The MultiShock Index (MSI) for Nigeria

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DRAFT

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Abstract

This reports presents the application of a Multi-Shock Index (MSI) to assess the compound vulnerability of Nigerian households to multiple, overlapping shocks. Using data from the Nigeria DIEM Household Survey, we construct both non-parametric and parametric versions of the MSI to capture observed and predicted exposure, respectively. The non-parametric MSI is based on binary incidence of shocks, while the parametric version relies on predicted probabilities from logistic models incorporating livelihood strategies, coping behaviors, and contextual factors. To enhance precision, we introduce a set of compound shock subindices, which reflect combinations of shocks across thematic domains—economic, agricultural, natural, and health-related. Our results reveal that compound shocks—especially those involving economic and health stressors such as rising food prices combined with sickness or death—have the most detrimental effects on household food security, as measured by the Food Consumption Score (FCS). Parametric subindices exhibit higher statistical sensitivity than their non-parametric counterparts, suggesting greater utility for predictive modeling and early warning systems. These findings highlight the inadequacy of analyzing shocks in isolation and support the growing policy emphasis on shock-responsive and adaptive social protection systems. The MSI provides policymakers and humanitarian actors with a reliable, scalable tool to identify at-risk populations, allocate resources more effectively, and strengthen the shock-responsiveness of social protection systems in Nigeria.

1. Introduction

Households across Nigeria face a complex array of shocks that interact, compound, and exacerbate vulnerabilities—often pushing families into cycles of food insecurity and poverty. These shocks range from environmental disruptions such as floods and droughts, to economic instabilities including inflation and job losses, to social and political threats such as conflict, displacement, or health crises. Traditional monitoring systems have struggled to capture the multi-dimensional and interrelated nature of these shocks, frequently relying on single-shock assessments or binary vulnerability proxies that miss the broader context in which households operate.

In response to these challenges, the Multi-Shock Index (MSI) was developed as an innovative tool to measure household-level exposure to multiple shocks and to assess their aggregate impact on food security. Rooted in a multidimensional understanding of vulnerability (Adger, 2006; Birkmann et al., 2013), the MSI provides both non-parametric and parametric representations of shock burden: the former captures observed, reported experiences, while the latter estimates the predicted probability of shock exposure based on household characteristics and contextual variables. This dual construction allows the MSI to serve both immediate humanitarian targeting and longer-term policy design needs.

By linking MSI scores to validated outcomes such as the Food Consumption Score (FCS)—an established indicator of dietary adequacy and food security—the framework provides empirical insight into how layered shocks translate into real-world deprivation. In addition, the MSI advances current measurement frameworks by incorporating both population weights and statistical controls for livelihood strategies, gender, education, and geography. The development and testing of this index using high-resolution household survey data from the Nigeria DIEM (Data in Emergencies Monitoring) initiative thus represents a significant methodological contribution to resilience analytics in low- and middle-income country settings.

This report outlines the conceptual foundation, construction methodology, empirical validation, and policy implications of the MSI in the Nigerian context, offering a rigorous yet practical tool for operationalizing the link between shocks, vulnerability, and food insecurity.

2. Methodology

The construction of a MSI for Nigeria DIEM survey involves a critical rethinking of how shocks are aggregated and weighted, with a specific focus on their relationship to food security outcomes and data completeness. This methodological refinement ensures that only empirically relevant and statistically robust indicators are used, thereby enhancing the reliability of the resulting index for analytical and policy purposes.

The first stage of the process begins with the identification of shocks experienced by households. These shocks, such as sickness, drought, conflict, and economic hardship, are captured as binary variables in the dataset. However, unlike earlier approaches that treated all shocks equally or selected them based solely on prevalence thresholds, this revised method incorporates a data-driven filter based on the Food Consumption Score (FCS). For each shock s_i, the sample is split into two groups: households that experienced the shock and those that did not. The mean FCS for each group is computed:

$$FCS_{shock} = E[FCS \mid s_i = 1], FCS_{nonshock} = E[FCS \mid s_i = 0]$$

The difference $\Delta_i = FCS_{shock} - FCS_{noshock}$ is used to assess the effect of each shock on food security. Only shocks with $\Delta_i < 0$—indicating a negative association with FCS—are retained for inclusion in the index. This filtering step aligns the index with impact-based selection rather than arbitrary thresholds. This is an empirical filtering criterion grounded in the theoretical linkage between shocks and welfare outcomes (Devereux, 2001).

Next, the script turns to coping strategies, which are included as explanatory variables or controls in many vulnerability models. However, recognizing that data quality varies across variables, only those coping strategy variables with less than 10% missingness are retained. This step ensures statistical validity and guards against bias introduced by high rates of nonresponse. The share of missing values is computed for each coping strategy c_j as:

$$MissingShare_j = \frac{\text{Count of Missing Observations in } c_j}{\text{Total Sample Size}} \times 100$$

Variables for which $MissingShare_j$<10% are included in the list of "good" coping strategies.

The filtered set of shocks is then used to create the compound shock categories. These include: economic shocks, agricultural shocks, natural shocks, conflict-related shocks, and household-level shocks. Each category aggregates related shocks using a logical OR operator. For instance, the economic shock group is defined as:

$$shock_{\text{economic}} = \| \left(shock_{\text{higher food prices}} = 1 \vee shock_{\text{higher fuel prices}} = 1 \vee \ldots\right)$$

The unweighted compounded shock index is computed as the sum of these five categories:

$$CompoundedIndex = shock_{\text{economic}} + shock_{\text{agriculture}} + shock_{\text{natural}} + shock_{\text{conflict}} + shock_{\text{household}}$$

To account for household-level representativeness, a population-weighted version of each component is computed by multiplying it with a final weight variable w_i:

$$shock^{\text{c}}_{\text{popwt}} = w_i \times shock^{\text{c}}$$

The weighted compounded index is then the sum of these weighted components:

$CompoundedIndex^{\text{popwt}} = \sum_c shock^{\text{c}}_{\text{popwt}},$
where c∈{economic, agriculture, natural, conflict, household}

Endogenous Shock Index

The parametric construction of the Endogenous Shock Index as implemented in the DIEM Nigeria household survey represents a significant methodological advancement over traditional binary or count-based indices. By leveraging a predictive modeling framework, the index accounts for the latent propensity of households to experience shocks based on a set of structural and contextual characteristics. This technique not only improves measurement precision but also embeds the index within an econometric framework that acknowledges the endogenous nature of shocks in complex environments. Key demographic and livelihood-related variables are accounted for, such as gender, education, and a comprehensive suite of coping strategies.

The core of the methodology lies in estimating parametric probabilities of shock occurrence via logistic regression. Each retained shock s_i is modeled using a logistic model:

$$\log\left(\frac{P(s_i)}{1 - P(s_i)}\right) = g(X_i, Z_i) + \epsilon_i$$

Here, X_i includes livelihood indicators such as agricultural production and coping strategies, while Z_i includes contextual controls such as education, gender, and district-level identifiers. The fitted probabilities from these models—denoted as $\hat{P}(s_i = 1)$—serve as shock intensity scores that vary continuously across households.

