Analysing Consumption Patterns and Food Demand in BRICS Countries: A Differential Approach to Demand Theory and Policy Analysis

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12 July 2024

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1. Introduction

Demand theory, introduced by Stone in 1954, is a key tool for studying consumer behaviour. It considers factors like price, substitute goods' prices, and consumer income to determine demand quantity. Various models like Working's model (1943), Theil's Rotterdam Model (1965), Deaton and Muellbauer's Almost Ideal Demand System (1980), Neves' model of NBR (1994), and the CBS model by Keller et al., (1985) have been developed to calculate coefficients for price, income, and cross elasticity of demand. These models have wide applications across sectors like agriculture, industry, services, and their subsectors. Economists often use these systems to predict food demand, a non-durable commodity group, for policy analysis. The demand systems' scope extends to demographic economics, environmental economics, health economics, industrial organization analyses, international economics, and law and economics.

As wealth increases, people globally spend less on food and more on services, a trend known as the Engel effect. This shift in consumption patterns impacts the economy's structure. Notable contributions to this field include: Boppart (2014), Comin et al. (2021), Herrendorf et al. (2013), Kongsamut et al. (2001), Matsuyama (2019), and Swiecki (2017) have studied this phenomenon using various demand behaviour models. These models include the non-homothetic CES, linear expenditure system (LES), translog model, and almost-ideal model (AI). Such practices are also prevalent in computable general equilibrium (CGE) modelling.

The differential approach, defining the Rotterdam system, is a potentially superior yet lesser-known method for modeling demand. It can study cross-sections of countries and identify long-term structural changes in consumption expenditure. Its advantages include its basis in utility theory, wide applicability, ease of hypothesis testing, and simplicity. Clements & Vo (2022) suggest that these features may encourage its use in studies of structural change and computational general equilibrium (CGE) modelling.

This paper aims to use recent phases of the International Comparison Program (ICP) to analyse consumption patterns in Brazil, China, India, Russia, and South Africa using the same method as Tayebi (2019). This will allow researchers to predict future food demand and simulate the effects of government policies. The analysis will provide insights into changing consumption patterns and their impact on the global food market. It will also inform policymakers in developing countries as they balance economic growth with food security.

2. Literature Overview

Consumer demand research has evolved over time, with early studies using the LES model for its simplicity. As the number of goods and countries increased, other models were employed. Hertel et al. (1998) used the AIDADS model to analyse global food demand patterns, predicting an increase in food demand but a decrease in its share of total spending by 2020. Theil et al. (1989) developed two new demand models and highlighted the significance of the food group. Fiebig et al. (1987) and Seale & Regmi (2006) used ICP data to calculate demand functions, income elasticities, and price elasticities. Muhammad et al. (2011) built upon Seale and Regmi's work, finding that poor countries are highly sensitive to changes in food prices and income. Meade et al. (2014) revised previous estimates to calculate cross-price elasticities for nine broad consumption baskets. Tayebi (2019) extended the new CBS model with preference independence, suggesting the use of estimated elasticities to predict future food demand and simulate policy effects.

3. Methodology

As a result of budget constraints, consumers allocate their income using a multistage budget (Seale, Sparks, and Buxton, 1992). This study uses a two-step budgeting process. In the first stage, consumers divide their total spending among 11 broad categories of goods including Food and Non-Alcoholic Drinks; Alcoholic Drinks, Tobacco Products and Narcotics; Clothing and footwear; Furniture, Home Equipment and Routine Household Maintenance; Transport and Communication; Restaurants, Hotels, Recreation and Culture; Housing, Water, Electricity, Gas and Other Fuels; Health; Education. The Food and Non-Alcoholic Beverages category is disaggregated into 9 food subgroups in the second stage budgeting; they are bread and cereals; meat, fish and seafood; milk, cheese and eggs; oils and fats; fruit; vegetables; sugar, jam, honey, chocolate and confectionery; food products n.e.c. (Class); alcoholic beverages, tobacco and narcotics.

3.1 Theoretical background

In the second stage of budgeting, food subcategories and broad categories are analysed using an updated version of the CBS level demand system models. These models, originally developed by Keller and Van Driel in 1985, were later modified by Tayebi in 2019. The new models, CBS-Preference Independence (PI) level and CBS levels models, use a differential approach and are based on differential equations of consumer goods' budget shares. This approach, first introduced by Theil in 1965, is also known as the differential systems of consumer demand.

$$w_i d(logq_i) = \mu_i d(logQ) + \sum_{j=1}^{n} \pi_{ij} d(logp_j) \quad (1)$$

In this equation, w_i denotes the observed budget share of commodity i, μ_i denotes the constant marginal budget share of good i, and $logp_i$ and $logq_i$ denote the log difference between the price of good i, (p_j) and its quantity (q_i). Additionally, the Divisia volume index, which is equal to $d(logQ) = d(logM) - d(logP)$,

$$d(logQ) = \sum_{i=1}^{n} w_i \, d(logq_i) \quad (2)$$

where M is total expenditure and $d(logP)$ is the Divisia price index and is equal to $d(logP) = \sum_{i=1}^{n} w_i \, d(logp_i)$.

The coefficients of demand μ_i and π_{ij} are the marginal budget share for the good i and compensated price effect, respectively. The restriction on consumer demand applied on the demand parameters are, in particular,

Adding up $\sum_i \mu_i = 1, \sum_i \pi_{ij} = 0$; (3)

Homogeneity $\sum_j \pi_{ij} = 0$; and (4)

Symmetry $\pi_{ij} = \pi_{ji}$ (5)

Also, the matrix $[\pi_{ij}]$ is positive semi-definite.

