

Food Price Monitoring in Nigeria

A Source-Audited Baseline of Spatial Dispersion and Persistence

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Abstract

Administrative food-price series inform early warning, social-protection design, inflation surveillance, and the allocation of scarce public resources. Their value depends on disciplined interpretation. This paper establishes a source-audited economic baseline for the National Bureau of Statistics (NBS) Selected Food Price Watch. It documents reported food-price dispersion and conditional relative-price persistence across Nigeria's states and the Federal Capital Territory (FCT). We reconstruct a fixed-vintage panel of 43 source-labelled food items, 37 jurisdictions, and January 2017–April 2019. The source contains 44,548 state/FCT–item–month records, of which 44,547 are finite and positive. Median item-level cross-jurisdiction log-price dispersion is non-monotonic, ranging from 0.134 in April 2017 to 0.186 in March 2018. In a state-item fixed-effect model of 42,955 consecutive observations, the conditional one-month persistence coefficient is 0.696 (two-way-clustered 95% confidence interval: 0.655–0.737). On a matched 26-outcome-month window, an equal-length split-panel point diagnostic is 0.858, showing that finite-time dynamic-panel treatment materially affects the exact magnitude. The paper establishes two empirical facts about this administrative series. Reported prices are geographically heterogeneous and short-run relative-price deviations are persistent. This reproducible baseline gives policy users and subsequent empirical work a verified account of the series before it is used to interpret deeper market processes.

Keywords food prices; geographic aggregation; price dispersion; relative-price persistence; Nigeria; price monitoring.

JEL codes Q11, Q18, R11, C23.

1 Introduction

Administrative food-price monitoring sits close to high-stakes public decisions. Governments use it to track food inflation and investigate pressure points; humanitarian early-warning systems use price movements alongside production, income, and shock information to assess emerging food-security risks; and food-assistance agencies use market analysis to design and monitor transfers, procurement, and other interventions (World Food Programme; Famine Early Warning Systems Network). In settings where local market data are scarce or delayed, a state-level series may be the only timely, consistently released evidence available to a decision-maker.

That practical value makes correct interpretation more, not less, consequential. A state average can reveal a geographic pattern that warrants attention. It cannot, by itself, identify the economic process behind the pattern. A high reported price may reflect a local supply disruption, but it may also reflect a product-definition difference, a unit or package difference, the selection of markets into the administrative average, or the aggregation of sharply different local prices. Treating an administrative series as a direct measure of market integration or household access can therefore turn a reporting feature into a diagnosis of structural failure. In a policy setting, that is not an abstract econometric concern. It can misdirect surveillance, targeting, and the use of public resources.

This paper addresses that risk by establishing the empirical properties of the National Bureau of Statistics (NBS) Selected Food Price Watch before asking the series to bear a structural interpretation. It reconstructs the April-2019 vintage and answers two questions. First, how widely do NBS-reported prices for the same source-labelled product differ across Nigeria’s states and the Federal Capital Territory (FCT), and how does that dispersion vary over time and products? Second, after separating state-item price levels from month-to-month relative-price deviations, how persistent are those deviations? The contribution is a source-audited baseline. It provides a fixed-vintage record of dispersion and conditional persistence that policy users and later research can use to assess the empirical content of the NBS price schedule.

Spatial-price theory clarifies why this baseline is needed. Spatial equilibrium concerns prices, flows, and transfer costs jointly, not simply whether two price series move together (Fackler and Goodwin, 2001). Simple correlation or co-movement does not establish market integration (Ravallion, 1986; Barrett and Li, 2002), while adjustment may be nonlinear because a price gap must first exceed a transfer-cost threshold (Baulch, 1997; Goodwin and Piggott, 2001). The geography of an administrative release also need not coincide with an

economic market (Moser, Barrett, and Minten, 2009). The paper makes the administrative series itself legible and leaves mechanism estimation to designs that observe the relevant market links and channels.

The direct Nigerian frontier is correspondingly more demanding than a state-average descriptive panel. Amare, Abay, and Hatzenbuehler (2024) combine food prices with pandemic and lockdown variation. Kassouri and Fofana (2025) analyse regional grain-market linkages, and Liu, Olabisi, and Maredia (2026) employ weekly prices, trader networks, routes, travel time, and conflict exposure. Their designs identify questions that the NBS aggregate alone cannot answer. This paper has a different task. It establishes a transparent descriptive foundation for the official series on which such mechanism-focused work may build.

The paper makes four linked contributions. It preserves the NBS source labels and documents the exact source vintage rather than silently harmonising heterogeneous products. It measures item-level cross-jurisdiction dispersion and shows how it changes over the 28-month period. It distinguishes pooled price persistence from conditional persistence after removing stable state-item price levels. Finally, it shows that the short time dimension matters materially for the exact persistence magnitude. Together, these results turn an administrative monitoring file into a documented empirical object rather than a convenient but opaque proxy for market performance.

2 Theory, literature, and the economic object

2.1 Observed price patterns versus economic mechanisms

A spatial price is an equilibrium outcome, not an observed explanation. Distance, road quality, storage, information, security, credit, rules, and trader behaviour can affect price differences through their effects on trade opportunities, transfer costs, and local market conditions. Evidence from Ghana and the former Zaire shows that transport and local conditions shape price responses and marketing margins (Badiane and Shively, 1998; Minten and Kyle, 1999); evidence from Niger shows that information can reduce dispersion (Aker, 2010); and storage and high trade costs can shape price dynamics (Porteous, 2019). Those mechanisms are economically central, but they are not variables in the NBS panel.

The analytic standard follows directly. The present study treats a reported state-item price as an observed administrative outcome. It measures the distribution and persistence of that outcome without assigning its cause. A later causal model can only interpret a movement in this series after specifying and observing the proposed shock or channel. The source audit

supplies the descriptive parameters against which that interpretation can be checked.

2.2 Measurement, aggregation, and product comparability

Relative-price dispersion is a valuable descriptive object (Engel and Rogers, 1996), but its construction is consequential. Same named foods can differ in quality, package size, and units of sale across locations (Deaton, 1988); seasonality requires explicit measurement (Gilbert, Christiaensen, and Kaminski, 2017); and spatial variation in food prices is substantial across sub-Saharan Africa (Bonilla-Cedrez, Chamberlin, and Hijmans, 2020). The NBS labels therefore define the comparison unit in this study. They permit within-label, within-month comparisons; they do not create a common price level across food products.