These predicted values are then grouped into five compound shock categories as in the non-parametric approach: economic, agricultural, natural, conflict-related, and household-level shocks. For each group, the predicted probabilities of relevant shocks are summed:

$$x_{\text{group}} = \sum_{S_i \in \text{group}} \hat{P}(s_i = 1)$$

This continuous summation approach respects both the magnitude and likelihood of exposure, unlike binary flags that treat all shocks equally. The overall parametric compounded shock index is the sum of all grouped components:

$$x_{\text{compound}} = x_{economic} + x_{agriculture} + x_{natural} + x_{conflict} + x_{\text{household}}$$

To adjust for survey design and household representativeness, a population-weighted version of each group index is calculated:

$wx_{\text{group}} = w_i \cdot x_{\text{group}}$, and $wx_{compound} = \sum_{\text{group}} wx_{\text{group}}$

The parametric approach offers several advantages: it captures latent exposure rather than just realized shocks, incorporates heterogeneity in shock determinants, and respects data quality constraints. As such, it reflects a shift from categorical to continuous vulnerability assessment, and from descriptive to model-based measurement—two trends increasingly emphasized in the disaster risk and resilience literature (Adger, 2006; Birkmann et al., 2013).

Normalization and validation

To facilitate cross-variable comparison and potential regression use, all indices and their components are normalized to a [0,1] scale using min-max scaling:

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Normalization standardizes the variables and removes unit dependency, a critical requirement when preparing indices for statistical modeling.

The final stage evaluates the validity and relevance of the constructed indices through correlation and regression analyses. The indices—both weighted and unweighted—are correlated with the Food Consumption Score (FCS). Furthermore, a linear regression models are estimated:

$$FCS = \beta_0 + \beta_1 \times shock_{index} + \gamma X + \epsilon$$

where X includes all other relevant factors influencing FCS.

These models help assess whether shock exposure, as operationalized through the indices, has statistically significant and negative effects on household welfare.

3. Data description

Designed to provide timely, granular insights into the socio-economic and food security conditions of rural and vulnerable populations, this dataset integrates modules on demographics, livelihoods, agriculture, food security, shocks, coping mechanisms, and humanitarian assistance. At its core, the dataset covers 12,595 households, each of which is geographically identified through standard administrative codes and names, including adm1_name, adm2_name, and adm3_name, reflecting Nigeria's subnational administrative structure. A central theme within the dataset is the exposure to shocks, which are recorded across multiple dimensions, such as economic, agricultural, natural, and conflict-related disruptions. Each is encoded as a binary variable indicating whether a household experienced the event. These data provide a foundation for constructing composite shock indices and for exploring the interaction between shocks and food security outcomes.

Food security itself is measured using several internationally recognized metrics. The Food Consumption Score (FCS) is available both as a total score (fcs) and in disaggregated form across food groups (fcs_staple_days, fcs_pulses_days, etc.). Complementing this is the Household Dietary Diversity Score (HDDS), with variables such as hdds_cereals, hdds_meat, and hdds_score, and the Reduced Coping Strategy Index (RCSI) captured via rcsi_score and related behavioral indicators. Moreover, the Food Insecurity Experience Scale (FIES) adds a subjective yet behaviorally grounded dimension, measuring direct experiences like fies_ranout, fies_hungry, and fies_skipped.

Another strength of the dataset lies in its detailed accounting of livelihood activities, covering agriculture, livestock, and fishing. Agricultural data include cropping systems, irrigation, seed sourcing, harvest volumes, and production difficulties. Livestock-related variables track herd size, production shocks, and marketing challenges, with distinctions drawn between increases due to acquisition and decreases due to distress sales or health issues. Similarly, fisheries data report the mode of fishing, production issues, and barriers to input access. These livelihood modules allow for in-depth analysis of production shocks and supply-side constraints at the household level.

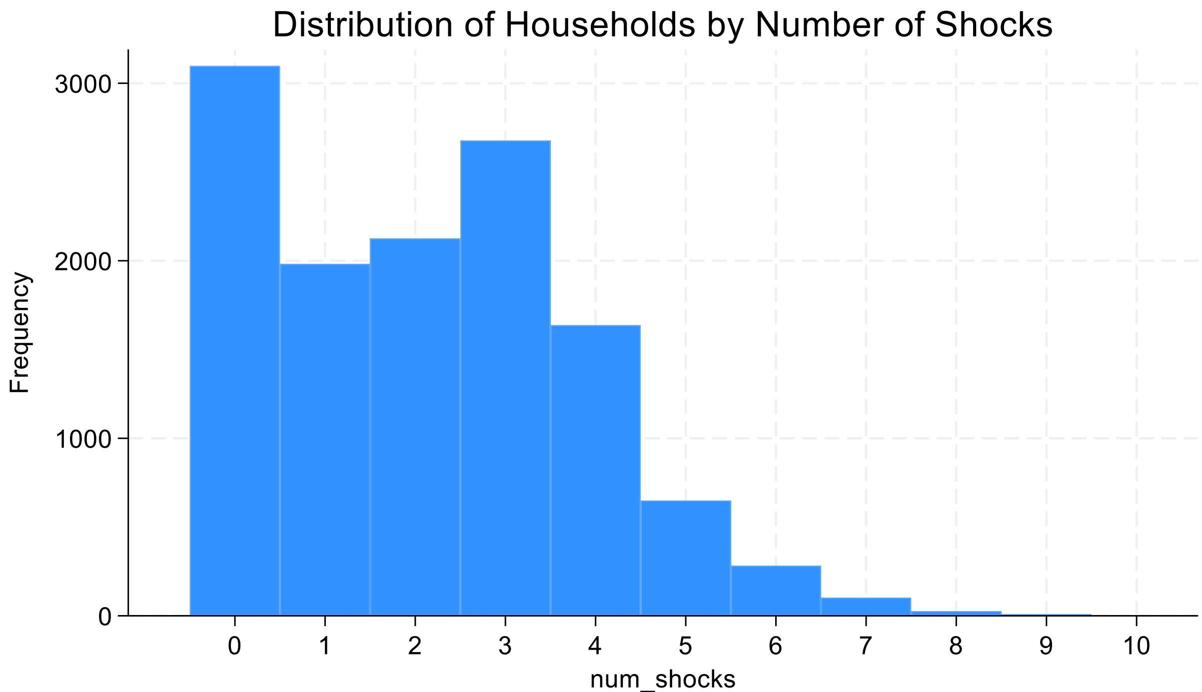
Coping strategies in the face of adversity are represented through a set of binary indicators. These variables not only reflect household-level adaptive behavior but also serve as proxies for resilience and socio-economic buffering capacity. Importantly, these variables are used in downstream econometric models to predict vulnerability, enabling endogenous modeling of shock susceptibility.