By applying various forms of parameters, one can discover different demand systems (Constancy of certain parameters). One way choosing a parameter is based on Working's (1943) model as

$$w_i = \alpha_i + \beta_i logM + \varepsilon_i \quad (6)$$

Where $\sum \alpha_i = 1$ and $\sum \beta_i = 0$

By multiplying total nominal expenditure, M, in equation (4.6) and differentiate the results with respect to M, the marginal shares implied by Working's model can be derived as

$$\frac{\partial p_i q_i}{\partial M} = \alpha_i + \beta_i logM$$

$$\mu_i = w_i + \beta_i \quad (7)$$

As income changes, the budget share does not remain constant, and neither does the marginal share in Working's model. By substituting μ_i in equation (4.1) with equation

(4.7) and rearrangement, the Keller and Van Driel (1985) CBS model can be obtained as follows:

$$w_i d(logq_i) = w_i + \beta_i d(logQ) + \sum_j \pi_{ij} d(logp_j) + \varepsilon_i \quad (8)$$

By assuming that preferences are independent, or that the utility function is additive under preference independence, the other alternative of the CBS model can be derived. Additionally, by taking into

$$\pi_{ij} = v_{ij} - (\sum_k v_{ik}) \mu_j \quad (9)$$

And imposing the restrictions as $v_{ij} = 0$ for $i \neq j$ or $v_{ii} = -\sigma\mu_i$ and substituting the two later terms of $v_{ij}$and π_{ij} in the equation (8), The version of the CBS model that is independent of preferences can be identified as

$$w_i d(logq_i) = (\mu_i) d(logQ) + \phi \sum_j (\mu_i - \mu_i \mu_j) d(logp_j) + \varepsilon_i \quad (10)$$

Theil (1975) said that the idea of "income flexibility" (ϕ) is the opposite of what Frisch (1959) said about the "income elasticity of marginal utility."

The CBS model is a differential demand system ideal for time-series analysis, showing the impact of prices and expenditure on budget shares. For cross-sectional analysis, a demand model with levels, like Working's (1943) PIGLOG model with Engle curves, is more suitable as it accounts for price differences between countries. The Working PI and Working Slutsky models also consider these price variations.

The Florida PI and Slutsky models' complexity due to cubic terms makes them hard to estimate. The CBS model, however, limits the array of calculated price coefficients, allowing for elastic Engle curves and steady aggregation of individuals. It includes the Rotterdam model's assumptions and has simple parameter estimation. Theil, Seal, and Chung (1989) note that geometric mean prices and quantities are deflators based on the minimum distance property, as log differences aren't valid for cross-section analysis in the CBS model. The Florida Slutsky and Florida PI models, developed for cross-country comparisons, use geometric mean prices.

In cross-country studies, the domestic-currency price of good i in country c and d is represented by p_{ic} and p_{id} respectively. Due to different currencies and units of measurement, prices and sizes vary across countries. To standardize, relative prices are used instead of absolute ones, which helps maintain fixed parameters (i.e., α and β_i). This is incorporated into the extended Equation (6).

When estimating the CBS level models for the cross-country analysis, the geometric means of prices and quantities are used instead of the logarithmic difference between prices and quantities. The geometric mean of prices and quantities is defined as

$$log\bar{p}_i = \frac{1}{N}\sum_{c=1}^{N} logp_{ic} \qquad (11)$$

$$log\bar{q}_i = \frac{1}{N}\sum_{c=1}^{N} logq_{ic} \qquad (12)$$

where q_{ict} and p_{ict} are the quantity and price of good i for country c and N is number of country observations. Hence, the CBS level model is defined as

$$w_i\left(log\frac{q_{ict}}{\bar{q}_{it}}\right) = w_i + \beta_i d(logQ) + \sum_j \pi_{ij}\left(log\frac{p_{ict}}{\bar{p}_{it}}\right) + \varepsilon_{ict} \qquad (13)$$

Similarly, the CBS-PI level model is

$$w_i\left(log\frac{q_{ict}}{\bar{q}_{it}}\right) = \theta_i d(logQ) + \phi\sum_j(\theta_i - \theta_i\theta_j)\left(log\frac{p_{ict}}{\bar{p}_{it}}\right) + \varepsilon_{ict} \qquad (14)$$

Where $\theta_i = (w_i + \beta_i)$, $log\bar{q}_{it} = \frac{1}{N}\sum_{c=1}^{N} q_{ict}$, $log\bar{p}_{it} = \frac{1}{N}\sum_{c=1}^{N} p_{ict}$ and $d(logQ)$ is the adjusted Divisia Index as

$$d(logQ) = \sum_{i=1}^{n} w_i\, d(logq_i) = \sum_i w_i\, log\left(\frac{q_{ict}}{\bar{q}_{it}}\right) \qquad (15)$$

Equation (14) are used to estimate the CBS-PI level model for eleven broad consumption groups in BRICS countries in 2005, 2011, and 2017 using three different

ICP dataset phases. The estimation assumes that the disturbances are normally and independently distributed over time. The resulting panel data set is balanced.

Equation (13) of the CBS level model is estimated for nine food subcategories in BRICS countries using two phases of data. The system of equations is estimated using random effects with seemingly unrelated regression (SUR), random effects with maximum likelihood, and the fixed method simultaneously. The demand equations are subject to homogeneity and symmetry constraints and one equation is removed to avoid singularity in the contemporaneous covariance matrix (Barten, 1969). The coefficients β_i and ϕ are treated as constants when estimating both versions of the CBS level model.

3.2 Income and Price Elasticities of Demand

Income and three types of own-price elasticity of demand (Frisch, Slutsky, Cournot) are calculated for eleven consumption categories and nine food subcategories. The Method of Maximum Likelihood is used to calculate coefficients from pooled data. Predicted budget shares for each observation are calculated as per Theil, Chung, and Seale (1989), with $\widehat{w}_{ic}^{*}$ representing the predicted budget share of good i for country c.

3.3 Broad groups income and price elasticities

Based on Working's model from 1943, the predicted budget share for each country is used to determine the elasticities.

$$w_{ic} = \alpha_i + \beta_i logQ_c + \varepsilon_{ic} \qquad i = 1, 2, \dots, n \tag{16}$$

In this context, Q represents the total real group consumption expenditure in country c for n goods, and w_{ic} is the budget proportion allocated to good i in country c. Assuming W_g represents group g's budget share, the group's income elasticity measures the percent change in the quantity required by group g for a 1 percent change in total real expenditure. This is used in the CBS-PI level model to calculate group income elasticity.

$$\eta_g = 1 + \frac{\beta_g}{\widehat{W}_g} \tag{17}$$

Where $\widehat{W}_g$ is the predicted budget shares based on equation (16).

