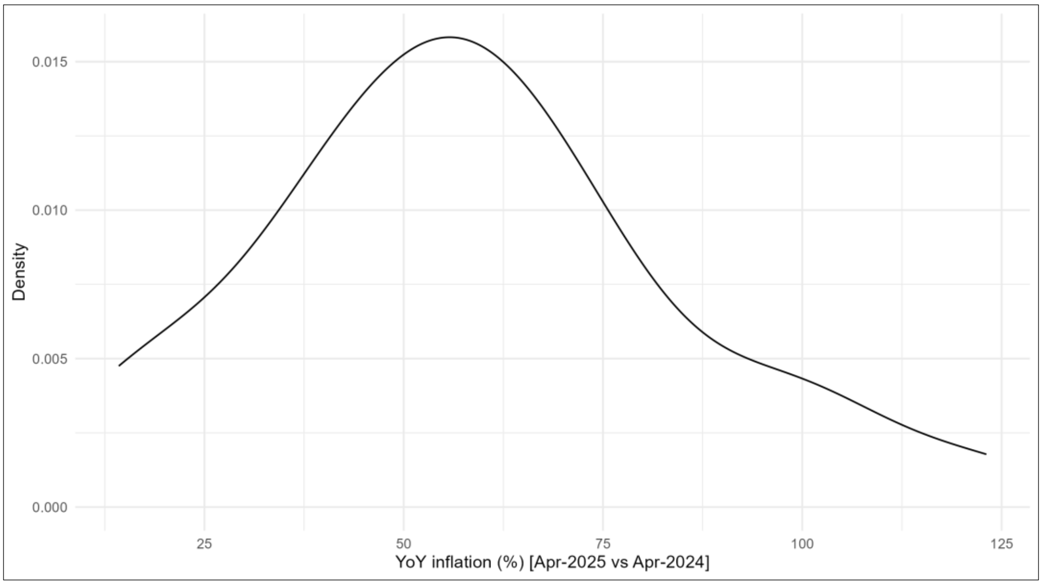

Figure 3. Kernel density distribution of year-on-year (YoY) inflation rates across food commodities.

3.1.2 Distribution and Dispersion of Food Price Inflation

The distribution of food price inflation reveals considerable heterogeneity across commodities, particularly in YoY terms. The YoY inflation distribution is right-skewed, with a concentration around 40–70% and a long upper tail driven by highly inflationary items (Figure 4). The standard deviation of YoY inflation (26.43 percentage points) underscores substantial dispersion in inflation exposure across food categories.

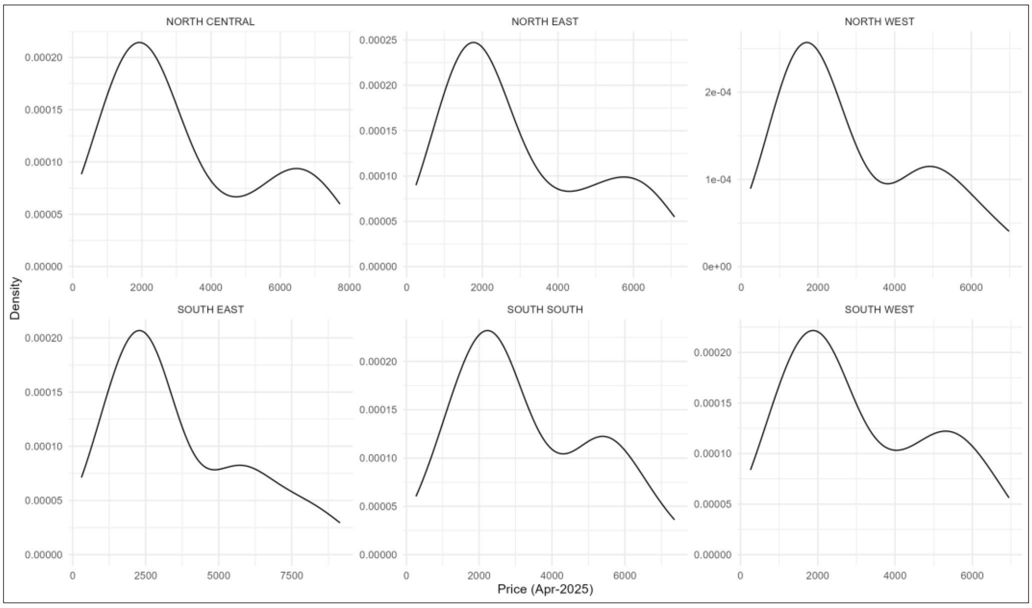

Figure 4. Density distribution of YoY inflation rates, showing right-skewness and high-inflation outliers.

MoM inflation exhibits a tighter distribution centered near zero, with a narrow interquartile range and fewer extreme outliers. This contrast highlights that food price instability in Nigeria is primarily an annual phenomenon, rather than a reflection of frequent monthly shocks (Figure 5).