Geographic aggregation is likewise an economic measurement choice, not a harmless convenience. Local rather than aggregate price information can change food-poverty measurement (Dietrich et al., 2026). Nigerian crowd-sourced monitoring efforts demonstrate both the policy value of timely granular information and the need to document product and sample construction (Adewopo et al., 2021; Arbia et al., 2023). The NBS series has a clear role as an official state-level monitoring resource whose empirical properties must be established before it motivates local-market or household-level claims.

2.3 Nigeria’s empirical literature

Research in Nigeria confirms that commodity, geography, and mechanism matter. Price transmission differs across Nigerian food-security crops and regions (Hatzenbuehler, Abbott, and Abdoulaye, 2017), while measured growing conditions can explain grain-price variation (Hatzenbuehler, Abbott, and Abdoulaye, 2020). Nigerian evidence on food security uses linked household information (Amolegbe et al., 2021). Comparative work reinforces the same measurement discipline. Retail prices alone do not identify marketing margins or trader behaviour in Ethiopia (Hirvonen et al., 2021), and studies in Niger and India connect price movements to measured weather shocks and trader expectations (Kakpo, Mills, and Brunelin, 2022; Letta, Montalbano, and Pierre, 2022). The implication is direct. A credible mechanism claim must observe the proposed shock or channel rather than infer it from a state-aggregate price pattern.

3 Conceptual scope and estimands

The paper has one explicit inferential boundary. Its empirical objects are reported state/FCT prices, their cross-jurisdiction distribution, and their within-series month-to-month relationship. They are not direct observations of trade, transfer costs, market connectivity, household purchases, or welfare. Keeping this boundary fixed allows the analysis to be assertive about what the NBS series reveals.

Let P_{ist} denote the NBS-reported nominal price of item i in jurisdiction s in month t . The relative log price is

$$r_{ist} = \log(P_{ist}) - \frac{1}{S_{it}} \sum_{s=1}^{S_{it}} \log(P_{ist}), \quad (1)$$

where S_{it} is the number of valid jurisdictions for item i in month t . A positive value means that the jurisdiction's reported price is above the equal-jurisdiction item-month mean. This removes the common item-month level; it does not make prices comparable across items.

The primary descriptive object is cross-jurisdiction dispersion.

$$D_{it} = \sqrt{\frac{1}{S_{it} - 1} \sum_s \left[\log(P_{ist}) - \overline{\log(P)}_{it} \right]^2}. \quad (2)$$

The paper also reports the median absolute deviation (MAD), a robust companion measure of log-price dispersion (Rousseeuw and Croux, 1993). Both are distributions of reported prices, not measures of efficiency, access, or transfer costs.

The secondary estimand is conditional persistence.

$$r_{ist} = a_{is} + \rho r_{is,t-1} + u_{ist}, \quad (3)$$

where a_{is} is a state-item fixed effect. In the model, it captures a durable state-item relative-price level, while ρ summarizes the month-to-month persistence of deviations around that level. The distinction is economically important. A place can have a persistently high reported price level without experiencing a new short-run divergence, and a short-run divergence can persist even after permanent level differences are removed. The relationship remains descriptive. A fall in r_{ist} can arise because the focal price falls, other jurisdictions' prices rise, or both.

The paper uses a leave-one-jurisdiction-out reference and an item-month median reference as construction checks. The former is nearly an algebraic rescaling of the inclusive-mean

deviation under complete coverage, so it is not treated as independent substantive evidence. The analysis does not move from prices to household food security. Price, production, availability, expenditure, diet, and food-security outcomes are distinct points in a causal process; this source observes only one of them.

4 Data and analytic-panel construction

The data are drawn from the NBS *Selected Food Price Watch* workbook ending in April 2019 (National Bureau of Statistics, 2019, 2025). The April 2019 vintage is the appropriate empirical object because it is the terminal cumulative workbook in the supplied archive. It provides a single, consistently structured 28-month record across the 36 states and the FCT. Earlier workbooks are overlapping release snapshots, so stacking them would double-count the same observations and obscure provenance. The paper therefore studies a fixed pre-COVID monitoring vintage, not current food-price conditions.

The workbook has a national worksheet and 37 jurisdictional worksheets, comprising the 36 states and the FCT. The national worksheet is not used as a reference price because it need not equal the equal-jurisdiction mean constructed from the state/FCT sheets. The extraction retains original item labels and treats each label as a separate series. The labels distinguish some forms or quantities, for example 500g bread and 170g evaporated milk, but leave others partly open, for example a bottle whose size is to be specified. A common source label is therefore a monitoring-series identifier rather than proof of identical package, quality, outlet, or local-market coverage across jurisdictions. The analysis uses neither household microdata nor a universal per-kilogram conversion.

The source contains 44,548 state/FCT–item–month records for 43 items; 44,547 are finite and positive. One source record is missing and is not imputed. An item-month is retained if at least 36 jurisdictions report a valid price; all 1,204 item-months meet this rule. The dynamic sample contains 42,955 observations with an immediately prior calendar-month observation for the same state-item. Table 1 gives the complete flow. The time span is only 28 months, so it cannot establish a long-run trend, stable seasonal process, structural break, or permanent-versus-transitory shock process.

Table 1: Coverage of the source-audited NBS price panel

Measure	Value
Jurisdictions in source	37
NBS item labels in source	43
Months in source	28
State-item-month source records	44,548
Finite positive price records	44,547
Item-months retained with at least 36 jurisdictions	1,204
Relative-price panel records	44,547
Consecutive-month relative-price records	42,955
Expected months in a complete state-item series	28

Notes: The source covers 36 states and the Federal Capital Territory. A reported state-item-month value is retained only when finite and strictly positive. No value is imputed; prices remain private.

5 Empirical approach and inference

The primary model estimates Equation (3) by state-item fixed-effect least squares. This is a deliberately economic, rather than purely mechanical, distinction. A pooled relationship mixes a persistent location-product price level with the persistence of a deviation from that level. The fixed-effect specification isolates the latter relationship within a state-item series. Inference uses two-way clustered standard errors by jurisdiction and item, with finite-sample adjustment. This recognises dependence across products within a jurisdiction and across jurisdictions within an item (Cameron, Gelbach, and Miller, 2011); the number and structure of clusters still matter for interpretation (Cameron and Miller, 2015; MacKinnon, Nielsen, and Webb, 2023).

The short time dimension is central to the interpretation. The source spans 28 calendar months, yielding 27 outcome months for the dynamic model. Over such a horizon, a durable state-item premium and a temporary deviation that is resolving slowly can be difficult to separate statistically. A lagged dependent variable with unit fixed effects can therefore suffer finite-time dynamic-panel bias (Nickell, 1981). This is not a technical footnote. If the persistence parameter is understated, an analyst can mistake a deviation that lingers for one that dissipates quickly; if it is overstated, an analyst can infer a durable pressure from a short-lived movement. The difference changes how a monitoring signal is read.

