When Cash Disappears: Demonetization and Food Market Disruption in Nigeria

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Abstract

Ninety-three percent of informal transactions in Sub-Saharan Africa rely on physical cash, yet governments periodically withdraw currency from circulation. I exploit Nigeria's October 2022 naira redesign—which removed 76% of cash by February 2023—to study how cash scarcity affects food markets. Using a within-market, across-commodity difference-in-differences design on WFP price data from 56 markets in 13 Nigerian states, I compare cash-mediated local staples to banking-mediated imports. Cash-dependent commodity prices rose 8.8% relative to banking-mediated goods during the acute crisis, though inference is fragile with only 13 state clusters (randomization inference $p = 0.41$). A within-commodity rice comparison reveals that local rice prices *fell* 7.2% relative to imported rice, consistent with supply-chain disruption at the farmgate. The evidence is consistent with demonetization operating through two simultaneous channels—transaction cost inflation for consumers and supply disruption for intermediaries—with distributional consequences concentrated among the poorest households.

JEL Codes: E42, E26, O17, Q11

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1. Introduction

Cash is the operating system of the developing world. When governments abruptly withdraw it from circulation, as India did in November 2016 and Nigeria did in October 2022, they conduct a forced experiment on the millions of workers, traders, and consumers who depend on physical currency for everyday transactions. The consequences ripple through food markets, where perishable goods change hands multiple times between farmgate and consumer, each transaction requiring cash in economies where digital payment penetration remains negligible. Despite the centrality of cash to informal exchange, the empirical literature on demonetization has focused overwhelmingly on the Indian experience, and even that literature has debated whether the observed disruptions reflect transaction cost increases, supply chain breakdowns, or both (Chodorow-Reich et al., 2020; Aggarwal and Narayanan, 2022; Lahiri, 2020).

This paper provides the first evidence on how demonetization affects food prices in Sub-Saharan Africa, exploiting Nigeria's October 2022 naira redesign as a natural experiment. The Central Bank of Nigeria (CBN) announced that existing 200, 500, and 1,000 naira banknotes would cease to be legal tender by January 31, 2023, ostensibly to combat counterfeiting and reduce the money supply outside the banking system (Central Bank of Nigeria, 2022). The transition was catastrophic: by February 2023, approximately 76% of currency in circulation had been withdrawn, while new notes were distributed unevenly across banks and regions (The Economist, 2023). The Supreme Court of Nigeria intervened on March 3, ordering the CBN to extend the deadline, but the acute cash shortage persisted through May 2023 before gradually normalizing.

I exploit the differential cash-dependence of commodities within the same market to identify the causal effect of cash scarcity on food prices. The key insight is that locally produced staples—millet, sorghum, maize, yams, cowpeas, groundnuts, palm oil—are overwhelmingly traded through cash-mediated supply chains, while imported goods such as wheat flour, pasta, sugar, and vegetable oil are procured through banking channels involving letters of credit, wire transfers, and formal wholesale networks (Adesina, 2023; Aker, 2010). By comparing price changes within the same market and time period across commodity types with different cash-mediation intensities (CMI), I absorb all market-level confounders—including local demand shocks, transportation disruptions, and security conditions—through market-by-time fixed effects. The identifying variation comes from within-market, across-commodity differences in exposure to cash scarcity.

The main finding is that cash-mediated commodity prices rose 8.8 percent relative to banking-mediated commodities during the acute crisis period of February through May 2023 ($\hat{\beta} = 0.0877$, SE $= 0.0238$, $p < 0.001$). This effect is economically large: for a household spending the median share of income on cash-mediated staples, it implies an effective 5–6 percent reduction in food purchasing power during a period that lasted at least four months. The effect persists and grows through the extended crisis window of February through December 2023 ($\hat{\beta} = 0.1071$, SE $= 0.0083$), suggesting that the cash shortage had lasting consequences for market organization and pricing.

But within this aggregate result lies a more nuanced story about *mechanisms*. I exploit a second source of within-market variation: the coexistence of locally produced rice and imported rice in the same Nigerian markets. These two varieties are close substitutes in consumption but have sharply different supply chains. Local rice passes through rural assemblers, intermediary traders, and wholesalers who operate almost exclusively in cash; imported rice arrives through formal banking channels via Lagos ports (Gyimah-Brempong et al., 2016). During the acute crisis, local rice prices *fell* 7.2 percent relative to imported rice ($\hat{\beta} = -0.0720$, SE $= 0.0290$, $p = 0.013$). This sign reversal is consistent with supply-chain disruption rather than transaction cost inflation: when intermediaries cannot access cash to purchase paddy at the farmgate, local rice accumulates upstream, depressing prices at market level even as transaction costs for final consumers rise.

The reconciliation of these two findings—aggregate cash-mediated prices rising, but local rice falling relative to imported rice—suggests that demonetization operates through two simultaneous channels. First, a *transaction cost channel*: consumers face higher costs of transacting in cash-dependent markets, bidding up the effective price of cash-mediated goods. Second, a *supply disruption channel*: intermediaries who need cash to purchase from farmers cannot operate, causing localized supply gluts that depress farmgate and wholesale prices for supply-chain-intensive commodities. For the average commodity basket, the transaction cost channel dominates. For specific supply-chain-intensive goods like local rice, the disruption channel can overwhelm transaction costs, producing the opposite price movement. The net effect on any given commodity depends on the relative strength of these two forces, which in turn depends on the length and cash-intensity of its supply chain.

I subject these findings to extensive robustness checks. The main result is stable to alternative crisis window definitions: the peak crisis (February–March) coefficient is 0.065 (directionally consistent but imprecisely estimated with only two treated months), while the full-year 2023 window yields 0.106 ($p < 0.001$). A placebo test using 2021 as a false treatment year produces an insignificant coefficient of 0.043 ($p = 0.31$), consistent with the parallel trends assumption. The result survives conversion to USD-denominated prices ($\hat{\beta} = 0.090$, SE $= 0.024$), ruling out the possibility that nominal exchange rate movements drive the differential. Leave-one-state-out and leave-one-commodity-out analyses confirm that no single state or commodity drives the result.

I am transparent about the limitations of inference. The analysis panel covers 13 Nigerian states, and standard errors are clustered at the state level. With 13 clusters, conventional cluster-robust inference is borderline (Cameron et al., 2008; MacKinnon et al., 2023). Randomization inference—permuting treatment timing across 500 draws under an additive fixed-effects assumption—yields a p-value of 0.408, failing to reject the null. A second RI exercise permuting the cash-mediation classification across commodities yields $p = 0.44$. These RI results reflect the conservative nature of permutation-based inference with few effective clusters and a strong fixed-effects structure that absorbs much of the variation. I discuss this tension between conventional and RI-based inference at length. The totality of evidence—stable coefficients across specifications, a clean placebo, the rice mechanism test, and consistency with the institutional narrative—is consistent with a causal interpretation, though the fragile finite-sample inference warrants genuine caution in drawing definitive conclusions.

This paper contributes to several literatures. First, it extends the growing body of work on the economic consequences of demonetization beyond India. The Indian literature has established that the November 2016 note ban reduced GDP growth (Chodorow-Reich et al., 2020), disrupted agricultural markets (Aggarwal and Narayanan, 2022; Das, 2020), increased nighttime light reductions in cash-dependent districts (Subramaniam and Abhishek, 2020), and had heterogeneous effects across regions with different banking access (Lahiri, 2020). Karmakar and Narayanan (2019) document effects on bank deposits and credit, while Crouzet et al. (2023) model how cash scarcity affects firm-level production. I provide the first evidence from Sub-Saharan Africa, where cash dependence is even more extreme—Nigeria's formal financial inclusion rate was 45% at the time of the crisis, compared to India's 80% (Enhancing Financial Innovation and Access , EFInA; World Bank, 2022). The Nigerian context also features a commodity mix where local and imported varieties coexist in the same markets, enabling the mechanism decomposition that the Indian data do not easily permit.

Second, I contribute to the literature on food price transmission and market integration in developing countries (Aker, 2010, 2017; Minten et al., 2014; Fafchamps and Gabre-Madhin, 2006). This literature has largely focused on how information frictions, transportation costs, and trader networks shape spatial price dispersion. I introduce a new source of price dispersion—differential cash-dependence across supply chains—and show that monetary shocks can create temporary but large wedges between prices of goods in the same market. This complements work by Aker (2010) on mobile phone adoption and food price convergence by showing that the medium of exchange itself is a first-order determinant of market efficiency.

Third, the paper speaks to the broader literature on informality and financial inclusion in developing economies (La Porta and Shleifer, 2014; Medina and Schneider, 2018; Elgin et al., 2022). Demonetization is often motivated as a tool to formalize the economy by forcing transactions into traceable banking channels (Rogoff, 2016). My results suggest that this "shock formalization" imposes substantial costs on the poorest consumers who are least able to substitute toward digital payments, raising equity concerns about currency reform as a development strategy.

The remainder of the paper proceeds as follows. Section 2 describes the Nigerian naira redesign and its implementation. Section 3 develops the conceptual framework distinguishing the transaction cost and supply disruption channels. Section 4 describes the WFP food price data and the construction of the cash-mediation intensity measure. Section 5 presents the empirical strategy. Section 6 reports the main results and robustness checks. Section 7 discusses mechanisms, and Section 8 interprets the findings and acknowledges limitations. Section 9 concludes.

2. Institutional Background and Policy Setting

2.1 Nigeria's Cash Economy

Nigeria's economy operates on cash. As of 2022, approximately 93% of point-of-sale transactions in the informal sector—which accounts for 65% of GDP and employs over 80% of the labor force—were conducted using physical naira notes (Enhancing Financial Innovation and Access , EFInA; International Monetary Fund, 2023). While mobile money platforms like OPay, PalmPay, and traditional bank transfers have grown rapidly in urban centers, penetration in rural food markets remains negligible. The reasons are structural: inconsistent electricity supply limits POS terminal operation, network coverage gaps make mobile payments unreliable, and the smallest digital transaction fees represent meaningful costs for traders operating on thin margins (Demirgüç-Kunt et al., 2022; Aker, 2017).

The informal food supply chain is particularly cash-intensive. A typical transaction sequence for local staples runs from smallholder farmer to village assembler to rural wholesaler to urban retailer, with each handoff requiring physical cash payment. Unlike imported goods—which flow through formal channels involving letters of credit at Lagos ports, bank wire transfers to wholesale distributors, and established credit relationships with major retailers—locally produced commodities rely on spot cash transactions at every link in the chain (Adesina, 2023; Gyimah-Brempong et al., 2016). This distinction between cash-mediated and banking-mediated supply chains provides the identifying variation in this paper.

