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Income and food price shocks, urban food security, and dietary deprivation: Evidence from Dakar, Senegal

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ABSTRACT

Understanding household food behavior is key to anticipating the welfare effects of economic shocks, particularly in urban areas where COVID-19 disrupted livelihoods and food access. While a growing body of literature documents the pandemic's effects on food security, few studies explicitly integrate households' pre-pandemic sensitivity to income and price changes. This study examines household food demand in Dakar, Senegal, and evaluates the simulated effects of COVID-19-related income contractions and food price increases on food security and diet quality. Using statistically matched household surveys, we estimate a censored Quadratic Almost Ideal Demand System model with subgroup-specific elasticities and develop a microsimulation model incorporating a heterogeneous Engel transmission channel across six counterfactual scenarios combining three income levels with two food price scenarios. The estimates reveal that households are highly sensitive to price shocks, particularly for staples and animal-source foods, while income shocks transmit partially to food expenditure, with subgroup-specific transmission. Simulated shocks reduce average caloric intake by 17%–36% and lower the food security rate from 52% at baseline to between 40% and 22% depending on the scenario, with statistically significant heterogeneity across sociodemographic groups. The Resilient Diet Deprivation index further reveals a simultaneous deterioration in diet quality through wider and deeper food group deficits, with the contribution of staples and animal-source foods to dietary deprivation rising across all scenarios. These findings underscore the importance of price stabilization policies, nutrition-sensitive interventions, and targeted social protection to strengthen household resilience in urban West Africa.

1. Introduction

Food security and diet quality are essential for human well-being, particularly in urban areas of developing countries (Headey and Alderman, 2019). Over recent decades, diets in many low- and middle-income urban settings have changed dramatically, shifting away from traditional, fiber-rich meals that included legumes toward highly processed dietary patterns high in refined carbohydrates, added sugars, unhealthy fats, and ultra-processed foods (Holmboe-Ottesen and Wandel, 2012). While these changes have often increased food availability and convenience, they have also raised important concerns for nutrition, health, and the resilience of household food systems.

Despite an overall increase in global food supply, food insecurity and malnutrition remain persistent challenges. In 2021, an estimated 828 million people were undernourished worldwide (FAO et al., 2022), while 45 million children suffered from acute malnutrition in 2022, with a substantial proportion of cases being severe (Noel et al., 2024). These trends highlight the difficulty of achieving Sustainable Development Goal 2, which aims to ensure universal access to safe, nutritious, and sufficient food. A growing body of evidence suggests that limited economic access to healthy foods is a key driver of both food insecurity and malnutrition (Ganpule et al., 2023; Headey et al., 2023).

The urban dimension of food insecurity deserves particular attention. With more than half of the global population now residing in urban areas and Sub-Saharan African urban populations projected to nearly triple by 2050 (United Nations, 2025), the structural vulnerability of urban food systems to economic shocks warrants closer attention. However, much of the food security literature has focused on rural settings or on aggregate national analyses, leaving urban households relatively underexamined (Crush and Riley, 2018). Urban households are particularly exposed to food market disruptions because they rely almost entirely on market purchases for food provisioning, lack

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subsistence buffers, and face high transportation and storage costs (Laborde et al., 2021; Onyango et al., 2023). This vulnerability becomes especially acute during economic shocks that simultaneously erode incomes and inflate food prices.

The COVID-19 pandemic represented a major shock to household livelihoods and food systems, particularly in developing countries. While these countries typically face heightened food insecurity, the emergence of the COVID-19 pandemic jeopardized years of efforts and progress in combating hunger and poverty (World Bank, 2021). In Senegal, as in many other contexts, the pandemic occurred amid rapid dietary transitions and persistently high levels of food insecurity, affecting nearly 44% of the population (National Agency of Statistics and Demography [ANSD], 2021a). Following the first reported case in March 2020, the government implemented restrictive measures, including market closures, curfews, and mobility restrictions, to curb virus transmission (Diallo, 2024). These measures disrupted informal economic activities, reduced household incomes, and contributed to rising prices of staple foods such as rice, millet, and fish (ANSD, 2021b; Le Nestour et al., 2020).

These restrictions were particularly disruptive in urban areas, where high population density and widespread informality heightened households' exposure to income and food price shocks. Evidence from neighboring Mali indicates that urban households experienced larger increases in food insecurity during the pandemic than their rural counterparts (Adjognon et al., 2021). The Dakar region therefore provides a particularly relevant case study. With more than four million inhabitants concentrated within just 0.3% of Senegal's land area, Dakar is one of the most densely populated metropolitan areas in West Africa (United Nations, 2025). Despite a marked decline in poverty, from 26.1% in 2011 to 9.0% in 2018 (ANSD, 2021a), the region continues to face significant structural vulnerabilities. Nearly one-third of households (31.5%) live in overcrowded conditions, as measured by persons-per-room ratios (ANSD, 2024a), while 21% of households were food insecure in 2021 (ANSD, 2024b). These conditions make urban households in Dakar particularly vulnerable to disruptions in food access and purchasing power.

In response to the crisis, various policy measures were implemented, including emergency food aid, cash transfers, and food price subsidies (Diouf et al., 2022). While these interventions aimed to protect vulnerable households, assessing their effectiveness requires a deeper understanding of how households respond to changes in income and food prices. Notably, most existing studies focus on the ex-post impacts of COVID-19, documenting realized changes in food insecurity through high-frequency surveys or panel data (Rudin-Rush et al., 2022; Sassi and Trital, 2023), paying limited attention to households' pre-pandemic sensitivity to economic shocks, especially in urban settings where market dependence amplifies vulnerability (Laborde et al., 2021). A smaller strand of the literature has taken a more structural approach, combining demand systems with food security simulations using pre-shock behavioral parameters (Harttgen et al., 2016; Nechifor et al., 2021; Tekleselassie et al., 2024; Zhao et al., 2024). Most closely aligned with our setting, Ansah et al. (2025) simulated food price and income shock impacts on household food demand in Ghana. However, their analysis focused on demand composition responses rather than welfare and food security outcomes and did not examine a COVID-19-specific shock.

This study addresses this gap by examining urban household food consumption behavior in Dakar in the period preceding the pandemic and simulating the effects of COVID-19-related income and price shocks on food security. We combine primary data collected by the *Consortium pour la recherche économique et sociale (CRES)* in 2021 from 640 households with representative data from the 2018/19 Harmonized Survey on Household Living Conditions (EHCVM) through a statistical matching procedure. Further, we estimate a Quadratic Almost Ideal Demand System (QUAIDS) model with subgroup-specific elasticities, and embed these estimates in a microsimulation framework to disentangle income and price shock effects across six counterfactual scenarios.

The results reveal heterogeneous household responses to food price and income changes across the expenditure distribution, with the poorest urban households bearing a disproportionate share of the welfare losses. By integrating statistical matching, censored QUAIDS, and a microsimulation with a heterogeneous Engel transmission channel, the framework extends beyond previous studies that focus primarily on rural or national contexts and applies uniform transmission elasticities. The analysis further documents substantial substitution between income and price channels, providing evidence relevant for the design of targeted food security policies and for strengthening urban food system resilience in Senegal and comparable developing country cities.

The remainder of this article is organized as follows. Section 2 presents the conceptual framework. Section 3 describes the data and empirical strategy, including the statistical matching procedure, the estimation of the QUAIDS model, and the microsimulation implementation process. Section 4 reports results, including the assessment of the quality of the statistical matching, descriptive analysis, elasticity estimates, and microsimulation outcomes. Section 5 presents the discussion and conclusions, along with the associated policy implications.

2. Conceptual framework

The empirical analysis of household consumption behavior generally relies on an underlying theoretical model of consumer choice. While traditional demand theory assumes a representative utility-maximizing household facing a budget constraint, recent contributions suggest that standard empirical models of consumer behavior can accommodate multiple theoretical interpretations (Miljkovic and Effertz, 2010). In this study, we adopt the standard neoclassical framework of household consumption, embedded within a broader demand analysis framework that explicitly accounts for household heterogeneity (Deaton, 1986).

Households are assumed to allocate their resources rationally subject to a budget constraint, first deciding how much to spend on food versus non-food items, and subsequently distributing their food budget across different food categories (Nsabimana, 2024). This hierarchical decision process is consistent with Engel's law, which posits that the composition of household consumption varies systematically with income and household characteristics (Lewbel, 2008). In line with this perspective, we assume that as household income increases, basic physiological needs are met first before households diversify toward more nutrient-dense or preferred foods (Lavoie, 1994).

A key premise of our framework is that household sensitivity to income and price changes is not constant but depends on pre-existing consumption patterns, market access, and vulnerability. In normal times, households adjust their food consumption smoothly in response to marginal changes in prices and income. However, during covariate shocks such as the COVID-19 pandemic, these adjustments may become more constrained owing to liquidity restrictions, mobility limitations, and disruptions in food supply chains (Onyango et al., 2023). Understanding this baseline sensitivity before the pandemic is therefore essential for interpreting the observed impacts during the crisis. The use of pre-pandemic demand parameters to simulate shock impacts rests on the assumption that structural preferences and substitution patterns are sufficiently stable over short horizons to serve as valid counterfactual benchmarks. Under this assumption, observed post-shock welfare changes can be attributed to the magnitude of the shock rather than to changes in underlying preferences.

Given the urban focus of this study, we explicitly consider the role of market dependence. Urban households are typically more reliant on purchased food and less able to substitute with own-production compared to rural households (Crush and Riley, 2018; Headey and Alderman, 2019). Moreover, lockdown measures and movement restrictions were more stringent in cities, amplifying the potential impact of both income and price shocks. This motivates our empirical focus on urban households and justifies the relevance of a market-based demand model. We further distinguish between two channels through which the

pandemic may have affected food security: (i) an income effect, driven by job losses, reduced remittances, and lower earnings; and (ii) a price effect, stemming from disruptions in transportation, market closures, and supply constraints that increased food prices.

Regarding the income channel, Diallo and Ndongo (2022) documented that informal food sector workers in Dakar experienced a decline of over 40% in their daily revenues during the restrictive periods of 2020. Simultaneously, remittances from Senegalese migrants decreased by 30% (UNDP, 2020). Concerning the price channel, more than a quarter (28.2%) of Dakar residents reported rice price increases during the first month of curfew (Le Nestour et al., 2020). The food prices increased by 3.3%, driven particularly by staples such as millet (12.4%), rice (9.6%), and fish (12.6%) (ANSD, 2021b). The simultaneous effect of declining incomes and rising food prices thus created conditions that were likely to expose households to heightened food insecurity risk.

To apply this framework, we estimate a QUAIDS model which allows for flexible Engel curves and accommodates nonlinearities in the relationship between income and food demand (Banks et al., 1997). Unlike much of the existing literature on food demand in Senegal (Gueye and Sene, 2024; Marivoet et al., 2021), our approach explicitly addresses three key econometric challenges: (i) the aggregation of unit values into community-level prices, (ii) the potential endogeneity of total food expenditure, and (iii) the possible censoring of household food expenditures owing to zero consumption in certain food categories. Further, we implement a microsimulation exercise to capture how pre-existing consumption patterns and demand sensitivities shape household responses to these shocks.

3. Data and methods

3.1. Data

The analysis relies on two complementary household surveys conducted in the Dakar region, namely the CRES/COVID-19 survey (2021) and the EHCVM 2018/19. The combined datasets enable us to analyze household food demand before the pandemic while assessing the sensitivity of households to income and price shocks during the COVID-19 crisis. The CRES/COVID-19 survey was conducted between February and March 2021 as part of a multi-country research project funded by the International Development Research Centre on the resilience of the informal food economy in Sub-Saharan Africa. The survey covers 640 households in the Dakar region and is based on a two-stage stratified random sampling design that uses the 2013 Population Census as a sampling frame. First, 64 census enumeration districts (DR) were selected with probability proportional to size. A full household listing was then conducted to update the roster of households within each selected DR. Second, 10 households per DR were randomly drawn, yielding a final sample of 640 households.

The questionnaire includes modules on household socio-demographic characteristics, housing conditions, employment and income dynamics, food security, and coping strategies during the pandemic. Table 1 reports the descriptive statistics of the sample. The average household size is 8.77 persons, and 63% of households are headed by men. Approximately 40% of household heads have no formal education, while only 10% have completed higher education, reflecting the socioeconomic heterogeneity of the Dakar urban population. Notably, the survey provides information on total household income and aggregate food expenditure but does not contain detailed data on quantities, prices, and expenditures by specific food items—information that is essential for estimating a demand system.

To overcome this limitation, we use the EHCVM 2018/19 survey conducted by the ANSD, which provides detailed data on household consumption, including quantities, expenditures, and unit values for a wide range of food items (ANSD, 2021a). The EHCVM 2018/19 was nationally and regionally representative and was conducted using a two-stage stratified sampling design based on the same census frame as the CRES/COVID-19 survey. Conducted prior to the COVID-19 pandemic, the EHCVM 2018/19 covers 1,020 households in the Dakar region. Thus, it serves as a benchmark for pre-crisis consumption patterns and enables the estimation of baseline food demand parameters.

Table 1
Descriptive statistics.

Variable	CRES/COVID-19 (n = 640)		EHCVM 2018/19 (n = 1020)	
	Mean	Std. Dev.	Mean	Std. Dev.
Household head characteristics				
Gender (male = 1)	0.63	0.48	0.66	0.47
Age (years)	54.24	14.44	52.30	14.10
Marital status (married = 1)	0.80	0.40	0.74	0.44
Occupation (yes = 1)	0.77	0.42	0.70	0.46
Education level				
No education	0.40	0.49	0.39	0.49
Primary	0.24	0.43	0.22	0.41
Secondary	0.26	0.44	0.23	0.42
Higher education	0.10	0.30	0.16	0.36
Household characteristics				
Household size	8.77	4.78	6.97	4.93
Children in the household (yes = 1)	0.53	0.50	0.49	0.50
Housing tenure status (renter = 1)	0.37	0.48	0.42	0.49
District				
Dakar	0.45	0.50	0.37	0.48
Pikine	0.35	0.48	0.36	0.48
Rufisque	0.11	0.32	0.18	0.38
Guediawaye	0.09	0.29	0.09	0.29
Expenditure quintile				
Poorest	0.20	0.40	0.20	0.40
Poor	0.20	0.40	0.20	0.40
Middle	0.20	0.40	0.20	0.40
Rich	0.20	0.40	0.20	0.40
Wealthiest	0.20	0.40	0.20	0.40

Notes: Binary variables are coded 0/1. Education categories are mutually exclusive and exhaustive. Expenditure quintiles are based on total household expenditure. All descriptive statistics are weighted using the survey sampling weights.
Source: Authors' calculations based on CRES/COVID-19 and EHCVM 2018/19 databases.

3.2. Statistical matching of datasets

Since neither dataset solely contains all the necessary information for the analysis, we employ a statistical matching procedure to combine them. Statistical matching is a widely used technique that integrates information from two independent surveys that share common variables but contain different sets of key outcomes (D'Orazio et al., 2006; Endres and Augustin, 2016; Kum and Masterson, 2010).

Within the context of the study, the CRES/COVID-19 survey serves as the recipient file, while the EHCVM 2018/19 serves as the donor file. The matching relies on a set of common household characteristics, including gender, age, education of the household head, household size, housing tenure status, socio-economic status, and geographic location. We implement a propensity score matching approach, which is a standard method in statistical matching owing to its ability to balance large sets of covariates across datasets (Kum and Masterson, 2010; Lewaa et al., 2021). A logistic regression is estimated where the dependent variable indicates whether a household belongs to the recipient (CRES/COVID-19) or donor (EHCVM 2018/19) dataset, and the independent variables consist of the common covariates.