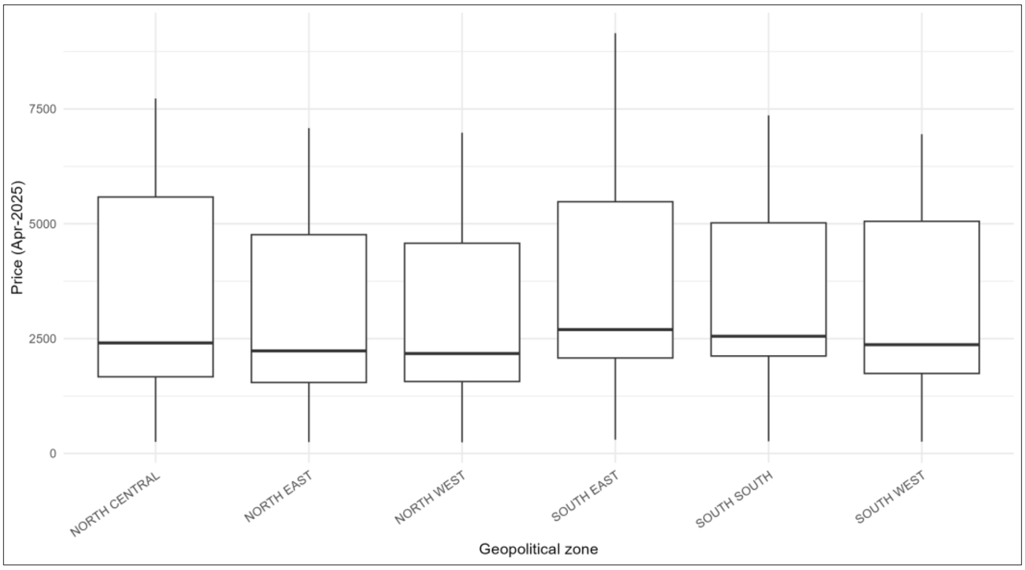

Figure 5. Boxplot of MoM inflation rates across commodities, indicating limited short-term dispersion.

3.1.3 Geopolitical Zonal Variability in Food Prices

Substantial spatial price heterogeneity is evident across Nigeria's six geopolitical zones. Zonal summary statistics for April 2025 show marked differences in mean price levels and dispersion, confirming incomplete spatial price convergence. For example, the coefficient of variation (CV) across zones exceeds 30% for onions (CV = 0.32) and 29% for sweet potatoes (CV = 0.30), while local broken rice (CV = 0.25) and frozen mackerel (CV = 0.23) also exhibit pronounced spatial dispersion.

Price ranges further emphasize regional disparities. Onion prices ranged from ₦1,113 to ₦2,274, frozen mackerel from ₦4,308 to ₦7,598, and broken local rice from ₦1,757 to ₦3,192 across zones (Figure 6). These persistent price gaps suggest weak market integration, likely driven by transportation costs, regional supply constraints, and uneven access to storage and distribution infrastructure.

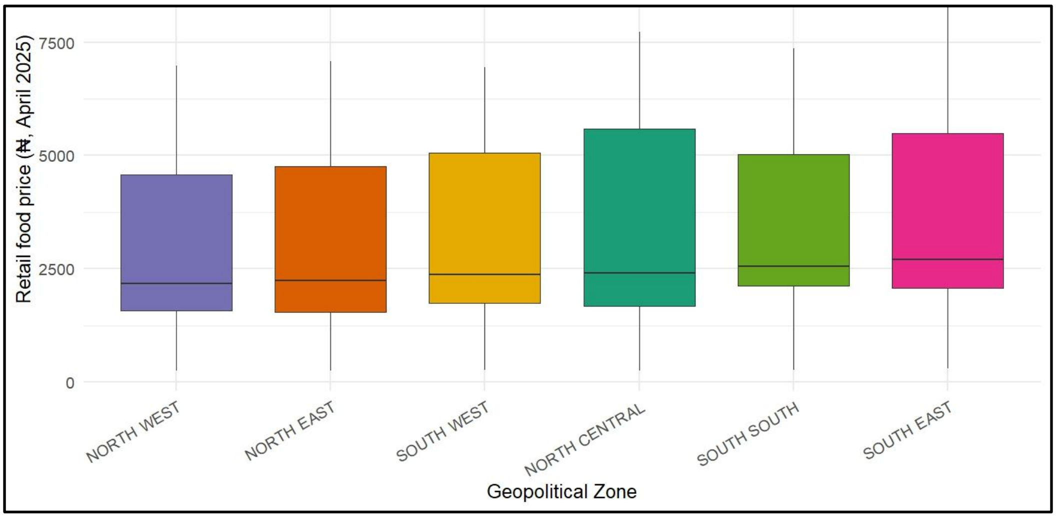

Figure 6. Boxplot of April-2025 food prices by geopolitical zone, highlighting spatial price dispersion.

3.1.4 Temporal Price Trends Based on Base-Index Normalization (Apr-2024 = 100)

Base-index normalization (April 2024 = 100) reveals divergent inflation trajectories across food commodities. While some items display gradual index growth, several staples and protein sources exhibit rapid index escalation exceeding 190–220 within one year. Unripe plantain, ripe plantain, yam tuber, and selected fish products dominate the upper tail of indexed price growth, reflecting accelerated inflation beyond aggregate averages.

The base-index trends demonstrate that food price inflation in Nigeria is highly commodity-specific, with a subset of items driving disproportionate increases in household food expenditure. These dynamics underline the importance of targeted food price monitoring and intervention, rather than reliance on aggregate inflation indicators alone.