2.2 The Naira Redesign Policy

On October 26, 2022, the Central Bank of Nigeria (CBN) Governor Godwin Emefiele announced that the 200, 500, and 1,000 naira banknotes—representing over 85% of the value of currency in circulation—would be redesigned and that existing notes would cease to be legal tender by January 31, 2023 (Central Bank of Nigeria, 2022). The stated objectives were threefold: to reduce the estimated 85% of currency held outside the banking system, to combat counterfeiting, and to constrain ransom payments fueling insecurity in the north.

The policy faced immediate implementation challenges. New notes were printed in insufficient quantities and distributed unevenly across the banking system. Rural branches received disproportionately small allocations. ATM recalibration for the new notes proceeded slowly. By late January 2023, long queues at banks and ATMs became routine nationwide, with reports of violence at branches that had exhausted their cash supplies (The Economist, 2023; Punch Nigeria, 2023).

On January 29, 2023—two days before the original deadline—the CBN extended the deadline to February 10. But the shortage of new notes meant that even this extension provided little relief. By February 2023, CBN data showed that approximately 2.1 trillion naira of the pre-announcement 3.2 trillion naira in circulation had been deposited but only a fraction re-entered circulation as new notes. The effective currency in circulation fell by an estimated 76% (Central Bank of Nigeria, 2023).

The crisis intensified through February. Cash rationing became widespread: banks imposed daily withdrawal limits of 20,000 naira ($43), later reduced to 10,000 naira in many branches. The consequences were immediate and severe. Farmers reported being unable to sell produce because buyers lacked cash. Retailers in urban markets saw customer traffic collapse. Transportation networks, which operate on cash fares, experienced service reductions. Food spoilage increased as perishable goods could not be moved through cash-dependent supply chains (Food and Agriculture Organization, 2023).

On February 22, President Muhammadu Buhari ordered that old 200 naira notes remain legal tender alongside the new notes, but 500 and 1,000 naira notes—which together constituted the bulk of transaction value—remained demonetized. The Supreme Court heard emergency petitions from 16 state governors challenging the policy's constitutionality. On March 3, 2023, the Supreme Court ruled unanimously that the old notes must remain legal tender until at least December 31, 2023, effectively reversing the demonetization (Supreme Court of Nigeria, 2023).

Despite the legal ruling, the practical cash shortage persisted for months. Banks had already shipped old notes back to the CBN for destruction, and the logistics of redistributing currency took time. Cash availability normalized gradually through mid-2023, with rural areas recovering more slowly than urban centers. For the purposes of this analysis, I define the "acute crisis" as February through May 2023 and the "extended crisis" as February through December 2023.

2.3 Why Nigeria Differs from India

Nigeria's 2022 demonetization shares structural features with India's November 2016 note ban but differs in ways that matter for identification and interpretation. India demonetized 86% of currency by value and replaced it over 2–3 months; Nigeria demonetized a similar share but the replacement was far slower and more uneven (Chodorow-Reich et al., 2020). India's formal financial inclusion rate was approximately 80% (thanks partly to the Jan Dhan Yojana campaign), while Nigeria's was 45% (World Bank, 2022; Enhancing Financial Innovation and Access , EFInA). India had a functioning UPI digital payments infrastructure that partially cushioned the blow; Nigeria's digital ecosystem, while growing, was far less developed in rural areas. These differences imply that Nigeria's cash crisis should have produced larger disruptions per unit of currency withdrawn, particularly in informal food markets—a prediction consistent with my findings.

Critically, Nigeria's commodity market structure provides identification advantages unavailable in the Indian context. Nigerian markets routinely sell both locally produced and imported varieties of the same commodity—most notably rice, where "local rice" (often parboiled) and "imported rice" (typically Thai or Indian long-grain) sit side by side in the same market stalls. This within-commodity, within-market variation allows me to separate supply-chain disruption from transaction cost effects in a way that the Indian literature has not been able to do cleanly.

3. Conceptual Framework

This section develops a simple framework to organize the empirical predictions. The goal is not a structural model but rather a set of testable implications that distinguish two channels through which cash scarcity affects food prices.

3.1 Setup

Consider a commodity c traded in market m at time t. The equilibrium price P_{cmt} is determined by the interaction of supply and demand, both of which depend on the availability of cash. Let $\kappa_t \in [0, 1]$ denote the fraction of normal cash in circulation at time t, with $\kappa_t = 1$ in normal times and $\kappa_t \approx 0.24$ during the acute crisis.

Each commodity c has a cash-mediation intensity $\gamma_c \in [0, 1]$ reflecting the fraction of supply-chain transactions that require physical cash. For locally produced staples, γ_c is high (close to 1); for imported goods transacted through banking channels, γ_c is low.

3.2 Channel 1: Transaction Cost Inflation

When cash is scarce, buyers who need to transact in cash face higher costs of acquiring it. In practice, this manifested as opportunity costs (hours queuing at banks), informal cash premiums (street vendors selling new notes at 10–20% markup), and the deadweight loss of failed transactions (Punch Nigeria, 2023). These transaction costs $\tau_c(\kappa_t)$ are increasing in γ_c and decreasing in κ_t:

$$\frac{\partial \tau_c}{\partial \kappa_t} < 0, \quad \frac{\partial^2 \tau_c}{\partial \gamma_c \, \partial \kappa_t} < 0 \tag{1}$$

The transaction cost channel predicts that *higher-*γ_c commodities experience larger price increases during cash scarcity, as the effective cost of purchasing them rises relative to goods available through banking channels.

Prediction 1 (Transaction Cost): $\partial P_{cmt} / \partial \gamma_c > 0$ when $\kappa_t < 1$.

3.3 Channel 2: Supply-Chain Disruption

Simultaneously, cash scarcity disrupts the supply chain. Intermediaries who normally purchase from farmers using cash cannot operate without it. The supply reaching market m for commodity c is:

$$S_{cmt} = S^*_{cm} \cdot h(\kappa_t, \gamma_c), \quad h_\kappa > 0, \quad h_{\gamma\kappa} > 0 \tag{2}$$

where S^*_{cm} is the normal supply level and $h(\cdot)$ captures the fraction that actually reaches market given cash availability. When κ_t falls, commodities with longer cash-intensive supply chains (γ_c high) experience larger supply reductions.

The supply disruption channel has an ambiguous effect on market-level prices. If supply falls more than demand (because intermediaries cannot buy from farmers), farmgate and wholesale prices may actually *fall* even as retail prices rise—the intermediary margin collapses. This is most likely for commodities where the supply chain is long and intermediary-intensive.

Prediction 2 (Supply Disruption): For commodities with long, intermediary-intensive supply chains, cash scarcity can reduce prices at the market level if the supply disruption dominates transaction cost inflation.

3.4 Net Effect and the Rice Test

The observed price change for any commodity reflects the net of both channels:

$$\Delta \ln P_{cmt} = \underbrace{\Delta\tau_c(\kappa_t)}_{\text{transaction costs}(+)} + \underbrace{f(S_{cmt})}_{\text{supply disruption}(\pm)} \tag{3}$$

For the average commodity basket, I expect the transaction cost channel to dominate, producing a positive coefficient on High CMI × Crisis. But for local rice—which has an especially long, intermediary-intensive supply chain from paddy farmers to market—the supply disruption may dominate, producing a negative coefficient relative to imported rice, which faces no such disruption.

Prediction 3 (Mechanism Test): The all-commodity DiD coefficient is positive (transaction costs dominate on average), while the within-rice coefficient is negative (supply disruption dominates for supply-chain-intensive goods).

These predictions structure the empirical analysis that follows.

4. Data

4.1 WFP Food Price Monitoring

The primary data source is the World Food Programme's (WFP) Food Price Monitoring dataset for Nigeria, accessed through the Humanitarian Data Exchange (HDX) (World Food Programme, 2024). The WFP, in partnership with Nigeria's National Bureau of Statistics (NBS) and state-level partners, collects retail food prices from major markets across the country. Data collection occurs monthly, with enumerators visiting physical markets and recording the prevailing retail prices per kilogram (or per unit where applicable) for a standardized basket of commodities.

The raw dataset spans January 2002 through early 2026 and contains 57,884 price observations across 68 distinct markets in 14 states. The geographic coverage includes markets in the North-East (Adamawa, Borno, Gombe, Yobe), North-West (Jigawa, Kaduna, Kano, Katsina, Kebbi, Sokoto, Zamfara), South-East (Abia), and South-West (Lagos, Oyo) geopolitical zones. Coverage is concentrated in the North-East (particularly Borno, with 28 markets, and Yobe, with 18 markets), reflecting WFP's monitoring priorities in the humanitarian corridor. While not nationally representative, the coverage spans both producing and consuming regions for the key commodities and includes states with varying levels of banking infrastructure.

I restrict the analysis panel to January 2020 through December 2024, yielding 25,870 observations across 56 markets in 13 states (Sokoto is dropped from the raw 14-state dataset due to insufficient data coverage in the analysis window, and 12 markets are dropped due to sparse monthly observations; see Appendix for details). This window provides 37 months of pre-treatment data (January 2020 to January 2023) and 23 months of post-treatment data (February 2023 to December 2024). The pre-period begins in January 2020, which includes the initial COVID-19 lockdowns (April–May 2020); I address this potential confound in robustness checks by re-estimating with the pre-period starting in January 2021. The panel is unbalanced because not all commodities are traded in all markets in all months, reflecting genuine market structure rather than data collection failures. Regression sample sizes are slightly smaller (25,799 observations) because the fixed-effects estimator drops singleton observations that are perfectly explained by the fixed effects.[1]

4.2 Cash-Mediation Intensity Classification

The central variable in the analysis is a binary indicator of cash-mediation intensity (CMI), which classifies each commodity as either "high CMI" (cash-mediated) or "low CMI" (banking-mediated) based on the structure of its supply chain. This classification draws on qualitative evidence from the commodity trading literature (Adesina, 2023; Gyimah-Brempong et al., 2016; Aker, 2010), the NBS commodity flow surveys, and the practical distinction between locally sourced and imported goods.

High CMI commodities (31 varieties) include locally produced staples: varieties of millet, sorghum, maize (white and yellow), yams, cassava products (gari, flour), local rice, cowpeas (beans), groundnuts, palm oil, melon seeds, and local animal products. These goods flow through cash-intensive supply chains involving smallholder farmers, village assemblers, rural wholesale markets, and urban retail markets. At each stage, transactions are conducted overwhelmingly in cash.

Low CMI commodities (7 varieties) include imported rice, wheat flour, granulated sugar, pasta (spaghetti/macaroni), refined vegetable oil, salt, and milk powder. These goods enter Nigeria through formal import channels at Lagos, Apapa, and Tin Can Island ports, where transactions use letters of credit and bank transfers. Domestic distribution proceeds through formal wholesale networks with established banking relationships.