As illustrated in Fig. 1, statistical matching relies on the Conditional

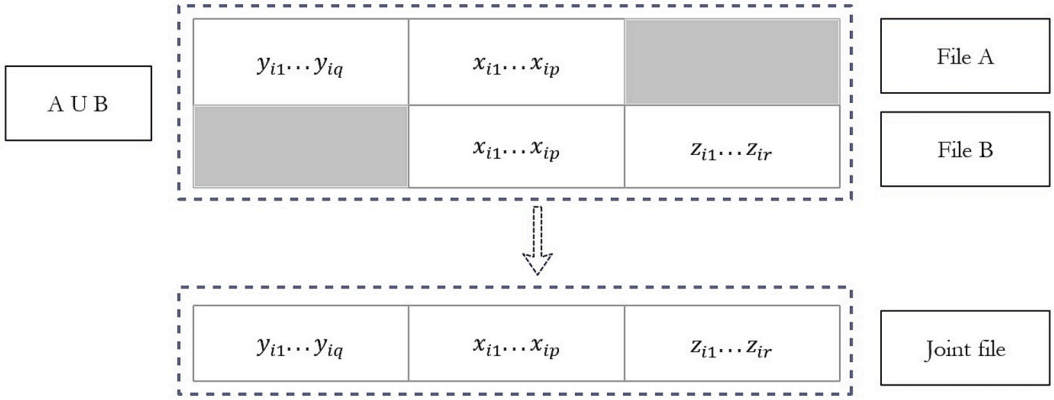


Fig. 1. Schematic representation of the principle of statistical matching.
Source: Adapted from Endres and Augustin (2016).

Independence Assumption between Y and Z conditional on X(Lewaa et al., 2021). That is, variable X is assumed to be the only source of association between the information contained in datasets A and B. More specifically, the conditional independence assumption implies that the joint probability density function of X, Y, and Z can be factorized as follows:

$$f(x,y,z) = f(y,z|x)f(x) = f(y|x)f(z|x)f(x) \quad (1)$$

where $f_{Y|X}$ denotes the conditional distribution of Y given X, $f_{Z|X}$ represents the conditional distribution of Z given X, and f_X is the marginal distribution of X. Datasets A and B provide the necessary information to estimate this relationship, particularly the marginal distribution of X, as well as the conditional relationships between X and Y, on the one hand, and between X and Z, on the other (D'Orazio et al., 2006).

To implement the matching, we first harmonize the sampling weights across datasets. As the two surveys were conducted in different years, their population totals differ: the EHCVM 2018/19 sample represents approximately 3.7 million individuals in the Dakar region, against 4.1 million for the CRES/COVID-19 2021 sample. The inverse cumulative distribution function (CDF) procedure of Kum and Masterson (2010) maps each recipient onto the donor occupying the same weighted quantile position within the matching cell.[1] To preserve quantile equivalence between the two distributions, the donor and recipient cumulative distributions must attain the same total weighted mass. Therefore, we rescale the EHCVM 2018/19 household weights by a single multiplicative factor equal to the ratio of the sum of CRES/COVID-19 weights to the sum of EHCVM weights. Matching is then based on seven common household-level variables observed in both surveys, namely gender, age group, and education level of the household head, household size, housing tenure status, department of residence, and total expenditure quintile.

To improve match quality, we adopt a two-step stratified scheme. At Step 1, donors and recipients are stratified jointly by the intersection of department and total expenditure quintile ($4 \times 5 = 20$ cells), such that each recipient is matched only to donors residing in the same department and the same quintile. Recipients in cells with insufficient donor coverage are forwarded to Step 2, where the stratification is relaxed by pooling the three peripheral departments (Pikine, Rufisque, and Guediawaye) into a single stratum while maintaining Dakar as a separate entity (10 cells). Within each non-empty cell, we estimate a cell-specific propensity score by logistic regression of survey membership on the seven matching variables, then apply the inverse-CDF algorithm with replacement.

Match quality is assessed through three complementary diagnostics. First, we test the joint distribution of the seven matching variables between the EHCVM 2018/19 and matched samples using Pearson χ^2 tests (Table A1). Second, we compare the distributional properties of total food expenditure across the two datasets using the Gini coefficient, interquantile ratios, the Kolmogorov-Smirnov test, and the Wilcoxon-Mann-Whitney rank-sum test (Table A2). Third, we examine mean food expenditure ratios across the seven covariables at the cell level (Table A3) to ensure that the matched dataset preserves the key distributional characteristics of the EHCVM 2018/19 donor file.

3.3. QUAIDS model

Originally introduced by Deaton and Muellbauer (1980a), the Almost Ideal Demand System (AIDS) model treats aggregate consumer behavior as the outcome of a single utility-maximizing consumer. While this model gained popularity in the 1990s, its quadratic form (QUAIDS) was developed by Banks et al. (1997) to increase flexibility and allow demand curves to be nonlinear in the logarithm of income and Engel curves. Moreover, the QUAIDS model is a structural utility-based model that captures individual behavior in response to prices, particularly uncompensated demand that maximizes utility given prices and income (Caro et al., 2017). Since its inception, the QUAIDS model has achieved international recognition, and a number of economists have widely applied it to study demand systems, particularly to assess household sensitivity to changes in prices and income (Caro et al., 2017; Nsabimana, 2024).

3.3.1. Analytical framework of the QUAIDS model

The model assumes that a household faces demand for a set K of goods, given a fixed budget m, representing either income or expenditures allocated to these goods. The QUAIDS model developed by Banks et al. (1997) is based on the following indirect utility function:

$$\ln V(p,m) = \left[\left(\frac{\ln m - \ln a(p)}{b(p)}\right)^{-1} + \lambda(p)\right]^{-1} \quad (2)$$

where $\ln a(p)$ denotes the translog price aggregator function defined as:

$$\ln a(p) = \alpha_0 + \sum_{i=1}^{K}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{K}\gamma_{ij}\ln p_i \ln p_j \quad (3)$$

where,

[1] The inverse-CDF algorithm of Kum and Masterson (2010) is a weighted variant of quantile-matching. Within each cell, donors and recipients are sorted by their propensity score, and weighted cumulative distribution functions F^D and F^R are constructed; recipient r_j with cumulative weight F_j^R is matched to the unique donor d_i satisfying $F_j^R \in (F_{i-1}^D, F_i^D)$. The procedure preserves the donor pool's weighted marginal distribution by construction and permits matching with replacement.

p_i represents the price of good $i(i = 1,\cdots,K)$. Further, $b(p)$ denotes the Cobb-Douglas price aggregator defined by:

$$b(p) = \prod_{i=1}^{K} p_i^{\beta_i} \tag{4}$$

and $\lambda(p)$ is a degree-zero homogeneous differentiable function of prices given by:

$$\lambda(p) = \sum_{i=1}^{K} \lambda_i \ln p_i \tag{5}$$

Let q_i denote the quantity of good i consumed by the household, and w_i its corresponding budget share, defined as $w_i = p_i q_i / m$. Applying Roy's (1943) identity to equation (2) yields the following budget share equation for good i:

$$w_i = \alpha_i + \sum_{j=1}^{K} \gamma_{ij} \ln p_j + \beta_i \ln\left(\frac{m}{a(p)}\right) + \frac{\lambda_i}{b(p)} \left[\ln\left(\frac{m}{a(p)}\right)\right]^2 i = 1,\cdots,K \tag{6}$$

When $\lambda_i = 0$, equation (6) reduces to the original AIDS specification proposed by Deaton and Muellbauer (1980a). To ensure consistency with demand theory, including adding-up condition, homogeneity property of degree zero in prices and income, and Slutsky symmetry conditions, the following parameter restrictions are imposed on the QUAIDS model:

$$\sum_i \alpha_i = 1, \sum_i \beta_i = 0, \sum_i \lambda_i = 0, \sum_i \gamma_{ij} = 0, \gamma_{ij} = \gamma_{ji}.$$

To account for household heterogeneity, socio-demographic variables, including gender, age, education level, marital status of the household head, household size, and area of residence (Ansah et al., 2020; Caro et al., 2017; Nsabimana, 2024) are incorporated into the QUAIDS model using the Ray (1983) method as parametrized by Poi (2012).

The expenditure function is decomposed as $e(p,z,\psi) = \overline{m_0}(z) \times \varphi(p,z,\psi) \times e^R(p,\psi)$, where $\psi = V(p,m)$ represents the household utility level. Additionally,

$$\overline{m_0}(z) = 1 + \rho' z \tag{7}$$

captures the increase in household expenditure owing to characteristics z, without considering changes in consumption habits and $\varphi(p,z,\psi)$ is defined as:

$$\ln\varphi(p,z,\psi) = \frac{\prod_{j=1}^{K} p_j^{\beta_j} \left(\prod_{j=1}^{K} p_j^{\eta_j' z} - 1\right)}{\frac{1}{\psi} - \sum_{j=1}^{K} \lambda_j \ln p_j} \tag{8}$$

This captures changes in relative prices and goods consumed, where ρ is a vector of parameters to be estimated, η_j denotes the j-th column of the $s \times K$ parameter matrix η and $c(p,z) = \prod_{j=1}^{K} p_j^{\eta_j' z}$ represents the demographic-price interaction term. Substituting these adjustments into equation (6) yields the QUAIDS budget share equation with demographics (Nsabimana, 2024; Poi, 2012), as follows:

$$w_i = \alpha_i + \sum_{j=1}^{K} \gamma_{ij} \ln p_j + (\beta_i + \eta_i' z) \ln\left(\frac{m}{\overline{m_0}(z) a(p)}\right) + \frac{\lambda_i}{b(p) c(p,z)} \left[\ln\left(\frac{m}{\overline{m_0}(z) a(p)}\right)\right]^2 \tag{9}$$

where the adding up restriction requires $\sum_{j=1}^{K} \eta_{kj} = 0$ for all $k = 1,\ldots,s$.

3.3.2. Estimation and aggregation of food prices

Household budget surveys do not directly provide prices for products purchased (Caro et al., 2017). Estimating prices as the ratio of expenditure to quantity consumed may introduce endogeneity, household-level heterogeneity, and measurement errors, leading to biased estimates (Deaton, 1988). To mitigate this issue, we follow Cox and Wohlgenant (1986) by estimating unit prices at a sufficiently low level of aggregation such that individual households cannot influence observed prices (Caro et al., 2017; Zhao et al., 2024). First, we estimate by Ordinary Least Squares (OLS) a pooled regression of log unit values on food group fixed effects, log quantity, household head characteristics, household composition, and department fixed effects.

$$\ln(uv_{h,k}) = \alpha_k + \beta \ln(q_{h,k}) + X_h' \gamma + F_d + \varepsilon_{h,k} \tag{10}$$

where $\ln(uv_{h,k})$ denotes the log unit value paid by household h for food group k per standard unit, α_k represents a food-group fixed effect, $\beta \ln\left(q_{h,k}\right)$ absorbs quantity-quality bias (Cox and Wohlgenant, 1986), X_h dontes a vector of household head characteristics (age, gender, education, and working status) and household composition (size, and presence of children under five), F_d is a department fixed effect, and $\varepsilon_{h,k}$ is the residual. Standard errors are clustered at the census DR level. The first-stage results appear in Table A6 of the Appendix. Second, we compute the predicted unit value for each household and apply the Duan (1983) smearing factor to correct for the retransformation bias from the logarithmic scale.

$$\widehat{p}_{h,k} = \exp(\widehat{\alpha}_k + \widehat{\beta} \ln(q_{h,k}) + X_h' \widehat{\gamma} + \widehat{F}_d) \times \widehat{\varphi} \tag{11}$$

with $\widehat{\varphi} = (1/N) \sum_h \exp(\widehat{\varepsilon}_{h,k})$. In our sample, $\widehat{\varphi} = 1.059$, indicating a non-negligible retransformation bias. Third, the predicted prices are aggregated at the DR level by simple mean within each food group.

$$\widehat{p}_k^g = \frac{1}{N_g} \sum\nolimits_{h \in g} \widehat{p}_{h,k} \tag{12}$$

where N_g denotes the number of households in DR_g consuming food group k. This aggregation assumes that households within the same DR face a homogeneous price environment, consistent with the urban context of our study and established practice in the food demand literature (Caro et al., 2017; Zhao et al., 2024). The resulting cluster-level price vector $(\widehat{p}_1^g, \widehat{p}_2^g, \cdots, \widehat{p}_{11}^g)$ is used as the price input in the QUAIDS estimation.

3.3.3. Endogeneity of total expenditures and censoring

The QUAIDS model faces two key challenges. First, there is potential endogeneity of total expenditures, which arises because budget shares w_i and total food expenditure m are determined simultaneously (Caro et al., 2017). Second, censoring occurs when households report zero expenditure on certain goods owing to non-preference, financial constraints, unavailability, or infrequent purchases (Caro et al., 2017; Nsabimana, 2024).

To address expenditure endogeneity, we use a control function approach (Blundell and Robin, 1999) in which the total food expenditure is first regressed on log of total non-food expenditure and household characteristics including gender, age, and education of the household head, household size, and department fixed effects (Poi, 2012; Vorsah et al., 2026). The first-stage residual is then included as an additional regressor in the budget share equations. Table A7 reports the estimated total food expenditure equation, where log non-food expenditure enters with a coefficient of 0.744 ($p < 0.01$) and an F-statistic of 196.81, well above the weak-instrument threshold of 10 reported by Stock and Yogo (2005).

Censoring is addressed using the two-step procedure developed by Shonkwiler and Yen (1999), which separates the household's decision to purchase a good from the expenditure conditional on a positive purchase. For each good i, the latent participation decision is given by:

$$D_i = 1(z'\theta_i > \nu_i) \tag{13}$$

where $z'\theta_i = \sum_{j \in K} \tau_{i,j} \ln p_j + \tau_{i,m} \ln m + \sum_{k \in K} \theta_{i,k} z_k$ represents the linear index of the first stage of probit for good i; $\tau_{i,j}$ denotes the coefficient on

$\ln p_j$; $\tau_{i,m}$ represents the coefficient on $\ln m$; $\theta_{i,k}$ is the coefficient on household characteristics (z_k); and ν_i denotes an error term. The observed budget share is $w_i = D_i \widetilde{w}_i$, where $\widetilde{w}_i$ is latent demand. The first stage is estimated via a probit model, and predicted values are used to generate cumulative distribution $\Phi(z'\widehat{\theta}_i)$ and density $\phi(z'\widehat{\theta}_i)$ functions used in the second-stage QUAIDS estimation (Caro et al., 2021; Nsabimana, 2024).

Following Yen et al. (2003) and Caro et al. (2021), the adding-up restriction is relaxed at the estimation stage, as imposing it in the presence of censoring, where several expenditure shares may take zero values, could bias the estimated parameters. The predicted budget shares are subsequently normalized ex post for each household to restore the adding-up condition and ensure consistency with demand theory.

3.3.4. Estimation of expenditure and price elasticities

Elasticities measure the sensitivity of demand to expenditure and price changes. In the augmented QUAIDS model accounting for endogeneity and censoring (Caro et al., 2017; Nsabimana, 2024), they are obtained by differentiating the budget share equation (9) with respect to $\ln p_j$ and $\ln m$, following Caro et al. (2021).

Let $L^* = \ln m - \ln a(p) - \ln \overline{m_0}(z)$ denote the adjusted log-expenditure ratio and $\beta_i^z = \beta_i + \eta_i' z$ the demographic adjusted linear expenditure coefficient. The expenditure term (μ_i) for good i, obtained by differentiating equation (9) with respect to $\ln m$ is given by:

$$\mu_i = \beta_i^z + \frac{2\lambda_i}{b(p)c(p,z)} L^* \tag{14}$$

where the first term β_i^z captures the linear expenditure effect and the second captures the quadratic correction that makes Engel curves nonlinear in $\ln m$.

The expenditure elasticity (σ_i) is defined as follows:

$$\sigma_i = 1 + \frac{1}{w_i^*}\left[\Phi_i \mu_i + \theta_{i,m}\phi_i \times (w_i - \delta_i z'\widehat{\theta}_i)\right] \tag{15}$$

where w_i denotes the observed mean budget share; $\Phi_i = \Phi(z'\widehat{\theta}_i)$ and $\phi_i = \phi(z'\widehat{\theta}_i)$ are the mean cumulative distribution and density functions obtained from the first-stage probit in equation (13), with $z'\widehat{\theta}_i$ representing the mean linear index; $w_i^* = w_i^0\Phi_i + \delta_i\phi_i$ denotes the censoring-corrected predicted share, where w_i^0 denotes equation (9) evaluated at the sample mean before any censoring adjustment; and δ_i is the censoring parameter.