In addition to exposure and response, the dataset also documents household needs and external assistance. This includes perceived needs and aid received from various actors such as WFP, FAO and government, and others. These variables are crucial for evaluating the targeting efficiency and coverage of emergency programs and for identifying gaps in assistance delivery.

Distribution of Households by Number of Shocks

Figure 1 provides a visualization of the exposure of Nigerian households to multiple shocks. From this figure, a nuanced pattern of vulnerability emerges, highlighting both the pervasiveness and intensity of shock exposure across the population.

Figure 1: Distribution of households by number of shocks



The distribution is right-skewed, indicating that while many households experienced no or few shocks, a non-negligible portion encountered multiple simultaneous or sequential disruptions. The modal value—the most frequent number of shocks—is zero, with over 3,000 households reporting no shock exposure during the survey period. This suggests that a substantial subset of the population remains relatively insulated, potentially due to geographic location, livelihood type, or access to buffers such as savings or social networks.

However, as the distribution progresses, there is a gradual decline in frequency for households reporting one, two, or three shocks, and then a steeper decline beyond four shocks. This tail represents a particularly vulnerable group: those households exposed to five or more shocks, which, although less common, likely face compounded disadvantages. Such clustering of shocks may include combinations of economic hardship, climatic stressors, health-related events, and conflict—all of which can interact to deepen poverty traps and limit recovery capacity. According to Barrett and Carter (2013), repeated or simultaneous shocks can lead to “poverty trap”, wherein households cross critical asset thresholds that hinder future livelihood rebuilding, leading to chronic food insecurity and long-term vulnerability.

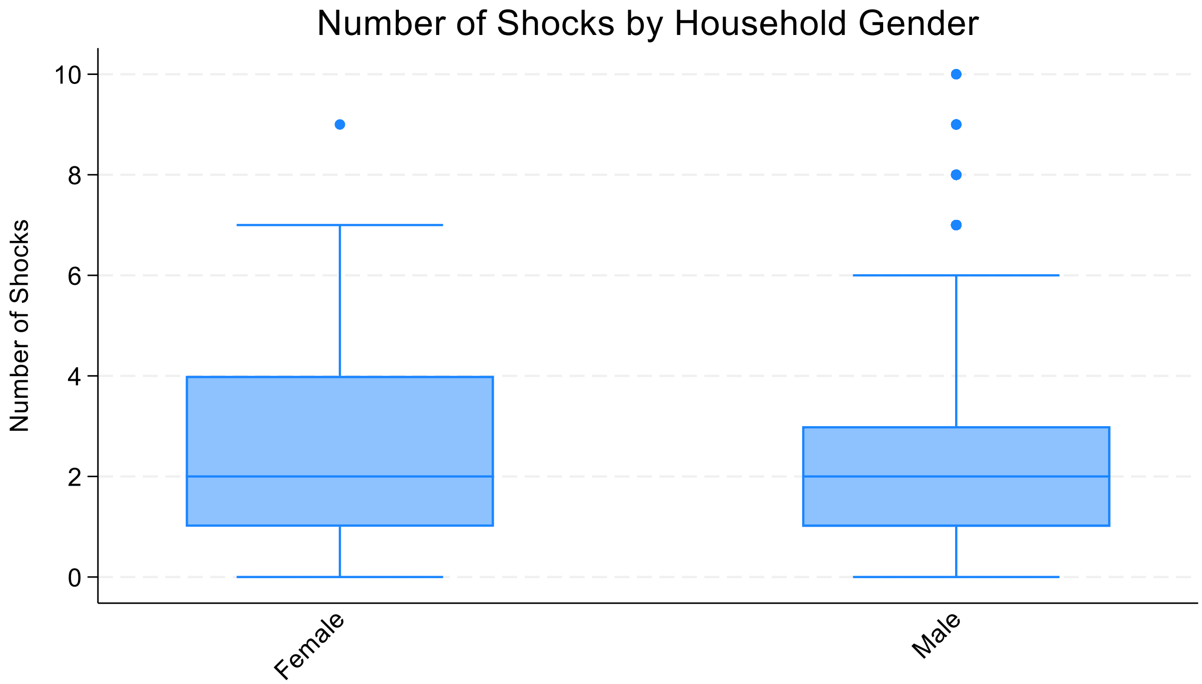
The occurrence of households experiencing as many as seven or more shocks—albeit infrequent—raises questions about resilience thresholds and adaptive capacity. These extreme cases are critical for humanitarian response planning, as they often signal systemic failure in social safety nets or environmental resilience. Studies by Heltberg et al. (2009) and FAO (2018) emphasize that exposure to multiple shocks not only increases immediate hardship but also compromises future income generation, productivity, and child welfare, especially in agriculture-dependent households.

Another noteworthy observation is the frequency of households experiencing two to four shocks, which together comprise a substantial portion of the population. This mid-range of the distribution suggests that vulnerability is not confined to the extremes; rather, a large segment of the population is under continuous stress. These households may not qualify for emergency assistance, yet are persistently at risk of sliding deeper into food insecurity and asset depletion. As noted by Carter et al. (2007), this group often faces “latent vulnerability,” where coping strategies become increasingly erosive—such as selling productive assets or reducing expenditures on health and education.

Number of Shocks by Household Gender

Figure 2 offers valuable insight into the gender-differentiated experience of shock exposure among Nigerian households. It visually compares the distribution of shocks experienced by female-headed and male-headed households, capturing key statistical features such as medians, interquartile ranges, and outliers. From Figure 2, it is evident that female-headed households tend to experience a greater number of shocks than their male-headed counterparts. The median number of shocks for female-headed households is around 2, slightly higher than that of male-headed households. Moreover, the interquartile range (IQR)—which captures the middle 50% of values—is wider for female-headed households, extending from approximately 1 to 4 shocks. In contrast, male-headed households have a narrower IQR, suggesting a more concentrated experience of shocks with less variability.

Figure 2: Number of Shocks by Household Gender



The presence of higher whiskers and more extreme outliers in the female-headed group further suggests that women-led households are more likely to face not just more frequent, but also more compound or severe shocks. These may include economic stress (such as rising food prices), climate-related hazards, or social vulnerabilities such as illness or loss of employment. This pattern reflects longstanding evidence in development literature that female-headed households are often structurally more vulnerable, due in part to limited access to land, credit, and social protection systems (Quisumbing et al., 2015).

Conversely, male-headed households, while still significantly affected by shocks, tend to report a slightly lower average number, with fewer extreme cases. This might reflect not just exposure but differences in reporting behavior, social roles, or gendered divisions in asset ownership and decision-making authority. The narrower spread could also reflect better access to informal networks or livelihood diversification options that buffer male-headed households from multiple overlapping shocks.