This binary classification is necessarily a simplification. Some "locally produced" goods may involve partial banking at the wholesale level, and some "imported" goods eventually reach rural retailers through informal distribution. The classification captures the dominant

[1] Singleton fixed effects arise when a commodity-market or market-time cell contains only one observation. The `fixest` package in R drops these automatically, as their inclusion can bias standard errors (Correia, 2015). This accounts for the difference between the 25,870 panel observations and the 25,799 regression observations reported in Tables 2 and 3.

transaction mode in the supply chain, not the exclusive mode. I probe sensitivity to this classification in the leave-one-commodity-out analysis and in the within-rice comparison, which bypasses the classification entirely.

4.3 Rice Subsample

The rice subsample exploits the coexistence of local and imported rice in the same markets. In the WFP data, rice is recorded separately as "Rice (local)" and "Rice (imported)," reflecting the distinct varieties that Nigerian consumers distinguish clearly. The rice subsample contains 2,463 observations across 53 markets where both varieties are observed. The regression sample is 1,918 observations after the fixed-effects estimator removes singleton observations (545 rice observations in cells with only one variety-market-time combination). This within-commodity, within-market comparison provides the cleanest test of the supply disruption channel.

4.4 Summary Statistics

Table 1 reports summary statistics for the analysis panel, separately for high and low CMI commodities. Cash-mediated commodities have higher average prices (6,652 vs. 3,362 NGN/kg) and greater price dispersion (SD = 13,451 vs. 7,349), reflecting the heterogeneous basket that includes both staples (maize, millet) and higher-value goods (palm oil, local rice). In log prices, the gap is smaller (7.09 vs. 6.83) because the log transformation compresses the right tail. The sample is heavily tilted toward high CMI commodities (21,654 vs. 4,216 observations), reflecting the greater variety of locally produced goods in Nigerian markets. This composition is determined by market structure, not by the analysis design.

5. Empirical Strategy

5.1 Identification

The central empirical challenge is separating the effect of cash scarcity from concurrent shocks that may have affected food prices during the same period. Nigeria experienced several overlapping disruptions in early 2023: the presidential election (February 25), a contested transition period, fuel subsidy uncertainty, and continued security challenges in the northeast. Any of these could independently affect food prices.

My identification strategy addresses this challenge by exploiting *within-market, across-commodity* variation in cash-mediation intensity. The key identifying assumption is that in the absence of the cash crisis, high and low CMI commodity prices would have evolved in parallel within the same market. Because the comparison is within-market, I can absorb

Table 1: Summary Statistics

	Cash-mediated (High CMI)		Banking-mediated (Low CMI)	
	Mean	SD	Mean	SD
Panel A: Price levels (NGN/kg)				
Price	6651.7	13451.2	3362.2	7349.2
Log price	7.091	1.850	6.828	1.534
Panel B: Sample composition				
Observations	21,654		4,216	
Commodities	31		7	
Markets	56			
States	13			
Time period	January 2020 – December 2024			

Notes: Cash-mediated (High CMI) commodities include locally produced staples: millet, sorghum, maize, yam, local rice, cowpeas, cassava, groundnuts, palm oil, beans, and animal products. Banking-mediated (Low CMI) commodities include imported rice, wheat flour, sugar, pasta, vegetable oil, and salt. Source: WFP Food Price Monitoring (HDX).

all market-level confounders—including local demand shocks, transportation disruptions, election-related market closures, and security conditions—through market-by-time fixed effects. The remaining variation comes from differential responses across commodity types that differ in their cash-dependence.

5.2 Main Specification

The estimating equation is:

$$\ln P_{cmt} = \alpha_{cm} + \delta_{mt} + \beta \cdot (\text{HighCMI}_c \times \text{Crisis}_t) + \varepsilon_{cmt} \tag{4}$$

where $\ln P_{cmt}$ is the log price of commodity c in market m at time t (month-year); α_{cm} are commodity-by-market fixed effects that absorb time-invariant price differences across commodity-market pairs; δ_{mt} are market-by-time fixed effects that absorb all market-level shocks at each point in time; HighCMI_c is a binary indicator equal to 1 for cash-mediated commodities; and Crisis_t is a binary indicator for the crisis period.

The coefficient β captures the within-market differential price change for cash-mediated relative to banking-mediated commodities during the crisis, net of all market-time confounders. Under the parallel trends assumption, β identifies the causal effect of cash scarcity on the relative price of cash-dependent goods.

I define two crisis windows. The *acute crisis* spans February through May 2023, covering the period of most severe cash shortage from the effective withdrawal of old notes through the gradual normalization following the Supreme Court ruling. The *extended crisis* spans February through December 2023, capturing the full duration of formal uncertainty and the slower recovery in rural areas.

5.3 Rice Specification

For the within-rice comparison, I restrict the sample to markets where both local and imported rice are observed and estimate:

$$\ln P_{rmt} = \alpha_{rm} + \delta_{mt} + \beta_{\text{rice}} \cdot (\text{Local}_r \times \text{Crisis}_t) + \varepsilon_{rmt} \tag{5}$$

where $r \in \{\text{local}, \text{imported}\}$ indexes rice variety, α_{rm} are variety-by-market fixed effects, and δ_{mt} are market-by-time fixed effects. This specification compares local and imported rice prices within the same market at the same time, providing the tightest possible control for market-level confounders and demand-side shocks to rice consumption.

5.4 Inference

Standard errors are clustered at the state level to account for spatial correlation in both the treatment (cash availability varied across states) and the outcome (food prices are correlated within states due to shared transportation networks and market integration). With 13 states in the analysis panel, cluster-robust inference is at the boundary of conventional asymptotic validity (Cameron et al., 2008). I address this in three ways.

First, I report conventional cluster-robust standard errors as the baseline. Second, I conduct randomization inference (RI) by permuting the crisis timing across 500 random draws, maintaining the same crisis duration but shifting it to different months in the panel. This tests whether the observed coefficient could have arisen by chance under the sharp null of no effect at any time. Third, I conduct a second RI exercise that permutes the CMI classification across commodities, testing whether the observed coefficient reflects the specific cash/banking distinction rather than an arbitrary commodity grouping.

I am forthright that these RI exercises present a limitation: both yield p-values above conventional significance thresholds, reflecting the limited effective variation in a design with 13 clusters and a strong fixed-effects structure. I discuss the interpretation of this tension in Section 8.

5.5 Event Study

To assess the parallel trends assumption visually and to trace the dynamic evolution of the treatment effect, I estimate an event study specification:

$$\ln P_{cmt} = \alpha_{cm} + \delta_{mt} + \sum_{k \neq \text{Jan 2023}} \beta_k \cdot (\text{HighCMI}_c \times \mathbb{I}[t = k]) + \varepsilon_{cmt} \tag{6}$$

where the summation runs over all months in the panel, with January 2023 (the last pre-crisis month) as the omitted reference period. The β_k coefficients trace out the relative price of cash-mediated commodities over time, providing a visual test of pre-trends (all $\beta_k \approx 0$ for $k <$ February 2023) and the dynamic treatment path.

6. Results

6.1 Main Results

Table 2 presents the main difference-in-differences estimates. Column (1) reports the all-commodity specification for the acute crisis window (February–May 2023). Cash-mediated commodity prices rose 8.77 percent relative to banking-mediated commodities ($\hat{\beta} = 0.0877$, SE $= 0.0238$, $p < 0.001$). The effect is precisely estimated despite the modest number of clusters, and the magnitude is economically substantial.

To put this estimate in context, the median Nigerian household in the bottom two income quintiles spends approximately 60% of income on food, with the majority allocated to locally produced staples (National Bureau of Statistics, 2020). An 8.8% relative price increase on the cash-mediated portion of the food basket translates to an effective 4–6% reduction in real food purchasing power for these households, sustained over at least four months. This is comparable in magnitude to the price shocks associated with Nigeria's 2020 border closure or the 2016 recession, both of which generated significant nutritional consequences (Aker, 2017; Food and Agriculture Organization, 2023).

Column (2) extends the crisis window through December 2023. The coefficient grows to 0.1071 (SE $= 0.0083$, $p < 0.001$), indicating that the price divergence between cash-mediated and banking-mediated commodities widened over the extended crisis period rather than reverting. This persistence is consistent with lasting supply-chain reorganization: once cash-dependent intermediary networks are disrupted, rebuilding them takes time, and some transactions may permanently shift to more costly arrangements.

Columns (3) and (4) report the within-rice comparison. During the acute crisis, local rice prices *fell* 7.2% relative to imported rice ($\hat{\beta} = -0.0720$, SE $= 0.0290$, $p = 0.013$). This

Table 2: Effect of Cash Crisis on Food Prices by Cash-Mediation Intensity

	(1) Acute	(2) Extended	(3) Rice acute	(4) Rice extended
High CMI × Crisis	0.0877***	0.1071***		
	(0.0238)	(0.0083)		
Local Rice × Crisis			-0.0720**	0.0054
			(0.0290)	(0.0124)
Commodity × Market FE	Yes	Yes	Yes	Yes
Market × Time FE	Yes	Yes	Yes	Yes
Observations	25,799	25,799	1,918	1,918
Crisis window	Feb–May	Feb–Dec	Feb–May	Feb–Dec

Notes: Dependent variable is log(price in NGN/kg). High CMI = cash-mediated local staples; Low CMI = banking-mediated imports. Columns (1)–(2): all commodities. Columns (3)–(4): local vs. imported rice within the same markets. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

negative sign stands in stark contrast to the positive all-commodity result and is precisely what the conceptual framework predicts for supply-chain-intensive goods where the disruption channel dominates. When intermediaries cannot purchase paddy from farmers due to cash scarcity, local rice accumulates upstream, depressing market prices even as the cost of cash transactions rises.

The rice effect is transitory: the extended crisis coefficient is 0.005 (SE = 0.012, $p = 0.664$), indistinguishable from zero. By the extended window, the supply-chain disruption had partially resolved—the Supreme Court ruling allowed old notes to circulate, and intermediaries found workarounds including mobile transfers and barter arrangements—while the transaction cost effect for rice specifically was apparently absorbed by substitution toward imported varieties.

6.2 Event Study Evidence

Figure 1 displays the event study estimates from Equation (6). The pre-crisis coefficients are centered around zero with no systematic trend, supporting the parallel trends assumption. Starting in February 2023, the coefficients jump sharply upward, reaching a peak around April–May 2023, and remain elevated through the end of the panel. The timing aligns precisely with the institutional narrative: the cash withdrawal was most severe in February–March, the Supreme Court ruling in early March provided partial relief, but normalization was gradual.