3.2 Regional Price Disparities and Market Integration

3.2.1 Spatial Price Dispersion and Coefficient of Variation Across Geopolitical Zones

Analysis of April-2025 food prices reveals substantial spatial price dispersion across Nigeria's geopolitical zones, indicating heterogeneous regional market conditions. Item-level dispersion metrics show that the coefficient of variation (CV) across zones frequently exceeds 0.20, reflecting large inter-regional price differentials for several commodities. The highest spatial dispersion is observed for onions (CV ≈ 0.32), sweet potatoes (CV ≈ 0.30), and local broken rice (CV ≈ 0.25), followed by frozen mackerel (CV ≈ 0.23) and tomatoes (CV ≈ 0.21) (Figure 7).

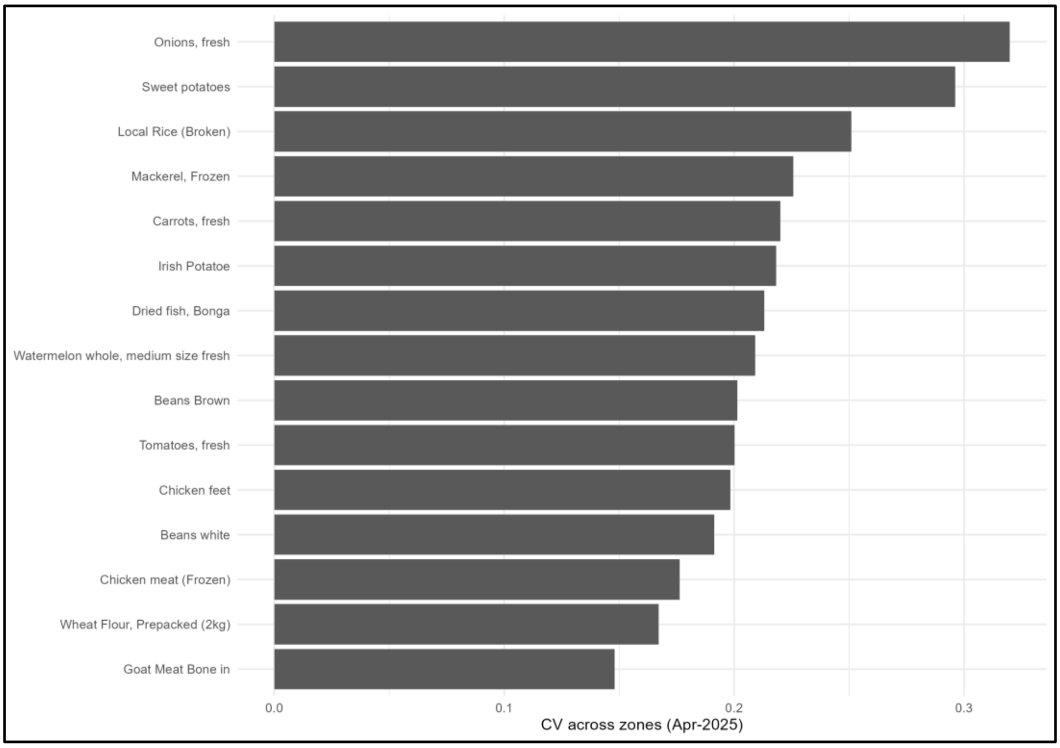

Figure 7. Bar chart of the top 15 food commodities ranked by spatial coefficient of variation (CV) across geopolitical zones.

3.2.2 Zonal Differences in Commodity Prices: ANOVA and Kruskal–Wallis Evidence

Formal statistical testing confirms the presence of systematic zonal price differences. The pooled one-way ANOVA on log-transformed prices indicates a statistically significant zonal effect ($p < 0.001$), suggesting that mean price levels differ across geopolitical zones. Complementary non-parametric testing using the Kruskal–Wallis test yields consistent results (χ^2 statistic significant at $p < 0.001$), reinforcing the robustness of zonal disparities independent of distributional assumptions.

Item-specific tests further reveal that a large share of commodities exhibit statistically significant spatial price differentiation after controlling for multiple comparisons using the Benjamini–Hochberg procedure. High-inflation staples and protein-rich foods are particularly prone to zonal price divergence, indicating uneven market integration across commodity groups.

3.2.3 Identification of Commodities with Persistent Spatial Price Segmentation

Combining dispersion metrics and statistical significance tests allows the identification of commodities with persistent spatial price segmentation. Using a joint criterion of high spatial CV ($\geq$ 0.15) and adjusted Kruskal–Wallis p-values < 0.05, multiple commodities emerge as structurally segmented markets. These include onions, sweet potatoes, local broken rice, frozen mackerel, and tomatoes, all of which display both large inter-regional price gaps and statistically significant zonal differentiation.

The persistence of segmentation among nutritionally important and widely consumed foods suggests that regional price signals are not efficiently transmitted, raising concerns for equitable food access and national food market integration. Such segmentation implies that households' exposure to food price inflation varies markedly by location, amplifying regional vulnerability.

3.2.4 Heatmap Visualization and Hierarchical Clustering of Commodity–Zone Price Patterns

Heatmap visualization of standardized (z-score) log-transformed prices reveals distinct spatial pricing regimes across commodities and zones. Clustering highlights groups of commodities that share similar regional price structures, separating relatively integrated items from those exhibiting strong north–south or coastal–inland price gradients (Figure 8 -9).