The paper consequently reports a contiguous equal-length split-panel point diagnostic following the bias-correction logic of Dhaene and Jochmans (2015). On the first 26 outcome

months, it compares the full-window fixed-effect relationship of 0.697 with two contiguous 13-month components and produces a 0.858 point diagnostic. The 0.161 difference shows that finite-time treatment materially affects the exact persistence magnitude. The full-sample fixed-effect estimate remains the primary reported statistic because it retains all 27 outcome months and permits two-way clustered inference. The split-panel result has a different role. It establishes the scale of finite-time sensitivity, but it discards one outcome month and lacks a separately validated uncertainty procedure. A generic pairs or fixed-design bootstrap can be miscentered in a dynamic fixed-effect setting; formal bootstrap inference requires a specified dynamic resampling design and coverage justification (Gonçalves and Kaffo, 2015). The paper therefore treats the two estimates jointly as evidence of positive persistence with an unresolved magnitude range. Arellano–Bond is a possible alternative dynamic-panel route (Arellano and Bond, 1991), but is not deployed mechanically.

Product-specific estimates are retained as an appendix-style heterogeneity description. Dynamic slopes need not be homogeneous (Pesaran and Smith, 1995; Pesaran and Yamagata, 2008), but 43 uncorrected product estimates are not treated as 43 separate structural tests.

The versioned design checks use a median reference, a complete 28-month state-item sample, and a source-anomaly screen. The screen flags, but never corrects, a focal record only if it changes by more than fivefold from the prior month and reverses by more than fivefold in the following consecutive month. The sensitivity drops only flagged focal records, recomputes references, and reruns the stated model. Leave-one-state/FCT and leave-one-item refits report influence ranges. Together, these checks protect the baseline from being driven by a single reported source component; they do not substitute for a different market-level design.

6 Results

6.1 Reported price dispersion

Figure 1 shows the monthly median and interquartile range of item-level cross-jurisdiction log-price dispersion. The median is non-monotonic. It reaches 0.134 in April 2017 and 0.186 in March 2018. The monitored geography therefore contains sustained and changing relative-price heterogeneity, not a single system-wide pattern that can be reduced to a simple narrative of improvement or deterioration.

Product differences are substantial. Table 2 and Figure 2 rank the six highest and six lowest source-labelled products. Chicken feet have the highest average reported dispersion (0.333), followed by yellow maize grain (0.299), white maize grain (0.291), tomato (0.278), onion bulb (0.264), and broken rice (Ofada) (0.249). Peak evaporated milk has the lowest average dispersion (0.051). This ranking identifies the source labels for which geographic spread is greatest and where later work should scrutinise comparability and proposed mechanisms most closely.

Appendix Table 9 provides a broader descriptive comparison based on observable source-label form and sale description. Fresh produce and fresh fish have the highest mean dispersion at 0.210, followed closely by loose staples and grains at 0.203. Animal products and preserved fish average 0.163, while processed and packaged products average 0.100. The pattern shows that geographic heterogeneity differs systematically across observable product forms and sale descriptions. It is a descriptive comparison rather than a test of the mechanism behind those differences.

Table 2: Products with the highest and lowest average reported price dispersion

Product	Group	Mean SD	Mean MAD
Chicken Feet	Highest dispersion	0.333	0.165
Maize grain yellow sold loose	Highest dispersion	0.299	0.225
Maize grain white sold loose	Highest dispersion	0.291	0.223
Tomato	Highest dispersion	0.278	0.186
Onion bulb	Highest dispersion	0.264	0.166
Broken Rice (Ofada)	Highest dispersion	0.249	0.147
Agric eggs(medium size price of one)	Lowest dispersion	0.089	0.058
Palm oil: 1 bottle,specify bottle	Lowest dispersion	0.087	0.064
Agric eggs medium size	Lowest dispersion	0.087	0.058
Wheat flour: prepacked (golden penny 2kg)	Lowest dispersion	0.086	0.059
Evaporated tinned milk carnation 170g	Lowest dispersion	0.083	0.058
Evaporated tinned milk(peak), 170g	Lowest dispersion	0.051	0.031

Notes: SD and MAD are computed across jurisdictions from log prices within a source-labelled item and month. MAD is a robust dispersion measure, not a price-level comparison across products.

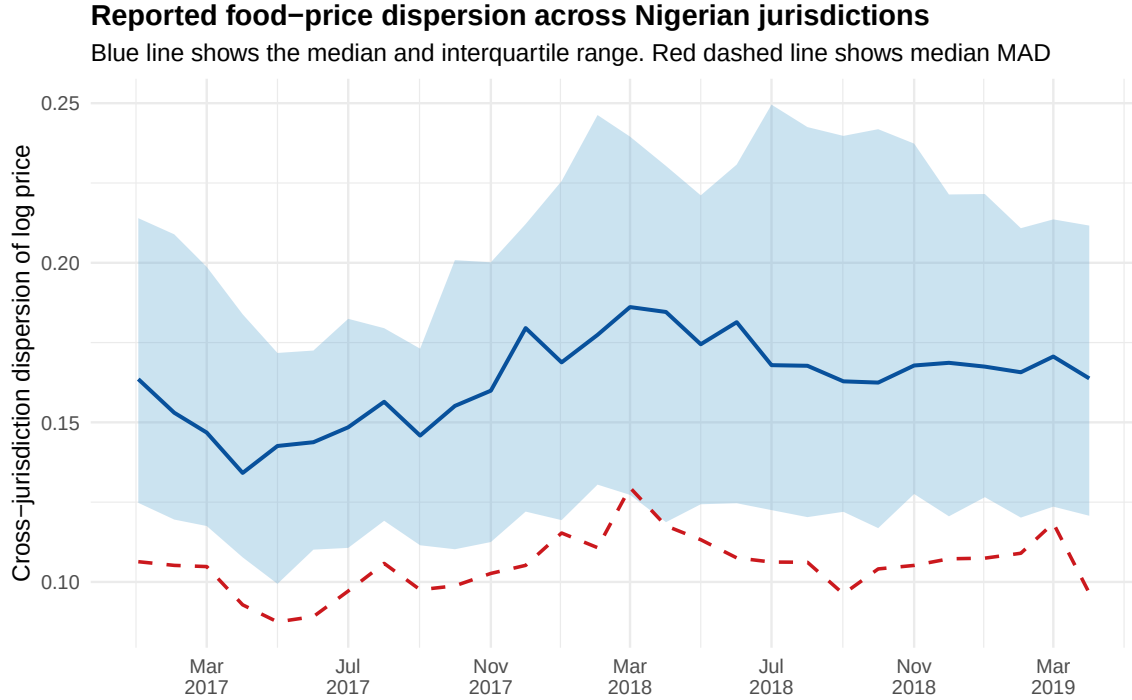


Figure 1: Median and interquartile range of item-level reported cross-jurisdiction price dispersion over time. The dashed line is median robust MAD.