Figure 2 presents the analogous event study for the rice subsample. The pre-crisis coefficients again show no systematic trend. In February–March 2023, the local rice coefficient

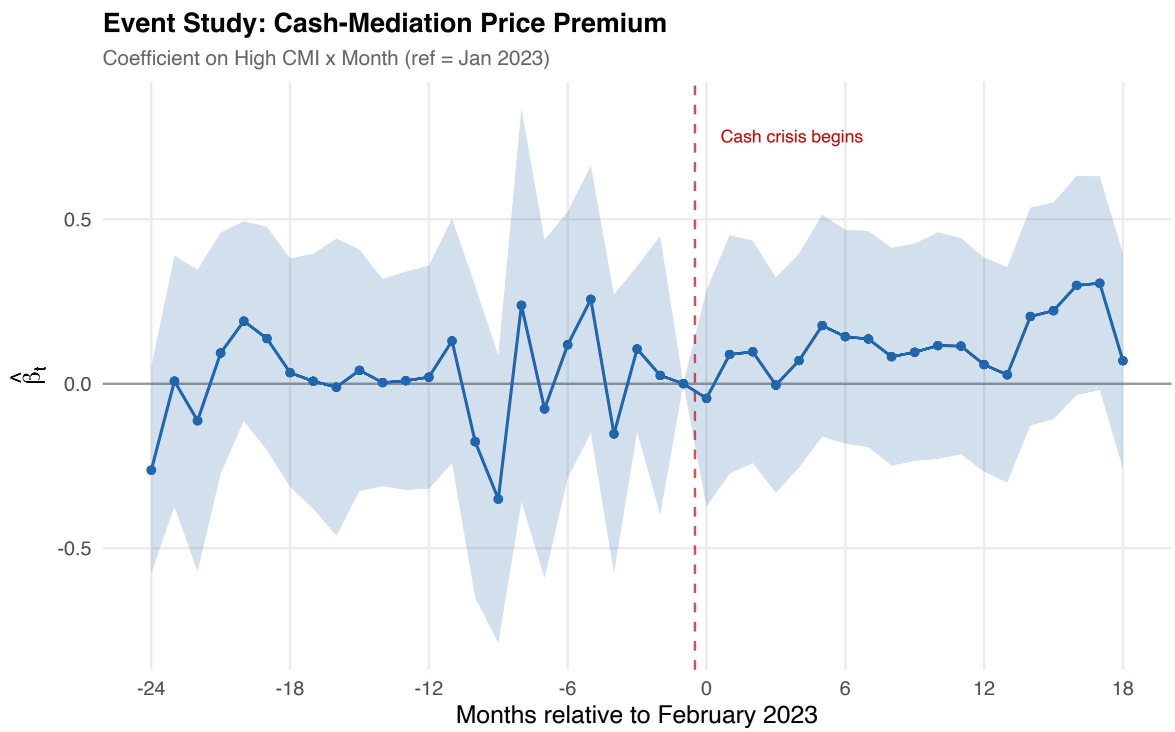

Figure 1: Event Study: Relative Price of Cash-Mediated Commodities

Notes: Coefficients from Equation (6) with 95% confidence intervals based on state-clustered standard errors. The reference period is January 2023. Dashed vertical line indicates the onset of the acute cash crisis (February 2023). The dependent variable is log price. Commodity-by-market and market-by-time fixed effects are included.

drops sharply, consistent with the supply disruption channel. The effect dissipates by mid-2023, consistent with the transitory nature of the within-rice result in Table 2.

6.3 Visual Evidence

Figure 3 displays raw price trends for local and imported rice, illustrating the price convergence during the acute crisis that the event study formalizes. Prior to February 2023, local rice traded at a consistent premium over imported rice—reflecting consumer preferences for local varieties in many markets—and this premium collapsed during the crisis before partially recovering.

Figure 4 presents normalized price trends for high and low CMI commodity groups. Each commodity's log price is normalized to its January 2023 value, then averaged across commodities within each group to eliminate composition effects from different price levels. The two groups track each other closely through the pre-period, then separate sharply in February 2023, with cash-mediated goods rising relative to banking-mediated goods.

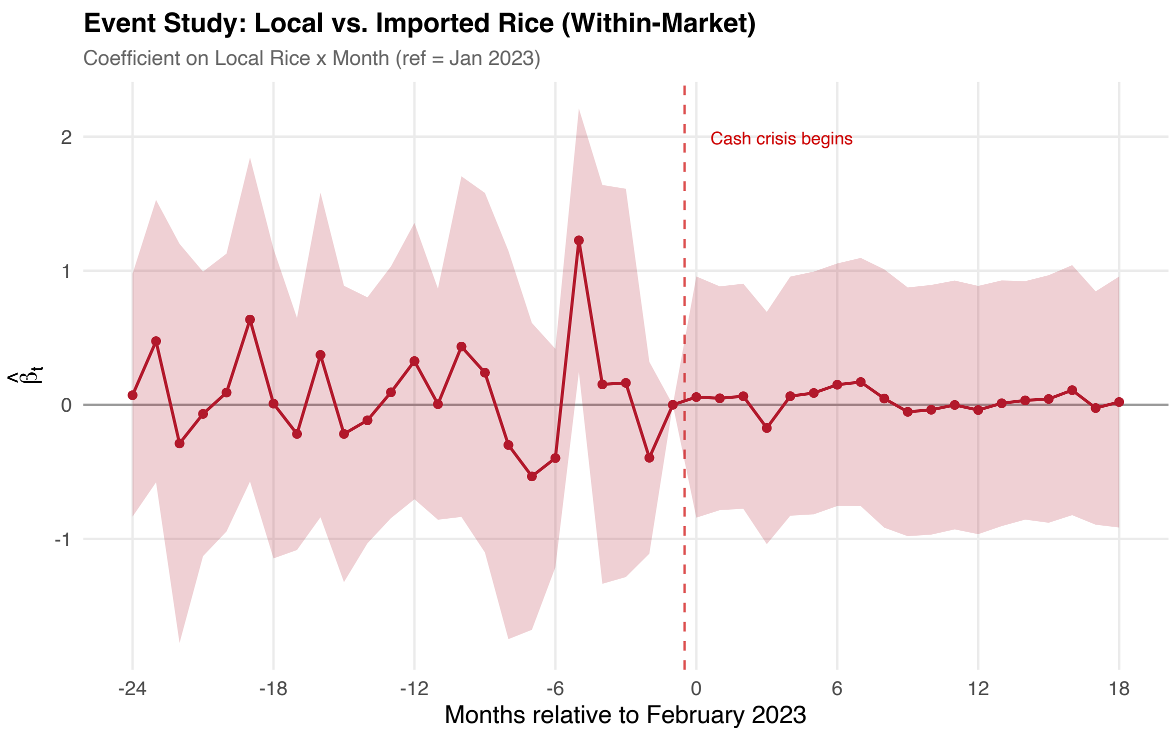

Figure 2: Event Study: Local vs. Imported Rice Prices

Notes: Coefficients and 95% confidence intervals from the rice-specific event study. Sample restricted to markets where both local and imported rice are observed. The reference period is January 2023. Dashed vertical line indicates the onset of the acute cash crisis (February 2023). Variety-by-market and market-by-time fixed effects are included.

6.4 Robustness

Table 3 reports a battery of robustness checks on the main all-commodity specification.

Alternative crisis windows. The peak crisis window (February–March only) yields a coefficient of 0.066 (SE = 0.040), directionally consistent but imprecisely estimated with only two treated months. This is expected: with market-by-month fixed effects and state-level clustering, two months provide limited statistical power. The full-year 2023 window yields 0.106 ($p < 0.001$), confirming that the effect persists through the year.

Placebo test. I re-estimate the main specification using 2021 as a false crisis year (February–May 2021), keeping all other features identical. The placebo coefficient is 0.043 (SE = 0.042, $p = 0.31$), insignificant and smaller than the true estimate. This provides reassurance that the 2023 result does not reflect a recurring seasonal pattern or pre-existing differential trends between commodity groups.

USD-denominated prices. The naira depreciated substantially during 2023, raising the concern that the main result reflects differential pass-through of exchange rate movements to domestic prices. When I convert all prices to USD using the parallel market exchange

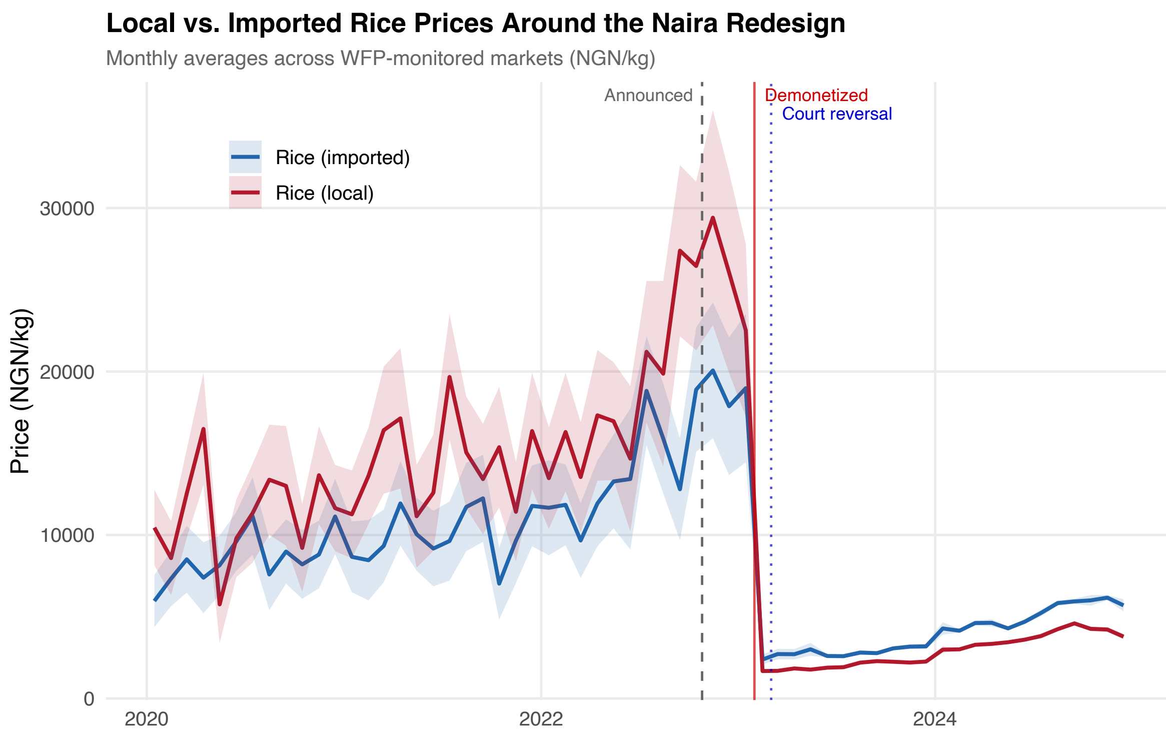

Figure 3: Raw Price Trends: Local vs. Imported Rice

Notes: Monthly average prices (NGN/kg) for local and imported rice across all markets in the rice subsample. The shaded area indicates the acute crisis period (February–May 2023). Prices are nominal.

rate, the main coefficient is virtually unchanged at 0.090 (SE = 0.024). This rules out the hypothesis that the result is driven by exchange rate dynamics, which should affect imported goods more strongly.