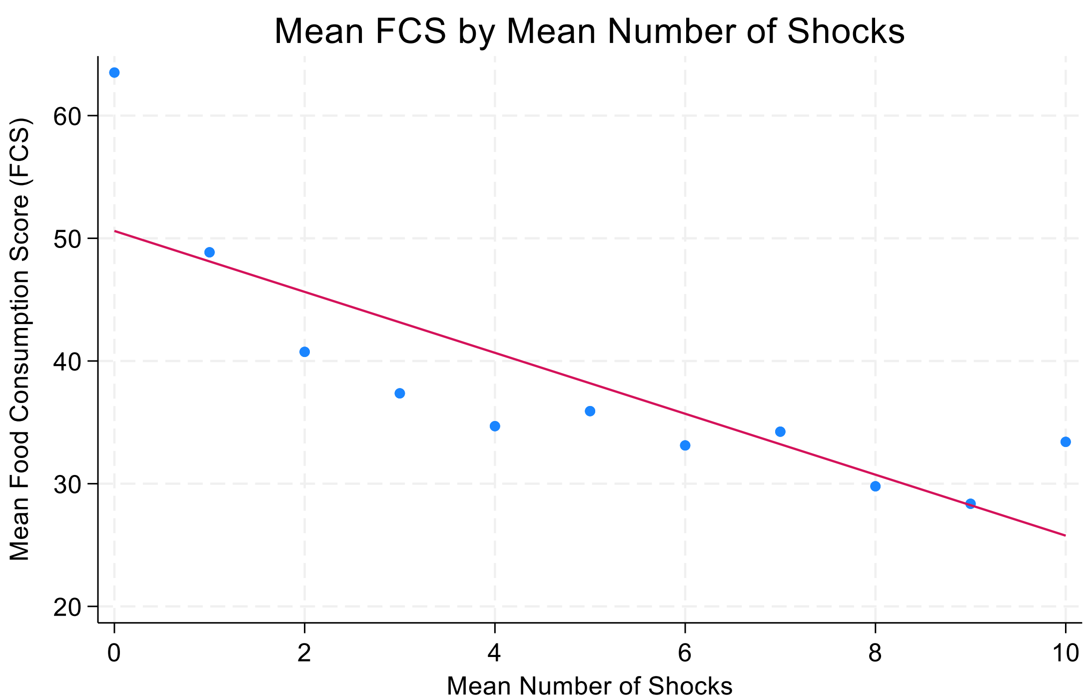
The implications of these differences are profound. Exposure to multiple shocks is closely linked with reduced resilience, as households must draw upon coping strategies that can erode long-term well-being—such as selling productive assets, withdrawing children from school, or reducing food consumption. When these behaviors are more common among female-headed households, the cycle of vulnerability is perpetuated across generations, particularly affecting children’s health and education outcomes (FAO, 2018).

Moreover, the gender disparities illustrated in this figure underscore the importance of mainstreaming gender in risk reduction and resilience programming. Simply put, gender-neutral interventions may not be sufficient to protect or empower those most at risk. There is a growing consensus in policy and academic literature that gender-sensitive targeting—including tailored cash transfers, agricultural support for women farmers, and enhanced access to financial services—can play a critical role in narrowing these vulnerability gaps (World Bank, 2022).

Food Consumption Score (FCS) by Mean Number of Shocks

Evidence of the negative association between the number of shocks experienced by households and their food consumption levels in Nigeria in reported in Figure 3. The downward-sloping red line indicates a strong negative linear trend: as the number of shocks increases, the average FCS systematically declines. Households that report experiencing no or only one shock tend to maintain FCS values near or above 50, indicating acceptable levels of food consumption. In contrast, households that face five or more shocks see their mean FCS drop below 35, and in the most extreme cases—up to 10 shocks—the FCS hovers near 30, signaling severe food insecurity. This pattern demonstrates a cumulative erosion of food security with increasing exposure to adverse events.

Figure 3: FCS by Mean Number of Shocks



This trend is consistent with theoretical and empirical findings in the resilience and food security literature. Shocks such as drought, market disruptions, or illness often reduce households' income and assets, forcing them to adopt negative coping strategies that compromise long-term well-being. These may include reducing meal sizes, consuming less diverse diets, selling productive assets, or withdrawing children from school. When multiple shocks occur either simultaneously or sequentially, these strategies become more frequent and more damaging (Maxwell et al., 2014). As a result, multi-shock households are more likely to experience protracted or chronic food insecurity.

Moreover, this trend supports the concept of shock multiplicity, where the impact of one shock may exacerbate the effects of another. For instance, households already affected by a health crisis may be more vulnerable to food price hikes due to depleted savings or reduced labor capacity. The relationship is not merely additive but often synergistic, meaning each additional shock has a progressively greater marginal impact on food security (FAO, 2018; Barrett & Santos, 2014). The linear trendline in the graph approximates this compounding effect, although the exact shape of the relationship could be non-linear in a more granular analysis.

The graph also reveals slight deviations from the trendline, especially at higher shock counts (e.g., 7–10 shocks), where FCS values do not always decline in a perfectly linear fashion. This variability might reflect the presence of resilience factors such as social networks, remittances, access to humanitarian aid, or localized agro-ecological advantages. However, the overall direction of the trend is unambiguous and statistically significant.