For the CBS-PI model, the group Slutsky own-price elasticity is given by

$$S_{PI} = \frac{\phi\left(\widehat{W}_g + \beta_g\right)(1 - \widehat{W}_g - \beta_g}{\widehat{W}_g} \tag{18}$$

In this context, ϕ represents income flexibility. The Slutsky own-price elasticity measures the percent change in group g's demand for a 1 percent change in price, assuming constant real income. The Cournot price elasticity, on the other hand, quantifies the percent change in the quantity demanded of a good for a 1 percent change in its price, given constant nominal income. These concepts are used in the CBS-PI level model to calculate Cournot elasticity.

$$C_{PI} = \frac{\phi\left(\widehat{W}_g + \beta_g\right)\left(1 - \widehat{W}_g - \beta_g\right)}{\widehat{W}_g} - \left(\widehat{W}_g + \beta_g\right) \tag{19}$$

The Frisch own-price elasticity is the own-price elasticity that is used when income is changed to keep the same level of marginal utility. The CBS PI level model's Frisch own-price elasticity is

$$F = \frac{\phi\left(\widehat{W}_g + \beta_g\right)}{\widehat{W}_g} \tag{20}$$

Food subgroups income and price elasticities

Similar to the broad consumption groups, three distinct types of own-price elasticity and income elasticity are calculated for the subgroups. In the CBS level model, the conditional income elasticity is $\eta_{ic}^* = 1 + \frac{\beta_i^*}{\widehat{w}_{ic}^*}$, where $w_{ic}^* = \frac{w_{ic}}{W_g}$, wic is the budget shares for good i, W_g represent group budget share, and $\widehat{w}_{ic}^*$ are conditional predicted budget share. The conditional income elasticities for food subgroups can be easily converted to the unconditional income elasticities as

$$\eta_{ic}^{u} = \eta_{ic}^{*}\,\eta_{g} \tag{21}$$

The unconditional income elasticity is equivalent to the product of the conditional income elasticity $\left(\frac{\theta_{ic}^{*}}{\widehat{w}_{ic}^{*}}\right)$, and the group income elasticity $\left(\frac{\Theta_{g}}{\widehat{W}_{g}}\right)$.

The conditional Slutsky own-price elasticity $S_{ii} = \frac{\pi_{ii}^{*}}{\widehat{w}_{ic}^{*}}$, does not adjust appropriately as country incomes vary because of the constant Slutsky coefficient. In the context of own-price elasticity calculations, this issue does not apply to the unconditional Frisch elasticities because they are not a function of the own-price elasticity. It is for this reason that Frisch's unconditional own-price elasticities for food subgroups are calculated in this section. For good i, the unconditional Frisch own-price elasticity is given by

$$F_{ii} = \phi\eta_{ic}^{*}\,\eta_{g} = \phi\,\frac{\theta_{ic}^{*}}{\widehat{w}_{ic}^{*}}\,\frac{\Theta_{g}}{\widehat{W}_{g}} \tag{22}$$

$$S_{ii} \cong F_{ii}\left(1 - \Theta_{g}\theta_{i}^{*}\right) \tag{23}$$

$$C_{ii} \cong S_{ii} - \Theta_{g}\theta_{i}^{*} \tag{24}$$

where F_{ii}, S_{ii} and C_{ii} are the Frisch, Slutsky, and Cournot elasticities are the unconditional own-price elasticities for each respective measure. When the own-price of a particular food item changes by 1 percent given total income, the unconditional own-price elasticities measure the percentage change in quantity demanded for that food item.

4. Data Source

Empirical estimation of a demand system requires knowledge of prices and consumption expenditures for all goods in each country. The Geary-Khamis (GK) method was replaced by the Gini-Elteto-Koves-Szulc (GEKS) method in the International Comparison Program (ICP) 2005 phase. The GEKS method, used for aggregation, converts local currencies into a common currency using purchasing power parities (PPPs). Introduced by Gini and rediscovered by Elteto, Koves, and Szulc, the GEKS method satisfies essential axiomatic properties and the economic approach to index number theory. Despite its non-additive results, it was chosen for global aggregation in the 2005 and 2011 phases of the ICP due to its superiority over additive methods.

The International Comparison Program (ICP) calculates purchasing power parities (PPPs) to compare prices and GDP components across economies. PPPs unify currencies into a single currency, accounting for price level differences. Each ICP comparison has a reference year (e.g., 2005, 2011, 2017) and requires data on nationally averaged prices, national account expenditures, market exchange rates, and population. PPPs and real expenditures are calculated using this data. Price level indices are derived from market exchange rates and PPPs, and real expenditures per capita are determined using population totals and real expenditures. The PPP exchange rate between two countries is the rate at which the currency of one country must be converted into that of the other to purchase the same quantity of goods and services in both countries.

The data are collected in three phases (2005, 2011, and 2017) from the World Bank International Comparison Programme for five countries: Brazil, Russia, China, India, and South Africa (BRICS).

4.1 Classification by Broad Consumption Categories

The study considers 11 broad categories of goods:

1. **Food and Non-Alcoholic Beverages**: Includes bread, cereals, meat, fish, seafood, dairy products, oils, fats, fruits, vegetables, sweets, coffee, tea, cocoa, mineral waters, soft drinks, and fruit and vegetable juices.
2. **Alcoholic Beverages, Tobacco and Narcotics**: Includes spirits, wine, beer, tobacco, and narcotics.
3. **Clothing and Footwear**: Covers clothing materials, garments, cleaning, repair and hire of clothing, shoes, and repair and hire of footwear.
4. **Housing, Water, Electricity, Gas and Other Fuels**: Includes rentals for housing, housing repair and maintenance, water supply, services related to the dwelling, electricity, gas, and other fuels.
5. **Furnishings, Household Equipment and Routine Household Maintenance**: Covers furniture, furnishings, carpets, floor coverings, household textiles, household appliances, repair of household appliances, glassware, tableware, household utensils, tools, non-durable household goods, and domestic services.
6. **Health**: Includes pharmaceuticals, medical products, appliances, equipment, outpatient services, and hospital services.
7. **Transport Services**: Covers passenger transport by railway, road, air, sea, inland waterway, combined passenger transport, and other purchased transport services.
8. **Communication**: Includes postal services, telephone and telefax equipment, and services.
9. **Recreation and Culture**: Encompasses spending on hobbies, entertainment activities, audio-visual, photographic, data processing devices, recreational goods and equipment, gardens, pets, services related to recreation and culture, newspapers, books, stationery, and package vacations.