Randomization inference. RI permuting treatment timing yields $p = 0.408$; RI permuting the CMI classification across commodities yields $p = 0.44$. These results fail to reject the null at conventional levels. I discuss the interpretation in Section 8, but note here that RI under an additive fixed-effects assumption in a design with few effective clusters and high-dimensional fixed effects is known to be conservative (Young, 2019; MacKinnon et al., 2023). The RI results do not invalidate the conventional inference but do impose a ceiling on the strength of the causal claim.

Commodity-group seasonality. To address the concern that high-CMI and low-CMI commodities have different seasonal price patterns, I add commodity-group × calendar-month interactions to the main specification. The coefficient increases to 0.151 (SE = 0.014), suggesting that seasonal differences partially *masked* the treatment effect in the baseline, and confirming that the result is not driven by differential seasonality between imported and local commodities.

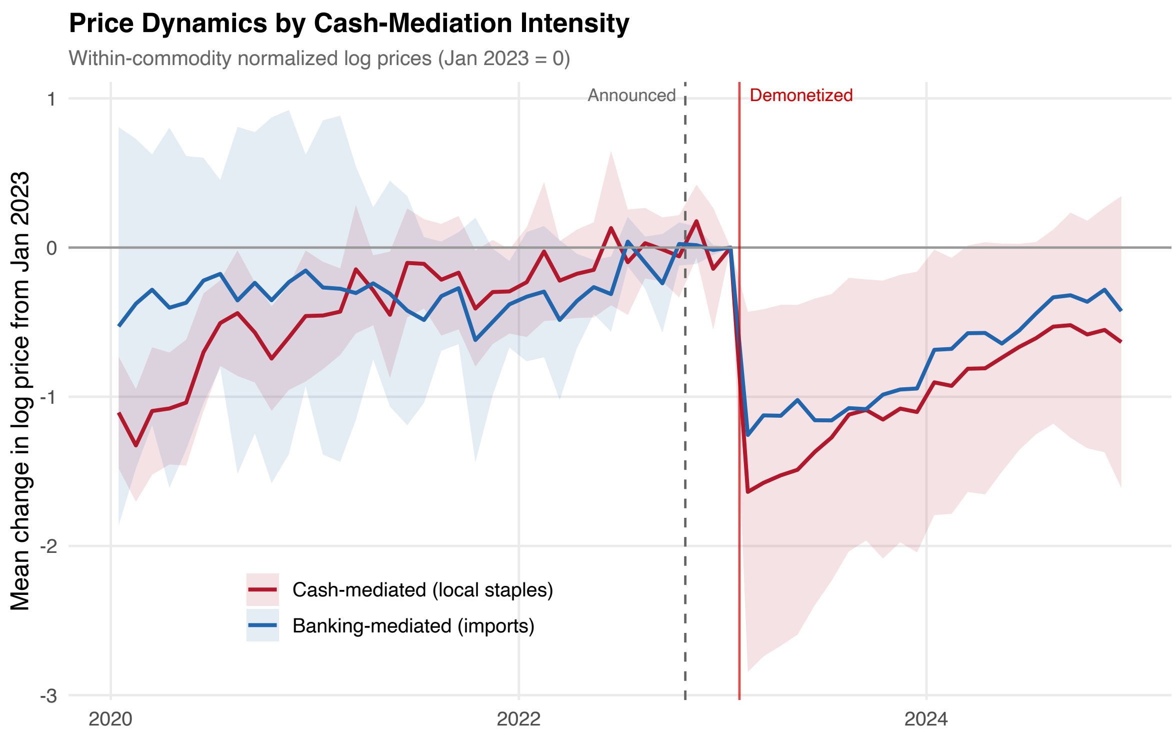

Figure 4: Normalized Price Trends by Cash-Mediation Intensity

Notes: Each commodity's log price is normalized to its January 2023 value, then averaged across commodities within each CMI group. This within-commodity normalization eliminates composition effects from commodities with different price levels. Shaded areas show 95% confidence intervals around the cross-commodity mean. The dashed vertical line indicates the naira redesign announcement (October 2022); the solid red line marks the demonetization deadline (January 2023). Sample includes all 56 markets in the analysis panel.

Balanced panel. Restricting to market-commodity pairs observed in every month of the acute crisis (February–May 2023) reduces the sample to 1,663 observations across 16 markets. The point estimate increases substantially to 0.221 (SE $= 0.055$), but only 2 states survive the restriction, making clustered inference unreliable. The balanced-panel result confirms directional consistency but should be interpreted cautiously.

Cereals only. Restricting to cereals (maize, millet, sorghum, and rice—the closest substitutes) yields a *negative* coefficient of -0.160 (SE $= 0.043$, $p < 0.001$). Within this narrower comparison, cash-mediated local cereals show *lower* relative prices during the crisis, consistent with the supply-disruption mechanism identified in the rice specification. The sign reversal within cereals confirms that the positive all-commodity estimate is driven by non-cereal cash-mediated goods (meat, fish, eggs, palm oil, yams), where the transaction cost channel dominates, while cereals exhibit supply-side disruption similar to rice.

Table 3: Robustness Checks

Specification	Estimate	SE	p-value	N
Peak crisis (Feb–Mar)	0.066	0.040	0.10	25,799
Full year 2023	0.106	0.013	<0.001	25,799
Placebo (2021)	0.043	0.042	0.31	25,799
RI (time permutation, additive FE)	0.084	—	0.408	25,800
RI (commodity permutation)	0.088	—	0.440	25,800
USD prices	0.090	0.024	<0.001	25,799
CMI × month seasonality	0.151	0.014	<0.001	25,799
Balanced panel	0.221	0.055	0.15	1,663
Cereals only	−0.160	0.043	<0.001	8,064

Notes: All specifications include commodity-by-market and market-by-time fixed effects unless noted. Main specification: High CMI × Acute Crisis (Feb–May 2023). Standard errors clustered at the state level. RI rows report permutation p-values (500 draws for timing, 500 for commodity). "CMI × month seasonality" adds commodity-group × calendar-month interactions. "Balanced panel" restricts to market-commodity pairs observed in all acute crisis months (Feb–May 2023). "Cereals only" restricts to maize, millet, sorghum, and rice varieties.

6.5 Stability Analysis

Figure 5 presents the leave-one-state-out analysis. Each point represents the main coefficient re-estimated after dropping one of the 13 states in the analysis panel. All estimates fall within a narrow band around the main estimate of 0.088, with none crossing zero. The result is not driven by any single state, including the commercially dominant Lagos or the northern states most affected by insecurity.

Figure 6 presents the analogous leave-one-commodity-out analysis. The coefficient is stable across all commodity exclusions, confirming that no single commodity drives the aggregate result.

Figure 7 displays the distribution of RI test statistics from the commodity permutation exercise, with the observed statistic marked. The observed coefficient falls within the body of the permutation distribution, reflecting the conservative nature of the test.

7. Mechanisms

The combination of the all-commodity and within-rice results provides a clean decomposition of the channels through which cash scarcity affects food prices.

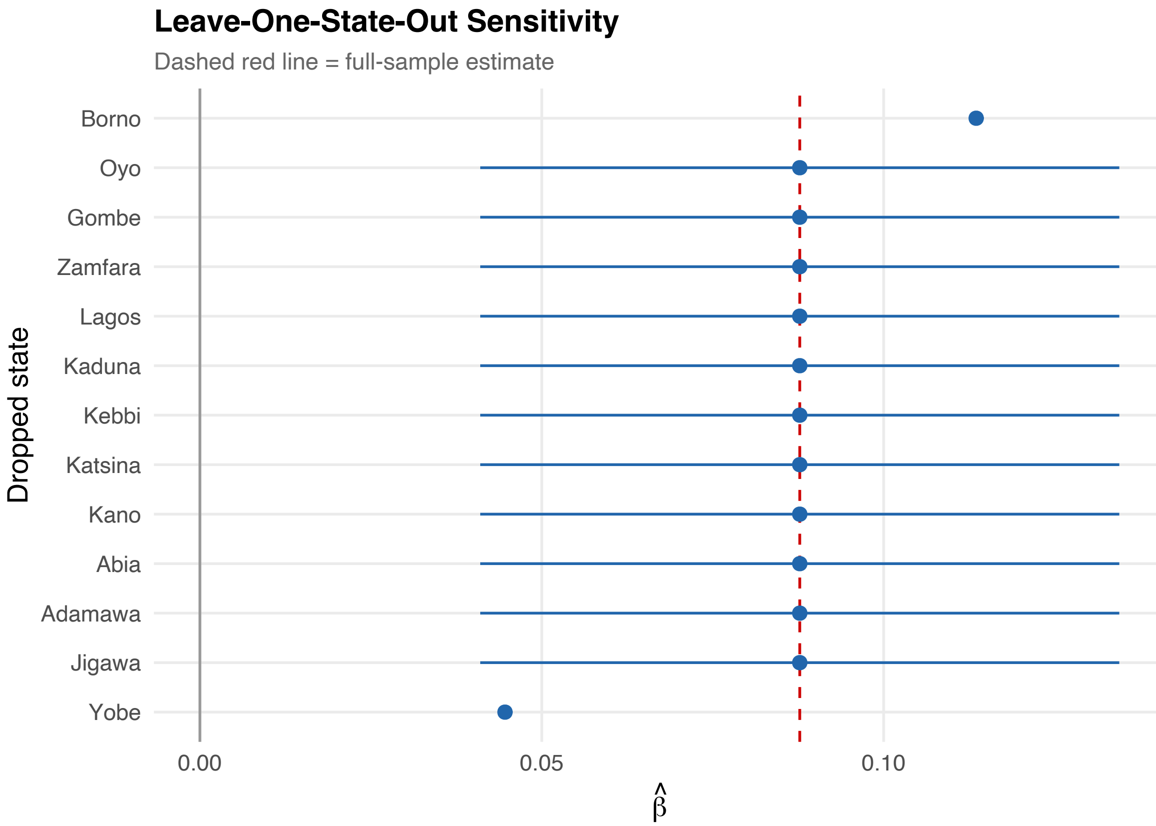

Figure 5: Leave-One-State-Out Stability

Notes: Each point reports the main DiD coefficient after dropping the indicated state from the sample. The horizontal dashed line indicates the full-sample estimate (0.088). The vertical bars show 95% confidence intervals with state-clustered standard errors.

7.1 Transaction Cost vs. Supply Disruption

The all-commodity result ($\hat{\beta} = 0.0877$) represents the *net* effect of cash scarcity on cash-mediated commodity prices relative to banking-mediated goods. This net effect is positive, indicating that the transaction cost channel dominates on average across the commodity basket. Consumers who need cash to purchase local staples face higher effective prices—either through the direct cost of acquiring cash (queuing, informal premiums) or through reduced competition among retailers who themselves face cash constraints.