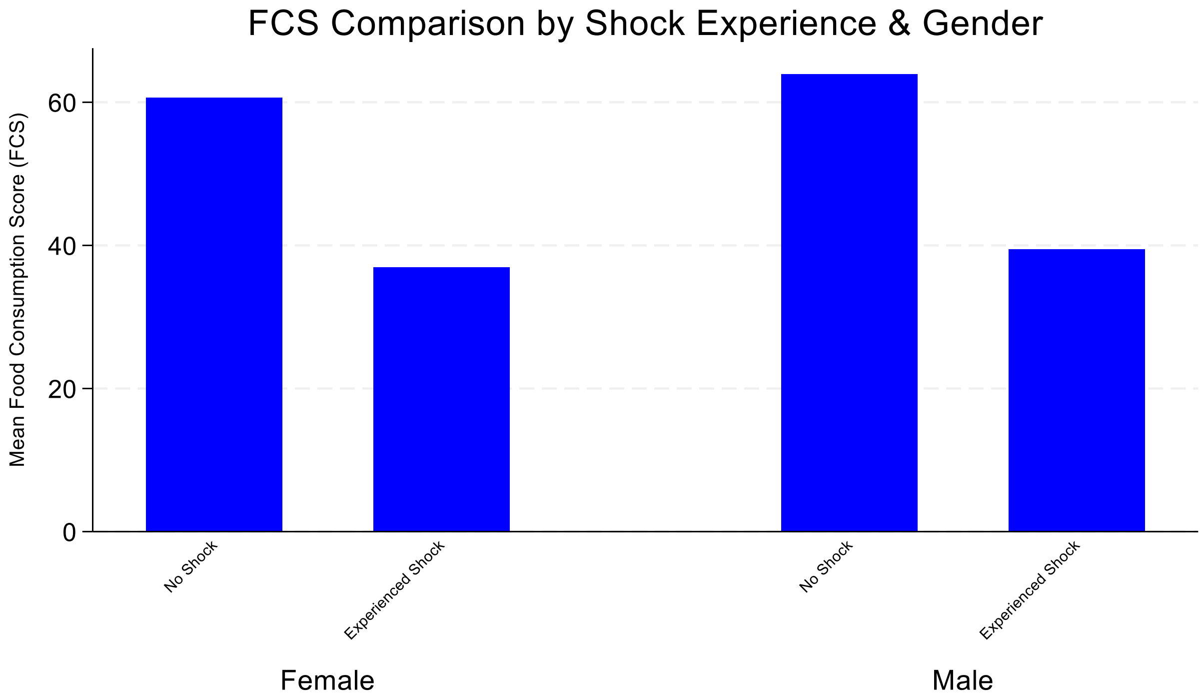
From a policy perspective, this evidence underscores the importance of shock-responsive social protection systems. Households exposed to recurrent shocks require not only immediate food assistance but also interventions that reduce future exposure and improve absorptive capacity, such as livelihood diversification, climate-smart agriculture, and financial inclusion (World Bank, 2022). Moreover, tracking both the number and types of shocks at the household level can improve targeting precision, ensuring that the most vulnerable are reached before food insecurity deepens.

FCS Comparison by Shock Experience & Gender

Figure 4 presents a striking visual representation of how food security, measured through the Food Consumption Score (FCS)**,** differs based on shock exposure and household gender. This comparison not only underscores the general vulnerability associated with experiencing shocks but also highlights the gendered disparities in food security outcomes within shock-affected populations in Nigeria.

On the left side of the chart, among female-headed households, those that did not experience any shocks report a high mean FCS—slightly above 60—indicating acceptable dietary diversity and meal frequency. However, when these households are exposed to shocks, their mean FCS drops dramatically to around 37. This represents a sharp decline of nearly 40%**,** signifying a substantial deterioration in food security. Such a pronounced drop suggests that female-headed households may lack adequate buffers—such as access to formal savings, land, or diversified income sources—that could help mitigate the nutritional consequences of adverse events.

Figure 4: FCS Comparison by Shock Experience & Gender



On the right side of the chart, male-headed households also display a significant reduction in FCS when exposed to shocks—from about 64 to 40. While the absolute levels are higher than those of their female counterparts in both scenarios, the magnitude of decline is similar. This implies that although both male- and female-headed households are vulnerable to shocks, female-headed households may be starting from a lower baseline of resilience, leaving them more susceptible to falling into food insecurity following external stressors.

These gender-based disparities in shock response are well-supported by a substantial body of literature. According to Quisumbing et al. (2015), female-headed households in sub-Saharan Africa typically face structural disadvantages in asset ownership, labor access, and financial services—factors that limit their capacity to withstand and recover from shocks. The Food and Agriculture Organization (FAO, 2021) notes that these households often bear a disproportionate burden of food insecurity, particularly when caregiving responsibilities and limited decision-making power further constrain their adaptive capacity.

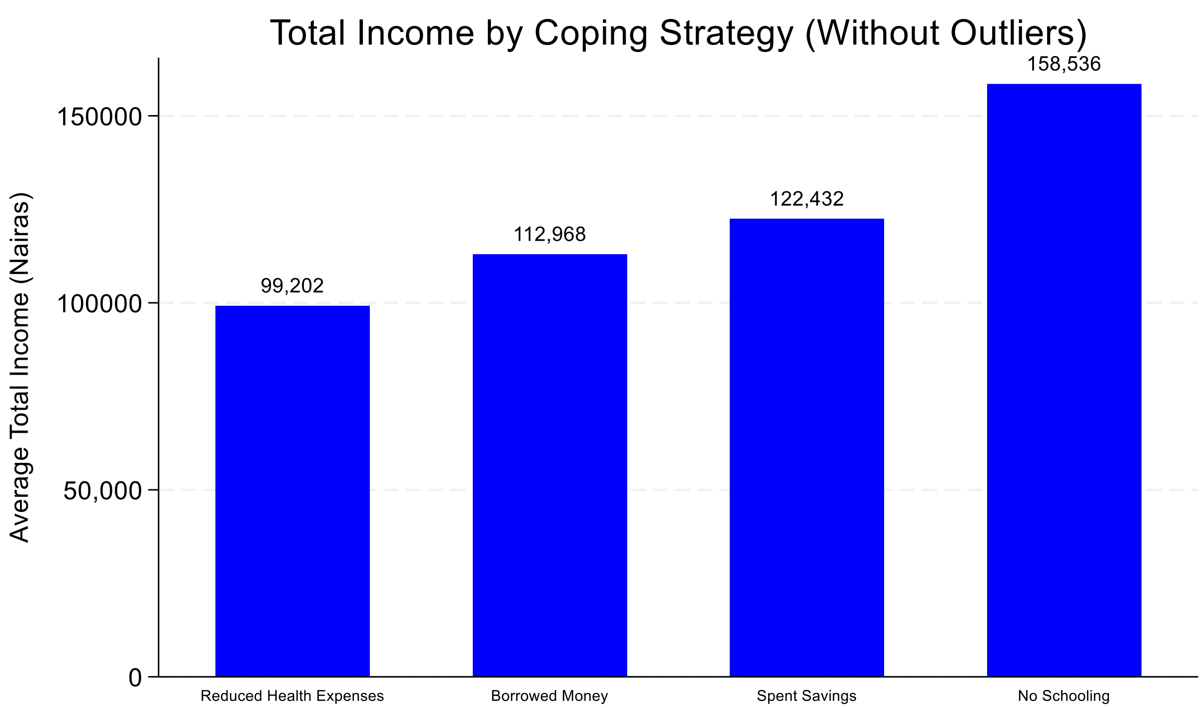
This trend also supports the broader finding that shock exposure is a strong and consistent predictor of food insecurity, aligning with the results shown in the previous scatterplot relating mean shocks to mean FCS. It reinforces the understanding that even a single shock can significantly degrade household food access, and that these effects are not gender-neutral. The declines in FCS presented here, though average values, likely mask even deeper vulnerabilities among female-headed households with children, the elderly, or those relying solely on agricultural labor for income.

In policy terms, these findings point to the need for gender-sensitive shock-responsive social protection systems. This includes tailoring cash transfers, food assistance, and livelihood support in ways that specifically address the constraints faced by female-headed households. Programs that expand access to credit, insurance, land rights, and agricultural inputs for women can serve as long-term resilience strategies, while immediate food support can buffer short-term nutritional losses during crisis periods (World Bank, 2022).