Hierarchical clustering using Ward's method further identifies clear commodity clusters, reflecting shared exposure to spatial frictions and market constraints. Highly perishable items and imported or logistics-intensive commodities tend to cluster together, characterized by elevated prices in southern zones and sharper dispersion nationwide. In contrast, some staples form clusters with comparatively uniform pricing, indicating stronger market integration.

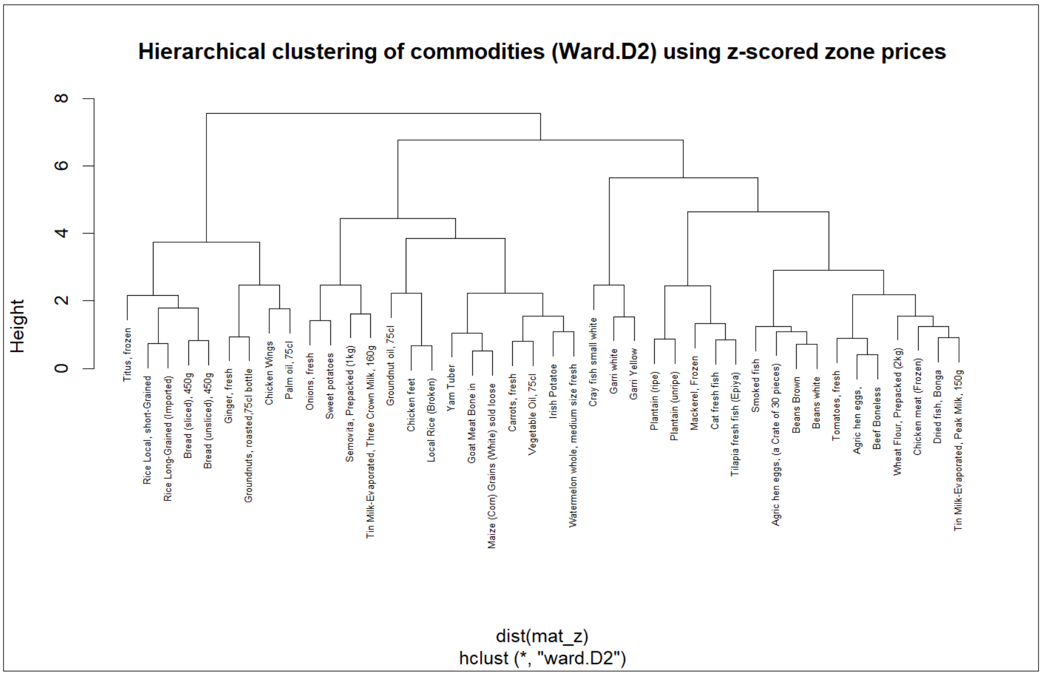

Figure 8. Dendrogram of food commodities based on Ward.D2 hierarchical clustering of zonal price patterns.