For the price effect, μ_{ij} denotes the uncensored price term obtained by differentiating equation (9) with respect to $\ln p_j$, as follows:

$$\mu_{ij} = \gamma_{ij} - \mu_i\left(\alpha_j + \sum\nolimits_k \gamma_{jk}\ln p_k\right) - \frac{\beta_j^z \lambda_i}{b(p)c(p,z)}(L^*)^2 \tag{16}$$

The price elasticity of good i with respect to the price of good j is given by:

$$e_{ij} = -\delta_{ij} + \frac{1}{w_i^*}\left[\Phi_i \mu_{ij} + \theta_{i,j}\phi_i \times (w_i - \delta_i z'\widehat{\theta}_i)\right] \tag{17}$$

where δ_{ij} is the Kronecker delta, with $\delta_{ij} = 1$ if $i = j$, and 0 otherwise.

As $\Phi_i \to 1$ and $\phi_i \to 0, w_i^* \to w_i^0$ and the censoring corrections, vanish, equations (15) and (17) reduce to $\sigma_i = 1 + \frac{\mu_i}{w_i^0}$ and $e_{ij} = -\delta_{ij} + \frac{\mu_{ij}}{w_i^0}$, respectively—the standard uncensored QUAIDS elasticity formulas of Poi (2012).

3.3.5. Implementation strategy

To estimate the augmented QUAIDS model, we first construct 11 food groups by aggregating the corresponding food products. Weekly household expenditures and quantities are aggregated within each group. Prices are derived from expenditures and quantities. Non-standard units reported in the survey are converted to grams to ensure comparability across products. For each household, group-level prices are calculated as a quantity-weighted average of the unit prices of the constituent products, with quantities consumed in grams used as weights. Unit price regressions controlling for socio-demographic characteristics are then used to obtain cluster-level food prices. Total expenditure endogeneity is addressed as described in Section 3.3.3, by including the first-stage residual as an additional regressor in the budget share equations. Finally, the censored QUAIDS is estimated simultaneously using the *quaidsce* command in Stata 16 (Caro et al., 2021). Initialization of α_0 followed Deaton and Muellbauer (1980b), Banks et al. (1997), and Poi (2012), setting $\alpha_0 = 10 < \min(\ln m)$.

3.4. Microsimulation framework

Microsimulation is a technique used to capture the potential impacts of macroeconomic shocks on households and individuals. It allows for estimating the short-term effects of shocks or policy interventions on household behavior, particularly in the context of poverty, inequality, and food security, among others. This approach is especially valuable when survey data capturing the actual impact of shocks are unavailable (Li and O'Donoghue, 2013). Microsimulation has been widely used during the COVID-19 shock to evaluate its effects on employment, income, consumption, poverty, and food security (Zhao et al., 2024). Fig. 2 illustrates the linkages between the QUAIDS model and the microsimulation model in evaluating the pandemic's impact on household food security. In essence, the QUAIDS model provides the price and expenditure elasticities that, combined with the Engel transmission elasticity (Table A8), generate the income elasticities, which serve as inputs to the microsimulation.

Since the QUAIDS model provides expenditure elasticities, we first convert them into income elasticities by applying the Engel transmission rule specified by Zhao et al. (2024), as follows:

$$\sigma_{i,g}^Y = \sigma_{i,g} \times \widehat{\eta}_{M,Y,g} \tag{18}$$

where $\widehat{\eta}_{M,Y,g}$ represents the food-expenditure-to-income transmission elasticity for subgroup g, estimated from the first-stage food expenditure equation. This conversion is applied separately for each expenditure subgroup $g \in \{B40, M20, T40\}$ to account for the well-documented heterogeneity of the Engel relationship across income levels (Banks et al., 1997). Using total household expenditure as the welfare proxy for income, we estimate $\widehat{\eta}_{M,Y,g}$ using within-household first-difference regressions that exploit the availability of both food expenditure and total consumption expenditure data before the COVID-19 outbreak and during the restriction period (Table A2, columns 2–4). The estimated transmission elasticities decline monotonically across expenditure subgroups: $\widehat{\eta}_{M,Y,B40} = 0.687$, $\widehat{\eta}_{M,Y,M20} = 0.662$, and $\widehat{\eta}_{M,Y,T40} = 0.605$, with the pooled estimate at 0.645 (column 1). This monotonic pattern empirically confirms Engel's law, whereby poorer households, who allocate a larger share of their budget to food, transmit total expenditure shocks more strongly to food expenditure, while wealthier households protect food consumption by adjusting non-food expenditure first.

The simulation begins with an initial level of household consumption and determines the household's new consumption following changes in prices and income. Using the notation of Ecker and Pauw (2024), the simulated consumption of household h for product group i, denoted by C_{hi}^1, is computed from the initial consumption C_{hi}^0, as follows:

$$C_{hi}^1 = C_{hi}^0 + \widehat{C}_{hi}^0\left(\sigma_i^Y . dM_h + \sum_{ij} e_{hij}^p . dp_k\right), k \in i \text{ and } k \in j \tag{19}$$

where C_{hi}^0 is the initial consumption reported in the household survey, σ_i^Y represents the income elasticity for group i, $\sum_{ij} e_{hij}^p$ denotes the house-

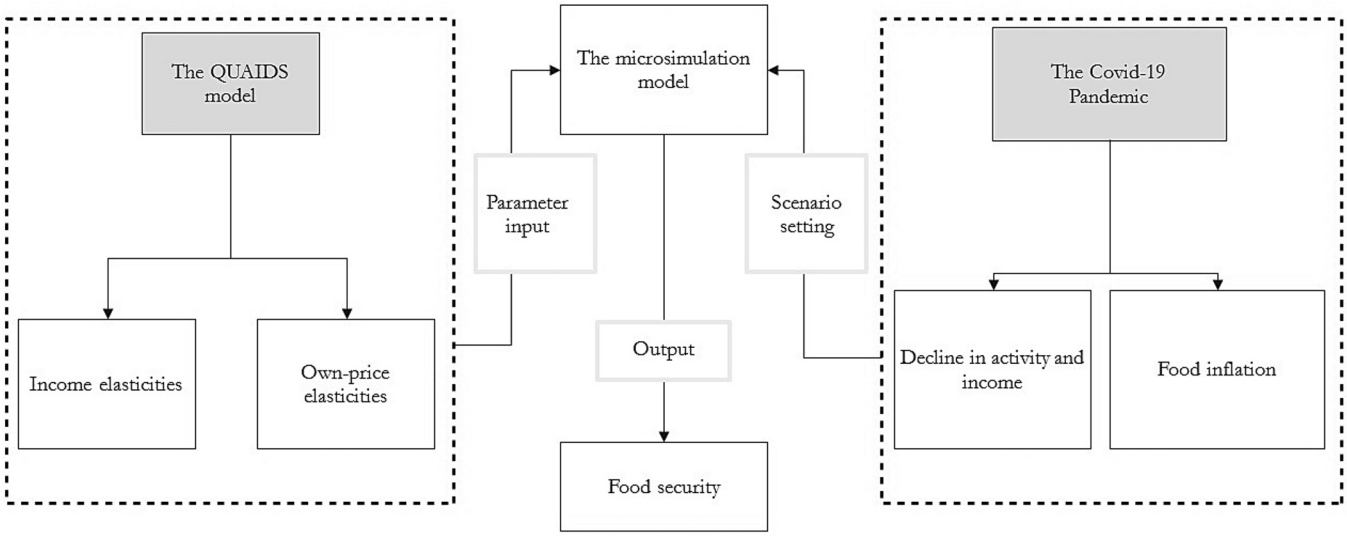


Fig. 2. Microsimulation model.
Source: Adapted from Zhao et al. (2024).

hold's price elasticity matrix, with e^p_{hii} as the own-price elasticity and $e^p_{hij}(i \neq j)$ as cross-price elasticities. dM_h represents the simulated percentage change in household income, and dp_k is the percentage change in the price of product group k. This formulation separates the effect of income changes, $\widehat{C}^0_{hi}.\sigma^Y_i.dM_h$, from the effect of price changes, $\widehat{C}^0_{hi} \times \sum_{ij} e^p_{hij}.dp_k$.

A standard approach in simulation analysis is to apply changes in income and/or prices and the corresponding elasticities to initial consumption quantities C^0_{hi}. However, censoring issues arise owing to zero consumption during survey recall periods (Zhao et al., 2024). To account for censoring, we introduce a latent consumption quantity $\widehat{C}^0_{hi}$, representing expected consumption based on household demographic and socio-economic characteristics. Empirically, a probit model is estimated for each product group i to predict the inverse Mills ratio. This is subsequently incorporated in the second stage of a linear model where the dependent variable is the observed consumption quantity. The predicted value from this linear specification corresponds to $\widehat{C}^0_{hi}$.

3.5. Measurement of food security and simulation scenarios

Food security in this study is measured using three core indicators, namely, quantity of food consumption, dietary patterns, and total individual energy intake. Two data limitations affect the interpretation of these estimates. Recall bias in weekly food quantity reporting (Beegle et al., 2012) and the exclusion of food consumed away from home (28.2% of total food expenditure, Table A4) from caloric intake calculations may lead to a moderate underestimation of baseline food security rates. Both limitations are common to household surveys in Sub-Saharan Africa and do not affect the internal consistency of the simulation results, expressed as changes relative to the same baseline.

Total individual energy intake is emphasized for its direct link to health outcomes and malnutrition risk, particularly in vulnerable contexts (Afshin et al., 2019). Dietary patterns complement this by revealing the calorie composition of consumed foods, while the quantity of food consumption informs both energy intake and dietary patterns (Ecker and Pauw, 2024; Zhao et al., 2024). Individual energy intake is derived by multiplying consumed food quantities by their energy content from the Food and Agriculture Organization of the United Nations (FAO) West African food composition table (Vincent et al., 2020). Household adult equivalents (AE) are computed to adjust for household size and composition, following FAO methodology, enabling meaningful cross-household comparisons. Globally, the EAT-Lancet reference diet recommends a daily intake of 2,500 kcal per adult equivalent (kcal/AE/day) as a healthy standard for an average adult (Ecker and Pauw, 2024). However, daily caloric requirements vary across contexts, with many countries establishing national guidelines reflecting cultural preferences and dietary environments. In Senegal, a threshold of 2,300 kcal/AE/day is adopted as the reference for food consumption (ANSD, 2021a). Therefore, households exceeding the 2,300 kcal/AE/day threshold are considered food secure, while those below it are classified as food insecure.

While caloric adequacy captures the quantitative dimension of food security, it does not account for nutritional imbalances across food groups that may persist even when energy thresholds are met. To capture the qualitative dimension of food security, we complement the caloric indicator with the Resilient Diet Deprivation (ReDD) index, a composite measure of overall diet quality analogous to the adjusted poverty gap in multidimensional poverty analysis (Alkire and Foster, 2011; Pauw et al., 2023). The index is constructed over the six nutritionally required food groups of the EAT-Lancet reference diet, including starchy staples, legumes, vegetables, animal-source foods, fruits, and dairy products, while excluding added sugars and beverages as non-required foods (Pauw et al., 2023; Willett et al., 2019). A household is diet-deprived if its per adult-equivalent intake falls below the EAT-Lancet benchmark in at least one food group. ReDD combines three components, namely incidence (H), breadth (A), and depth (G) into a single multiplicative index (ReDD = H × A × G). The incidence (H) is the share of the population that is diet-deprived, breadth (A) denotes the average number of food group deprivations as a share of total food groups among diet-deprived households, and depth (G) represents the average relative caloric gap between observed and reference intakes across deprived households and deprived food groups (Ecker and Pauw, 2024; Pauw et al., 2023). The index can further be decomposed to identify the contribution of each food group to overall diet deprivation. Within the microsimulation framework, income and price shocks translate into changes in food quantities and caloric intakes by food group, allowing counterfactual ReDD values to be computed under each scenario and compared with the baseline.

The simulation considers three income contractions combined with two price scenarios (Table 2). The three income contraction scenarios are anchored in the empirical evidence on income losses documented in Senegal during the COVID-19 episode. The lower-bound scenario (R20)

Table 2
Simulated scenarios and their transmission to food expenditure by household subgroup.

Scenario	ΔY (%)	ΔP (%)	ΔM (%)Bottom 40% ($\hat{\eta}_{B40} = 0.687$)	ΔM (%)Middle 20% ($\hat{\eta}_{M20} = 0.662$)	ΔM (%)Top 40% ($\hat{\eta}_{T40} = 0.605$)
R20 + P1	−20	+3.3 (uniform)	−13.7	−13.2	−12.1
R20 + P2	−20	Variable [a]	−13.7	−13.2	−12.1
R30 + P1	−30	+3.3 (uniform)	−20.6	−19.9	−18.2
R30 + P2	−30	Variable [a]	−20.6	−19.9	−18.2
R40 + P1	−40	+3.3 (uniform)	−27.5	−26.5	−24.2
R40 + P2	−40	Variable [a]	−27.5	−26.5	−24.2

Notes: Variable price increases by food group (P2): cereals (+10%), tubers (+6%), legumes (+5%), vegetables (+7%), meat/fish (+10%), fruits (+5%), dairy (+5%), oils (+5%), sugar (+5%), other (+2%), beverages (+3%) (ANSD, 2021b).
Source: Authors' calculations based on the CRES/COVID-19 2021 data.

assumes a 20% income reduction, representing the average shock for moderately affected households with diversified income sources in urban Dakar. The central scenario (R30) applies a 30% income contraction, calibrated on the documented decline in remittances from Senegalese migrants during 2020 (UNDP, 2020), an important income source for urban households in Dakar. The upper-bound scenario (R40) assumes a 40% income decline, reflecting the income shock experienced by informal food sector workers in Dakar, who experienced a decline in their daily revenues by over 40% during the restrictive periods of 2020 (Diallo and Ndongo, 2022). This range captures the heterogeneous income-loss experiences across Dakar households, from moderately to severely affected.

On the price side, scenario P1 applies a uniform 3.3% price increase across all food groups, consistent with the average food consumer price inflation rate observed in Senegal during 2020 (ANSD, 2021b). Scenario P2 applies differentiated price increases by food group, reflecting the heterogeneous price pressures documented during the restriction period: cereals (10%, driven by millet at 12.4% and rice at 9.6%), tubers (6%), legumes (5%), vegetables (7%), meat and fish (10%, driven by fish at 12.6%), fruits (5%), dairy (5%), oils (5%), sugar (5%), other foods (2%), and beverages (3%) (ANSD, 2021b). These differentiated increases are corroborated by survey evidence from Le Nestour et al. (2020), who report that 28.2% of Dakar residents experienced rice price increases during the first month of curfew. The combination of three income contractions and two price scenarios yields six counterfactual simulations (R20 + P1, R20 + P2, R30 + P1, R30 + P2, R40 + P1, and R40 + P2), allowing the joint assessment of demand-side and supply-side channels through which the COVID-19 shock affected food security in Dakar urban households.

4. Results

4.1. Assessment of the quality of the statistical matching

The two-step procedure achieves full coverage of the 640 recipient households. Step 1, based on the 20 strata defined by the intersection of administrative department and expenditure quintile, matches 571 recipients (89.2%) to donors drawn from the EHCVM 2018/19 sample. The remaining 69 recipients (10.8%) are matched at Step 2 under the relaxed stratification, with 10 cells defined by an indicator of residence in Dakar (versus the three peripheral departments) and expenditure quintile. The 640 matched recipients draw on 603 unique EHCVM donors (Table 3), reflecting the with-replacement structure of the inverse-CDF algorithm. Donor multiplicity remains moderate. Approximately 91.3% of recipient households are matched to a donor used by only one recipient. Additionally, no donor is used more than five times.