Total Income by Coping Strategy[1]

In Figure 5, we explore the relationship between household income levels and the type of coping strategies employed by Nigerian households facing shocks or economic strain. A clear gradient emerges across the coping strategies, suggesting that households with higher incomes tend to employ less erosive or more strategic responses, while lower-income households resort to more immediate, high-cost trade-offs**.** Among the four strategies analyzed, households that withdrew children from school ("No Schooling") reported the highest mean income—₦158,536. This might appear counterintuitive, as withdrawing from school is often seen as a last-resort, high-cost coping strategy. However, it is possible that these households face region-specific shocks, such as prolonged insecurity, that affect schooling access independently of income, or that school closure is a protective measure in regions experiencing violence or displacement (Save the Children, 2020).

Figure 5: Total Income by Coping Strategy



Households that spent savings and borrowed money had mid-range incomes of ₦122,432 and ₦112,968, respectively. These households likely have some access to financial resources or credit, allowing them to deploy monetary coping strategies that delay more damaging options

[1] We selected coping strategies with the least missing values

such as asset sales. The use of savings, while somewhat protective, may still reflect financial stress if deployed repetitively without replenishment (Dercon, 2002). Borrowing may provide short-term liquidity but introduces risk if households lack the future income needed for repayment.

In contrast, households that reduced health expenditures reported the lowest average income (₦99,202). This is particularly concerning, as it implies that the poorest households compromise essential needs like healthcare in response to financial stress. Such choices may provide short-term economic relief but have severe long-term consequences, including untreated illness, increased child mortality, and diminished labor productivity. Numerous studies have found that health-related coping, especially foregone care, is a hallmark of extreme poverty and systemic exclusion from financial safety nets (World Bank, 2021).

The pattern observed in Figure 5 is broadly consistent with coping hierarchy theory in vulnerability research. According to this theory, households progress through a sequence of strategies—from reversible to irreversible—depending on their shock severity and resource availability (Maxwell et al., 2003). Wealthier households typically have access to "insurance-like" strategies such as savings or remittances, while poorer households exhaust these options quickly and turn to more damaging, irreversible coping mechanisms.

4. Application

Descriptive

As shown in Table 1, both indices are normalized (range 0–1) and right-skewed, but the non-parametric MSI shows a higher mean and wider dispersion, indicating that more weight is assigned to households based on direct shock counts, whereas the parametric version, derived from predicted probabilities via logit models, is more conservative in scale.

Table 1: Descriptive statistics

Statistic	Non-Parametric MSI	Parametric MSI
Mean	0.058	0.038
Std. Dev	0.101	0.075
Min	0	0
Max	1	1
25th Percentile	0.003	0.003
Median	0.022	0.014
75th Percentile	0.063	0.036

Correlation

The correlation (see Table 2) analysis reveals several important findings about the relationship between multishock exposure and food security, as measured through the Food Consumption Score (FCS). First, the non-parametric Multishock Index (MSI), which aggregates observed shocks weighted by population exposure, has a moderate negative correlation with FCS ($r = -0.176$, $p < 0.0001$). This result is statistically highly significant and suggests that as the number and intensity of experienced shocks increase, household food consumption deteriorates. The relatively stronger correlation of this index with FCS implies that it captures direct, observable exposure more effectively—particularly relevant in settings where food access is highly sensitive to physical or economic disruptions. The strength and direction of this correlation align with empirical literature from sub-Saharan Africa showing that household food security is eroded with cumulative shocks (Hoddinott, 2006; FAO, 2020).

Table 2: Correlation

Pair	Correlation Coefficient	P-Value
Non-Parametric MSI vs FCS	-0.176	0.00
Parametric MSI vs FCS	-0.093	0.00
Non-Parametric vs Parametric MSI	0.540	0.00

In contrast, the parametric MSI, constructed from predicted probabilities of shock exposure using logistic regression, shows a weaker negative correlation with FCS ($r = -0.093$, $p < 0.0001$). While still statistically significant, the magnitude is smaller, reflecting that this index—by design—incorporates latent vulnerabilities and modeled likelihoods of shock experience rather than actual reported exposure. This suggests that while the parametric MSI may be conceptually appealing for predictive or structural modeling, it might be less sensitive to acute variations in food consumption outcomes when compared to direct observational indices.

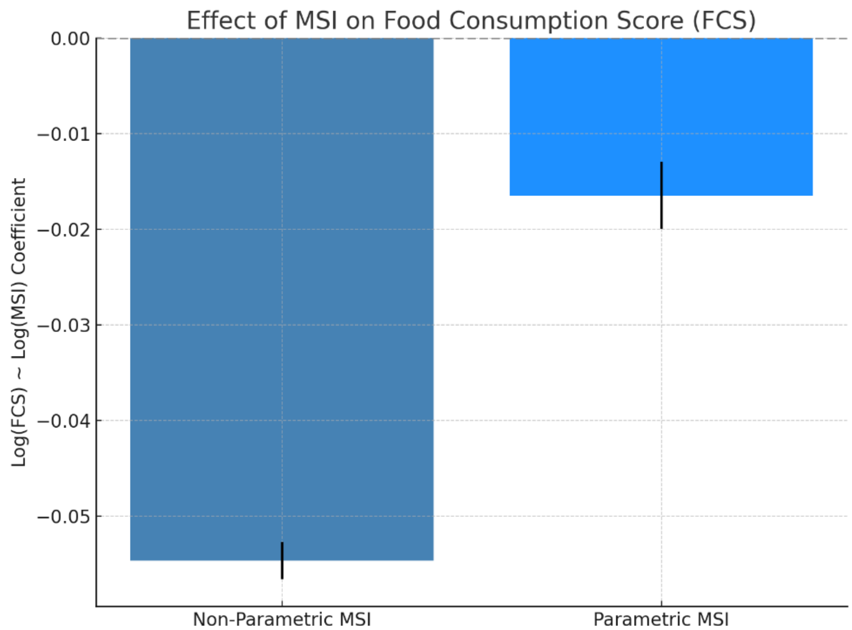
The correlation between the two indices themselves is moderately positive ($r = 0.54$, $p < 0.0001$), indicating that while they are related and capture overlapping information, they are not interchangeable. Each provides a different lens: the non-parametric MSI reflects actual experience and may be more reactive to recent events, while the parametric MSI captures modeled susceptibility based on structural and behavioral factors, including livelihood type and coping strategies. This conceptual distinction is also borne out in their differential explanatory power in regression analysis, where the non-parametric MSI demonstrated stronger predictive capability.

In summary, both indices are valid and statistically significant in capturing dimensions of shock vulnerability. However, the non-parametric index is more tightly linked to current food insecurity, making it particularly useful for early warning systems and emergency targeting. The parametric index, on the other hand, may be more suited for resilience profiling and risk forecasting, where endogeneity and selection into shock exposure need to be controlled.