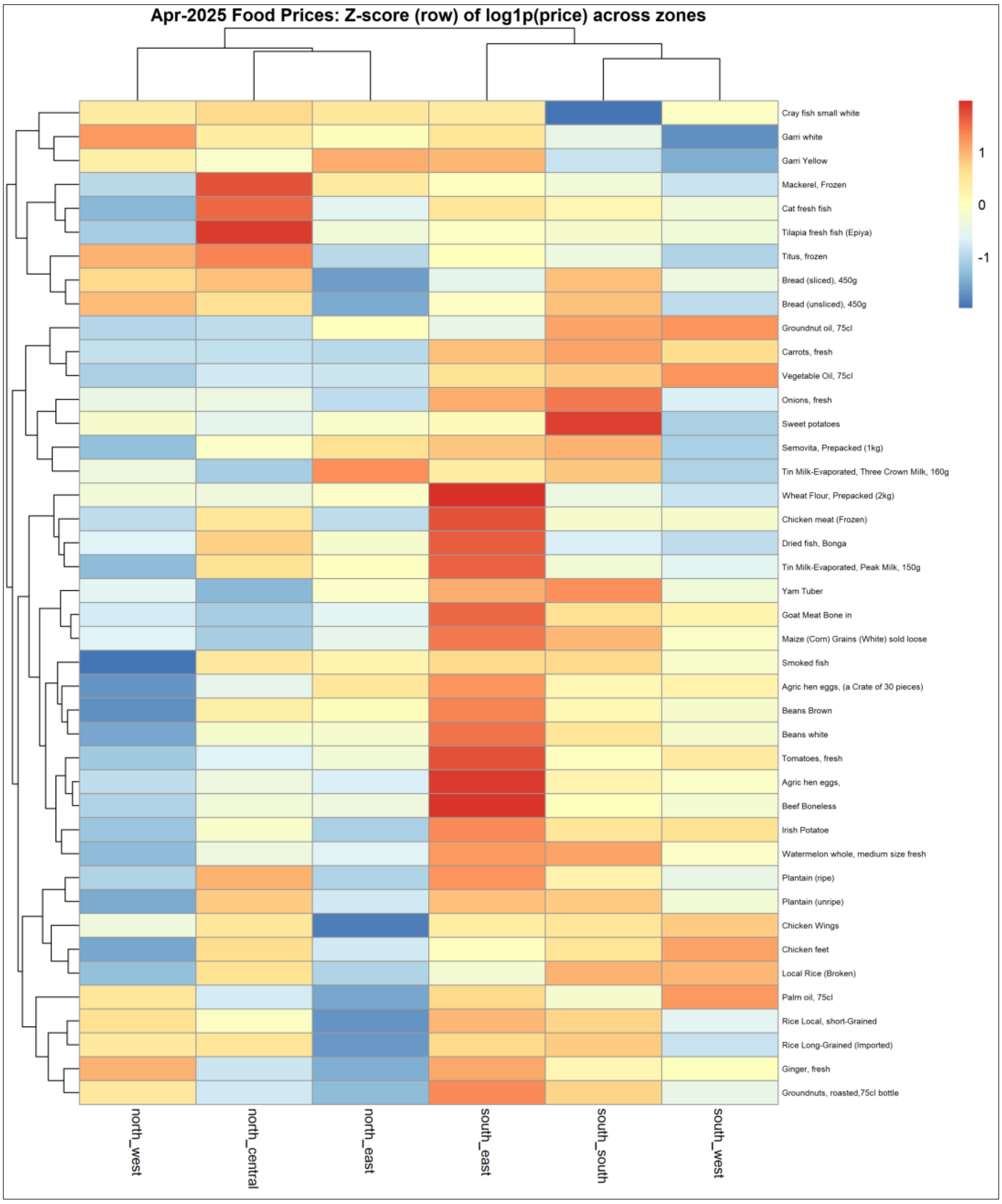

Figure 9. Heatmap of z-score standardized April-2025 food prices across geopolitical zones with hierarchical clustering.

3.3 Vulnerability-Relevant Commodity Groups and Price Pressure (Objective 3)

3.3.1 Price Volatility Characteristics of Food Commodities

Volatility metrics computed across the three observation points (Apr-2024, Mar-2025, Apr-2025) show clear differences in instability across commodities. Across all 42 items, temporal variability (SD_{3t}) averaged ₦438.99 (median ₦290.81; range ₦0.95–₦1,527.33), while the relative volatility (CV_{3t}) averaged 0.160 (median 0.175; range 0.000–0.389). Short-run change instability (rolling variance proxy; available for 27 complete items) averaged 7.96×10^5 (median 4.41×10^5) and reached a maximum of 3.38×10^6, indicating that for some foods, month-to-month change magnitudes are highly uneven.

The highest relative volatility (CV_{3t}) was observed for Plantain (unripe) (0.389), Plantain (ripe) (0.349), Yam tuber (0.334), Tilapia fresh fish (Epiya) (0.333), and Beans brown (0.309). Rolling-variance "shock-like" behavior was dominated by fish products and animal protein items, led by Tilapia fresh fish (Epiya) (3.38×10^6), Titus (frozen) (2.85×10^6), Mackerel (frozen) (2.70×10^6), and Catfish (fresh) (2.65×10^6), reflecting large consecutive change swings.

3.3.2 Multivariate Classification of Commodities Using PCA and k-Means Clustering

To classify vulnerability-relevant price behavior, PCA was performed on a complete feature set (n = 27 commodities) capturing YoY inflation, MoM inflation, SD_{3t}, CV_{3t}, rolling variance proxy, and zonal dispersion (zone CV). The PCA indicates a strong low-dimensional structure: PC1 explains 51.12% of total variance and PC2 explains 24.03%, giving 75.15% cumulative variance in the first two components.

Loadings show that PC1 is driven primarily by temporal volatility and sustained inflation, with the largest absolute contributions from CV_{3t} (|loading| = 0.514), YoY (0.496), SD_{3t} (0.446), and rolling variance (0.422). PC2 reflects instability and spatial segmentation, dominated by rolling variance (0.516), zone CV (0.511), SD_{3t} (0.475), and MoM (0.399) (Figure 10-11). These patterns indicate that the commodity space is structured by two dominant forces: (i) inflation–volatility intensity, and (ii) short-run instability coupled with spatial price dispersion.

Applying k-means clustering (k = 3) in the standardized indicator space yields three interpretable commodity regimes: a fish-dominated high-volatility cluster, a spatially segmented perishables cluster, and a high-inflation staples cluster.