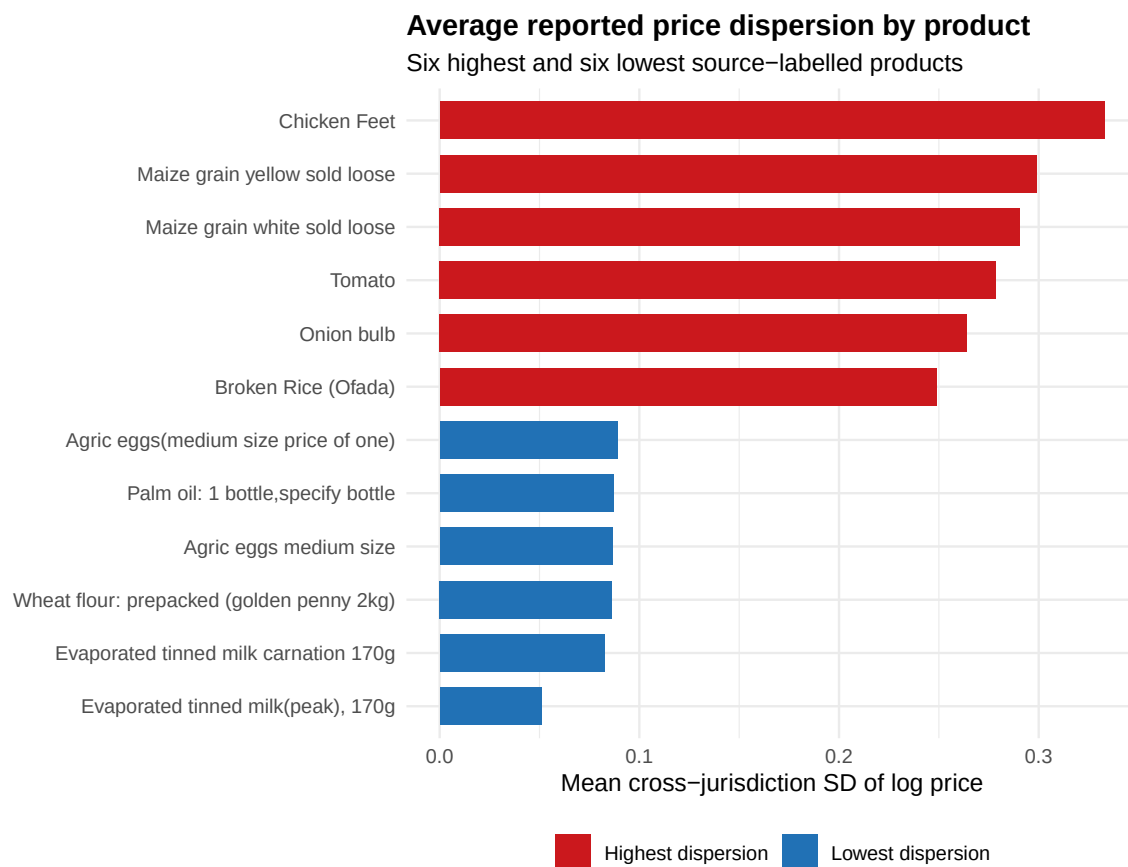


Figure 2: Source-labelled products with the highest and lowest average reported cross-jurisdiction price dispersion.

6.2 Conditional relative-price persistence

The pooled raw relationship confounds durable state-item price premia with short-run persistence and is therefore not used as the main estimate. After state-item fixed effects remove time-invariant premia, the primary one-month coefficient is 0.696 with a two-way-clustered 95% confidence interval of 0.655–0.737. Under the stated within-series model, a one-log-point higher relative reported price in the prior month is associated with a 0.696-log-point higher relative reported price in the current month. The result establishes strong positive short-run persistence in the reported administrative series, conditional on durable state-item differences.

The equal-length split-panel point diagnostic is 0.858. The 0.161 difference from the matched-window fixed-effect relationship makes the practical inference clear. The series supports a confident finding of positive persistence, but the 28-month horizon does not support a single precise persistence magnitude. For an economist or policy analyst, that distinction separates a monitoring signal that appears moderately persistent from one that may be substantially more persistent. Table 3 reports both estimates; its appendix reports the component estimates, the equal-length construction, and the legacy unequal-split stress diagnostic.

Table 3: Conditional persistence of reported state-item relative prices

Estimator	ρ	95% confidence interval	Observations
State-item fixed effects	0.696	[0.655, 0.737]	42,955
Equal-length split-panel diagnostic	0.858	Not reported	41,364

Notes: The primary estimate uses state-item fixed effects and two-way jurisdiction/item clustered inference. The equal-length split-panel diagnostic uses the first 26 outcome months as two contiguous 13-month blocks. It is a point-bias diagnostic, not a separately inferential estimate. Both results describe persistence in a reported price aggregate; neither estimates arbitrage or market integration.