To assess the quality of the statistical matching, we combine statistical tests with graphical diagnostics. Table A1 reports Pearson χ^2 tests comparing the joint distribution of the seven matching variables across the two samples. Moreover, five of the seven variables, namely gender, age, education, household size, and expenditure quintile, exhibit no statistically significant difference at conventional levels, indicating that the matching preserves the joint covariate structure. Table A2 compares the distributional shape of monthly food expenditure across the original and matched datasets. The Gini index differs by only 0.002 between the two samples (0.320 versus 0.322), and the seven interquantile ratios are nearly identical, with the p50/p25 and p90/p50 ratios identical to two decimal places. Two non-parametric tests of distributional equality reinforce this finding. The Kolmogorov-Smirnov test yields $D = 0.020$ ($p = 0.997$), and the Wilcoxon-Mann-Whitney rank-sum test yields $z = 0.403$ ($p = 0.678$). Neither rejects the null of identical distributions.

Table 3
Number of matched households.

Number of neighbors	Number of households in matched database	Share of matched households (%)	Number of corresponding households in the EHCVM 2018/19 database
1	584	91.3	584
2	22	3.4	11
4	24	3.8	6
5	10	1.6	2
	640	100	603

Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A3 presents the ratios of mean food expenditures across the seven matching variables. The overall ratio is 99.6%, and all values fall within the 80–120% acceptable range (Rios-Avila, 2016), with the sole exception of the smallest household size class (121.3%). The ratios remain close to unity across all categories (98.4% for male-headed and 101.7% for female-headed households, 99.3% in the department of Dakar, and very close to unity across the five expenditure quintiles), confirming that the matched database preserves the underlying distribution of monthly food expenditure.

Figs. 3 and 4 corroborate these statistical diagnostics graphically. Fig. 3 presents the kernel density estimates of the logarithm of monthly food expenditure in the two samples. The two curves exhibit a near-identical shape, central tendency, and dispersion. Fig. 4 displays the empirical cumulative distribution functions, which overlap almost perfectly across the entire support. The negligible horizontal distance between the two CDFs further confirms that the matching procedure does not introduce systematic differences in the distribution of food expenditure.

4.2. Pre-pandemic urban food consumption patterns

Fig. 5 indicates that food expenditures account for 43% of total household spending. This reflects the continued predominance of basic subsistence needs and a relatively high level of economic vulnerability. The food budget share declines monotonically across expenditure quintiles, from 50.8% among the poorest households to 33.7% among the richest, in line with Engel's first law. As reported in Table A4, 71.8% of food expenditure is devoted to food consumed within the household, while 28.2% corresponds to food consumed outside the household. The

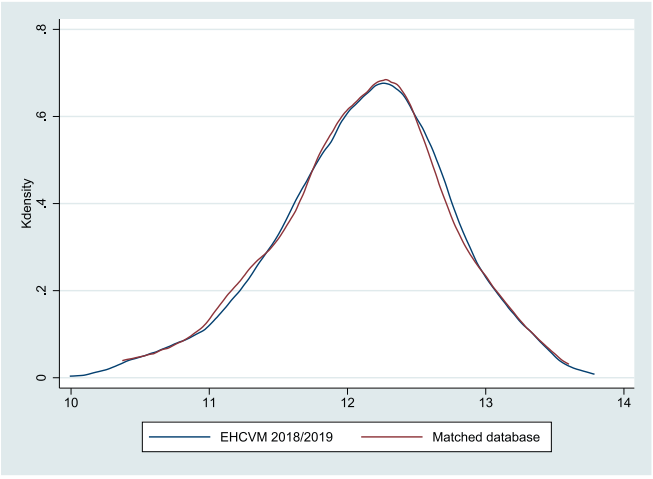


Fig. 3. Kernel density distribution of monthly food consumption expenditure before and after matching.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

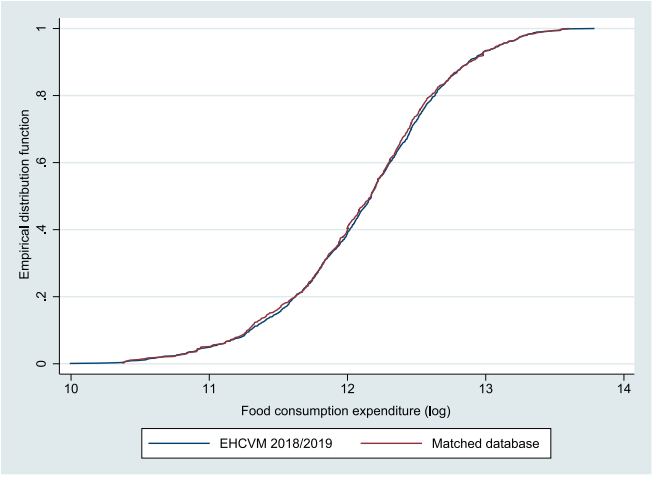


Fig. 4. Cumulative distribution of monthly food consumption expenditure before and after matching.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

share of out-of-home food expenditures ranges from 36.3% among the poorest households to 27.5% among the richest households.

Household food consumption was recorded using a weekly recall. Households reported purchases and quantities for 127 individual food items, which were aggregated into 11 food groups. Table 4 summarizes, for each group, the proportion of consuming households, average weekly expenditure, budget share, and average quantity consumed per adult equivalent. The participation rates in Table 4 reveal substantial heterogeneity across food groups. Sugar and confectionery (97.4%), cereals (95.3%), beverages (94.1%), dairy and eggs (93.3%), and oils and fats (92.1%) are consumed by virtually all households. Conversely, tubers and plantains (86.6%) and legumes and seeds (69.2%), both recommended in the EAT-Lancet reference diet, are less universally consumed.

The presence of zero-consumption households in 10 of the 11 food groups (only sugar falls below the 5% censoring threshold) justifies the censoring correction applied in the QUAIDS estimation. Across food groups, mean expenditure patterns reveal the central role of animal-source foods in Dakar's diet. Households spend the most on meat and

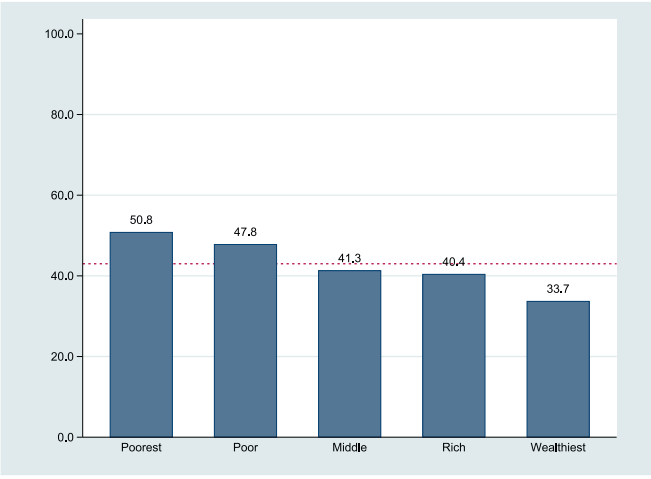


Fig. 5. Share of food expenditures in household budgets by total consumption expenditure quintiles.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

fish (2,261 XOF per week), followed by cereals (1,239 XOF), which translate into a 31% budget share for animal-source foods. In quantity terms, however, cereals dominate consumption at 1.89 kg per household per week, followed by meat, fish and seafood (1.24 kg) and vegetables (0.78 kg). Oils and fats average 0.41 kg per week, while legumes remain modest at less than 0.15 kg per household.

Beyond the descriptive consumption patterns documented in Table 4, we compare household dietary energy intake with the EAT-Lancet reference diet for a healthy and sustainable diet (Willett et al., 2019). Table 5 reports this comparison. Average daily caloric intake reaches 2,638 kcal per adult equivalent (AE), slightly above the EAT-Lancet benchmark of 2,500 kcal. Consumption of vegetables, dairy products, and animal-source proteins is broadly aligned with recommended levels. However, the dominance of cereals in household quantity consumption (1.89 kg per week) translates into an excessive share of starchy staples in total energy intake (47% versus 34% recommended), adding nearly 400 kcal above the reference. Oils and fats (23% versus 18%) and sugar (9% versus 5%) jointly contribute almost a third of total intake, well above the corresponding EAT-Lancet shares. Legumes and fruits remain markedly under-consumed, contributing only 3% and 1% of total calories against recommended levels of 23% and 5%.

Fig. 6 depicts how household food budget shares vary with income and reveals three distinct stages of dietary change. In the first stage, lower-income households prioritize caloric adequacy, with rising shares devoted to cereals, vegetables, fats, tubers, and animal-source foods. Over the same income range, the shares of fruits, dairy products, sugar, and beverages decline, likely reflecting household size constraints that favor inexpensive, energy-dense staples over more nutrient-rich foods. The second stage corresponds to a dietary transition in which households gradually diversify away from staple-dominated diets toward foods richer in micronutrients, particularly fruits and dairy products. This shift occurs when monthly per capita income ranges between 43,930 and 90,395 XOF, equivalent to 1.6–3.3 times the poverty line (27,783 XOF). In the third stage, higher-income households allocate smaller budget shares to staples and larger shares to more nutrient-dense foods. Nonetheless, budget shares for sugar and beverages also increase at higher income levels, which may heighten exposure to non-communicable disease risks such as diabetes, obesity, and hypertension (Afshin et al., 2019). However, the budget share of fruits and dairy remains slightly higher than that of sugar and beverages, potentially offsetting some of these risks among wealthier households. Fig. 6 further corroborates Bennett's law (1941). At low-income levels, households rely predominantly on staple foods cereals, tubers, fats, and vegetables.

Table 4
Weekly expenditure and average quantity consumed per adult equivalent.

Food groups	% of households consuming	Average weekly expenditure (XOF)	Share of total food expenditure (%)	Average quantity consumed (kg)
Cereals	95.3	1,239	18.1	1.89
Tubers and plantains	86.6	205	2.7	0.45
Legumes and seeds	69.2	131	1.4	0.13
Vegetables	90.8	1.024	14.2	0.78
Meat, fish and seafood	89.7	2,261	31.0	1.24
Fruits	88.4	359	4.8	0.45
Dairy products and eggs	93.3	596	8.5	0.29
Oils and fats	92.1	543	7.7	0.41
Sugar and confectionery	97.4	364	5.4	0.42
Beverages	94.1	417	6.0	0.05
Other foods	7.1	58	0.1	0.02

Notes: The per-adult-equivalent quantities are computed using the age and gender coefficients established by the West African Economic and Monetary Union (WAEMU) and the, as reported in Table A5.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table 5
Household caloric intake vs. EAT-Lancet reference.

Food groups	Household Intake (kcal/AE/day)	Share of Diet (%)	EAT-Lancet Reference (kcal/AE/day)	Share of Reference Diet (%)	Difference (kcal)	Difference (%)
Starchy staples	1,249	47	850	34	399	47
Legumes	68	3	575	23	−507	−88
Vegetables	100	4	78	3	22	29
Meat, fish and seafood	163	6	151	6	12	8
Fruits	25	1	126	5	−101	−80
Dairy	168	6	153	6	15	10
Oils and fats	614	23	447	18	167	37
Sugar	245	9	120	5	125	104
Beverages	6	0	0	0	6	–
Total energy intake kcal/AE/day)	2,638	100	2,500	100	138	6

Notes: The 11 QUAIDS food groups are recorded into 9 categories aligned with the EAT-Lancet reference diet (Willett et al., 2019). Starchy staples aggregate cereals and tubers/plantains. "Other foods" is excluded as it has no EAT-Lancet equivalent.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

As income rises, the budget share of staples initially increases more rapidly than that of animal-source foods. However, beyond an annual per capita income of 342,086 XOF (approximately 2.6% above the food poverty threshold of 333,400 XOF), expenditure on animal-source foods exceeds that on staple foods.

4.3. Urban food demand sensitivity before COVID-19

4.3.1. Results of QUAIDS model estimation

The estimated parameters of the QUAIDS model are reported in Tables A9–A11. Most parameters are statistically significant. The linear (β) and quadratic (λ) expenditure terms are significant for nine of the eleven food groups, indicating that budget shares are highly responsive to total food expenditure and that the Engel curves exhibit significant curvature. In most equations β and λ share the same sign, implying that the curvature accelerates monotonically with expenditure rather than reversing direction within the observed range. The censoring correction parameter (δ) is positive and significant at the 1% level in nine equations, confirming that the participation and expenditure decisions are positively correlated. Most own- and cross-price effects (γ_{ij}) are significant, with nine of the eleven own-price coefficients reaching conventional significance levels, confirming that demand responds to both own and relative prices.

Among demographic factors, age, gender, education, household size, and location significantly influence food demand. Male-headed households allocate larger budget shares to meat, fish, and dairy, and smaller shares to oils, fruits, and sugar, consistent with documented gender differences in dietary preferences in urban West Africa (Sylla and Diagne, 2026). Older household heads allocate slightly higher shares to cereals, sugar, and beverages, and slightly lower shares to meat. Higher education is associated with larger shares for meat and vegetables and a smaller share for oils. Larger households consume more cereals, tubers, and vegetables but less meat, fruits, sugar, and beverages, reflecting substitution toward cheaper, energy-dense foods as household size increases. Spatial differences relative to Dakar are modest, with Guediawaye households allocating higher shares to cereals and lower shares to beverages, while Rufisque households consume more meat and less sugar and oils. Additionally, significant first-stage residuals for all eleven food groups confirm the endogeneity of total food expenditure and the necessity of correcting for it in the demand model (Blundell and Robin, 1999), with the correlation parameter ($\rho = 0.944$, $p < 0.01$) further supporting the joint modelling of participation and expenditure decisions.

4.3.2. Expenditure and price elasticities of food demand

Table 6 presents the estimated mean expenditure and own-price elasticities for the 11 food groups. All expenditure elasticities are positive and statistically significant, indicating that all food categories are normal goods. The elasticities cluster tightly around unity, suggesting that a 10% increase in household expenditure leads to an approximately proportional increase in demand for most food groups. The largest expenditure responses are observed for beverages (1.029), meat, and fish and seafood (1.019), which behave as weak luxuries, while the smallest are observed for tubers and plantains (0.973) and sugar and confectionery (0.976), which behave as weak necessities. Cereals (0.982) lie just below unity, reflecting their centrality as staple foods, particularly rice, in Dakar's diet, consistent with their dominance in weekly consumption quantities.

With respect to own-price elasticities, two categories of food groups emerge. The first comprises price-inelastic goods, which includes cereals

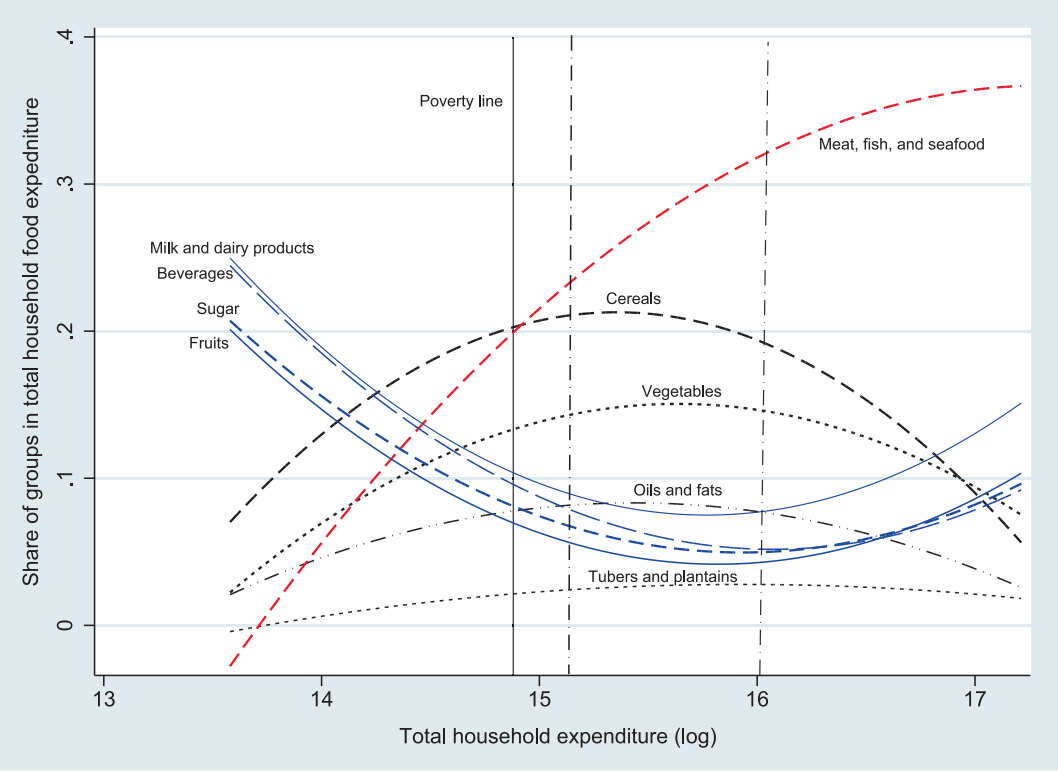


Fig. 6. Budget shares of food groups by household income. *Notes: The poverty line depicted here is calculated by multiplying the individual poverty threshold (333,400 XOF) by the average household size (8.77). The resulting threshold* ($\log = 14.88$) *is presented as a vertical reference line.*
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table 6
Expenditure and own-price elasticities.