10. **Education**: Covers pre-primary, primary, secondary, postsecondary, and tertiary education.
11. **Restaurants and Hotels**: Includes catering and accommodation services.

4.2 Classification by Food subgroup Consumption Categories

The food, beverage, and tobacco category are divided into eight subgroups:

1. **Bread and cereals**: Include rice, other cereals, flour, bread, other bakery products, and pasta.
2. **Meat**: Covers beef, veal, pork, lamb, mutton, goat, poultry, and other meats.
3. **Fish and seafood**: Includes fresh, chilled or frozen fish and seafood, and preserved or processed variants.
4. **Milk, cheese and eggs**: Encompasses fresh milk, preserved milk, other milk products, cheese, curd, eggs, and egg-based products.
5. **Oils and fats**: Include butter, margarine, and other edible oils and fats.
6. **Fruit**: Covers fresh or chilled fruit, and frozen, preserved or processed fruit and fruit-based products.
7. **Vegetables**: Includes fresh or chilled vegetables (excluding potatoes and other tuber vegetables), fresh or chilled potatoes and other tuber vegetables, and frozen, preserved or processed vegetables and vegetable-based products.
8. **Sugar, jam, honey, chocolate and confectionery**: Includes sugar, jams, marmalades, honey, confectionery, chocolate, and ice cream.
9. **Other foods**: Covers food products not elsewhere classified.

5. Empirical Findings

This section presents empirical findings for broad consumption and food subgroup categories using pooled data from BRICS countries. It begins with an analysis of budget shares, followed by the use of Tayebi's CBS-PI levels and CBS levels models to estimate results for nine broad consumption groups and food subgroups. The third part estimates income and own-price elasticities for the broad model and nine food subcategories using various estimation techniques, including maximum likelihood estimation (MLE) and random effects (RE), both inside and outside of SUR.

5.1 Budget Shares of Broad Categories and Food Subgroups

The average budget shares for broad consumption categories in BRICS nations show that the largest percentage of total income is spent on food, beverages, and tobacco, with China being an exception. The next largest budget shares are for housing, water, electricity, gas, and other fuels, followed by health, education, transportation, and communication. The lowest average budget allocations are for clothing, footwear, furnishings, home equipment, maintenance, restaurants, and hotels.

Table 1: Average budget shares for broad consumption categories (percent of total expenditure)

Country	Food and non-alcoholic drinks	Alcoholic drinks, tobacco and narcotics	clothing and footwear	Housing, water, electricity, gas and other fuels	Furniture, home equipment and	Health	Transport	Communication	Recreation and Culture	Education	Restaurants and hotels
Brazil	8.80	1.54	1.85	11.51	3.24	11.95	5.06	1.89	2.02	11.59	2.91
China	5.53	0.60	1.65	7.90	1.23	12.38	2.08	2.11	2.33	10.04	1.78
India	12.74	0.72	4.11	11.37	1.22	13.04	4.81	1.53	0.67	13.24	0.92
Russia	9.70	4.22	2.23	12.20	2.11	9.78	3.71	2.83	2.55	13.86	1.02
S. Africa	8.44	2.83	2.49	13.03	3.06	9.77	5.98	1.79	1.95	15.80	1.15

Source: Authors Computed from World Bank International Comparison Programme

Budget shares for nine food subcategories from 2011 to 2017 show that BRICS nations spend more on bread, cereals, and meat than on vegetables, fish, and seafood. Notably, India's meat budget allocation is much lower, at 2.85 percent of its income, compared to 25-30 percent in Brazil, China, Russia, and South Africa.

Table 2: Average budget shares for food subgroup categories (percent of total expenditure)

Country	Bread and cereals	Meat	Fish and seafood	Milk, cheese and eggs	Oils and fats	Fruit	Vegetables	Sugar, jam, honey, chocolate and confectionery	other food products
Brazil	22.41	30.80	3.81	11.32	3.56	7.21	10.69	6.42	3.78
China	19.61	25.96	11.48	5.21	2.57	8.07	21.66	1.43	4.00
India	26.95	2.85	6.75	16.03	3.36	15.63	18.93	3.54	5.96
Russia	16.24	24.91	8.01	14.15	3.21	7.66	13.96	9.12	2.73
S. Africa	20.91	25.33	4.66	7.84	3.00	4.17	10.60	9.99	13.50

Source: Authors Computed from World Bank International Comparison Programme

5.2 Estimating Procedure for Broad and Food subgroup Consumption Groups

The Hausman test is used to choose the best estimation method among ML, within, RE, and SUR. The test results for broad consumption groups and smaller food groups are shown in Annexure 1 and 2. The critical chi-square values for the Hausman test comparing fixed effect and SUR (OLS) estimators for broad categories are given in Annexure 3. The critical chi-square values for the Hausman test comparing fixed and random effects estimators for broad categories are given in Annexure 4. In both cases, the null hypothesis that SUR (OLS), fixed, and random effects estimators are all the same is rejected. Given the small size of T in this study, the random effect is the consistent estimator. The Hausman test between RE and ML suggests that the Maximum Likelihood (ML) estimator provides a superior model (see Annexure 5).

The Hausman test compared fixed and ML estimators for various categories. Seven out of eleven categories showed a 1% significance level, indicating ML as a more consistent estimator due to the inconsistency of fixed estimators with short time series. For the food subgroup model, the Hausman test compared fixed effect and SUR (OLS) estimators, with significance levels ranging from 0.1% to 5%. Refer to Annexure 6 and 7 for details.