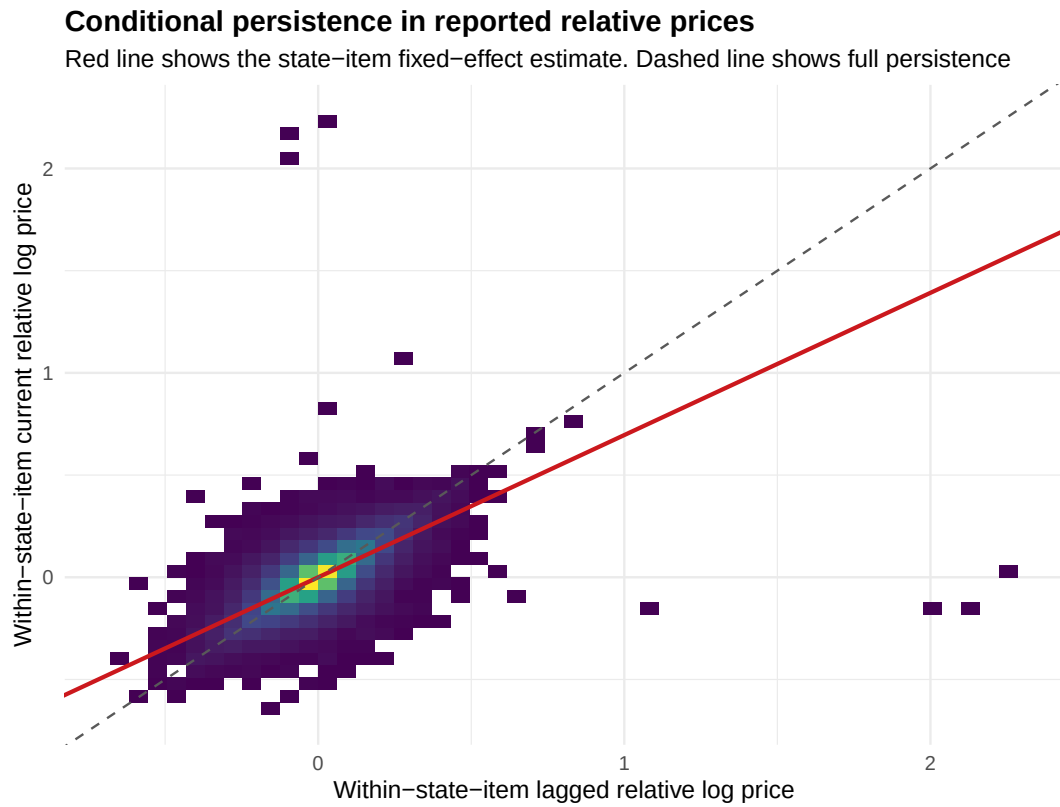


Figure 3: Within-state-item relationship between current and preceding-month relative log prices. The red line is the state-item fixed-effect slope; the dashed line denotes full persistence.

6.3 Construction and influence checks

The primary fixed-effect coefficient is similar under a median reference (0.687), when restricting to complete state-item series (0.696), and after excluding three rule-defined transient reversals and recomputing references (0.719). It ranges from 0.691 to 0.706 across 37 jurisdiction-deletion estimation-influence refits and from 0.690 to 0.709 across 43 item-deletion refits. Table 4 distinguishes reference definitions, sample perturbations, and estimation-influence checks. The conventional fixed-effect relationship is not dominated by the stated source components.

Table 4: Sensitivity and influence checks for conditional persistence

Diagnostic	ρ or range	95% CI	Observations/refits
Primary: mean reference, state-item FE	0.696	[0.655, 0.737]	42,955
Item-month median reference	0.687	[0.647, 0.727]	42,955
Complete 28-month state-item series	0.696	[0.655, 0.737]	42,930
Exclude 3 transient one-month reversals	0.719	[0.693, 0.744]	42,949
Leave one jurisdiction out	0.691–0.706	–	37 refits
Leave one item out	0.690–0.709	–	43 refits

Notes: The primary analysis retains source-reported values. The rule-defined transient-reversal sensitivity excludes only 3 focal records, recomputes all item-month references, and never alters a source value. Jurisdiction-deletion refits recompute item-month references after the omission; item-deletion refits preserve the price-reference construction for retained items. Leave-one-out reference definitions are reported separately as algebraic construction checks, not as independent robustness evidence.

7 Discussion and conclusion

The NBS series establishes a clear empirical fact. Reported price differences across Nigerian states and the FCT are heterogeneous across food labels, change over time, and display positive conditional monthly persistence after durable state-item levels are removed. National averages can therefore conceal geographically uneven price signals. The main value of the paper is to establish exactly what those signals look like in a fully audited vintage of a series that is routinely used for monitoring.

That baseline changes the standard for work that follows. A structural claim about a route, conflict event, policy, weather shock, or market connection cannot be inferred from the reported price pattern alone; it requires the proposed channel, relevant geography, and a defensible identification strategy. A household-access claim likewise requires a standardised

local price schedule matched independently to household timing and outcomes. These are not generic caveats. They are the empirical conditions needed to distinguish a genuine economic mechanism from an administrative aggregation, reporting, or product-comparability artifact.

The paper provides a reproducible benchmark for a specific, widely used public series. It documents the series' coverage, item definition, geographic dispersion, conditional persistence, finite-time sensitivity, and influence profile. Studies that use the NBS Selected Food Price Watch to diagnose market integration or motivate a causal price mechanism should confront these measured properties before drawing a structural interpretation.

Prices are one observed point in the longer process through which production, trade, transport, public policy, and household resources shape food access. This source-audited baseline fixes that point with precision. The next generation of Nigerian spatial-market research should add the observed market pairs, channels, shocks, and household links needed to explain it.

Data availability

The analysis uses the April-2019 NBS *Selected Food Price Watch* workbook, whose provenance, filename, and SHA-256 checksum are reported in Appendix A; the corresponding NBS report is cited below. The author will release a code-only replication archive, source-download instructions, and a software manifest after confirming the source's redistribution terms. Until then, the workbook and all row-level state-item-month derivatives remain private. All manuscript tables and figures are generated from the private source-to-output workflow. This manuscript uses no restricted household microdata.

A Source provenance and reproducibility record

This appendix records the fixed source vintage, parsing rules, and disclosure boundary. The checksum identifies the exact workbook used in the private source-to-output run; it is not a substitute for obtaining the source through its official provider. The calculation never stacks overlapping workbook vintages, uses only the 37 state/FCT sheets (not the national sheet), preserves original item labels, and applies no price imputation.

Table 5: Fixed-vintage provenance and reproducibility record

Field	Recorded value
Source provider	National Bureau of Statistics, Nigeria
Workbook filename	<code>SELECTED_FOOD prices APR_2019.xlsx</code>
SHA-256 fingerprint	<code>3998b6e5ecb58140bb2174dcbf2991</code> <code>8464fdd893a36ff24ad574130928baf5</code>
Source period	2017-01-01 to 2019-04-01
Included sheets	36 state sheets plus the FCT; national sheet excluded
Parsing rule	Original item labels; monthly columns identified from the ItemLabels header; no stacked vintages
R runtime	R version 4.6.1 (2026-06-24)
Key R package versions	readxl 1.5.0; fixest 0.14.2; dplyr 1.2.1

Notes: The SHA-256 fingerprint is a 64-character cryptographic identifier for the exact workbook used in this run. The package versions record the software environment used to import the workbook, estimate models, and transform the analytic panel. The NBS report is cited in the manuscript; the source workbook and row-level derivatives remain private until redistribution terms are confirmed.

B Source-labelled item registry

Table 6 reproduces the source’s item labels and records their observed state/FCT and valid-month coverage. It is an audit of labels, not evidence that products have identical quality, package, outlet, or market coverage across jurisdictions. The main analysis compares prices within an exact source label and month only; it never interprets the product ranking as a standardized cross-product price comparison.