Regression results

Figure 6 visually compares the estimated effect of two different Multishock Indices (MSIs) on the Food Consumption Score (FCS), using a log-log regression specification. The height of each bar represents the regression coefficient of the log-transformed MSI on the log-transformed FCS, while the error bars show the 95% confidence intervals.

Figure 6: Regression results



From the plot, both indices exhibit statistically significant negative associations with food security. However, the non-parametric MSI displays a notably stronger and more precise effect. The coefficient is approximately -0.055, indicating that a 1% increase in the non-parametric MSI corresponds to an estimated 5.5% decrease in household food consumption. The confidence interval is narrow, reflecting high certainty in the estimate. This highlights the empirical strength of the non-parametric index in capturing real-time vulnerability stemming from actual reported shocks.

In contrast, the parametric MSI, which is based on predicted shock exposure from a structural model, has a weaker coefficient of about -0.016. This implies a 1% increase in parametric MSI is associated with only a 1.6% reduction in FCS. While still significant, the impact is smaller and the confidence interval is wider, suggesting greater uncertainty in the estimate. This likely reflects the index's more conservative design, which filters shock exposure through modeled probabilities based on livelihood, gender, and district factors.

The difference in magnitudes and precision between the two indices is important. It underscores that while both measures are valid, the non-parametric MSI may be more effective for immediate targeting, monitoring, and early warning systems, especially in humanitarian or emergency response contexts. Meanwhile, the parametric MSI offers value for policy modeling, especially where endogeneity and unobserved heterogeneity are concerns.

This visualization reinforces the conclusion that shock exposure has a statistically and substantively meaningful effect on food security, and that index construction methodology matters. The non-parametric approach appears to better capture acute vulnerability, while the parametric approach provides a more structural, risk-based lens.

Compound shock subindices

The creation and analysis of compound shock subindices in this context aim to improve the understanding of how multidimensional and simultaneous shocks affect household food security outcomes in Nigeria. These subindices are designed by combining the top two most prevalent shocks from each group—economic, agricultural, natural, conflict-related, and household-level shocks—into 2x2 and 3x3 bundles. The rationale behind this lies in the growing recognition that households, especially in fragile contexts, rarely experience shocks in isolation; rather, they face interacting and compounding shocks that together amplify vulnerability (Birkmann et al., 2013; FAO, 2021).

The relevance of such composite measures is twofold. First, composite indices reflect real-world interdependencies among shocks—for example, high food prices may coincide with agricultural pest outbreaks, or conflict might disrupt both economic access and natural resources. By aggregating shocks in probabilistic and weighted forms, the subindices offer a more accurate risk landscape for policy analysis (Adger, 2006; Heltberg et al., 2009). Second, the predictive modeling approach—where compound shocks are treated as endogenous and their probabilities are estimated using logistic regression—ensures internal consistency with livelihood characteristics and contextual variables. This aligns with empirical work showing that exposure to shocks is structurally patterned by household assets, gender, and spatial factors (Barrett & Carter, 2013; Krishna, 2007).

Subindices that incorporate predicted values of compound shock exposure offer a data-driven basis for targeting social protection. Ranking these subindices based on their statistical association with the Food Consumption Score (FCS)—provides critical insights into which multidimensional threats most severely affect household wellbeing. The inclusion of gender disaggregation furthers this by identifying how compound vulnerabilities may differ between male- and female-headed households (Johnson et al., 2016).

The elasticities reported in Table 3 for the compound shock indices in relation to the Food Consumption Score (FCS) provide vital insights into the severity and interactive nature of different shocks affecting household food security in Nigeria. The analysis leverages both parametric (based on predicted probabilities) and non-parametric (based on binary incidence) formulations of shock exposure, which together enrich the understanding of how multiple stressors impact consumption behaviors.

Table 3: Elasticities of FCS with respect to shocks subindices

Combination of shocks	Parametric	Non parametric
Higher food prices & higher fuel prices	-0.345***	-0.180***
Higher food prices & plant disease & animal disease	-0.052***	-0.023
Higher food prices & flood & drought	-0.067***	-0.093**
Higher food prices & sickness or death	-0.454***	-0.139***
Higher fuel prices & plant disease	-0.162***	-0.057***
Higher fuel prices & animal disease	-0.002	-0.01
Higher fuel prices & flood & drought	-0.073***	-0.085**
Higher fuel prices & sickness death	-0.440***	-0.126***
Plant disease & animal disease	-0.023***	0.01
Plant disease & flood	0.278***	0.079**
Plant disease & drought	-0.346***	-0.158***
Plant disease & sickness or death	-0.215***	0.006
Higher food prices & higher fuel prices & plant disease	-0.169***	-0.079***
Higher food prices & higher fuel prices & animal disease	-0.029***	-0.042*
Higher food prices & higher fuel prices & flood	-0.073***	-0.085**
Higher food prices & higher fuel prices & sickness death	-0.388***	-0.124***
Higher fuel prices & plant disease & animal disease	-0.049***	-0.013
Higher fuel prices & plant disease & flood	0.278	0.114
Higher fuel prices & plant disease & sickness or death	-0.166***	-0.007
Plant disease & animal disease & flood	0.013*	0.001

Note: =* p<0.10 ** p<0.05 *** p<0.01

Dominance of economic & health shocks

The combination of higher *food prices and sickness or death* yields the strongest negative elasticity under both parametric (–0.454) and non-parametric (–0.139) specifications. This confirms that households facing simultaneous price shocks and health-related disruptions suffer the greatest decline in food security. Health shocks, especially the death or illness of a member, may reduce labor availability and increase medical spending, while food price shocks simultaneously squeeze consumption budgets—a dual burden that directly curtails dietary intake. This result aligns with findings by Dercon (2002) and Carter et al. (2007), who emphasize the compounding effects of economic and health shocks in driving vulnerability and food insecurity.

Synergistic economic shocks: food & fuel prices

The combination of higher food prices and higher fuel prices also exhibits a significant negative impact (parametric: –0.345; non-parametric: –0.180). These shocks are tightly linked to market dynamics and inflationary pressures that affect both food availability and accessibility. This compound index is one of the most consistent and significant across both specifications, suggesting that policies targeting market stabilization and subsidies during price surges could be highly effective.

Agricultural shocks and mixed signals

Interestingly, plant disease & flood exhibits positive elasticities (parametric: +0.278; non-parametric: +0.079), which may seem counterintuitive. A plausible interpretation is that households affected by agricultural production shocks may receive food aid, increase ownconsumption from early harvests, or benefit from external support programs, thereby temporarily boosting food scores. Similar patterns are noted by Maxwell et al. (2014), who show that in some contexts, post-shock interventions may obscure the immediate negative effects of shocks on food access.