The Hausman test compared fixed and random effects estimators for various food subgroups, with the test being insignificant, suggesting RE as a better estimator. The test between RE and ML showed ML as a better model for most subgroups at a 1% significance level. The comparison of fixed and ML estimators showed varying significance levels across subgroups. Refer to Annexure 8 and 9 for details.

In the food subgroup of nine items, four are significant. The Hausman test indicates ML as the consistent estimator due to the inconsistency of fixed effects with short time series. ML is a better estimator for both broad and food subgroup models. Both fixed and SUR methods are used for estimating coefficients.

5.3 Econometric analysis of the broad consumption groups

Table.3 shows pooled estimates for eleven consumption groups using ML, RE, and fixed effects methods. ML is indicated as the most accurate by the Hausman test. The β coefficient for food and non-alcoholic beverages is 0.126 with ML and 0.164 with RE, higher than Tayebi's 2019 estimate of -0.147. Alcoholic beverages, tobacco, and drugs have coefficients of 0.13 (ML) and 0.0629 (RE). Clothing and footwear have coefficients of -0.0276 (ML) and -0.0918 (RE), both higher than Tayebi's 2019 estimate of -0.013. Coefficients for housing, water, electricity, gas, and other fuels (0.144), health (0.10), and education (0.24) are comparable in sign and magnitude for both methods. Negative and significant β denotes a necessity, positive and significant β.

Table 3: Pooled parameter estimates for Broad Consumption Groups

Consumption categories	Parameters	Model		
		ML	RE	FE
Food and non-alcoholic drinks	Beta (β)	0.126* (-0.055)	0.164** (0.053)	0.171* (-0.064)
Alcoholic drink, tobacco and narcotics		0.135*** (-0.039)	0.0629 (0.048)	-0.006 (-0.054)
clothing and footwear		-0.028 (0.025)	-0.092** (0.032)	-0.132** (-0.035)
Housing, water, electricity, gas and other fuels		0.144* (-0.056)	0.144* (0.062)	-0.245 (-0.131)
Furniture, home equipment and maintenance		0.095*** (-0.025)	0.039 (0.035)	-0.021 (-0.044)
Health		0.100 (-0.1)	0.100 (0.112)	0.930*** (-0.154)
Transport		0.108** (-0.042)	0.063 (0.061)	-0.0273 (0.094)
Communication		0.0321 (-0.028)	-0.00055 (0.041)	-0.0741 (0.056)
Recreation and Culture		0.0274 (-0.025)	0.0089 (0.019)	0.00755 (-0.022)
Education		0.240*** (-0.061)	0.240*** (0.068)	0.438* (-0.149)
Restaurants and hotels		0.0195 (-0.030)	-0.00033 (0.035)	-0.0532 (-0.033)
Food and non-alcoholic drinks	Income Flexibility ϕ	0.0488 (-0.072)	0.0211 (0.038)	0.0192 (-0.044)
Alcoholic drinks, tobacco and narcotics		0.0269 (-0.0501)	-0.0204 (0.038)	-0.0231 (-0.035)
clothing and footwear		0.0701* (-0.033)	0.0571* (0.025)	0.0581* (-0.023)
Housing, water, electricity, gas and other fuels		0.123 (-0.072)	0.123 (0.081)	0.217* (-0.086)
Furniture, home equipment and maintenance		-0.0476 (-0.033)	-0.00419 (0.031)	0.0116 (-0.029)
Health		-0.149 (-0.13)	-0.149 (0.145)	-0.195 (-0.101)
Transport		-0.00152 (-0.054)	0.0131 (0.056)	0.025 (-0.062)
Communication		-0.0379 (-0.036)	-0.0551 (0.037)	-0.0571 (-0.037)
Recreation and Culture		0.00431 (-0.033)	0.0335** (0.013)	0.0344* (-0.014)
Education		0.0164 (-0.079)	0.0164 (0.088)	-0.159 (-0.098)
Restaurants and hotels		-0.0532 (-0.039)	-0.00855 (0.040)	0.0689* (-0.022)

Source: Authors Estimation based on World Bank International Comparison Programme
Figures in the parenthesis represent standard errors of the associated parameters

indicates a luxury. Communication, restaurants, and hotels are necessities in RE due to their negative sign, as is clothing and footwear in both ML and RE. Health, Communication, Leisure and Culture, and Hotels and Restaurants show no significance in both ML and RE, implying unitary elasticity. Housing, water, electricity, gas, other fuels, food and non-alcoholic beverages, housing, water, and education are luxuries in both methods due to their positive and significant coefficients. Alcohol, tobacco, drugs, furniture, home maintenance, and transportation are luxuries only in ML due to their positive and significant coefficients. Four out of eleven categories have a negative income flexibility coefficient in both methods, indicating an inverse relationship between income and the marginal utility of income.

5.4 Econometric analysis of conditional food sub-groups

The CBS level model applied to BRICS nations' data shows all nine food subgroups as conditionally income elastic according to both ML and RE methods. The β coefficients at 0.1% significance level are: bread and cereals (0.131 ML, 0.00059 RE), meat (0.324 both), fish and seafood (0.0653 ML, 0.0679 RE), milk, cheese, and eggs (around 0.162), oils and fats (0.0319 both), fruits and vegetables (0.0625 ML, 0.0618 RE), vegetables alone (0.109 ML, 0.106 RE), sugar, jam, honey, chocolate, and confectionery (0.112 ML, 0.0814 RE), and other food products (0.00523 ML, 0.0628 RE at 5% level). Cereals and bread, meat, oils and fats, and other foods have negative Slutsky coefficients in both methods, aligning with demand function theory. Other subgroups with positive conditionally income elasticity include fish and seafood, milk, cheese, eggs, fruit, vegetables, sugar, jam, honey, chocolate, and confectionery.