Table 6: Source-labelled NBS item registry and observed coverage

Source item label	Jurisdictions	Months	Valid records	Missing/nonpositive
Agric eggs medium size	37	28	1036	0
Agric eggs(medium size price of one)	37	28	1036	0
Beans brown,sold loose	37	28	1036	0
Beans:white black eye. sold loose	37	28	1036	0
Beef Bone in	37	28	1036	0
Beef,boneless	37	28	1035	1
Bread sliced 500g	37	28	1036	0
Bread unsliced 500g	37	28	1036	0
Broken Rice (Ofada)	37	28	1036	0
Catfish (obokun) fresh	37	28	1036	0
Catfish :dried	37	28	1036	0
Catfish Smoked	37	28	1036	0
Chicken Feet	37	28	1036	0
Chicken Wings	37	28	1036	0
Dried Fish Sardine	37	28	1036	0
Evaporated tinned milk carnation 170g	37	28	1036	0
Evaporated tinned milk(peak), 170g	37	28	1036	0
Frozen chicken	37	28	1036	0
Gari white,sold loose	37	28	1036	0

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Table 6 continued

Source item label	Jurisdictions	Months	Valid records	Missing/nonpositive
Gari yellow,sold loose	37	28	1036	0
Groundnut oil: 1 bottle, specify bottle	37	28	1036	0
Iced Sardine	37	28	1036	0
Irish potato	37	28	1036	0
Mackerel : frozen	37	28	1036	0
Maize grain white sold loose	37	28	1036	0
Maize grain yellow sold loose	37	28	1036	0
Mudfish (aro) fresh	37	28	1036	0
Mudfish : dried	37	28	1036	0
Onion bulb	37	28	1036	0
Palm oil: 1 bottle,specify bottle	37	28	1036	0
Plantain(ripe)	37	28	1036	0
Plantain(unripe)	37	28	1036	0
Rice Medium Grained	37	28	1036	0
Rice agric sold loose	37	28	1036	0
Rice local sold loose	37	28	1036	0
Rice,imported high quality sold loose	37	28	1036	0
Sweet potato	37	28	1036	0
Tilapia fish (epiya) fresh	37	28	1036	0
Titus:frozen	37	28	1036	0

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Table 6 continued

Source item label	Jurisdictions	Months	Valid records	Missing/nonpositive
Tomato	37	28	1036	0
Vegetable oil:1 bottle,specify bottle	37	28	1036	0
Wheat flour: prepacked (golden penny 2kg)	37	28	1036	0
Yam tuber	37	28	1036	0

Notes: Labels are reproduced from the April-2019 source workbook. They document the source's item definition but do not establish equal quality, package, outlet, or market coverage across jurisdictions.

C Dynamic-persistence diagnostic details

The main split-panel diagnostic uses the first 26 outcome months, divided into two contiguous 13-month blocks. The 27-month unequal 13/14 split is retained only as a stress diagnostic. Both are reported to reveal sensitivity to finite-time dynamic fixed-effect bias. Table 7 reports the component slopes and construction; it does not turn either diagnostic into a separately inferential or structural estimate. Figure 4 displays product-specific fixed-effect slopes as descriptive heterogeneity with one-way jurisdiction-clustered intervals.

Table 7: Split-panel dynamic fixed-effect diagnostic components

Component	ρ	Outcome months	Interpretation
Primary full-window state-item FE	0.696	27	Primary descriptive FE relationship
Unequal split: first contiguous block	0.524	13	Component only
Unequal split: second contiguous block	0.555	14	Component only
Unequal 13/14 split point diagnostic	0.852	27	Stress diagnostic only; unequal halves
Equal-window full state-item FE	0.697	26	Full estimate on common equal-split window
Equal split: first contiguous 13-month block	0.524	13	Component only
Equal split: second contiguous 13-month block	0.548	13	Component only
Equal 13/13 split point diagnostic	0.858	26	Diagnostic only; no confidence interval

Notes: The equal 13/13 diagnostic uses the first 26 outcome months. Both point diagnostics are shown only to reveal finite-time sensitivity. They are not confidence-interval estimates, bias-corrected structural parameters, or measures of market integration.

D Finite-cluster stability diagnostics

Table 8 reports delete-one-jurisdiction and delete-one-item refits for the full fixed-effect relationship and both split-panel diagnostics. These are influence checks, not confidence intervals. The separate one-way delete-one dispersions must not be combined into a two-way standard error. They nevertheless show that neither the reported fixed-effect relationship nor the point diagnostics are driven by a single jurisdiction or source-labelled item.