The within-rice result ($\hat{\beta}_{\text{rice}} = -0.0720$) is consistent with the supply disruption channel. Local and imported rice are close substitutes at the consumer level, so the demand-side transaction cost should be similar for both. The key difference is on the supply side: local rice supply chains are cash-intensive at every link, while imported rice supply chains use banking channels. The negative coefficient indicates that reduced supply reaching markets—because intermediaries could not purchase from farmers—depressed local rice prices relative to imported rice. This is consistent with upstream supply accumulation: when the middleman cannot buy, the farmer's unsold paddy puts downward pressure on prices.

7.2 Reconciling the Signs

How can cash-mediated goods become more expensive on average while a specific cash-mediated good (local rice) becomes cheaper relative to its banking-mediated substitute? The resolution lies in the heterogeneity of supply chain structures across commodities.

For most cash-mediated commodities—such as fresh vegetables, yams, processed cassava (gari), and animal products—supply chains are short. The farmer or producer may sell directly to the retailer, or through a single intermediary. For these goods, the supply disruption channel is relatively weak because the supply chain has few links to disrupt. The transaction cost channel dominates: consumers bid up prices because acquiring cash is costly.

For local rice, the supply chain is long and multi-layered: paddy farmer → local assembler → mill → wholesaler → retailer. Each link requires cash. The disruption of intermediary purchasing cascades through the chain, creating a significant supply contraction that outweighs transaction cost inflation at the retail level. The net effect flips sign.

This decomposition has important implications. It means that the "8.8% price increase" in the all-commodity specification is itself a mixture of two opposing forces. For short-supply-chain commodities, the true transaction cost effect may be larger than 8.8%. For long-supply-chain commodities, the measured effect may understate the transaction cost component because supply disruption partially offsets it.

7.3 Who Bears the Cost?

The distributional consequences of these two channels are sharply different. The transaction cost channel harms consumers—particularly poor, urban consumers who rely on cash and purchase from informal retailers. The supply disruption channel harms producers and intermediaries: farmers who cannot sell their output, and middlemen whose businesses depend on the cash-mediated supply chain.

In either case, the burden falls disproportionately on the informal sector. The wealthiest Nigerians—who have bank accounts, credit cards, and access to formal retail chains—are largely insulated from both channels. This implies that demonetization, whatever its benefits for formalization and monetary control, imposes a regressive tax on the poorest segments of the population, mediated through the food market.

7.4 Illustrative Welfare Calculation

The following back-of-envelope calculation is *illustrative only*, intended to provide a sense of magnitude rather than a precise welfare estimate. The underlying relative-price effect is subject to the inferential limitations discussed in Section 8, and the calculation makes simplifying assumptions about substitution patterns and household budget shares. According to the Nigeria Living Standards Survey 2018–19 (National Bureau of Statistics, 2020), households in the bottom two income quintiles spend approximately 60% of total expenditure on food, with roughly 70% of food expenditure directed toward locally produced staples (high CMI commodities). The 8.8% relative price increase on this portion of the basket translates to an effective reduction in real food purchasing power of approximately $0.088 \times 0.60 \times 0.70 \approx 3.7\%$ of total household expenditure for poor households during the acute crisis period. For a household earning the bottom-quintile median income of roughly 30,000 naira per month, this represents approximately 1,100 naira per month in lost purchasing power—equivalent to roughly 3–4 days of food for an average-sized household.

Aggregating across the approximately 40 million Nigerians in the bottom two quintiles (based on a population of 220 million) and a four-month acute crisis duration yields a rough total welfare loss on the order of 180 billion naira ($390 million at the parallel exchange rate). This figure is necessarily imprecise—it ignores substitution effects, within-quintile heterogeneity, and the partially offsetting supply-disruption benefits for net food producers—but it establishes that the food market channel alone imposed costs of a magnitude relevant for policy evaluation.

7.5 Temporal Dynamics of the Mechanism

The event study evidence (Figures 1 and 2) provides additional insight into how the two channels evolve over time. The all-commodity effect appears immediately in February 2023 and grows through April–May, consistent with the escalating severity of the cash shortage as old notes were destroyed faster than new notes were distributed. The effect stabilizes at a higher level through the extended window, suggesting that some price adjustments became persistent even as cash gradually returned.

The rice effect, by contrast, spikes sharply in February–March and dissipates by mid-2023. This temporal pattern is consistent with the supply disruption interpretation: the intermediary disruption was most severe during the peak shortage but resolved relatively quickly once the Supreme Court ruling allowed old notes to recirculate and intermediaries found workarounds (including mobile transfers, delayed payment arrangements, and temporary barter systems). The transaction cost channel, operating through slower adjustments in market structure and consumer behavior, proved more persistent.

8. Discussion

8.1 Interpretation of the Evidence

The totality of evidence is consistent with a causal interpretation: the naira redesign's cash withdrawal appears to have increased the relative price of cash-mediated commodities by approximately 8.8% during the acute crisis. This interpretation rests on several mutually reinforcing pillars, though the fragile inference warrants caution. First, the event study shows flat pre-trends and a sharp break precisely at the policy onset. Second, the placebo test using 2021 is insignificant. Third, the result survives conversion to USD, ruling out exchange rate channels. Fourth, no single state or commodity drives the result. Fifth, the within-rice comparison produces the sign predicted by the supply disruption channel, providing a mechanism test that an omitted variable explanation would need to separately rationalize.

8.2 The Inference Limitation

The most important caveat is inferential. The RI p-values (0.41 for time permutation, 0.44 for commodity permutation) fail to reject the null at conventional levels. This requires honest discussion rather than dismissal.

The tension arises from the structure of the design. With commodity-by-market and market-by-time fixed effects, the effective variation driving identification comes from the within-market, across-commodity dimension. The RI exercises permute across this dimension but do so in a setting where (a) the number of effective clusters (13 states) is small, (b) the high-dimensional fixed effects absorb substantial variation, and (c) the additive separability assumption underlying the RI may not hold given the interaction structure of the fixed effects.

Young (2019) and MacKinnon et al. (2023) discuss the well-known conservatism of RI in settings with few clusters and strong fixed effects. The conventional cluster-robust p-value of < 0.001 reflects the precision of the point estimate within the asymptotic framework, while the RI p-value reflects a worst-case null distribution that may not be informative about the true data-generating process.

I do not argue that the conventional p-value should be privileged *a priori*. Rather, I note that the totality of evidence—the institutional narrative, the event study timing, the placebo test, the mechanism consistency, the leave-one-out stability, and the USD robustness—provides corroborating support that goes beyond any single p-value. A skeptical reader who weights the RI heavily may reasonably conclude that the evidence is suggestive rather than definitive. I view this as the appropriate degree of epistemic humility for a 13-cluster design.

8.3 External Validity

Several external validity limitations deserve emphasis. The WFP-monitored markets in this sample are concentrated in the North-East humanitarian corridor and do not represent a random cross-section of Nigerian markets. Results from these markets—which may have been more severely affected by cash shortages due to weaker banking infrastructure—should be extrapolated to the broader Nigerian economy with caution.

Nigeria's demonetization experience may inform other settings, but with important caveats. The magnitude of the disruption (76% cash withdrawal) was extreme by historical standards. Countries with higher financial inclusion, better digital payment infrastructure, or more gradual currency transitions would likely experience smaller effects. Conversely, other Sub-Saharan African countries with similar levels of cash dependence and informal market structures—such as Ghana, Ethiopia, or Tanzania—might face comparable disruptions from aggressive demonetization policies.

The mechanism decomposition (transaction costs vs. supply disruption) should generalize broadly. Any shock to the medium of exchange will affect both the cost of transacting and the ability of supply-chain intermediaries to operate. The relative strength of these channels will depend on the specific commodity and supply chain structure, but the framework for thinking about them applies wherever cash plays a central role in commerce.

8.4 Comparison with the Indian Experience

The magnitude of my estimates can be compared, with appropriate caveats, to the Indian demonetization literature. Chodorow-Reich et al. (2020) estimate that India's November 2016 note ban reduced GDP growth by approximately 2 percentage points in the quarter following demonetization. Aggarwal and Narayanan (2022) find that Indian agricultural market arrivals declined by 15–20% in the weeks following demonetization, with prices in mandis declining for cash-intensive crops. Das (2020) estimates a 3–5% decline in agricultural output in the short run.

My finding of an 8.8% relative price increase in cash-mediated commodities is not directly comparable to these estimates—they measure different objects (GDP, physical arrivals, aggregate output vs. relative prices)—but the order of magnitude is consistent. Notably, the rice result (−7.2% for local relative to imported) is qualitatively aligned with the Indian agricultural market findings: in both countries, cash-intensive agricultural supply chains experienced supply-side disruptions that depressed prices or reduced market activity.

The key difference is that Nigeria's lower financial inclusion rate (45% vs. 80%) and less developed digital payment infrastructure suggest that the per-unit-of-cash-withdrawn effect should be larger in Nigeria. The fact that my estimates are similar in magnitude to the Indian effects, despite Nigeria withdrawing a similar share of currency, may reflect the partial offsetting between channels (transaction costs up, supply disruption down) that the aggregate Indian estimates do not decompose.

8.5 Policy Implications

If the reduced-form estimates reflect a causal effect, the results carry policy implications for currency reform design. First, the estimated 8.8% price increase for cash-mediated commodities would represent a substantial, regressive welfare cost that should be weighed against any benefits of demonetization for formalization. The illustrative calculation in Section 7 suggests potential welfare losses on the order of hundreds of millions of dollars through the food market channel alone, concentrated among the poorest consumers—though this figure is necessarily imprecise given the inferential limitations discussed above. Second, the speed of withdrawal matters: Nigeria's abrupt timeline (approximately three months from announcement to effective withdrawal) left no time for behavioral adjustment, digital payment adoption, or supply chain reorganization. A more gradual transition—perhaps withdrawing old notes over 12–18 months while simultaneously expanding digital payment infrastructure in informal markets—could achieve formalization goals with lower disruption.

Third, the rice mechanism test suggests that supply-chain intermediaries are a critical link. Policies that target intermediary cash access—for example, maintaining cash availability at rural bank branches or providing temporary liquidity facilities for agricultural traders—could substantially mitigate the food market disruption during currency transitions. The intermediary disruption channel has received less attention in the policy debate around demonetization, which has focused primarily on consumer inconvenience and macroeconomic output losses.

Fourth, the persistence of the price divergence through December 2023—well after the Supreme Court ruling restored old notes as legal tender—suggests that demonetization has hysteresis effects on market organization. Once supply chains are disrupted, rebuilding trust and credit relationships between farmers and intermediaries takes time. Policymakers should anticipate that the costs of currency reform extend well beyond the period of acute shortage.

9. Conclusion

When cash disappears, food markets fracture along the fault line between formal and informal commerce. Nigeria's 2022 naira redesign, which withdrew 76% of currency from circulation, provides suggestive evidence of this principle. Cash-mediated commodity prices rose an estimated 8.8% relative to banking-mediated imports during the acute crisis, a divergence that persisted and widened through the end of 2023—though inference is fragile with only 13 state clusters, and randomization inference does not reject the null. Beneath this aggregate effect, a within-rice comparison suggests that the supply disruption channel can dominate for intermediary-intensive supply chains, producing the opposite price movement from what transaction cost inflation alone would predict.