However, not all agricultural shocks are benign: combinations like plant disease & drought or plant disease & sickness/death retain the expected negative association with FCS, showing that shock intensity, timing, and response mechanisms are key to shaping outcomes.

Robustness of parametric indices

Across almost all combinations, the parametric estimates yield larger-magnitude elasticities than their non-parametric counterparts. This suggests that predicted probabilities, as continuous measures, better capture the intensity and likelihood of shock exposure and hence yield more statistically powerful indicators. The parametric approach is more sensitive and preferable for policy modeling, in line with Barrett and Carter (2013), who argue for endogenous modeling of shocks and vulnerabilities.

Above findings carry substantial implications for the design and delivery of food security and social protection policies in Nigeria. The differentiated effects of compound shock combinations on household food consumption scores (FCS) underscore the urgency of building more nuanced and adaptive intervention strategies.

One of the most pressing recommendations is to prioritize households experiencing dual-burden shocks, particularly those simultaneously affected by economic constraints—such as rising food prices—and health-related hardships like sickness or death. The elasticity estimates reveal that these combinations consistently exhibit the strongest negative impact on food consumption. Social protection mechanisms, including cash transfers and food voucher schemes, should be tailored to identify and reach these high-risk groups more effectively. This approach not only enhances targeting efficiency but also ensures that limited resources are allocated where vulnerability is most severe.

To address the root causes of these shocks, policy attention should be directed toward stabilizing food and fuel prices, which remain the most potent economic triggers of reduced food access. The government can mitigate these risks by investing in market regulation systems, enhancing food price surveillance, and implementing temporary subsidies or price caps during crises. These tools are particularly critical in preventing cascading effects when fuel and food shocks co-occur, a scenario that has shown markedly negative outcomes in both parametric and non-parametric models.

Beyond immediate market interventions, shock-responsive social safety nets must be expanded and recalibrated to recognize compound vulnerabilities. Programs like Nigeria's National Social Safety Nets Project (NASSP) are well-positioned to adopt these more granular indices. Incorporating compound shock indicators—especially those derived from parametric models based on predictive probabilities—into eligibility assessments can elevate their responsiveness and precision. This is strongly aligned with recent guidance from the World Bank (2022) advocating for adaptive social protection systems capable of responding in real-time to intersecting risks.

In rural and agrarian communities, the intersection of health and agricultural shocks presents a dual challenge that requires integrated solutions. Strengthening primary healthcare infrastructure at the community level can cushion households against health shocks, while investments in climate-resilient agriculture—such as drought-tolerant crops and sustainable water management—can reduce the incidence and severity of climate-induced food shocks. Supporting farmers through early warning systems, extension services, and crop insurance schemes will further reinforce local resilience capacities.

Overall, the evidence calls for a paradigm shift from reactive, uniform interventions to proactive, data-driven, and tailored protection systems that reflect the compound nature of shocks in the Nigerian context. Ensuring food security in the face of multi-dimensional risks demands both institutional innovation and political will.

Conclusion

The Multi-Shock Index (MSI) for Nigeria provides a rigorous and innovative framework for assessing household vulnerability in the context of multiple, overlapping shocks. Its design is rooted in both theory and empirical best practices, combining traditional, observed shock data with model-based estimates of shock susceptibility. The MSI is applied to Nigeria's DIEM household survey data, offering both non-parametric and parametric versions, each tailored to different analytical objectives.

At its core, the MSI responds to the limitations of conventional shock indices, which often fail to account for the complexity of household exposure to shocks and their compounding effects on food security. The non-parametric version aggregates binary shock indicators, filtered by their demonstrated impact on food consumption (FCS), and weighted by household population weights. This version reflects realized exposure and is particularly useful for rapid assessment and targeting in emergency contexts. It captures the immediate, observable burden of shocks and their strong negative association with food security.

The parametric version, by contrast, estimates the probability of shock exposure through logistic regression models incorporating livelihood and demographic variables such as gender, education, and district identifiers. It represents a forward-looking risk model, identifying latent vulnerability that may not yet have manifested in observable shock indicators. This approach is valuable for resilience profiling, program targeting, and understanding structural determinants of vulnerability.

Both indices are normalized and subjected to validation through correlation and regression analyses with the FCS. Results show that while both indices are negatively and significantly correlated with food security outcomes, the non-parametric MSI demonstrates a stronger statistical association, suggesting greater sensitivity to acute food insecurity conditions. The parametric MSI, while less directly tied to current food outcomes, provides a robust basis for policy simulation and anticipatory planning.

Elasticity estimates derived from subindices reinforce this insight. For instance, the combination of higher food prices and sickness or death was found to have the most severe impact on the Food Consumption Score (FCS), with parametric elasticity at –0.454 and non-parametric at –0.139. Similarly, economic shock pairings (like food and fuel price inflation) and agriculture-health combinations (like plant disease and sickness) also exhibit significantly negative associations with food security. These findings support the growing consensus in literature that compound and synergistic shocks are critical drivers of chronic poverty and food insecurity (Dercon, 2002; Barrett & Carter, 2013; Maxwell et al., 2014).

Taken together, these indices offer a comprehensive toolkit for identifying, quantifying, and responding to household vulnerability in Nigeria. The non-parametric index is ideal for immediate use in early warning systems and humanitarian targeting. The parametric index, with its econometric rigor and structural basis, informs strategic resilience planning and social protection design. As Nigeria and similar contexts grapple with recurrent crises—economic, climatic, and social—the MSI provides a nuanced, data-driven lens through which policymakers can prioritize interventions, allocate resources effectively, and build long-term adaptive capacity across vulnerable populations.

This approach aligns with global best practices in resilience analytics and contributes to ongoing efforts in the humanitarian and development sectors to integrate multidimensional risk into policy design (Adger, 2006; Birkmann et al., 2013; FAO, 2021). Its application to the Nigerian context demonstrates the importance of localized, evidence-based tools for navigating complex crisis environments.

While the Multi-Shock Index (MSI) developed for Nigeria offers a powerful and multi-dimensional approach to quantifying household vulnerability, there remains scope for meaningful improvement. One critical enhancement would involve incorporating a temporal dimension into the index construction, enabling tracking of shock exposure and coping dynamics over time. Currently, the MSI is static and cross-sectional, limiting its use in detecting the persistence of vulnerability or recovery patterns across survey waves. Additionally, integrating climate-specific and market-based shocks—such as rainfall anomalies, conflict events, and commodity price fluctuations—through geospatial data linkages could enrich the precision of both the parametric and non-parametric indices. On the methodological front, leveraging machine learning techniques (e.g., random forests or gradient boosting) to predict shock probabilities could outperform standard logistic models in capturing non-linear interactions between risk factors. Finally, the inclusion of psychosocial shocks and subjective well-being indicators would broaden the MSI's scope to reflect not just material but also mental and social dimensions of vulnerability—thus aligning more closely with evolving global definitions of multidimensional poverty and resilience.

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