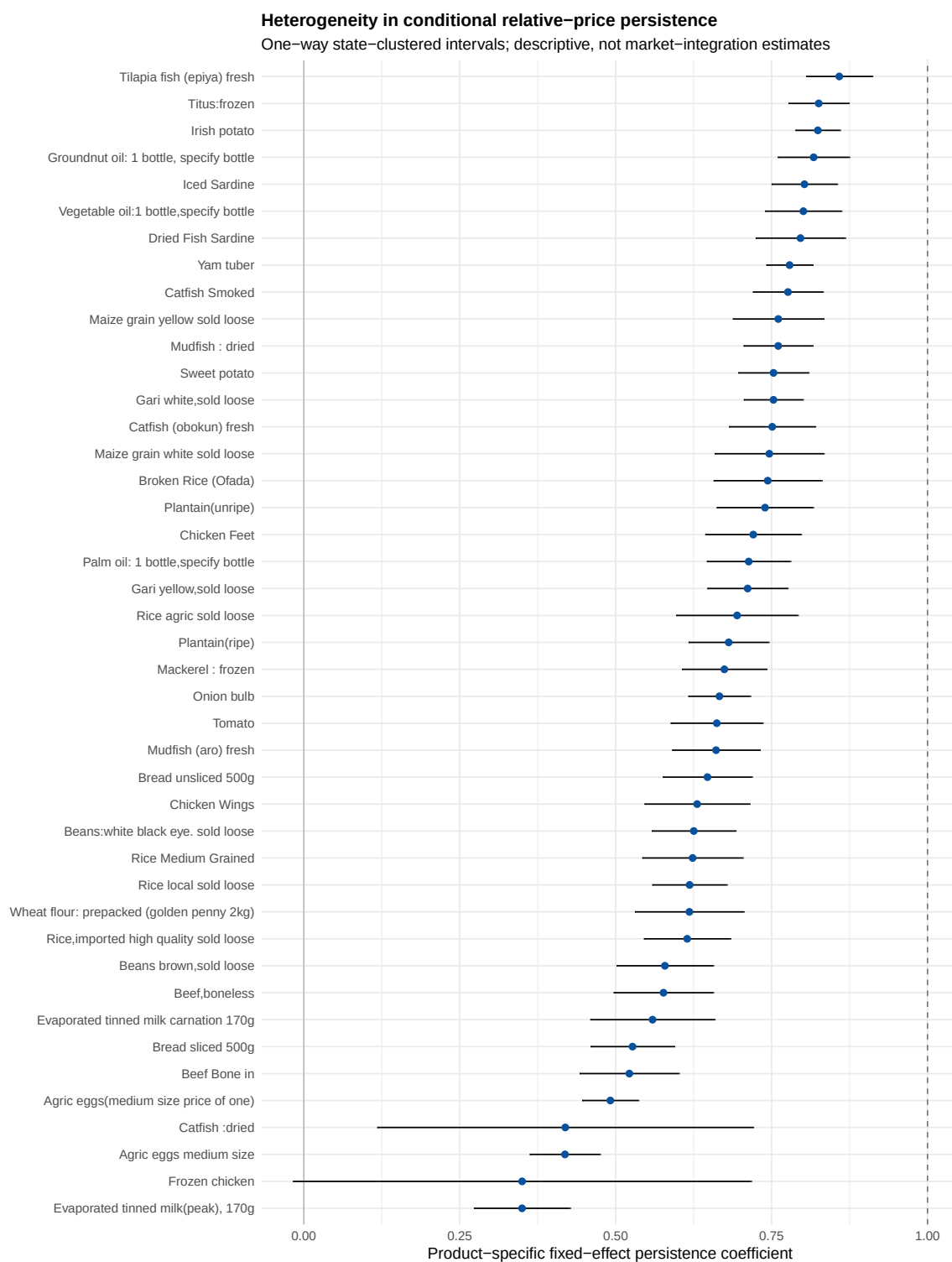


Figure 4: Product-specific state fixed-effect persistence estimates. Intervals are one-way jurisdiction clustered and show descriptive heterogeneity only.

Table 8: Finite-cluster deletion stability diagnostics

Estimator	Omitted dimension	Refit range	Max. absolute deviation
State-item fixed effects	Jurisdiction deletion	0.691–0.706	0.010
State-item fixed effects	Item deletion	0.690–0.709	0.013
Equal 13/13 split point diagnostic	Jurisdiction deletion	0.852–0.867	0.008
Equal 13/13 split point diagnostic	Item deletion	0.849–0.866	0.010
Unequal 13/14 split stress diagnostic	Jurisdiction deletion	0.846–0.861	0.009
Unequal 13/14 split stress diagnostic	Item deletion	0.844–0.860	0.008

Notes: Each row refits the reported-price panel after dropping one jurisdiction or one source-labelled item. Jurisdiction deletions recompute item-month relative-price references. These are stability diagnostics, not confidence intervals. One-way delete-one dispersions are deliberately not combined into a two-way standard error. The equal 13/13 diagnostic is the split used in the main manuscript table.

E Product-type descriptive comparison

Table 9 groups source labels by observable product form and sale description. The grouping is intended to make the dispersion pattern economically readable while preserving the source’s own label definitions. It does not replace product-specific analysis or create standardised commodity classes.

Table 9: Descriptive reported-price dispersion by source-label product group

Product group	Labels	Item-months	Mean SD	Median SD	Interquartile range
Fresh produce and fresh fish	10	280	0.210	0.208	0.162–0.256
Loose staples and grains	11	308	0.203	0.190	0.156–0.235
Animal products and pre-served fish	14	392	0.163	0.154	0.110–0.201
Processed and packaged products	8	224	0.100	0.094	0.080–0.123

Notes: Groups classify the source labels by observable product form and sale description. They are descriptive summaries, not standardised commodity classes, market types, or causal tests. SD is cross-jurisdiction dispersion of log reported price within an item and month.

References

- Adewopo, J. B., G. Solano-Hermosilla, L. Colen, and F. Micale. 2021. Using crowd-sourced data for real-time monitoring of food prices during the COVID-19 pandemic: Insights from a pilot project in northern Nigeria. *Global Food Security* 29:100523. <https://doi.org/10.1016/j.gfs.2021.100523>.
- Aker, J. C. 2010. Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics* 2(3):46–59. <https://doi.org/10.1257/app.2.3.46>.
- Amare, M., K. A. Abay, and P. L. Hatzenbuehler. 2024. Spatial market integration during a pandemic: Evidence from food markets in Nigeria. *Agricultural Economics* 55(1):86–103. <https://doi.org/10.1111/agec.12809>.
- Amolegbe, K. B., J. Upton, E. Bageant, and S. Blom. 2021. Food price volatility and household food security: Evidence from Nigeria. *Food Policy* 102:102061. <https://doi.org/10.1016/j.foodpol.2021.102061>.
- Arellano, M., and S. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58(2):277–297. <https://doi.org/10.2307/2297968>.
- Arbia, G., G. Solano-Hermosilla, V. Nardelli, F. Micale, G. Genovese, I. L. Amerise, and J. Adewopo. 2023. From mobile crowdsourcing to crowd-trusted food price in Nigeria: Statistical pre-processing and post-sampling. *Scientific Data* 10(1):446. <https://doi.org/10.1038/s41597-023-02211-1>.
- Badiane, O., and G. E. Shively. 1998. Spatial integration, transport costs, and the response of local prices to policy changes in Ghana. *Journal of Development Economics* 56(2):411–431. [https://doi.org/10.1016/S0304-3878\(98\)00072-8](https://doi.org/10.1016/S0304-3878(98)00072-8).
- Barrett, C. B., and J. R. Li. 2002. Distinguishing between equilibrium and integration in spatial price analysis. *American Journal of Agricultural Economics* 84(2):292–307. <https://doi.org/10.1111/1467-8276.00298>.
- Baulch, B. 1997. Transfer costs, spatial arbitrage, and testing for food market integration. *American Journal of Agricultural Economics* 79(2):477–487. <https://doi.org/10.2307/1244145>.