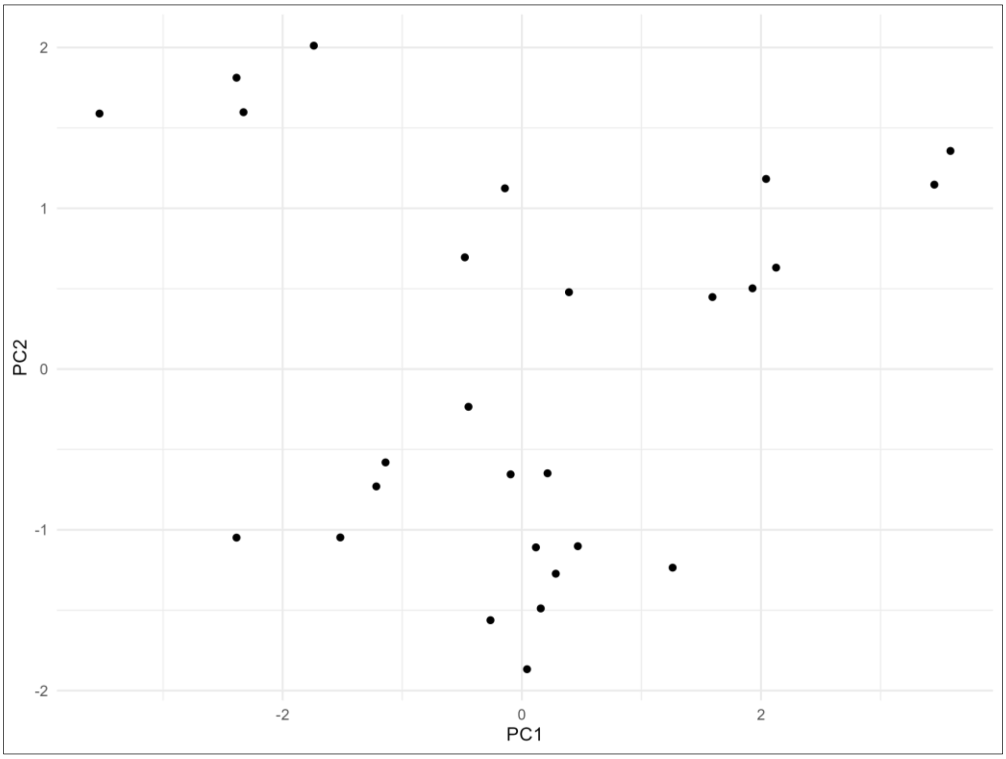

Figure 10. PCA scatter plot (PC1 vs. PC2) summarizing multivariate differentiation of commodities using inflation, volatility, and spatial dispersion indicators (*PCA_scatter_PC1_PC2*).

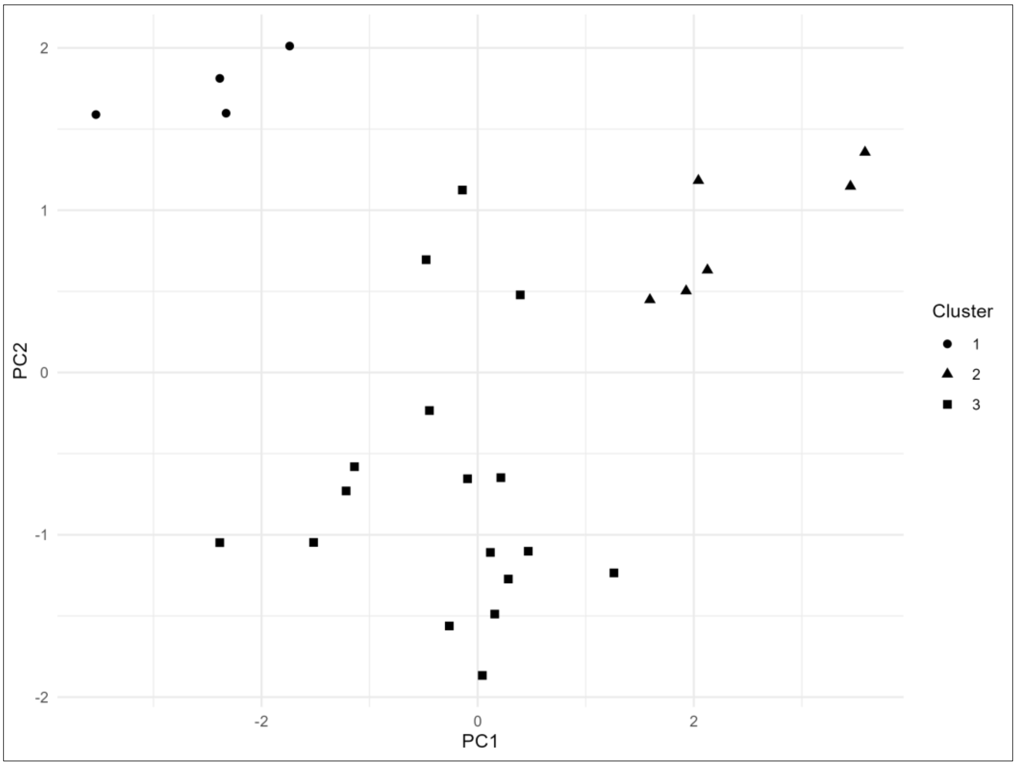

Figure 11. PCA scatter plot with k-means cluster membership (k = 3), showing distinct commodity regimes of food price behavior (*5.9_PCA_clusters_kmeans*).

3.3.3 Composite Food Price Pressure Index (FPPI) and Commodity Ranking

A Composite Food Price Pressure Index (FPPI) was constructed for the 27 complete commodities using standardized components of YoY inflation, MoM inflation, temporal volatility (CV_{3t} and rolling variance proxy), and spatial dispersion (zone CV). FPPI values ranged from −0.646 to 1.298 (mean 0.138, median −0.069), indicating that a subset of commodities concentrates the highest pressure burden.

The highest FPPI items were led by Plantain (unripe) (FPPI = 1.298; YoY = 123.1%; CV_{3t} = 0.389), followed by Tilapia fresh fish (Epiya) (1.021; YoY = 94.0%; CV_{3t} = 0.333), Plantain (ripe) (0.920; YoY = 103.9%), and Yam tuber (0.870; YoY = 98.2%; MoM = 4.62%). High-pressure protein items were also prominent, including Catfish (fresh) (0.725), Titus (frozen) (0.698), and Mackerel (frozen) (0.673). Notably, some commodities rank high due to strong spatial segmentation, such as Onions (fresh) (zone CV = 0.320; FPPI = 0.376) and Mackerel (frozen) (zone CV = 0.226; FPPI = 0.673), confirming that vulnerability is shaped by both inflation intensity and regional dispersion (Figure 12).