Food group	Expenditure elasticities of demand					Own-price elasticities of demand				
	Overall	Bottom 40%	Top 40%	HH with no education	HH with at least primary	Overall	Bottom 40%	Top 40%	HH with no education	HH with at least primary
Cereals	0.982***	1.003***	0.940***	0.978***	0.960***	−0.931***	−0.879***	−0.954***	−0.879***	−0.867***
	(0.057)	(0.058)	(0.054)	(0.056)	(0.054)	(0.260)	(0.228)	(0.317)	(0.258)	(0.270)
Tubers and plantains	0.973***	0.967***	0.979***	0.974***	0.976***	−0.348***	−0.357***	−0.339***	−0.346***	−0.343***
	(0.044)	(0.046)	(0.041)	(0.043)	(0.042)	(0.099)	(0.101)	(0.099)	(0.099)	(0.100)
Legumes and seeds	1.000***	0.998***	1.002***	1.000***	1.001***	−1.046***	−1.048***	−1.044***	−1.046***	−1.045***
	(0.013)	(0.014)	(0.012)	(0.013)	(0.012)	(0.026)	(0.028)	(0.025)	(0.026)	(0.026)
Vegetables	0.983***	0.975***	0.995***	0.985***	0.988***	−1.204***	−1.273***	−1.141***	−1.200***	−1.201***
	(0.019)	(0.020)	(0.018)	(0.019)	(0.018)	(0.080)	(0.089)	(0.079)	(0.080)	(0.080)
Meat, fish and seafood	1.019***	1.011***	1.027***	1.018***	1.021***	−0.917***	−0.992***	−0.859***	−0.928***	−0.920***
	(0.007)	(0.005)	(0.008)	(0.006)	(0.007)	(0.106)	(0.076)	(0.142)	(0.100)	(0.109)
Fruits	0.983***	0.986***	0.982***	0.984***	0.983***	−0.944***	−0.946***	−0.944***	−0.945***	−0.945***
	(0.016)	(0.017)	(0.015)	(0.016)	(0.016)	(0.042)	(0.041)	(0.042)	(0.041)	(0.042)
Dairy products and eggs	0.992***	0.989***	1.001***	0.994***	0.998***	−1.213***	−1.211***	−1.224***	−1.213***	−1.222***
	(0.018)	(0.019)	(0.017)	(0.018)	(0.017)	(0.100)	(0.100)	(0.099)	(0.100)	(0.099)
Oils and fats	1.005***	1.005***	1.002***	1.003***	1.002***	−0.912***	−0.958***	−0.874***	−0.912***	−0.920***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.054)	(0.061)	(0.051)	(0.054)	(0.055)
Sugar and confectionery	0.976***	0.970***	0.994***	0.982***	0.988***	−0.927***	−0.922***	−0.932***	−0.923***	−0.927***
	(0.030)	(0.031)	(0.028)	(0.030)	(0.029)	(0.201)	(0.174)	(0.227)	(0.189)	(0.211)
Other foods	1.008***	1.009***	1.004***	1.007***	1.006***	−0.911***	−0.909***	−0.911***	−0.911***	−0.911***
	(0.022)	(0.022)	(0.020)	(0.021)	(0.020)	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)
Beverages	1.029***	1.021***	1.038***	1.031***	1.032***	−0.727***	−0.740***	−0.718***	−0.727***	−0.726***
	(0.016)	(0.016)	(0.014)	(0.015)	(0.015)	(0.050)	(0.049)	(0.049)	(0.050)	(0.048)

Notes: HH=Head of household, Standard errors are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

(−0.931), tubers and plantains (−0.348), meat, fish and seafood (−0.917), fruits (−0.944), oils and fats (−0.912), sugar (−0.927), other foods (−0.911), and beverages (−0.727). Demand for these goods is relatively unresponsive to price changes, with tubers and plantains being the least sensitive, as a 10% price increase reduces demand by only 3.5%. The second category consists of price-elastic goods, namely legumes and seeds (−1.046), vegetables (−1.204), and dairy products (−1.213). For these goods, a 10% price increase reduces demand by approximately 10.5% for legumes, 12% for vegetables, and 12.1% for dairy products. The price-elastic status of vegetables and dairy is consistent with their lower budget shares and their substitutability with cheaper, more energy-dense staples in the Dakar diet.

Heterogeneity across subgroups is modest, with the bottom 40% being slightly more expenditure-responsive for cereals (1.003 vs 0.940 for the top 40%) and more price-sensitive for meat (−0.992 vs −0.859), vegetables (−1.273 vs −1.141), and oils (−0.958 vs −0.874) than the top 40%, while elasticities across education subgroups remain essentially identical.

Table A12 presents the estimated cross-price elasticities. Positive values indicate substitutability between two goods, while negative values indicate complementarity. Complementarity is strongest between oils and fats and meat and fish, between tubers and plantains and vegetables, and between tubers and legumes, reflecting the composition of commonly consumed meals in Senegal. A further complementarity between sugar and oils likely captures their joint use in processed food products. Conversely, legumes and vegetables, as well as sugar and dairy products or fruits, exhibit substitutability, indicating potential shifts toward lower-cost, calorie-dense foods in response to price changes.

Tables A13a–A13d disaggregate the elasticity structure by expenditure quintile and education level. The qualitative pattern is preserved across all subgroups, but magnitudes differ systematically, with bottom 40% households exhibiting stronger reactions than top 40% households, particularly for the oils-meat complementarity and the vegetables-sugar substitution. Differences across education subgroups are minimal. The robustness of the qualitative structure across subgroups, combined with the stronger price reactions among bottom 40% households, supports the use of subgroup-specific elasticities in the microsimulation of the COVID-19 shock that follows.

4.4. Simulated effects of income and price shocks

The microsimulation assesses how changes in income and prices affect household food consumption and food security based on the estimated elasticities. Table 7 presents the simulated effects of the six combined income and price shocks on caloric intake and food security. The results indicate a substantial deterioration in both total energy intake and the proportion of food-secure households across all six counterfactual scenarios. Overall, average caloric intake declines from 2,638 kcal/AE/day at baseline to 2,194 kcal under R20 + P1 (−16.8%) and falls progressively to 1,695 kcal under R40 + P2 (−35.8%). The food security rate falls from 51.8% at baseline[2] to 22.4% under the most severe scenario (R40 + P2), corresponding to relative reductions ranging from 22.8% (R20 + P1) to 56.8% (R40 + P2). All declines are statistically significant at the 1% level.

Table 7
Simulated impacts of income and price shocks on caloric intake and food security.

Scenario	Caloric intake (kcal/AE/day)	Caloric intake (variation %)	Food security (%)	Food security (variation pts)	% change of Food security
Reference	2,638	—	51.8	—	—
R20 + P1	2,194	−16.8	40.0	−11.8***	−22.8
R20 + P2	2,026	−23.2	35.5	−16.3***	−31.5
R30 + P1	2,029	−23.1	35.4	−16.4***	−31.7
R30 + P2	1,860	−29.5	28.8	−23.0***	−44.4
R40 + P1	1,863	−29.4	29.0	−22.8***	−44.0
R40 + P2	1,695	−35.8	22.4	−29.4***	−56.8

Notes: Statistical significance of differences relative to the reference scenario is assessed using survey-adjusted Wald tests based on linearized standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

The simulations reveal a substantial independent effect of both the income and price channels. On the income side, each additional 10-percentage-point income contraction lowers caloric intake by approximately 6.3 percentage points under either price scenario. On the price side, switching from uniform (P1) to differentiated (P2) price increases lowers caloric intake by an additional 6.4 percentage points at every income level. Both increments are approximately equal in magnitude and reflect the additive structure of the simulation framework, in which income and price effects enter linearly with fixed elasticities. The six scenarios should therefore be read as a sensitivity analysis rather than as independent results.

However, the food security rate is not subject to the same mechanical property in either dimension as it depends non-linearly on the distribution of households around the 2,300 kcal/AE/day threshold. At the aggregate level, a 10-percentage point income contraction reduces the food security rate by 4.6 percentage points under P1 from R20 to R30 and by 6.4 percentage points from R30 to R40, while the effect of switching from P1 to P2 rises from 4.5 percentage points under R20 to 6.6 percentage points under R30 and R40.

Table 8 reports the heterogeneous impacts across socio-demographic subgroups under each of the six scenarios. The expenditure gradient reveals the expected vulnerability pattern, with the food security rate among Bottom 40% households falling from 50.9% at baseline to 17.9% under R40 + P2, compared with a decline from 52.6% to 26.5% for the Top 40%. Middle 20% households exhibit a trajectory similarly severe to the Bottom 40%, highlighting the broad-based vulnerability of non-affluent urban households. Gender disparities are modest but consistent, with female-headed households appearing slightly more resilient (−54.1% relative decline) than male-headed households (−58.7%). The education gradient is non-monotonic, with households headed by individuals with no formal education being the most severely affected (−67.2% relative decline), those with primary education being the most resilient (−40.5%), and households headed by individuals with secondary or higher education falling in between (−54.6%).

Table A14 confirms that the food security declines documented in Table 8 are statistically significant at the 1% level across virtually all socio-demographic subgroups and all six scenarios. The only exception is the modest decline observed under R20 + P1 for primary-educated households (−2.1 percentage points, significant only at the 10% level), consistent with the resilience pattern noted earlier. Overall, the simulations reveal substantial, widespread, and statistically significant declines in caloric adequacy and food security across all socio-demographic dimensions, with the steepest declines concentrated among the lowest expenditure quintile and households headed by individuals with no formal education.

4.5. Multidimensional dietary deprivation (ReDD)

Table 9 reports the ReDD estimates for the baseline and the effects of the simulated shocks. The baseline ReDD of 0.283 reflects substantial

[2] The 51.8% baseline food security rate is derived from a caloric adequacy threshold of 2,300 kcal/AE/day applied to the matched sample. However, this measure is not directly comparable to the Food Insecurity Experience Scale (FIES) based estimates cited in the introduction (44% nationally, ANSD, 2021a; 21% in Dakar, ANSD, 2024b), which capture self-reported food insecurity experience over a 12-month reference period and apply a different measurement approach.

Table 8
Heterogeneous effects on food security, by socio-demographic groups.

Group	Reference (%)	R20 + P1 (%)	R20 + P2 (%)	R30 + P1 (%)	R30 + P2 (%)	R40 + P1 (%)	R40 + P2 (%)	Δ R40 + P2 (%)
All households	51.8	40.0	35.5	35.4	28.8	29.0	22.4	−56.8
Male-headed	49.1	37.5	32.7	32.7	27.5	28.0	20.3	−58.7
Female-headed	55.8	43.6	39.8	39.3	30.6	30.6	25.6	−54.1
Bottom 40% (Q1 + Q2)	50.9	36.1	31.9	31.9	25.7	25.7	17.9	−64.8
Middle 20% (Q3)	51.3	43.1	37.3	37.3	27.6	28.8	18.5	−63.9
Top 40% (Q4 + Q5)	52.6	40.9	36.8	36.4	30.9	30.9	26.5	−49.6
No formal education	45.7	32.3	28.9	28.6	22.1	22.1	15.0	−67.2
Primary	45.7	43.5	37.1	37.1	29.7	30.8	27.2	−40.5
Secondary and above	64.3	47.9	43.3	43.3	37.2	37.2	29.2	−54.6

Notes: Δ R40 + P2 (%) reports the relative change in the food security rate under the most severe scenario compared to the reference.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table 9
Effects of simulated shocks on multidimensional dietary deprivation (ReDD).

Component	Reference	R20 + P1	R20 + P2	R30 + P1	R30 + P2	R40 + P1	R40 + P2
Incidence (H)	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Breadth (A)	0.665	0.711	0.743	0.752	0.785	0.786	0.813
Depth (G)	0.426	0.458	0.473	0.479	0.497	0.503	0.523
ReDD = H × A × G	0.283	0.326	0.352	0.360	0.390	0.395	0.426
Δ ReDD vs baseline (%)	—	14.9	24.1	27.0	37.7	39.5	50.2

Notes: Differences in the reported percentage changes are attributable to rounding of displayed values. For example, the full-precision baseline ReDD is 0.2834, and the R20 + P1 value is 0.3255, yielding a 14.9% change. When limited to three decimal places (0.283 and 0.326), the same calculation yields 15.2%.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

dietary deprivation in urban Dakar prior to any shock. The incidence component (H = 1.000) indicates that all households experience deprivation in at least one food group, suggesting that dietary inadequacy is a structural feature of the Dakar food environment rather than a characteristic confined to the poorest households. The simulated shocks worsen overall diet quality, with ReDD rising by 14.9% under R20 + P1 and progressively to 50.2% under R40 + P2. Since H remains at unity under all scenarios, the deterioration is driven entirely by the breadth (A) and depth (G) components. Breadth increases from 0.665 to 0.813 under R40 + P2 (+22.3%), indicating that deprived households fall short across a wider range of food groups. Depth rises from 0.426 to 0.523 (+22.7%), reflecting wider caloric gaps relative to EAT-Lancet benchmarks. The systematic gap between paired scenarios, P2 versus P1 at each income level, confirms that differentiated price increases amplify nutritional impacts beyond what uniform inflation would suggest.

Table 10 decomposes the depth component (G) by food group. At baseline, legumes and fruits dominate the caloric gap, accounting for 34.5% and 31.6% of G, respectively, and together explaining nearly two thirds of the overall caloric gap. Under the simulated shocks, the relative contribution of meat and fish rises markedly, from 8.6% at baseline to 12.2% under R40 + P2, driven by the 10% price increase applied to this group. The share of starchy staples nearly doubles, from 4.2% to 8.1%, as staples deteriorate faster than other food groups. Conversely, the shares of legumes and fruits decline slightly, from 34.5% to 29.3% and from 31.6% to 27.5%, respectively, not because deprivation eases but because other groups deteriorate faster. These findings highlight that economic shocks deepen existing nutritional deficits unevenly across food groups, with animal source foods and starchy staples emerging as increasingly prominent dimensions of dietary deprivation under price stress.

5. Discussions and conclusions

This study contributes to the literature on food demand, dietary transitions, and food security in developing countries by estimating a censored QUAIDS model with heterogeneous elasticities by expenditure subgroup and integrating the estimated demand system into a micro-simulation framework. We simulate the effects of COVID-19-related income contractions and food price increases on caloric adequacy and

Table 10
Contribution of food groups to the depth component (G) of the ReDD index.