- Bonilla-Cedrez, C., J. Chamberlin, and R. J. Hijmans. 2020. Seasonal, annual, and spatial variation in cereal prices in sub-Saharan Africa. *Global Food Security* 26:100438. <https://doi.org/10.1016/j.gfs.2020.100438>.
- Cameron, A. C., J. B. Gelbach, and D. L. Miller. 2011. Robust inference with multiway clustering. *Journal of Business and Economic Statistics* 29(2):238–249. <https://doi.org/10.1198/jbes.2010.07136>.
- Cameron, A. C., and D. L. Miller. 2015. A practitioner’s guide to cluster-robust inference. *Journal of Human Resources* 50(2):317–372. <https://doi.org/10.3368/jhr.50.2.317>.
- Deaton, A. 1988. Quality, quantity, and spatial variation of price. *American Economic Review* 78(3):418–430.
- Dhaene, G., and K. Jochmans. 2015. Split-panel jackknife estimation of fixed-effect models. *Review of Economic Studies* 82(3):991–1030. <https://doi.org/10.1093/restud/rdv007>.
- Dietrich, S., V. Giuffrida, B. Martorano, G. Schmerzeck, and M. Tiberti. 2026. Lost in aggregation? On the importance of local food price data for food poverty estimates. *American Journal of Agricultural Economics*, advance online publication, 19 March. <https://doi.org/10.1002/ajae.70067>.
- Engel, C., and J. H. Rogers. 1996. How wide is the border? *American Economic Review* 86(5):1112–1125.
- Fackler, P. L., and B. K. Goodwin. 2001. Spatial price analysis. In B. L. Gardner and G. C. Rausser, eds., *Handbook of Agricultural Economics*, Vol. 1B, 971–1024. Elsevier. [https://doi.org/10.1016/S1574-0072\(01\)10025-3](https://doi.org/10.1016/S1574-0072(01)10025-3).
- Famine Early Warning Systems Network (FEWS NET). “Monitoring and Forecasting Acute Food Insecurity.” Accessed June 4, 2026. <https://fews.net/>.
- Gilbert, C. L., L. Christiaensen, and J. Kaminski. 2017. Food price seasonality in Africa: Measurement and extent. *Food Policy* 67:119–132. <https://doi.org/10.1016/j.foodpol.2016.09.016>.
- Gonçalves, S., and M. Kaffo. 2015. Bootstrap inference for linear dynamic panel data models with individual fixed effects. *Journal of Econometrics* 186(2):407–426. <https://doi.org/10.1016/j.jeconom.2015.02.017>.

- Goodwin, B. K., and N. E. Piggott. 2001. Spatial market integration in the presence of threshold effects. *American Journal of Agricultural Economics* 83(2):302–317. <https://doi.org/10.1111/0002-9092.00157>.
- Hatzenbuehler, P. L., P. C. Abbott, and T. Abdoulaye. 2017. Price transmission in Nigerian food security crop markets. *Journal of Agricultural Economics* 68(1):143–163. <https://doi.org/10.1111/1477-9552.12169>.
- Hatzenbuehler, P. L., P. C. Abbott, and T. Abdoulaye. 2020. Growing condition variations and grain prices in Niger and Nigeria. *European Review of Agricultural Economics* 47(1):273–295. <https://doi.org/10.1093/erae/jbz028>.
- Hirvonen, K., B. Minten, B. Mohammed, and S. Tamru. 2021. Food prices and marketing margins during the COVID-19 pandemic: Evidence from vegetable value chains in Ethiopia. *Agricultural Economics* 52(3):407–421. <https://doi.org/10.1111/agec.12626>.
- Kakpo, A., B. F. Mills, and S. Brunelin. 2022. Weather shocks and food price seasonality in sub-Saharan Africa: Evidence from Niger. *Food Policy* 112:102347. <https://doi.org/10.1016/j.foodpol.2022.102347>.
- Kassouri, Y., and N. Z. F. Fofana. 2025. Spatial price integration and spillover linkages between regional grain markets in Nigeria. *Review of Development Economics* 29(3):1849–1862. <https://doi.org/10.1111/rode.13190>.
- Letta, M., P. Montalbano, and G. Pierre. 2022. Weather shocks, traders’ expectations, and food prices. *American Journal of Agricultural Economics* 104(3):1100–1119. <https://doi.org/10.1111/ajae.12258>.
- Liu, J., M. Olabisi, and M. K. Maredia. 2026. Market integration and the impact of violence on trade networks: Evidence from Nigeria. *European Review of Agricultural Economics* 53(3):1000–1053. <https://doi.org/10.1093/erae/jbag005>.
- MacKinnon, J. G., M. O. Nielsen, and M. D. Webb. 2023. Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics* 232(2):272–299. <https://doi.org/10.1016/j.jeconom.2022.04.001>.
- Minten, B., and S. Kyle. 1999. The effect of distance and road quality on food collection, marketing margins, and traders’ wages. *Journal of Development Economics* 60(2):467–495. [https://doi.org/10.1016/S0304-3878\(99\)00049-8](https://doi.org/10.1016/S0304-3878(99)00049-8).

- Moser, C., C. B. Barrett, and B. Minten. 2009. Spatial integration at multiple scales: Rice markets in Madagascar. *Agricultural Economics* 40(3):281–294. <https://doi.org/10.1111/j.1574-0862.2009.00380.x>.
- National Bureau of Statistics (NBS), Nigeria. 2019. *Selected Food Prices Watch: April 2019*. Abuja, Nigeria: National Bureau of Statistics. https://www.nigerianstat.gov.ng/pdfuploads/Selected_Food_Price_Watch_-_APRIL_2019.pdf.
- National Bureau of Statistics (NBS), Nigeria. 2025. *Nigeria: Selected Food Price Watch* [Data catalogue]. Created January 17, 2025; last modified January 24, 2025. Accessed June 5, 2026. <https://microdata.nigerianstat.gov.ng/index.php/catalog/162/related-materials>.
- Nickell, S. 1981. Biases in dynamic models with fixed effects. *Econometrica* 49(6):1417–1426. <https://doi.org/10.2307/1911408>.
- Pesaran, M. H., and R. Smith. 1995. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* 68(1):79–113. [https://doi.org/10.1016/0304-4076\(94\)01644-F](https://doi.org/10.1016/0304-4076(94)01644-F).
- Pesaran, M. H., and T. Yamagata. 2008. Testing slope homogeneity in large panels. *Journal of Econometrics* 142(1):50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>.
- Porteous, O. 2019. High trade costs and their consequences: An estimated dynamic model of African agricultural storage and trade. *American Economic Journal: Applied Economics* 11(4):327–366. <https://doi.org/10.1257/app.20170442>.
- Ravallion, M. 1986. Testing market integration. *American Journal of Agricultural Economics* 68(1):102–109. <https://doi.org/10.2307/1241654>.
- Rousseeuw, P. J., and C. Croux. 1993. Alternatives to the median absolute deviation. *Journal of the American Statistical Association* 88(424):1273–1283. <https://doi.org/10.1080/01621459.1993.10476408>.
- World Food Programme (WFP). “Market Analysis.” Accessed July 12, 2026. <https://www.wfp.org/market-analysis>.