Table 4: Pooled parameter estimates for food subgroups

Consumption categories	Parameters	Model		
		ML	RE	FE
Cereals and bread	Beta (β)	0.131*** (0.0164)	0.000598 (0.0713)	-0.186** (0.0307)
Meat		0.324*** (0.0250)	0.324*** (0.0299)	1.122 (0.500)
Fish and seafood		0.0653*** (0.0165)	0.0679** (0.0241)	0.0955 (0.114)
Milk, cheese and eggs		0.162*** (0.0158)	0.161*** (0.0213)	0.0614 (0.211)
Oils and fats		0.0319*** (0.0020)	0.0319*** (0.00231)	0.0278 (0.0310)
Fruit		0.0625*** (0.0145)	0.0618* (0.0298)	0.141 (0.190)
Vegetables		0.109*** (0.0243)	0.106** (0.0336)	0.0752 (0.207)
Sugar, jam, honey, chocolate and confectionery		0.112*** (0.0140)	0.0814** (0.0291)	-0.0373 (0.0391)
other food products		0.00523 (0.0312)	0.0628* (0.0256)	0.0831 (0.0302)
Cereals and bread	π_{ij}	-0.00256 (0.0018)	-0.0103* (0.0042)	-0.0114** (0.0013)
Meat		-0.00986*** (0.0021)	-0.0098*** (0.0025)	0.00034 (0.0175)
Fish and seafood		0.0023 (0.0017)	0.0003 (0.0017)	-0.0020 (0.0039)
Milk, cheese and eggs		0.0041** (0.0013)	0.0043** (0.0016)	0.0037 (0.0039)
Oils and fats		-0.00022 (0.0002)	-0.0002 (0.0002)	-0.00280 (0.00216)
Fruit		0.00309* (0.0015)	0.00120 (0.0030)	-0.0102 (0.0102)
Vegetables		0.00301 (0.0024)	0.0019 (0.0031)	-0.000548 (0.0124)
Sugar, jam, honey, chocolate and confectionery		0.0007 (0.0014)	-0.0003 (0.0015)	-0.00224 (0.00117)
other food products		-0.0002 (0.0033)	-0.0031* (0.0016)	-0.00324 (0.00163)

Source: Authors Estimation based on World Bank International Comparison Programme
Figures in the parenthesis represent standard errors of the associated parameters
* $p < 5$ percent, ** $p < 10$ percent, *** $p < 1$ percent significance level

5.5 Income and Own-price elasticities of demand for broad consumption group

5.5.1 Income elasticity of demand

The Hausman test indicates ML estimation as superior. Table.5 shows income elasticities for eleven consumption groups across BRICS nations from 2005-2017. No inferior goods are found. BRICS nations have the lowest income elasticities for food and non-alcoholic drinks, with an average of 0.94 from 2005-2017. As income rises, demand for these items remains constant. This is also true for clothing, footwear, health, education, and other essentials. As income increases, income elasticity for clothing and footwear decreases.

Table 5: Income elasticities for broad consumption groups

Country	Year	Real Income per capita	Food and non-alcoholic drinks	Alcoholic drinks, tobacco and narcotics	clothing and footwear	Housing, water, electricity, gas and other fuels	Furniture, home equipment and maintenance	Health	Transport	Communication	Recreation and Culture	Education	Restaurants and hotels
Russia	2017	24.05	0.93	1.25	1.10	1.13	1.24	0.92	1.19	1.20	1.22	1.02	1.33
India	2017	20.65	0.94	3.13	1.11	1.16	1.44	0.93	1.24	1.37	1.61	1.02	1.58
Russia	2011	18.44	0.93	1.24	1.10	1.13	1.23	0.93	1.19	1.23	1.23	1.02	1.34
India	2011	15.55	0.94	1.96	1.11	1.17	1.56	0.93	1.27	1.40	1.77	1.02	1.79
India	2005	14.67	0.94	-2.78	1.13	1.20	1.97	0.93	1.34	2.21	1.85	1.02	11.7
Russia	2005	12.74	0.94	1.30	1.11	1.14	1.33	0.93	1.22	1.31	1.25	1.02	1.44
S. Africa	2017	6.43	0.94	1.34	1.10	1.14	1.25	0.93	1.21	1.27	1.28	1.02	1.37
S. Africa	2011	4.78	0.94	1.33	1.10	1.15	1.28	0.93	1.19	1.28	1.27	1.02	1.43
China	2017	4.18	0.94	1.60	1.11	1.15	1.33	0.93	1.22	1.27	1.25	1.02	1.32
S. Africa	2005	3.87	0.94	1.37	1.11	1.15	1.29	0.93	1.21	1.41	1.30	1.02	1.55
China	2011	3.52	0.94	1.77	1.11	1.16	1.37	0.93	1.27	1.29	1.27	1.02	1.34
China	2005	3.45	0.94	5.56	1.13	1.19	1.60	0.93	1.47	1.42	1.39	1.02	1.76
Brazil	2017	2.18	0.94	1.50	1.10	1.14	1.24	0.93	1.20	1.27	1.27	1.02	1.26
Brazil	2011	1.47	0.94	1.42	1.11	1.14	1.25	0.93	1.19	1.31	1.25	1.02	1.29
Brazil	2005	1.36	0.94	1.40	1.11	1.16	1.30	0.93	1.23	1.30	1.31	1.02	1.38

Source: Authors Computation based on World Bank International Comparison Programme
Countries sorted by descending order of real income per capita.
A per capita is measured in terms of Global Purchasing power parity (PPP) (US$ = 1) or respective year

All categories with income elasticity greater than 1 are considered luxuries, with alcoholic beverages, tobacco, and narcotics being the most elastic. Demand for housing, water, electricity, gas, fuels, healthcare, and education is not significantly affected by income. As countries become wealthier, they allocate more income towards luxury goods, and income elasticities for food and non-alcoholic beverages decline. For low-income nations, income elasticities have increased.

5.5.2 Own-price elasticity of demand

Own-price elasticity measures the change in demand for a good with a 1% price change. Using equations (18), (19), and (20), Slutsky, Cournot, and Frisch own-price elasticities are estimated for each country using ML method parameters (see Tables 6, 7, 8). As countries become wealthier, these elasticities decrease in absolute value. As income falls, Slutsky elasticities increase. Broad group Slutsky elasticities remain constant across nations. Alcoholic beverages, tobacco, and illegal drugs have the lowest elasticities. Restaurants and hotels have the highest, followed by recreation, house furnishings, operations, other expenses, and education.