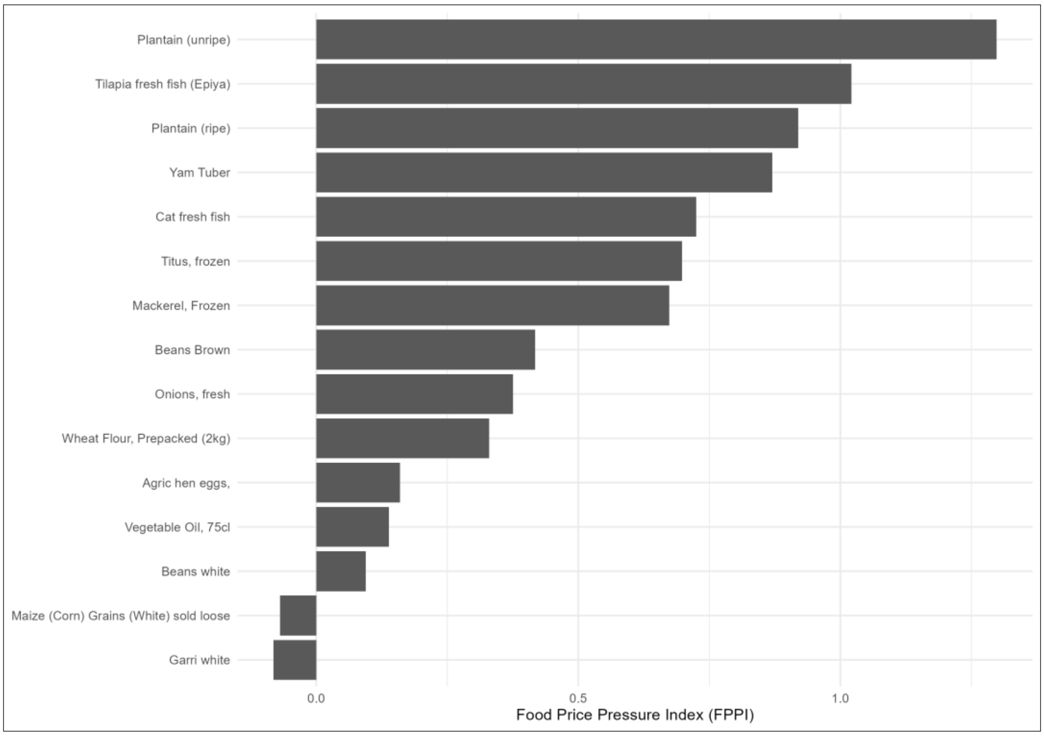

Figure 12. Top 15 commodities ranked by the Composite Food Price Pressure Index (FPPI), summarizing sustained inflation, volatility, and spatial dispersion effects (*5.11_top15_FPPI_bar*).

3.3.4 Cluster-Based Interpretation of Food Price Vulnerability

Cluster data show three distinct vulnerability-relevant regimes (n = 27 complete commodities).

Cluster 1 (n = 4) represents an acute volatility–protein shock group, consisting of Tilapia (fresh), Catfish (fresh), Titus (frozen), and Mackerel (frozen). This cluster records the highest mean YoY inflation (78.60%), with elevated temporal volatility (mean CV_{3t} = 0.296) and meaningful spatial dispersion (mean zone CV = 0.151), consistent with high cost sensitivity and instability in protein supply chains.

Cluster 3 (n = 17) represents a high-inflation staple basket, dominated by major household foods such as plantain (ripe/unripe), yam tuber, beans (brown/white), garri (white/yellow), maize, rice (local and imported), palm oil, vegetable oil, wheat flour, chicken wings, beef boneless, eggs, and evaporated milk. Despite a negative mean MoM (−0.914%), this group shows persistently high annual inflation (mean YoY = 64.56%) and high relative volatility (mean CV_{3t} = 0.257), implying sustained pressure on everyday consumption.

Cluster 2 (n = 6) captures a spatially segmented perishables/logistics-sensitive group (Onions, Irish potato, Chicken feet, Chicken meat (frozen), Sweet potatoes, Tomatoes). This cluster exhibits the highest spatial dispersion (mean zone CV = 0.235) and the highest mean MoM inflation (3.99%), while having a lower average YoY (27.74%) relative to the high-inflation staple cluster—indicating that short-run and regional market frictions are central vulnerability drivers for these foods.

5 Discussion

This study advances the understanding of food price dynamics in Nigeria by demonstrating that inflationary pressure is spatially uneven, and commodity-specific. While rising food prices have been widely documented in national statistics and policy reports, the present analysis reveals how aggregate indicators conceal pronounced heterogeneity across food items and geopolitical zones, with important implications for food security, market integration, and policy effectiveness.

4.1 Structural Food Inflation in Context of Existing Evidence

The finding of widespread and persistent year-on-year (YoY) food price inflation is consistent with recent empirical studies on Nigeria, which attribute food price escalation to a combination of exchange-rate depreciation (Umaru et al., 2025), rising input costs, climate-induced production shocks (CJID, 2022), and insecurity along supply corridors. The relatively modest month-on-month (MoM) changes observed in this study further support this interpretation, indicating that recent price pressures reflect accumulated macroeconomic and supply-side constraints rather than short-term market fluctuations.