Food group	Reference		R20 + P1		R20 + P2		R30 + P1		R30 + P2		R40 + P1		R40 + P2	
	Abs.	%	Abs.	%	Abs.	%	Abs.	%	Abs.	%	Abs.	%	Abs.	%
Starchy staples	0.02	4.2	0.03	5.5	0.03	6.6	0.03	6.1	0.04	7.3	0.03	6.7	0.04	8.1
Legumes and seeds	0.15	34.5	0.15	32.9	0.15	31.9	0.15	31.7	0.15	30.6	0.15	30.5	0.15	29.3
Vegetables	0.03	7.1	0.03	7.4	0.04	7.7	0.04	8.0	0.04	8.3	0.04	8.7	0.05	9.0
Meat, fish and seafood	0.04	8.6	0.05	10.0	0.05	10.8	0.05	10.7	0.06	11.5	0.06	11.4	0.06	12.2
Fruits	0.13	31.6	0.14	30.5	0.14	29.6	0.14	29.6	0.14	28.6	0.14	28.5	0.14	27.5
Dairy and eggs	0.06	14.0	0.06	13.6	0.06	13.3	0.07	13.9	0.07	13.6	0.07	14.2	0.07	13.8
Total G	0.43	100.0	0.46	100.0	0.47	100.0	0.48	100.0	0.50	100.0	0.50	100.0	0.52	100.0

Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

multidimensional dietary deprivation in urban Dakar using statistically matched datasets and six counterfactual scenarios combining three income levels with two price scenarios. The combination of subgroup-specific elasticities and a heterogeneous Engel transmission channel allow the analysis to preserve the structural differences across income groups throughout the simulation, providing novel evidence for an urban West African context that remains relatively underexplored compared to East Africa and South Asia.

Our demand system results highlight the central role of household socio-demographic characteristics in shaping food consumption decisions. Consistent with prior studies (Ansah et al., 2020; Caro et al., 2017; Zhao et al., 2024), household size, education, gender of the household head, and place of residence significantly shape food demand patterns. The dietary structure documented in our sample aligns with Headey et al. (2023) and Ecker and Pauw (2024), with low-income urban households relying heavily on calorie-dense staples such as cereals, oils, and sugar rather than on nutrient-rich foods. The baseline caloric intake of 2,638 kcal per adult equivalent per day exceeds the EAT-Lancet reference of 2,500 kcal. However, only 51.8% of households meet the minimum daily energy requirement of 2,300 kcal, revealing persistent vulnerabilities and dietary inadequacy among low-income households.

On income responsiveness, our findings partially support Bennett's Law (Bennett, 1941). Consistent with the findings of Rathu Manannalage et al. (2023) for Sri Lanka, shifts toward animal-source foods emerge only beyond an income threshold close to the monetary poverty line, with poorer households prioritizing inexpensive calories. This pattern reinforces the principle that caloric sufficiency precedes diet diversification in low-income urban contexts. Unlike Ansah et al. (2020) in Ghana, who find highly elastic demand for meat, we estimate generally lower income elasticities for animal-source foods in Dakar, suggesting that affordability and market constraints limit dietary upgrading even as incomes rise. However, the analysis does not capture quality substitution within food groups, most notably shifts toward higher-quality protein sources within the meat and fish category, which may understate the full extent of dietary upgrading at higher income levels.

Our cross-price elasticities confirm intuitive patterns of complementarity and substitution consistent with Dakar households' culinary practices. Strong complementarity is observed between cereals and dairy products, cereals and vegetables, and cereals and fruits, reflecting the central role of cereal-based dishes accompanied by vegetable sauces and dairy preparations in the urban Dakar diet, echoing patterns documented in other West African contexts (Ansah et al., 2020). Households shift toward legumes when meat and fish prices rise, consistent with the role of legumes as a more affordable and nutrient-dense alternative (Gazan et al., 2021). Further, rising dairy prices prompt reallocation toward oil-based dishes, consistent with the dominant role of oils in urban Senegalese meal preparation (Sylla and Diagne, 2026).

The microsimulation reveals substantial and statistically significant declines in food security across all six scenarios, with strong heterogeneity along the expenditure gradient. Bottom 40% households experience the steepest relative decline under R40 + P2. This expenditure gradient is consistent with Ivanic and Martin (2008) and Laborde et al. (2021), who respectively documented disproportionate impacts on urban net food-buying households during the 2007–2008 food price crisis and estimated that COVID-19-induced poverty increases in Sub-Saharan Africa were nearly three times larger in urban than in rural areas. Amare et al. (2021) similarly observed a 6–15 percentage-point increase in food insecurity among poorer Nigerian households under COVID-19 lockdowns. Notably, Middle 20% households exhibit a trajectory as severe as the Bottom 40%, indicating that vulnerability extends well beyond the conventional poverty threshold. This broad-based fragility echoes Rudin-Rush et al. (2022) and is consistent with Savy et al. (2020), who documented a generalized deterioration in dietary diversity scores among urban households in Dakar-Pikine during the 2007–2008 food price crisis.

The education gradient is non-monotonic, with households headed by individuals with no formal education being the most severely affected, households with primary education being the most resilient, and households with secondary or higher education falling in between. This pattern likely reflects structural differences in employment composition across education groups, with lower-educated individuals disproportionately concentrated in highly vulnerable informal activities, while slightly more educated groups were more engaged in diversified self-employment with greater adaptability.

Gender disparities are modest but consistent, with female-headed households appearing slightly more resilient than male-headed households. Women in West African contexts often have greater access to informal financial arrangements through participation in rotating savings and credit associations, commonly known as *tontines*, which can provide a crucial buffer during periods of economic hardship (Guérin, 2006). Additionally, evidence indicates that women tend to adopt a wider range of coping and income diversification strategies during crises, including engaging in small-scale income-generating activities to secure food and other essential needs for their households (Chagomoka et al., 2016).

Beyond caloric sufficiency, the ReDD index reveals that the simulated shocks simultaneously deepen the qualitative dimension of food insecurity. The baseline incidence of 1.000 indicates that all households experience deprivation in at least one EAT-Lancet food group prior to any shock, pointing to a structural dietary inadequacy in urban Dakar that predates the COVID-19 episode (Marivoet et al., 2021). The growing contribution of animal-source foods to deprivation depth aligns with demand system estimates demonstrating high price sensitivity for this food group in the Senegalese context (Gueye and Sene, 2024), and corroborates findings from Madzorera et al. (2021) who document that price increases for animal-source foods were the strongest dietary quality predictor during the COVID-19 pandemic across Burkina Faso, Ethiopia, and Nigeria. More broadly, it confirms that economic shocks affect diet quality as much as caloric quantity (Ecker and Pauw, 2024; Pauw et al., 2023; Zhao et al., 2024).

The findings have several policy implications for improving diet quality and strengthening food security in Dakar in the context of income and price shocks such as those experienced during COVID-19. The results call for a combination of price-based, social protection, and nutrition-sensitive policies rather than reliance on income growth or untargeted transfers alone. First, price stabilization policies targeting key food commodities are an essential complement to income support measures in safeguarding urban food security. The price channel is particularly valuable to target when income losses are severe, as its effect on food security rates amplifies across income levels and socio-demographic groups as households approach the caloric threshold. In this regard, strategic food reserves and targeted subsidies for cereals and animal-source products could provide a direct buffer against price volatility and partially offset welfare losses among vulnerable urban households (Gueye and Sene, 2024).

Second, the ReDD decomposition reveals that legumes and fruits account for nearly two thirds of overall dietary depth at baseline, with their deficits persisting and even deepening under all simulated shocks. These results point to the need for nutrition-sensitive interventions that support a reorientation of household diets toward more diverse and nutrient-rich food groups, through targeted subsidies and investments in the supply chains of legumes and fruits. Food group-specific price monitoring systems would further enable policymakers to detect early

signals of nutritional deterioration that uniform inflation indicators would otherwise mask (Ecker and Pauw, 2024; Pauw et al., 2023).

Third, social protection programs should extend their eligibility criteria beyond conventional poverty thresholds. Our simulations reveal that Bottom 40% and 20% of middle-income households experience substantial food security declines, reflecting the structural fragility of market-dependent urban food systems. Cash transfers remain important not only for the poorest households but also for a broader set of urban households exposed to price volatility and income disruptions.

However, several data and methodological limitations highlight promising avenues for future research. Our microsimulation applies pre-pandemic demand parameters to COVID-period shocks under the assumption that consumption behavior remained structurally stable. While the within-household first-difference estimates of the Engel transmission elasticity provide direct evidence of behavioral stability across the pre-COVID-19 and restriction periods, dynamic adjustments and adaptive responses are not fully captured. Future research could extend the framework using panel survey designs that track adjustments across multiple periods. Second, cross-sectional and recall-based consumption data may introduce measurement errors (Beegle et al., 2012), and the omission of detailed food-away-from-home consumption, which accounts for 28.2% of total food expenditure in the sample, likely leads to underestimation of caloric intake and food security rates. Third, the statistical matching procedure between the EHCVM 2018/19 and CRES/COVID-19 2021 surveys relies on a conditional independence assumption that cannot be directly tested. Although we estimate within-household first-difference transmission elasticities on the matched panel as a partial validation, additional matched samples and complementary panel data could improve robustness. Fourth, the scope of the analysis is restricted to urban Dakar, and extending the framework to rural Senegal and other West African capitals constitutes a natural next step. Finally, sample size constraints prevent the estimation of demand elasticities for more finely defined subgroups based on household total expenditure beyond the pooled sample and the Bottom 40% and Top 40% household total expenditure groups examined in this study. Larger datasets would allow a more nuanced assessment of heterogeneity in consumption responses across the expenditure distribution, thereby generating stronger evidence for the design of targeted food policy interventions.

Despite these limitations, combining demand system estimation with microsimulation offers a powerful and policy-relevant framework for understanding how urban households adjust food consumption under economic stress. The findings provide comparative evidence for West Africa and highlight the regressive impact of COVID-19 economic shocks on urban dietary outcomes in Dakar. The combined evidence on caloric inadequacy, multidimensional dietary deprivation, and heterogeneous vulnerability underscores the importance of considering both income and price channels in any assessment of pandemic-induced food insecurity, and points to actionable priorities for strengthening food security through targeted price stabilization, extended social protection, and nutrition-sensitive interventions.

CRediT authorship contribution statement

Mamadou Abdoulaye Diallo: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdoulaye Diagne:** Writing – review & editing, Validation, Funding acquisition, Conceptualization, Project administration, Writing – original draft, Supervision.

Ethics declaration

Studies in human

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place.

This study was approved by the Senegalese National Health Research Ethics Committee (CNERS).

(Approval No. 00083/MSAS/DPRS/CNERS)

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of AI use

The authors used Claude (Anthropic) during the preparation of this manuscript to assist with text editing and code development. All outputs were reviewed and edited by the authors, who bear full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

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Table A1
Covariate balance between EHCVM 2018/19 and matched samples.

Variable	Category	EHCVM 2018/19 (%)	Matched (%)	Pearson χ^2	p-value
Gender	Female	34.1	35.6	0.394	0.530
	Male	65.9	64.4		
Age	≤35 years	13.6	10.8	3.699	0.157
	36–55 years	44.4	43.8		
	Over 55 years	42.0	45.5		
Education	None	40.4	39.7	5.441	0.142
	Primary	21.6	24.8		
	Secondary	24.6	25.3		
	Post-secondary	13.4	10.2		
Household size (quantile)	Q1	32.8	28.1	5.428	0.143
	Q2	22.8	26.7		
	Q3	20.6	20.9		
	Q4	23.8	24.2		
Housing tenure status	Non-tenant	57.7	64.1	6.751	0.009***
	Tenant	42.4	35.9		
Department	Dakar	41.2	39.1	14.805	0.002***
	Pikine	30.6	35.9		
	Rufisque	20.0	14.1		
	Guediawaye	8.2	10.9		
Expenditure quintile	Poorest	20.3	20.3	2.130	0.712
	Poor	22.0	20.2		
	Middle	18.1	20.8		
	Rich	19.9	19.7		
	Wealthiest	19.7	19.1		

Notes: Pearson χ^2 tests compare the joint distribution of each stratification variable between the EHCVM 2018/19 donor pool (n = 1,020) and the matched database (n = 640). Five of the seven variables exhibit no statistically significant difference at conventional levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A2
Gini index and interquantile ratios of monthly household food expenditures.

	Gini	p90/p10	p90/p50	p50/p10	p75/p25	p75/p50	p50/p25
EHCVM 2018/19	0.320	4.94	2.04	2.42	2.19	1.43	1.53
Matched database	0.322	4.99	2.04	2.45	2.16	1.41	1.53

Notes: The Kolmogorov-Smirnov (Kolmogorov-Smirnov D0 = 0.020, p-value = 0.997) and Wilcoxon-Mann-Whitney (Wilcoxon-Mann-Whitney z = 0.403, p-value = 0.678) tests are computed on log daily expenditure (rank-invariant to the time-unit choice). Both tests fail to reject the null of identical distributions, confirming that the CDF-based matching procedure (Kum and Masterson, 2010) preserves the distributional structure of the donor pool.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A3
Comparison of average monthly food expenditures (XOF).

	EHCVM 2018/19 (N = 1,020)	Matched sample (n = 640)	Ratio
Gender			
Female	224,658	228,503	101.7%
Male	217,088	213,567	98.4%
Age			
20–35 years	156,341	173,364	110.9%
36–55 years	206,789	197,993	95.7%
Over 55 years	253,368	249,695	98.6%
Education			
No education	208,007	218,087	104.8%
Primary	203,585	193,329	95.0%
Secondary	235,658	219,218	93.0%
Higher education	247,799	281,335	113.5%
Household size (quantile)			
Quantile 1	135,361	164,227	121.3%
Quantile 2	199,863	203,223	101.7%
Quantile 3	240,953	222,594	92.4%
Quantile 4	335,772	298,494	88.9%
Housing tenure status			
Non-tenant (Owner/Free housing)	256,708	248,139	96.7%
Tenant (Renter)	168,655	170,099	100.9%
Department			
Dakar	223,223	221,667	99.3%
Pikine	219,859	215,64	98.1%
Rufisque	207,623	206,384	99.4%

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Table A3 (*continued*)

	EHCVM 2018/19 (N = 1,020)	Matched sample (n = 640)	Ratio
Guediawaye	228,485	232,848	101.9%
Expenditure quintile			
Poorest	87,779	87,294	99.4%
Poor	153,759	152,249	99.0%
Middle	199,33	198,493	99.6%
Rich	264,396	263,142	99.5%
Wealthiest	394,536	394,532	100.0%
Overall	219,678	218,901	99.6%

Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A4
Composition of household expenditures by total consumption expenditure quintile.

	Poorest	Poor	Middle	Rich	Wealthiest	Overall
Share of non-food expenditures (%)	49.2	52.2	58.7	59.6	66.3	57.0
Share of food expenditures (%)	50.8	47.8	41.3	40.4	33.7	43.0
Within household (% of food)	63.7	69.2	73.9	71.9	72.5	71.8
Outside household (% of food)	36.3	30.8	26.1	28.1	27.5	28.2
Total	100	100	100	100	100	100

Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A5
Age and gender-specific coefficients for adult equivalent scale estimation.

	Male	Female
Less than 1 year	0.255	0.255
1–3 years	0.450	0.450
4–6 years	0.620	0.620
7–10 years	0.690	0.690
11–14 years	0.860	0.760
15–18 years	1.030	0.760
19–50 years	1.000	0.760
51 years and over	0.790	0.660

Source: WAEMU Commission and World Bank (2019).

Table A6
Quality-adjusted price aggregation model.