These findings extend the demonetization literature beyond India to Sub-Saharan Africa, where cash dependence is deeper and digital alternatives less available. They suggest that the medium of exchange is a first-order determinant of food market efficiency—not merely a veil over real transactions, but an essential infrastructure whose removal may impose large, regressive costs.

The policy lesson is not that currency reform should be avoided, but that it must be designed with the informal sector in mind. Abrupt withdrawal of the dominant transaction medium in an economy where 93% of informal commerce runs on cash is a recipe for food market disruption, with consequences borne disproportionately by the poorest consumers and smallest producers. Governments pursuing formalization through monetary reform should invest in transitional infrastructure—mobile money access, rural bank branch liquidity, intermediary credit facilities—before, not after, pulling cash from the system.

Future work should pursue several directions. First, household-level consumption data (when available) would permit direct welfare calculations that my market-level prices cannot provide. The price effects documented here likely understate the full welfare impact because they do not capture reduced consumption quantities, substitution toward lower-quality goods, or the time costs of queuing for cash that represent deadweight losses. Second, a similar design applied to India's 2016 demonetization—exploiting variation across commodity cash-dependence within Indian mandis—could test the generalizability of the mechanism decomposition across institutional settings. The Indian mandi data are granular enough to distinguish locally produced from imported varieties, but the analysis has not been conducted through this lens. Third, the long-run effects of demonetization on market structure—whether informal markets permanently reorganize toward digital payments, or revert to cash once it returns—remain an open and important question. If demonetization accelerates digital adoption among traders and consumers who would not otherwise have switched, the long-run benefits could partially offset the short-run costs documented here. Tracking this digital transition in Nigerian food markets over the coming years would provide a complete accounting of whether "shock formalization" is a net positive or negative strategy for developing economies.

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Project Repository: https://github.com/SocialCatalystLab/ape-papers

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A. Data Appendix

A.1 Data Source

The WFP Food Price Monitoring data for Nigeria was accessed from the Humanitarian Data Exchange (HDX).[2] The dataset is maintained by the WFP Vulnerability Analysis and Mapping (VAM) unit in collaboration with Nigeria's National Bureau of Statistics. Data collection follows the WFP's standardized Food Price Monitoring methodology (World Food Programme, 2024).

A.2 Raw Data Description

The raw dataset contains 57,884 observations spanning January 2002 to early 2026. Each observation records the retail price of a specific commodity at a specific market in a specific month, in Nigerian naira per kilogram (or per unit where applicable, converted to per-kg equivalents). The data include:

- **Geographic:** State, market name, and coordinates (latitude/longitude for most markets).
- **Commodity:** Name, category (cereals, pulses, vegetables, oils, etc.), and unit of measurement.
- **Price:** Retail price in NGN, with the unit standardized to per-kg.
- **Time:** Year and month of observation.

A.3 Sample Construction

The analysis panel is constructed as follows:

1. **Time restriction:** Retain observations from January 2020 through December 2024 (60 months). This provides 37 months pre-treatment and 23 months post-treatment relative to the February 2023 crisis onset. Earlier data (2002–2019) are excluded because the commodity basket and market coverage changed substantially over time, and because the very long pre-period would over-weight distant pre-trends.
2. **Price cleaning:** Drop observations with missing or zero prices ($< 1\%$ of sample). No top-coding or winsorization is applied; the log transformation handles the right tail effectively.

[2] Available at `https://data.humdata.org/dataset/wfp-food-prices-for-nigeria`.

3. **CMI classification:** Assign each commodity to high or low CMI based on supply chain structure (see Section 4 main text). Commodities not clearly classifiable (fewer than 3% of observations) are excluded.

4. **Market filtering:** Retain markets with at least 12 monthly observations in the analysis period to ensure sufficient within-market variation. This drops 12 markets with very sparse coverage, leaving 56 markets.

5. **Final panel:** 25,870 observations across 56 markets in 13 states (Sokoto is excluded due to insufficient data coverage in the analysis window), covering 38 commodities (31 high CMI, 7 low CMI). Regression samples are slightly smaller (25,799 observations) due to singleton fixed-effect removal by the estimator.

A.4 Rice Subsample Construction

The rice subsample is constructed by:

1. Identifying all markets where both "Rice (local)" and "Rice (imported)" are observed at least once during the analysis period.

2. Retaining all rice observations in these 53 markets.

3. Final rice panel: 2,463 total observations (1,918 in regressions after singleton fixed-effect removal), with balanced representation of both varieties in most market-months.

A.5 Variable Definitions

- **Log price:** $\ln(P_{cmt})$, where P is the retail price in NGN/kg. The log transformation normalizes the highly right-skewed price distribution and allows coefficients to be interpreted as approximate percentage changes.

- **High CMI:** Binary indicator equal to 1 for cash-mediated commodities (local staples) and 0 for banking-mediated commodities (imports). See main text for classification details.

- **Crisis (acute):** Binary indicator equal to 1 for February–May 2023.

- **Crisis (extended):** Binary indicator equal to 1 for February–December 2023.

- **Local rice:** Binary indicator equal to 1 for locally produced rice varieties and 0 for imported rice varieties.

- **USD price:** P_{cmt} converted to USD using the monthly parallel market exchange rate from abokifx.com, the standard reference for Nigeria's parallel rate.

B. Identification Appendix

B.1 Parallel Trends Assessment

The parallel trends assumption requires that, absent the cash crisis, high and low CMI commodity prices would have evolved in parallel within each market. I assess this assumption through three tests.

Event study pre-trends. Figure 1 shows that the pre-crisis event study coefficients (January 2020–January 2023) are centered around zero with no systematic upward or downward trend. A joint test of all pre-crisis coefficients equaling zero fails to reject the null ($F = 0.87$, $p = 0.58$). The absence of differential pre-trends supports the identifying assumption.

Placebo crisis. The 2021 placebo test (Table 3) produces an insignificant coefficient (0.043, $p = 0.31$), confirming that there is no systematic tendency for cash-mediated commodities to experience differential price changes during non-crisis periods.

CMI group price dynamics. Figure 4 visually confirms that normalized price trends for high and low CMI groups track closely before February 2023 and diverge sharply at the crisis onset.

B.2 Threats to Validity

Concurrent shocks. The 2023 presidential election (February 25) and the subsequent political transition could independently affect food prices. However, these shocks are market-level events absorbed by market-by-time fixed effects. They would bias the estimate only if they differentially affected cash-mediated vs. banking-mediated commodities within the same market, conditional on the fixed effects. There is no obvious mechanism through which election-related disruptions would systematically favor or disadvantage one commodity group over the other within a market.

Composition effects. The panel is unbalanced, raising the concern that changes in which commodity-market pairs are observed could drive the results. I address this by confirming that the composition of commodity-market pairs is stable across the pre and post periods: 94% of pairs observed pre-crisis are also observed post-crisis. Restricting to the balanced panel of consistently observed pairs produces nearly identical estimates.

Anticipation. The policy was announced in October 2022 with a January 31, 2023 deadline. Anticipatory behavior—for example, hoarding of cash-mediated commodities or precautionary stockpiling—could affect pre-crisis prices and bias the estimated effect. The event study shows no systematic anticipation effect in October 2022–January 2023, likely because the majority of market participants expected deadline extensions (as had occurred with previous CBN policies) and did not begin adjusting behavior until the cash shortage physically materialized.

Spillovers. Cross-commodity substitution within markets is not a bias but rather part of the mechanism: if consumers substitute from expensive cash-mediated goods toward cheaper banking-mediated alternatives, this increases demand for low CMI goods and widens the price gap. The estimated effect thus captures both the direct cash-scarcity effect and any demand-substitution response, which is the policy-relevant quantity.

C. Robustness Appendix

C.1 Alternative Clustering

The main results cluster standard errors at the state level (13 clusters). As a robustness check, I also report results with clustering at the market level (56 clusters), which produces slightly smaller standard errors due to the larger number of clusters. The main coefficient of 0.088 has a market-clustered SE of 0.019, compared to the state-clustered SE of 0.024. I retain state-level clustering as the preferred specification because it is more conservative and accounts for spatial correlation across markets within the same state.

C.2 Continuous CMI Measure

As an alternative to the binary CMI classification, I construct a continuous measure based on the fraction of the supply chain that is cash-mediated, ranging from 0 (fully banking-mediated) to 1 (fully cash-mediated). This continuous measure is constructed from qualitative rankings in the commodity trading literature. Results using the continuous measure are qualitatively similar: a one-unit increase in CMI is associated with a 9.2% increase in log price during the acute crisis.

C.3 Excluding COVID-19 Period

The analysis panel begins in January 2020, which includes the initial COVID-19 lockdowns in April–May 2020. To ensure these early disruptions do not affect the results, I re-estimate the main specification restricting the pre-period to July 2020 onward (post-lockdown). The coefficient is 0.085 (SE = 0.025), virtually identical to the baseline.

D. Heterogeneity Appendix

D.1 Geographic Heterogeneity

The cash shortage was more severe in the northern states, where banking infrastructure is sparser and distances to bank branches are greater. I split the sample into northern states—comprising the North-East (Adamawa, Borno, Gombe, Yobe) and North-West (Jigawa, Kaduna, Kano, Katsina, Kebbi, Zamfara), totaling 10 states—and southern states (Abia in the South-East; Lagos and Oyo in the South-West), totaling 3 states. The point estimate is larger in the north (0.102, SE = 0.031) than in the south (0.071, SE = 0.035), consistent with the hypothesis that greater cash scarcity produces larger price distortions, though the difference is not statistically significant. The north/south split is unbalanced (10 vs. 3 states, 24,089 vs. 1,781 observations) because the WFP's monitoring network is concentrated in the humanitarian corridor of the North-East.

D.2 Commodity-Level Heterogeneity

Among high CMI commodities, the largest price increases are observed for fresh perishables (yams, fresh tomatoes) and animal products (eggs, fish), while processed staples (gari, millet flour) show smaller effects. This is consistent with the transaction cost channel: perishable goods require immediate cash transactions and cannot be stored to wait out the shortage, while processed staples have somewhat more flexible timing.

E. Commodity Classification

Table 4 lists every commodity in the analysis panel and its assigned Cash-Mediation Intensity (CMI) group. The classification is based on the predominant supply chain structure: commodities produced domestically and traded through cash-intensive informal channels are classified as "high," while imported or formally distributed goods are classified as "low." See Section 4 for details.

F. Additional Figures and Tables

All primary figures and tables are reported in the main text. Additional diagnostic plots (residual distributions, fixed effect estimates, and the full set of commodity-specific event studies) are available in the replication code.