These findings align with the Central Bank of Nigeria (CBN) inflation outlooks, which emphasize cost-push drivers fuel prices, transport costs, and foreign exchange scarcity as dominant contributors to food inflation (Bank, 2025). The concentration of high inflation among staples such as yam, plantain, and rice echoes concerns raised in Nigeria's National Development Plan (2021–2025) regarding the vulnerability of staple food supply chains to systemic shocks (NDP, 2021).

4.2 Regional Market Fragmentation and Integration Challenges

The evidence of persistent spatial price dispersion across Nigeria's geopolitical zones corroborates earlier findings on weak market integration in domestic food markets. Previous research has shown that high transaction costs, poor road infrastructure, and insecurity significantly limit spatial price transmission in Nigeria. The large coefficients of variation identified for perishable and transport-sensitive commodities in this study reinforce the view that arbitrage mechanisms remain constrained, particularly between surplus-producing and deficit-consuming regions.

Government assessments, including the Federal Ministry of Agriculture and Food Security (FMAFS) sector reviews, have repeatedly highlighted logistical bottlenecks and post-harvest losses as major impediments to efficient food distribution (ijeoma, 2024). The present results provide empirical support for these assessments by quantifying the extent to which such bottlenecks translate into measurable regional price disparities. Importantly, the findings suggest that national price stabilization efforts may have uneven effects unless complemented by region-specific infrastructure and market-access interventions.

4.3 Commodity-Specific Vulnerability and Volatility in the Literature

The identification of protein-rich foods and perishables as high-volatility commodities is consistent with broader literature on food price instability in developing economies (Minot, 2014; Sarris, 2019). Studies across West Africa have shown that fish, meat, and fresh produce are particularly sensitive to fuel price changes, storage limitations, and supply disruptions (Essuman, 2019). In Nigeria, recent analyses have linked volatility in fish prices to rising energy costs and inadequate cold-chain infrastructure (Chan et al., 2024), a pattern clearly reflected in the present results.

4.4 Food Price Pressure, Policy Programmes, and National Vision

The composite Food Price Pressure Index (FPPI) highlights commodities, such as plantain, yam, onions, and fish products, that pose the greatest risk to food security due to compounded price pressures. These findings are highly relevant to ongoing government programmes, including the Agricultural Promotion Policy (APP), the National Agricultural Technology and Innovation Policy (NATIP), and targeted interventions under the CBN's agricultural financing schemes. While these programmes aim to boost production and stabilize prices, the present results suggest that greater attention is needed on distribution efficiency, regional market integration, and perishability management. From a strategic perspective, the findings align with Nigeria's long-term development aspirations under Vision 2050 and the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 10 (Reduced Inequalities). Reducing spatial food price disparities and stabilizing high-pressure commodities are essential not only for food security but also for inclusive economic growth and social stability.

4.5 Implications for Policy Design and Monitoring

The results imply that effective food price policy in Nigeria requires a shift from uniform national responses toward commodity and region-specific strategies. Strengthening transport infrastructure, investing in storage and cold-chain systems, and improving security along food supply routes could substantially enhance market integration. Moreover, integrating composite indicators such as the FPPI into routine monitoring by agencies such as the NBS could improve early warning systems for food price stress and guide targeted interventions.

4.6 Limitations and Directions for Future Research

Although this study provides comprehensive insights, it is constrained by the use of discrete time points rather than continuous monthly series. Future research could build on this framework by incorporating longer time series, spatial econometric models, and household consumption data to directly link price pressure to nutritional and welfare outcomes. Such extensions would further strengthen the evidence base for designing resilient and inclusive food systems in Nigeria.

Conclusion

This study provides a comprehensive assessment of food price dynamics in Nigeria by integrating spatio-temporal inflation analysis, regional price dispersion, and multivariate vulnerability assessment. The findings demonstrate that food price pressure in Nigeria is multidimensional, commodity-specific, and spatially uneven, with substantial differences by aggregate inflation indicators. Sustained year-on-year inflation, persistent regional price disparities, and pronounced volatility in key staples and protein-rich foods jointly contribute to heightened food security risks.

By identifying vulnerability-relevant commodities through a composite Food Price Pressure Index, the study advances existing approaches to food price analysis and offers a practical framework for prioritizing policy interventions. The results underscore the importance of improving market integration, strengthening food supply chains, and adopting regionally targeted strategies rather than uniform national responses.

Supplementary Materials: Available at https://github.com/zubairgis/nigeria-hensard/blob/main/Food%20Prices%20in%20Nigeria.xlsx

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Data Availability Statement

The data presented in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full Meaning
ANOVA	Analysis of Variance
BH	Benjamini–Hochberg (False Discovery Rate adjustment)
CBN	Central Bank of Nigeria
CV	Coefficient of Variation
FDR	False Discovery Rate
FPPI	Food Price Pressure Index
FMAFS	Federal Ministry of Agriculture and Food Security
GDP	Gross Domestic Product
KW	Kruskal–Wallis Test
LMICs	Low- and Middle-Income Countries
MoM	Month-on-Month
NATIP	National Agricultural Technology and Innovation Policy
NBS	National Bureau of Statistics (Nigeria)
PCA	Principal Component Analysis
SDGs	Sustainable Development Goals
YoY	Year-on-Year

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