Variable	Coefficient	Std. Error
Food group fixed effects *(ref. Cereals and cereal products)*		
Tubers and plantains	−0.490***	(0.022)
Legumes and seeds	0.195***	(0.031)
Vegetables, spices and condiments	0.652***	(0.022)
Meat, fish and seafood	0.976***	(0.019)
Fruits	0.057	(0.038)
Dairy products and eggs	0.980***	(0.024)
Oils and fats	0.567***	(0.022)
Sugar and confectionery	0.156***	(0.033)
Other food products	1.056***	(0.085)
Beverages	2.285***	(0.049)
Quantity (log)	−0.075***	(0.006)
Household head characteristics		
Age (years)	0.000	(0.000)
Gender (male = 1)	−0.003	(0.012)
Education *(ref. No education)*		
Primary	−0.015	(0.017)
Secondary	0.028**	(0.013)
Post-secondary	0.048*	(0.024)
Head working (yes = 1)	−0.019	(0.017)
Household composition		
Household size	0.009***	(0.002)
Children under 5 (yes = 1)	−0.008	(0.012)
Department *(ref. Dakar)*		
Pikine	−0.022	(0.018)
Rufisque	0.031	(0.044)

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Table A6 (*continued*)

Variable	Coefficient	Std. Error
Guediawaye	−0.059***	(0.019)
Constant	6.537***	(0.041)
Observations	5,543	
R-squared	0.826	
Duan smearing factor	1.059	

Notes: OLS regression with standard errors clustered at the census enumeration district (DR) level. The dependent variable is the log of the unit price of food product j paid by household h, expressed in XOF per standard unit. Quantity (log) is included to absorb quality variation following Cox and Wohlgenant (1986). The Duan (1983) smearing factor (1.059) is applied to correct for the retransformation bias arising from the logarithmic specification. Predicted prices are subsequently aggregated to the DR level by simple averaging within each food group. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A7
First-stage regression of the food expenditure endogeneity correction.

Variable	Coefficient	Std. Error
Instrument (excluded)		
Log non-food expenditure	0.744***	(0.053)
Household head characteristics		
Age (years)	0.003	(0.002)
Gender (male = 1)	−0.108*	(0.056)
Education *(ref. No education)*		
Primary	0.033	(0.081)
Secondary	0.212***	(0.068)
Higher	0.317***	(0.099)
Household size	0.029***	(0.006)
Department *(ref. Dakar)*		
Pikine	0.268***	(0.068)
Rufisque	0.373***	(0.089)
Guediawaye	0.171	(0.105)
Constant	−1.491*	(0.780)
Observations	612	
R-squared	0.505	
F-statistic on instrument	196.81***	

Notes: OLS regression with standard errors clustered at the DR level. The residual of this regression is used as a control function in the QUAIDS demand system to correct for the endogeneity of total food expenditure (Blundell and Robin, 1999). The validity of the instrument (log non-food expenditure) is established by the F-statistic of 196.81, well above the Stock-Yogo (2005) weak-instrument threshold of 10. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A8
Engel transmission elasticities for Dakar urban households.

Variable	(1) Within-HH FD Pooled	(2) Within-HH FD Bottom 40%	(3) Within-HH FD Middle 20%	(4) Within-HH FD Top 40%
Log of total household expenditure	0.645***	0.687***	0.662***	0.605***
	(0.077)	(0.112)	(0.100)	(0.158)
Constant	−0.072	−0.071	−0.048	−0.048
	(0.050)	(0.071)	(0.085)	(0.105)
Controls	Yes	Yes	Yes	Yes
Number of clusters	64	64	53	60
N	640	262	131	247
R^2	0.485	0.505	0.549	0.464

Notes: Within-household first-difference regressions of Δlog(food expenditure) on Δlog(total expenditure). Columns (2)–(4) report subgroup-specific estimates by expenditure quintile. All specifications include controls for gender, age, education, household size, and department fixed effects. Robust standard errors clustered at the DR level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Authors' calculations based on the CRES/COVID-19 2021 data.

Table A9
Alpha, beta, lambda, and delta parameters.

Food group	α	β	λ	δ
Cereals	−1.239***	−0.591***	−0.046***	0.254***
	(0.206)	(0.055)	(0.006)	(0.007)
Tubers and plantains	−0.126**	−0.011	−0.001	0.025***
	(0.055)	(0.013)	(0.001)	(0.002)
Legumes and seeds	0.056	−0.022*	−0.001	−0.000
	(0.050)	(0.012)	(0.001)	(0.002)
Vegetables, spices, and condiments	−0.257**	−0.145***	−0.013***	0.145***
	(0.129)	(0.028)	(0.002)	(0.004)
Meat, fish and seafood	0.399**	0.259***	0.015***	0.217***
	(0.186)	(0.044)	(0.004)	(0.007)
Fruits	−0.065	−0.001	0.002	0.100***
	(0.125)	(0.032)	(0.002)	(0.007)
Dairy, dairy products and eggs	1.056***	0.332***	0.026***	0.148***
	(0.177)	(0.041)	(0.004)	(0.007)
Oils and fats	−0.044	0.084***	0.007***	0.071***
	(0.100)	(0.020)	(0.002)	(0.004)
Sugar and confectionery	0.973***	0.231***	0.019***	0.148***
	(0.131)	(0.023)	(0.002)	(0.007)
Other foods	0.044***	0.006*	0.001**	−0.002
	(0.014)	(0.003)	(0.000)	(0.002)
Beverages	0.050	−0.140***	−0.008***	0.118***
	(0.131)	(0.029)	(0.002)	(0.006)

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. δ captures the probability of censoring for each food group.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A10
Estimated gamma parameters (γ_{ij}).

	Cer.	Tub.	Leg.	Veg.	Meat	Fruits	Dairy	Oils	Sugar	Oth. food.	Bev.
Cereals	2.060***	0.033	0.073*	0.281**	−1.079***	−0.189*	−0.663***	−0.350***	−0.522***	−0.000	0.354***
	(0.405)	(0.047)	(0.044)	(0.127)	(0.189)	(0.106)	(0.234)	(0.091)	(0.164)	(0.010)	(0.089)
Tubers		−0.201***	0.090***	0.132***	−0.052	0.064***	−0.042	−0.006	−0.027	−0.000	0.009
		(0.028)	(0.015)	(0.033)	(0.036)	(0.017)	(0.030)	(0.026)	(0.028)	(0.005)	(0.014)
Legumes			0.042**	−0.141***	−0.138***	0.040***	0.053*	−0.095***	0.026	0.025***	0.025*
			(0.017)	(0.026)	(0.028)	(0.016)	(0.029)	(0.019)	(0.027)	(0.004)	(0.013)
Vegetables				0.344***	−0.074	0.025	−0.198**	0.033	−0.437***	−0.022***	0.057
				(0.103)	(0.084)	(0.047)	(0.079)	(0.050)	(0.065)	(0.008)	(0.038)
Meat					0.451***	−0.206***	0.504***	0.663***	−0.015	0.000	−0.054
					(0.134)	(0.055)	(0.110)	(0.061)	(0.092)	(0.008)	(0.058)
Fruits						0.059	−0.048	0.007	0.178***	0.004	0.065**
						(0.047)	(0.064)	(0.040)	(0.062)	(0.004)	(0.033)
Dairy							−0.182	−0.082	0.630***	0.024***	0.005
							(0.163)	(0.065)	(0.106)	(0.006)	(0.065)
Oils								−0.181***	0.022	−0.011*	−0.001
								(0.064)	(0.056)	(0.006)	(0.027)
Sugar									0.344***	−0.000	−0.198***
									(0.097)	(0.006)	(0.046)
Other foods										−0.011***	−0.009***
										(0.002)	(0.003)
Beverages											−0.253***
											(0.044)

Notes: The matrix is symmetric by construction ($\gamma_{ij} = \gamma_{ji}$). Only the upper triangle is reported. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A11
Estimated η and ρ parameters.

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. foods (10)	Bev. (11)	ρ
Gender (male = 1)	0.0008	0.0001	−0.0000	−0.0001	0.0053***	−0.0024***	0.0034***	−0.0042***	−0.0020***	0.0001*	−0.0009	−0.970**
	(0.0005)	(0.0002)	(0.0002)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0000)	(0.0006)	(0.381)
Age	0.0001***	−0.0000***	0.0000	−0.0000	−0.0002***	−0.0000***	−0.0001***	0.0000	0.0001***	−0.0000	0.0002***	0.089***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.034)
Education	−0.0003	0.0001	0.0001	0.0004*	0.0020***	−0.0003	−0.0000	−0.0014***	−0.0005	−0.0000**	−0.0002	−0.698***
	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0000)	(0.0004)	(0.263)
Married	0.0002	−0.0003	−0.0003	−0.0009	−0.0022***	0.0020***	−0.0065***	0.0029***	0.0023**	−0.0000	0.0029***	1.398*
	(0.0008)	(0.0002)	(0.0002)	(0.0006)	(0.0007)	(0.0007)	(0.0009)	(0.0006)	(0.0009)	(0.0001)	(0.0008)	(0.718)
Household size	0.0004***	0.0001***	−0.0000	0.0004***	−0.0003***	−0.0001*	−0.0001	0.0001	−0.0001*	−0.0000***	−0.0003***	−0.005
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.012)
Pikine	0.0001	−0.0004*	0.0009***	−0.0014***	0.0018***	0.0010*	0.0018***	−0.0002	−0.0002	0.0001**	−0.0037***	−0.260**

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Table A11 (*continued*)

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. foods (10)	Bev. (11)	ρ
	(0.0005)	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0004)	(0.0008)	(0.0001)	(0.0007)	(0.108)
Rufisque	−0.0018*	0.0005	0.0010***	−0.0004	0.0045***	0.0007	−0.0043***	−0.0040***	−0.0049***	0.0000	0.0087***	−0.272
	(0.0010)	(0.0004)	(0.0004)	(0.0008)	(0.0012)	(0.0008)	(0.0011)	(0.0009)	(0.0013)	(0.0001)	(0.0011)	(0.299)
Guediawaye	0.0016**	−0.0002	0.0004	−0.0007	0.0009*	0.0015**	0.0005	−0.0000	0.0004	0.0001*	−0.0045***	−0.410***
	(0.0007)	(0.0003)	(0.0003)	(0.0007)	(0.0005)	(0.0007)	(0.0009)	(0.0006)	(0.0010)	(0.0001)	(0.0008)	(0.147)
Selection residual	0.0047***	0.0005**	0.0006***	0.0018***	−0.0039***	−0.0030***	−0.0009*	−0.0019***	−0.0027***	−0.0003***	0.0051***	0.944***
	(0.0005)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0007)	(0.0000)	(0.0007)	(0.316)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. η parameters are reported at 4 decimals to preserve information on the small magnitude of demographic shifters on budget shares; ρ parameters (selection-equation coefficients) are reported at 3 decimals. Department of Dakar serves as the reference category for district fixed effects. ρ denotes the coefficient of the demographic variables in the selection equation. Indices $i = 1 \ldots 11$ refer to the following food groups: (1) Cereals and cereal products, (2) Tubers and plantains, (3) Legumes and seeds, (4) Vegetables, spices and condiments, (5) Meat, fish and seafood, (6) Fruits, (7) Dairy products and eggs, (8) Oils and fats, (9) Sugar and confectionery, (10) Other foods, and (11) Beverages.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A12
Uncompensated (Marshallian) price elasticities, overall.

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
Cereals (1)	−0.931***	−0.050	0.004	0.054	−0.626	−0.089	0.146	−0.035	−0.017	0.058	−0.031
	(0.260)	(0.112)	(0.093)	(0.221)	(0.675)	(0.132)	(0.304)	(0.133)	(0.194)	(0.079)	(0.060)
Tubers (2)	−0.020	−0.348***	−0.311***	−0.442***	0.314	−0.206**	0.153	−0.003	0.064	−0.005	−0.038
	(0.117)	(0.099)	(0.071)	(0.149)	(0.494)	(0.103)	(0.198)	(0.106)	(0.119)	(0.020)	(0.107)
Legumes (3)	−0.039	−0.088***	−1.046***	0.225***	0.086	−0.062**	−0.120**	0.110***	−0.096**	−0.029***	−0.008
	(0.039)	(0.023)	(0.026)	(0.047)	(0.145)	(0.030)	(0.061)	(0.031)	(0.040)	(0.011)	(0.032)
Vegetables (4)	0.077	−0.069***	0.083***	−1.204***	0.065	0.002	0.039	−0.065*	0.198***	0.016*	−0.006
	(0.061)	(0.025)	(0.028)	(0.080)	(0.226)	(0.049)	(0.089)	(0.039)	(0.049)	(0.009)	(0.044)
Meat (5)	0.004	−0.003	0.031	−0.083	−0.917***	0.017	0.030	0.029	−0.088*	0.030	0.005
	(0.075)	(0.038)	(0.030)	(0.077)	(0.106)	(0.049)	(0.056)	(0.043)	(0.051)	(0.028)	(0.031)
Fruits (6)	−0.098**	0.056***	0.001	−0.017	−0.003	−0.944***	0.016	−0.051	0.123**	−0.004	0.014
	(0.043)	(0.021)	(0.023)	(0.052)	(0.179)	(0.042)	(0.075)	(0.037)	(0.049)	(0.011)	(0.040)
Dairy (7)	0.075	−0.007	0.046	0.010	0.082	−0.007	−1.213***	−0.071*	0.062	−0.005	0.059
	(0.071)	(0.024)	(0.028)	(0.058)	(0.202)	(0.040)	(0.100)	(0.039)	(0.057)	(0.012)	(0.042)
Oils (8)	0.094*	0.028	0.063***	−0.032	−0.459***	−0.016	0.112*	−0.912***	0.052	0.013	−0.023
	(0.051)	(0.024)	(0.021)	(0.045)	(0.155)	(0.034)	(0.067)	(0.054)	(0.044)	(0.009)	(0.032)
Sugar (9)	0.126	0.107	0.210**	−0.311	−0.310	0.229*	0.380*	−0.400**	−0.927***	0.056	−0.142
	(0.234)	(0.153)	(0.106)	(0.241)	(0.394)	(0.130)	(0.200)	(0.198)	(0.201)	(0.086)	(0.089)
Oth. food. (10)	−0.131**	0.021	−0.186***	0.170**	−0.119	−0.035	−0.135	0.098*	0.039	−0.911***	0.068
	(0.063)	(0.041)	(0.041)	(0.079)	(0.236)	(0.046)	(0.092)	(0.055)	(0.061)	(0.018)	(0.049)
Beverages (11)	−0.031	0.045	−0.031	0.065	−0.242	−0.083**	−0.175**	−0.007	−0.040	0.021	−0.727***
	(0.060)	(0.037)	(0.029)	(0.063)	(0.180)	(0.041)	(0.079)	(0.046)	(0.057)	(0.019)	(0.050)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Diagonal elements are own-price elasticities. Positive off-diagonal elements indicate substitutability; negative elements indicate complementarity. Indices 1–11: (1) Cereals, (2) Tubers, (3) Legumes, (4) Vegetables, (5) Meat and fish, (6) Fruits, (7) Dairy, (8) Oils and fats, (9) Sugar, (10) Other foods, and (11) Beverages.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A13a
Uncompensated (Marshallian) price elasticities, bottom 40%.