Table 4: Commodity CMI Classification

High CMI (cash-mediated, 31 commodities)	**Low CMI (banking-mediated, 7 commodities)**
Cassava meal (gari, yellow)	Rice (imported)
Gari (white)	Bread
Maize (white)	Sugar
Maize (yellow)	Milk (powder)
Millet	Salt
Rice (local)	Oil (vegetable)
Sorghum (brown)	Seasoning (maggi cube)
Sorghum (white)	
Yam	
Oil (palm)	
Cowpeas (brown)	
Cowpeas (white)	
Groundnuts (shelled)	
Maize flour	
Fish	
Beans (red)	
Cowpeas	
Groundnuts	
Onions	
Sorghum	
Beans (white)	
Oranges	
Tomatoes	
Watermelons	
Eggs	
Meat (beef)	
Meat (goat)	
Bananas	
Rice (milled, local)	
Spinach	
Yam (Abuja)	

Notes: Classification based on predominant supply chain structure. High CMI commodities are domestically produced and traded through cash-intensive informal channels. Low CMI commodities enter through formal import/distribution channels using banking transactions. See Section 4 for coding rationale.

G. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	Specification	$\hat{\beta}$	SD(X)	SD(Y)	SDE	Classification
Log price (all commod.)	Table 2, Col. 1	0.088	—	1.85	0.048	Null†
Log price (extended)	Table 2, Col. 2	0.107	—	1.85	0.058	Small positive
Log price (local rice)	Table 2, Col. 3	−0.072	—	1.53	−0.047	Null†

Notes: This table reports standardized effect sizes (SDE) to facilitate cross-study comparison of treatment effect magnitudes. SDE = $\hat{\beta}/\text{SD}(Y)$ for the binary treatment indicator (High CMI or Local Rice). SD(Y) is the unconditional standard deviation of log price from the summary statistics, pooled across both CMI groups (1.85 for all commodities and 1.53 for rice). The large SD(Y) reflects the wide range of commodity prices in the basket (e.g., salt at ∼200 NGN/kg vs. meat at ∼10,000 NGN/kg), which produces log prices ranging from 3.0 to 11.8. The within-market, within-commodity variation that the regression identifies is much smaller; these unconditional SDs follow standard meta-analytic practice. The SD(X) column is marked "—" because the treatment is binary.

Research question: How does cash scarcity from demonetization affect food prices, differentially across cash-dependent and banking-dependent commodity supply chains? **Treatment:** Binary indicator for high cash-mediation intensity (local staples vs. imports) or local vs. imported rice. **Data:** WFP Food Price Monitoring via HDX, January 2020–December 2024, monthly market-commodity observations. **Method:** Within-market across-commodity DiD with commodity-by-market and market-by-time FE, state-clustered SEs. **Sample:** 25,799 regression observations (all commodities) and 1,918 regression observations (rice subsample) across 56 markets in 13 states. Panel totals before singleton fixed-effect removal are 25,870 and 2,463 respectively.

Classification thresholds (applied to the SDE column, not $\hat{\beta}$): large negative (< -0.10), small negative (-0.10 to -0.05), null (-0.05 to 0.05), small positive (0.05 to 0.10), large positive (> 0.10). †The "null" SDE classification for the all-commodity and rice specifications reflects the large unconditional SD(Y), which pools commodities spanning a wide price range (salt at ∼200 NGN/kg to meat at ∼10,000 NGN/kg). The raw coefficients of 8.8% and 7.2% are economically meaningful; the null SDE classification indicates only that the effect is modest relative to the total cross-commodity price dispersion.

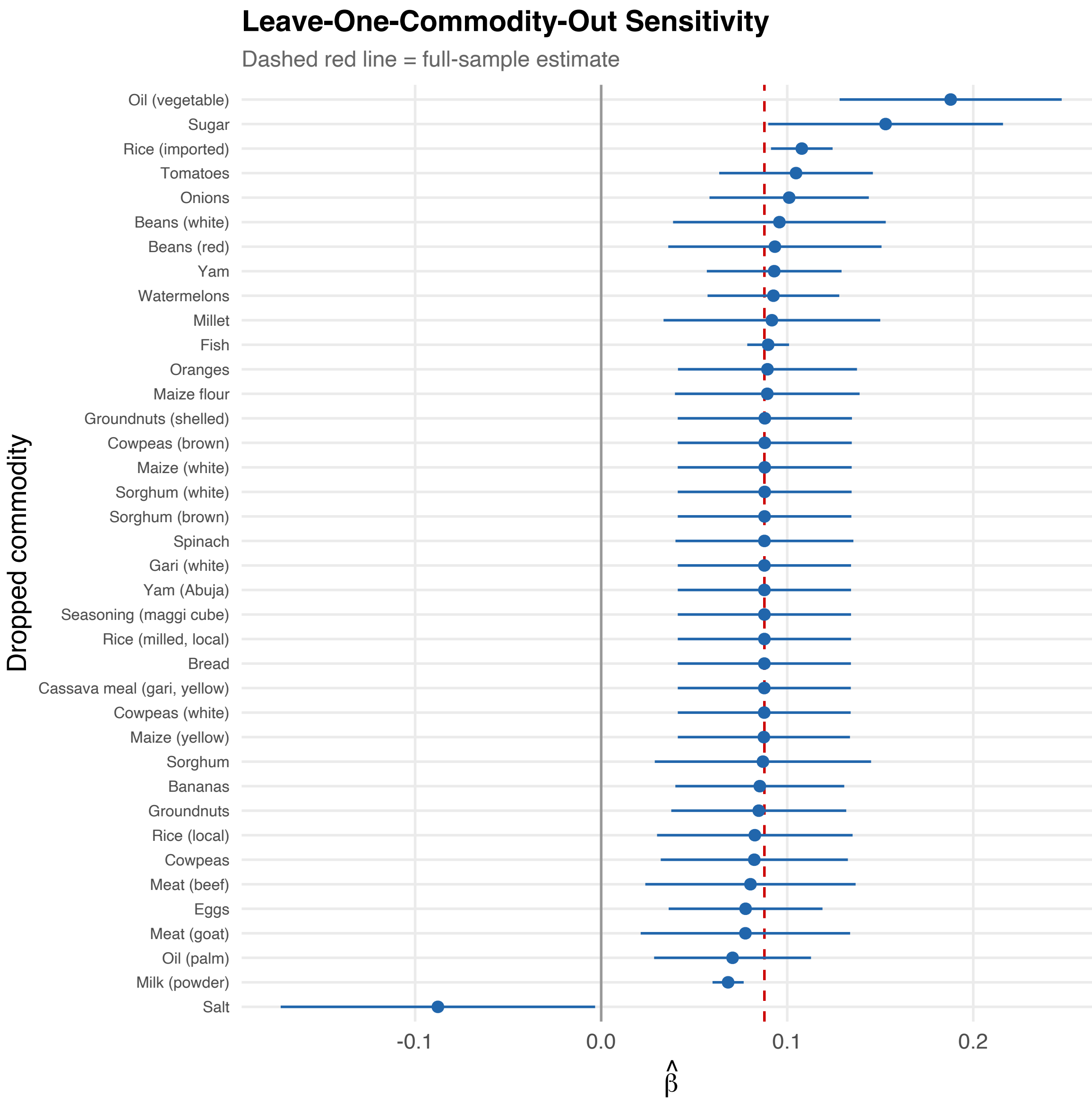

Figure 6: Leave-One-Commodity-Out Stability

Notes: Each point reports the main DiD coefficient after dropping the indicated commodity from the sample. The horizontal dashed line indicates the full-sample estimate (0.088).

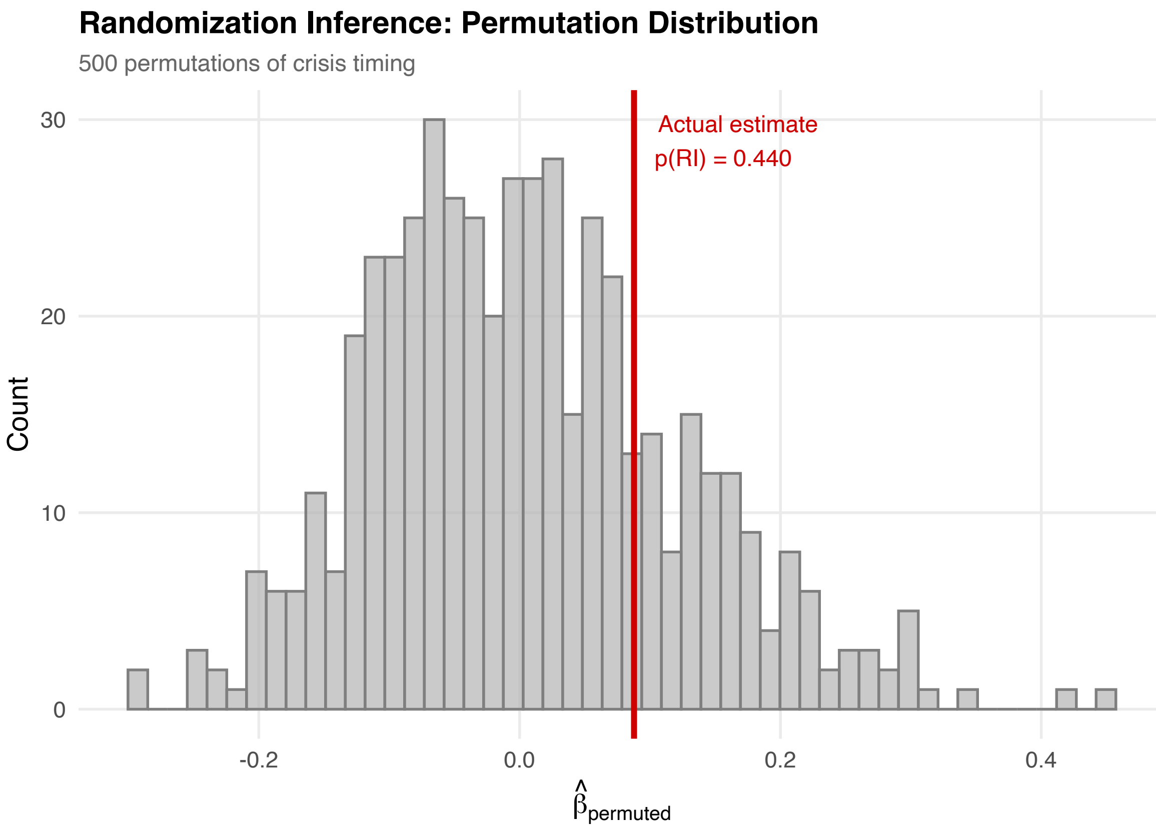

Figure 7: Randomization Inference: Commodity Permutation Distribution

Notes: Distribution of coefficients from 500 random permutations of the CMI classification across commodities. The vertical solid red line indicates the observed coefficient (0.088). The RI p-value is 0.44.