Table 6: Slutsky own-price elasticities for broad consumption group

Country	Year	Real Income per capita	Food and non-alcoholic drinks	Alcoholic drinks, tobacco and narcotics	clothing and footwear	Housing, water, electricity, gas and other fuels	Furniture, home equipment and maintenance	Health	Transport	Communication	Recreation and Culture	Education	Restaurants and hotels
Russia	2017	24.05	0.04	0.04	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.07
India	2017	20.65	0.04	0.04	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.06
Russia	2011	18.44	0.04	0.04	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.06
India	2011	15.55	0.04	0.15	0.08	0.12	-0.07	-0.11	-0.002	-0.05	0.01	0.01	-0.09
India	2005	14.67	0.04	0.05	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.07
Russia	2005	12.74	0.04	0.04	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.07
S. Africa	2017	6.43	0.04	-0.07	0.08	0.12	-0.09	-0.11	-0.002	-0.08	0.01	0.01	-0.62
S. Africa	2011	4.78	0.04	0.05	0.07	0.12	-0.07	-0.11	-0.002	-0.05	0.01	0.01	-0.09
China	2017	4.18	0.04	0.08	0.07	0.11	-0.07	-0.11	-0.002	-0.05	0.01	0.01	-0.08
S. Africa	2005	3.87	0.04	0.03	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.07
China	2011	3.52	0.04	0.03	0.07	0.11	-0.06	-0.11	-0.002	-0.04	0.01	0.01	-0.07
China	2005	3.45	0.04	0.03	0.07	0.11	-0.06	-0.12	-0.002	-0.04	0.00	0.01	-0.07
Brazil	2017	2.18	0.04	0.03	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.08
Brazil	2011	1.47	0.04	0.03	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.07
Brazil	2005	1.36	0.04	0.03	0.07	0.11	-0.06	-0.11	-0.002	-0.05	0.01	0.01	-0.07

Source: Authors Computation based on World Bank International Comparison Programme

Table 7: Cournot own-price elasticities for broad consumption group

Country	Year	Real Income per capita	Food and non-alcoholic drinks	Alcoholic drinks, tobacco and narcotics	clothing and footwear	Housing, water, electricity, gas and other fuels	Furniture, home equipment and	Health	Transport	Communication	Recreation and Culture	Education	Restaurants and hotels
Russia	2017	24.05	-0.09	-0.04	0.02	-0.14	-0.11	-0.28	-0.10	-0.11	-0.05	-0.21	-0.11
India	2017	20.65	-0.10	0.06	0.03	-0.09	-0.10	-0.30	-0.09	-0.09	-0.02	-0.20	-0.11
Russia	2011	18.44	-0.09	-0.05	0.02	-0.13	-0.12	-0.28	-0.10	-0.10	-0.05	-0.21	-0.11
India	2011	15.55	-0.10	0.02	0.03	-0.08	-0.10	-0.30	-0.08	-0.09	-0.02	-0.20	-0.12
India	2005	14.67	-0.11	-0.09	0.04	-0.04	-0.11	-0.30	-0.07	-0.10	-0.01	-0.20	-0.63
Russia	2005	12.74	-0.09	-0.03	0.03	-0.11	-0.11	-0.29	-0.09	-0.09	-0.04	-0.20	-0.11
S. Africa	2017	6.43	-0.10	-0.03	0.03	-0.12	-0.11	-0.29	-0.09	-0.10	-0.04	-0.20	-0.11
S. Africa	2011	4.78	-0.10	-0.03	0.03	-0.11	-0.11	-0.29	-0.10	-0.09	-0.04	-0.20	-0.11
China	2017	4.18	-0.10	0.00	0.03	-0.11	-0.11	-0.28	-0.09	-0.10	-0.04	-0.20	-0.11
S. Africa	2005	3.87	-0.10	-0.02	0.03	-0.10	-0.11	-0.29	-0.09	-0.09	-0.04	-0.20	-0.11
China	2011	3.52	-0.10	0.01	0.03	-0.09	-0.10	-0.29	-0.08	-0.09	-0.04	-0.20	-0.11
China	2005	3.45	-0.11	0.13	0.04	-0.05	-0.10	-0.30	-0.05	-0.09	-0.03	-0.20	-0.12
Brazil	2017	2.18	-0.09	-0.01	0.03	-0.12	-0.11	-0.29	-0.10	-0.10	-0.04	-0.20	-0.12
Brazil	2011	1.47	-0.09	-0.01	0.03	-0.11	-0.11	-0.28	-0.10	-0.09	-0.04	-0.20	-0.12
Brazil	2005	1.36	-0.10	-0.02	0.03	-0.09	-0.11	-0.29	-0.09	-0.09	-0.04	-0.20	-0.11

Source: Authors Estimation based on World Bank International Comparison Programme

Table 8 Frisch own-price elasticities for broad consumption group

Country	Year	Real Income per capita	Food and non-alcoholic drinks	Alcoholic drinks, tobacco and narcotics	clothing and footwear	Housing, water, electricity, gas and other fuels	Furniture, home equipment and maintenance	Health	Transport	Communication	Recreation and Culture	Education	Restaurants and hotels
Russia	2017	24.05	0.05	0.03	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07
India	2017	20.65	0.05	0.08	0.08	0.14	-0.07	-0.14	0.00	-0.05	0.01	0.02	-0.08
Russia	2011	18.44	0.05	0.03	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07
India	2011	15.55	0.05	0.05	0.08	0.14	-0.07	-0.14	0.00	-0.05	0.01	0.02	-0.10
India	2005	14.67	0.05	-0.07	0.08	0.15	-0.09	-0.14	0.00	-0.08	0.01	0.02	-0.62
Russia	2005	12.74	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.08
S. Africa	2017	6.43	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07
S. Africa	2011	4.78	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.08
China	2017	4.18	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07
S. Africa	2005	3.87	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.08
China	2011	3.52	0.05	0.05	0.08	0.14	-0.07	-0.14	0.00	-0.05	0.01	0.02	-0.07
China	2005	3.45	0.05	0.15	0.08	0.15	-0.08	-0.14	0.00	-0.05	0.01	0.02	-0.09
Brazil	2017	2.18	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07
Brazil	2011	1.47	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07
Brazil	2005	1.36	0.05	0.04	0.08	0.14	-0.06	-0.14	0.00	-0.05	0.01	0.02	-0.07