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
Cereals (1)	−0.879***	−0.027	0.019	0.018	−0.605	−0.131	0.122	−0.028	0.017	0.042	−0.030
	(0.228)	(0.075)	(0.081)	(0.185)	(0.669)	(0.121)	(0.291)	(0.111)	(0.168)	(0.049)	(0.044)
Tubers (2)	−0.031	−0.357***	−0.310***	−0.439***	0.325	−0.219**	0.162	0.007	0.059	−0.007	−0.037
	(0.117)	(0.101)	(0.074)	(0.152)	(0.509)	(0.106)	(0.201)	(0.110)	(0.121)	(0.024)	(0.109)
Legumes (3)	−0.039	−0.087***	−1.048***	0.235***	0.091	−0.064**	−0.124**	0.111***	−0.104**	−0.030**	−0.009
	(0.040)	(0.026)	(0.028)	(0.050)	(0.149)	(0.032)	(0.063)	(0.034)	(0.042)	(0.012)	(0.032)
Vegetables (4)	0.091	−0.039	0.087***	−1.273***	0.034	−0.017	0.053	−0.043	0.221***	0.031	−0.003
	(0.066)	(0.035)	(0.033)	(0.089)	(0.236)	(0.054)	(0.093)	(0.048)	(0.057)	(0.019)	(0.045)
Meat (5)	−0.029	−0.003	0.008	−0.021	−0.992***	−0.013	0.010	0.055***	−0.058**	0.012	0.015
	(0.032)	(0.016)	(0.013)	(0.036)	(0.076)	(0.022)	(0.032)	(0.020)	(0.023)	(0.012)	(0.017)
Fruits (6)	−0.090**	0.039***	0.007	−0.010	0.005	−0.946***	0.011	−0.027	0.112**	−0.001	0.014
	(0.036)	(0.014)	(0.021)	(0.047)	(0.181)	(0.041)	(0.074)	(0.033)	(0.046)	(0.005)	(0.040)
Dairy (7)	0.092	−0.010	0.033	0.000	0.126	0.000	−1.211***	−0.085**	0.084	−0.001	0.055
	(0.066)	(0.017)	(0.026)	(0.053)	(0.205)	(0.039)	(0.100)	(0.035)	(0.053)	(0.007)	(0.042)

(*continued on next page*)

Table A13a (*continued*)

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
Oils (8)	0.100*	0.051*	0.065***	−0.019	−0.508***	−0.018	0.112	−0.958***	0.068	0.018	−0.024
	(0.054)	(0.031)	(0.024)	(0.051)	(0.162)	(0.037)	(0.070)	(0.061)	(0.049)	(0.015)	(0.033)
Sugar (9)	0.158	0.079	0.167*	−0.314	−0.212	0.236**	0.376**	−0.352**	−0.922***	0.041	−0.137*
	(0.202)	(0.123)	(0.089)	(0.199)	(0.379)	(0.112)	(0.185)	(0.163)	(0.174)	(0.068)	(0.081)
Oth. food. (10)	−0.141**	0.025	−0.185***	0.173**	−0.140	−0.035	−0.133	0.099*	0.041	−0.909***	0.070
	(0.064)	(0.043)	(0.042)	(0.080)	(0.242)	(0.048)	(0.093)	(0.056)	(0.062)	(0.019)	(0.050)
Beverages (11)	−0.030	0.009	0.005	0.053	−0.247	−0.077**	−0.185**	−0.002	0.013	0.009*	−0.740***
	(0.044)	(0.013)	(0.022)	(0.042)	(0.178)	(0.036)	(0.075)	(0.029)	(0.043)	(0.005)	(0.049)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Diagonal elements are own-price elasticities. Positive off-diagonal elements indicate substitutability; negative elements indicate complementarity. Indices 1–11: (1) Cereals, (2) Tubers, (3) Legumes, (4) Vegetables, (5) Meat and fish, (6) Fruits, (7) Dairy, (8) Oils and fats, (9) Sugar, (10) Other foods, and (11) Beverages.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A13b
Uncompensated (Marshallian) price elasticities, top 40%.

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
Cereals (1)	−0.954***	−0.085	−0.028	0.084	−0.533	−0.010	0.202	−0.071	−0.061	0.077	−0.044
	(0.317)	(0.164)	(0.115)	(0.281)	(0.683)	(0.153)	(0.328)	(0.170)	(0.239)	(0.118)	(0.077)
Tubers (2)	−0.028	−0.339***	−0.311***	−0.443***	0.284	−0.206**	0.146	−0.002	0.067	−0.003	−0.035
	(0.124)	(0.099)	(0.069)	(0.147)	(0.467)	(0.098)	(0.195)	(0.102)	(0.119)	(0.019)	(0.104)
Legumes (3)	−0.042	−0.088***	−1.044***	0.219***	0.073	−0.063**	−0.119**	0.111***	−0.091**	−0.028***	−0.006
	(0.040)	(0.022)	(0.025)	(0.045)	(0.135)	(0.028)	(0.060)	(0.029)	(0.040)	(0.009)	(0.030)
Vegetables (4)	0.047	−0.093***	0.084***	−1.141***	0.050	0.010	0.021	−0.075**	0.179***	0.004	−0.004
	(0.064)	(0.025)	(0.027)	(0.079)	(0.213)	(0.047)	(0.087)	(0.037)	(0.050)	(0.009)	(0.042)
Meat (5)	0.029	−0.003	0.051	−0.137	−0.859***	0.042	0.045	0.007	−0.115	0.045	−0.002
	(0.113)	(0.058)	(0.045)	(0.115)	(0.142)	(0.073)	(0.081)	(0.065)	(0.077)	(0.043)	(0.044)
Fruits (6)	−0.105**	0.066**	−0.002	−0.020	−0.010	−0.944***	0.019	−0.062	0.129**	−0.006	0.015
	(0.051)	(0.027)	(0.025)	(0.057)	(0.171)	(0.042)	(0.075)	(0.040)	(0.052)	(0.014)	(0.040)
Dairy (7)	0.039	−0.004	0.060**	0.023	−0.002	−0.024	−1.224***	−0.050	0.050	−0.007	0.069*
	(0.077)	(0.028)	(0.029)	(0.061)	(0.192)	(0.040)	(0.099)	(0.040)	(0.060)	(0.014)	(0.041)
Oils (8)	0.097*	0.006	0.058***	−0.047	−0.390***	−0.009	0.116*	−0.874***	0.038	0.009*	−0.025
	(0.051)	(0.020)	(0.018)	(0.042)	(0.145)	(0.032)	(0.065)	(0.051)	(0.042)	(0.005)	(0.031)
Sugar (9)	0.056	0.134	0.258**	−0.295	−0.498	0.200	0.366*	−0.419*	−0.932***	0.070	−0.131
	(0.264)	(0.179)	(0.120)	(0.278)	(0.401)	(0.147)	(0.213)	(0.228)	(0.227)	(0.101)	(0.096)
Oth. food. (10)	−0.116*	0.022	−0.189***	0.168**	−0.097	−0.028	−0.131	0.090*	0.038	−0.911***	0.065
	(0.066)	(0.042)	(0.040)	(0.078)	(0.223)	(0.044)	(0.090)	(0.053)	(0.062)	(0.019)	(0.048)
Beverages (11)	−0.044	0.068	−0.050	0.075	−0.267	−0.092*	−0.173**	−0.002	−0.072	0.029	−0.718***
	(0.077)	(0.055)	(0.037)	(0.083)	(0.177)	(0.047)	(0.084)	(0.062)	(0.071)	(0.028)	(0.049)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Diagonal elements are own-price elasticities. Positive off-diagonal elements indicate substitutability; negative elements indicate complementarity. Indices 1–11: (1) Cereals, (2) Tubers, (3) Legumes, (4) Vegetables, (5) Meat and fish, (6) Fruits, (7) Dairy, (8) Oils and fats, (9) Sugar, (10) Other foods, and (11) Beverages.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A13c
Uncompensated (Marshallian) price elasticities, no formal education.

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
Cereals (1)	−0.879***	−0.048	0.000	0.041	−0.565	−0.083	0.149	−0.049	−0.013	0.054	−0.034
	(0.258)	(0.105)	(0.091)	(0.214)	(0.670)	(0.129)	(0.303)	(0.128)	(0.190)	(0.073)	(0.064)
Tubers (2)	−0.025	−0.346***	−0.311***	−0.442***	0.307	−0.209**	0.152	−0.001	0.063	−0.005	−0.037
	(0.119)	(0.099)	(0.071)	(0.149)	(0.491)	(0.102)	(0.199)	(0.106)	(0.119)	(0.020)	(0.107)
Legumes (3)	−0.040	−0.087***	−1.046***	0.225***	0.083	−0.063**	−0.121**	0.110***	−0.096**	−0.029***	−0.008
	(0.040)	(0.023)	(0.026)	(0.047)	(0.143)	(0.030)	(0.061)	(0.031)	(0.040)	(0.011)	(0.032)
Vegetables (4)	0.070	−0.069***	0.084***	−1.200***	0.055	0.000	0.037	−0.064*	0.197***	0.015*	−0.005
	(0.061)	(0.025)	(0.028)	(0.080)	(0.224)	(0.048)	(0.089)	(0.038)	(0.049)	(0.009)	(0.044)
Meat (5)	−0.004	−0.003	0.027	−0.074	−0.928***	0.012	0.028	0.033	−0.083*	0.027	0.006
	(0.068)	(0.034)	(0.027)	(0.070)	(0.100)	(0.044)	(0.052)	(0.040)	(0.047)	(0.026)	(0.028)
Fruits (6)	−0.097**	0.053***	0.002	−0.015	−0.003	−0.945***	0.015	−0.046	0.121**	−0.003	0.015
	(0.043)	(0.020)	(0.022)	(0.051)	(0.176)	(0.041)	(0.075)	(0.036)	(0.049)	(0.009)	(0.040)
Dairy (7)	0.066	−0.007	0.047*	0.011	0.070	−0.010	−1.213***	−0.068*	0.062	−0.005	0.060

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Table A13c (*continued*)

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
	(0.072)	(0.024)	(0.028)	(0.057)	(0.199)	(0.040)	(0.100)	(0.038)	(0.057)	(0.012)	(0.041)
Oils (8)	0.095*	0.026	0.060***	−0.035	−0.436***	−0.012	0.116*	−0.912***	0.053	0.013	−0.025
	(0.050)	(0.023)	(0.020)	(0.044)	(0.152)	(0.034)	(0.066)	(0.054)	(0.044)	(0.008)	(0.032)
Sugar (9)	0.108	0.096	0.198**	−0.307	−0.331	0.219*	0.371*	−0.364**	−0.923***	0.050	−0.132
	(0.221)	(0.139)	(0.098)	(0.222)	(0.383)	(0.121)	(0.193)	(0.181)	(0.189)	(0.078)	(0.085)
Oth. food. (10)	−0.127**	0.020	−0.186***	0.167**	−0.108	−0.034	−0.134	0.097*	0.039	−0.911***	0.067
	(0.063)	(0.041)	(0.040)	(0.078)	(0.233)	(0.046)	(0.091)	(0.054)	(0.061)	(0.018)	(0.049)
Beverages (11)	−0.034	0.051	−0.037	0.066	−0.240	−0.084*	−0.171**	−0.007	−0.048	0.023	−0.727***
	(0.064)	(0.042)	(0.031)	(0.068)	(0.179)	(0.043)	(0.080)	(0.050)	(0.060)	(0.021)	(0.050)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Diagonal elements are own-price elasticities. Positive off-diagonal elements indicate substitutability; negative elements indicate complementarity. Indices 1–11: (1) Cereals, (2) Tubers, (3) Legumes, (4) Vegetables, (5) Meat and fish, (6) Fruits, (7) Dairy, (8) Oils and fats, (9) Sugar, (10) Other foods, and (11) Beverages.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A13d
Uncompensated (Marshallian) price elasticities, at least some formal education.

	Cer. (1)	Tub. (2)	Leg. (3)	Veg. (4)	Meat (5)	Fruits (6)	Dairy (7)	Oils (8)	Sugar (9)	Oth. food. (10)	Bev. (11)
Cereals (1)	−0.867***	−0.058	−0.015	0.038	−0.459	−0.049	0.177	−0.076	−0.023	0.057	−0.044
	(0.270)	(0.117)	(0.094)	(0.224)	(0.654)	(0.131)	(0.303)	(0.134)	(0.199)	(0.083)	(0.057)
Tubers (2)	−0.031	−0.343***	−0.311***	−0.443***	0.293	−0.212**	0.151	0.002	0.065	−0.004	−0.035
	(0.123)	(0.100)	(0.070)	(0.148)	(0.478)	(0.100)	(0.197)	(0.104)	(0.120)	(0.020)	(0.105)
Legumes (3)	−0.042	−0.087***	−1.045***	0.226***	0.078	−0.064**	−0.121**	0.112***	−0.096**	−0.029***	−0.007
	(0.040)	(0.023)	(0.026)	(0.047)	(0.139)	(0.029)	(0.060)	(0.031)	(0.040)	(0.011)	(0.031)
Vegetables (4)	0.057	−0.067***	0.088***	−1.201***	0.018	−0.008	0.033	−0.054	0.200***	0.017*	0.000
	(0.063)	(0.025)	(0.027)	(0.080)	(0.219)	(0.048)	(0.089)	(0.038)	(0.050)	(0.009)	(0.043)
Meat (5)	0.004	−0.003	0.034	−0.088	−0.920***	0.018	0.029	0.028	−0.092*	0.032	0.006
	(0.080)	(0.040)	(0.031)	(0.082)	(0.109)	(0.051)	(0.059)	(0.046)	(0.054)	(0.030)	(0.032)
Fruits (6)	−0.101**	0.059**	0.000	−0.017	−0.008	−0.945***	0.016	−0.053	0.125**	−0.004	0.015
	(0.047)	(0.023)	(0.023)	(0.053)	(0.173)	(0.042)	(0.075)	(0.037)	(0.050)	(0.012)	(0.040)
Dairy (7)	0.052	−0.005	0.052*	0.016	0.027	−0.019	−1.222***	−0.058	0.063	−0.004	0.066
	(0.073)	(0.024)	(0.028)	(0.057)	(0.195)	(0.039)	(0.099)	(0.038)	(0.058)	(0.012)	(0.041)
Oils (8)	0.107**	0.029	0.061***	−0.033	−0.444***	−0.012	0.114*	−0.920***	0.052	0.013	−0.025
	(0.052)	(0.024)	(0.020)	(0.045)	(0.150)	(0.034)	(0.067)	(0.055)	(0.045)	(0.009)	(0.032)
Sugar (9)	0.079	0.118	0.233**	−0.300	−0.425	0.209	0.369*	−0.397*	−0.927***	0.062	−0.132
	(0.246)	(0.163)	(0.111)	(0.255)	(0.392)	(0.136)	(0.204)	(0.209)	(0.211)	(0.092)	(0.091)
Oth. food. (10)	−0.121*	0.021	−0.188***	0.167**	−0.100	−0.030	−0.132	0.092*	0.039	−0.911***	0.066
	(0.064)	(0.041)	(0.040)	(0.078)	(0.227)	(0.045)	(0.090)	(0.053)	(0.061)	(0.019)	(0.048)
Beverages (11)	−0.044	0.041	−0.023	0.067	−0.274	−0.088**	−0.181**	0.002	−0.033	0.020	−0.726***
	(0.057)	(0.033)	(0.027)	(0.058)	(0.170)	(0.039)	(0.076)	(0.042)	(0.053)	(0.017)	(0.048)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Diagonal elements are own-price elasticities. Positive off-diagonal elements indicate substitutability; negative elements indicate complementarity. Indices 1–11: (1) Cereals, (2) Tubers, (3) Legumes, (4) Vegetables, (5) Meat and fish, (6) Fruits, (7) Dairy, (8) Oils and fats, (9) Sugar, (10) Other foods, and (11) Beverages.
Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

Table A14
Food security changes under alternative price scenarios, by household characteristics (percentage points).

Group	Reference (%)	R20 + P1	R20 + P2	R30 + P1	R30 + P2	R40 + P1	R40 + P2
Male-headed	49.1	−11.6***	−16.5***	−16.5***	−21.6***	−21.2***	−28.9***
Female-headed	55.8	−12.2***	−16.1***	−16.5***	−25.2***	−25.2***	−30.2***
Bottom 40% (Q1 + Q2)	50.9	−14.8***	−18.9***	−18.9***	−25.1***	−25.1***	–32.9***
Middle 20% (Q3)	51.3	−8.2***	−14.0***	−14.0***	–23.7***	–22.5***	–32.8***
Top 40% (Q4 + Q5)	52.6	−11.8***	−15.8***	−16.2***	−21.7***	−21.7***	−26.1***
No formal education	45.7	−13.4***	−16.7***	−17.1***	–23.6***	–23.6***	−30.7***
Primary	45.7	−2.1*	−8.6***	−8.6***	−15.9***	−14.8***	−18.5***
Secondary and above	64.3	−16.4***	−20.9***	−20.9***	−27.1***	−27.1***	−35.1***

Notes: The reference column reports the observed prevalence of food security within each subgroup. Values in the remaining columns indicate changes in food security prevalence, expressed in percentage points relative to the observed situation, under six simulated scenarios. Negative values indicate declines in food security. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' calculations based on the CRES/COVID-19 and EHCVM 2018/19 databases.

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