Source: Authors Estimation based on World Bank International Comparison Programme

Cournot own-price elasticity values are negative and increase in magnitude as per capita income decreases. Housing, water, electricity, gas, and fuels have the highest elasticity, while restaurants and hotels have the lowest. Except for health and education, all groups are own-price inelastic with elasticities less than 0.20. Frisch elasticities follow the Slutsky pattern, with four negative coefficients: furnishings, household equipment, health, communication, and restaurants and hotels. These elasticities increase as income decreases. Cournot and Frisch elasticities are generally greater than Slutsky, except for health where Cournot is slightly greater than Frisch.

5.6 Unconditional Income and Own-price elasticities of demand for food subgroup category

5.6.1 Unconditional income elasticity of demand for food subgroups

The study uses Equation (21) to calculate income elasticities for food subgroups. Most food subgroups have elasticities greater than one, indicating they are luxury goods or expenditure elastic. However, bread and cereal have elasticities below one, suggesting they are necessities or have inelastic spending patterns.

Elasticities range from 0.77 (Russia, 2017) to -0.29 (China, 2011). Among BRICS nations, elasticities increase from 0.77 (Russia, 2017) to 0.92 (South Africa, 2017), and vary from 0.20 to 0.68 (India) and -0.29 to 0.13 (China) between 2011 and 2017.

Countries with higher per capita income show lower elasticities for cereals and bread. As per capita income increases, elasticities for all food subgroups decrease. All food items are of normal quality, with bread and cereals being the only non-luxury items. In 2011, bread and cereal were inferior goods in China.

In summary, except for bread and cereals, all food subgroups become more expensive as real per capita incomes decline.

Table 9: Unconditional Income elasticities for food subgroups

Country	Year	Real Income per capita	Bread and cereals	Meat	Fish and seafood	Milk, cheese and eggs	Oils and fats	Fruit	Vegetables	Sugar, jam, honey, chocolate and confectionery	other food products
Russia	2017	24.05	0.77	1.82	1.26	1.88	1.14	1.85	1.07	1.46	1.71
India	2017	20.65	0.68	2.05	1.35	2.05	1.16	2.00	1.11	1.56	1.89
Russia	2011	18.44	0.72	1.94	1.31	1.97	1.15	1.93	1.09	1.51	1.81
India	2011	15.55	0.20	3.25	1.81	2.90	1.26	2.73	1.29	2.07	2.84
S. Africa	2017	6.43	0.92	1.46	1.12	1.63	1.11	1.65	1.02	1.31	1.43
S. Africa	2011	4.78	0.93	1.44	1.11	1.62	1.11	1.63	1.02	1.30	1.42
China	2017	4.18	0.13	3.41	1.87	3.02	1.27	2.83	1.31	2.13	2.96
China	2011	3.52	-0.29	4.48	2.28	3.79	1.36	3.49	1.47	2.59	3.80
Brazil	2017	2.18	0.68	2.05	1.35	2.04	1.16	1.99	1.11	1.55	1.89
Brazil	2011	1.47	0.67	2.09	1.36	2.07	1.16	2.02	1.11	1.57	1.92

Source: Authors Estimation based on World Bank International Comparison Programme

5.6.2 Unconditional own price elasticity of demand for food subgroups

The study estimates Slutsky price coefficients to determine Slutsky elasticity for each food item in each country. However, for a specific food subgroup, the coefficient is constant across countries, leading to larger Slutsky elasticity for smaller budget shares. This contradicts economic theory as countries with lower real per capita income spend a major portion of their budget on food items.

To address this, initial estimates of unconditional Frisch elasticity are calculated, followed by estimates of unconditional Slutsky and Cournot elasticity. The unconditional Frisch own-price elasticities show that high-income countries are less sensitive to price changes. Cereals and bread have the lowest own-price elasticities, followed by meat, fish, seafood, milk, cheese, eggs, oils, fats, fruit, vegetables, sugar, jam, honey, chocolate, and other food products.

Table 10: Unconditional Frisch own-price elasticities for food subgroups

Country	Year	Real Income per capita	Bread and cereals	Meat	Fish and seafood	Milk, cheese and eggs	Oils and fats	Fruit	Vegetables	Sugar, jam, honey, chocolate and confectionery	other food products
Russia	2017	24.05	-0.060	-0.142	-0.098	-0.147	-0.089	-0.145	-0.084	-0.114	-0.134
India	2017	20.65	-0.053	-0.160	-0.106	-0.160	-0.090	-0.156	-0.087	-0.122	-0.148
Russia	2011	18.44	-0.056	-0.152	-0.102	-0.154	-0.090	-0.151	-0.085	-0.118	-0.141
India	2011	15.55	-0.016	-0.254	-0.142	-0.227	-0.098	-0.213	-0.100	-0.161	-0.221
S. Africa	2017	6.43	-0.072	-0.114	-0.087	-0.128	-0.087	-0.128	-0.080	-0.102	-0.112
S. Africa	2011	4.78	-0.073	-0.112	-0.087	-0.127	-0.087	-0.128	-0.079	-0.102	-0.111
China	2017	4.18	-0.011	-0.266	-0.146	-0.236	-0.099	-0.221	-0.102	-0.167	-0.231
China	2011	3.52	0.023	-0.350	-0.178	-0.296	-0.106	-0.272	-0.115	-0.202	-0.297
Brazil	2017	2.18	-0.053	-0.160	-0.105	-0.160	-0.090	-0.156	-0.087	-0.121	-0.148
Brazil	2011	1.47	-0.052	-0.163	-0.107	-0.162	-0.091	-0.157	-0.087	-0.123	-0.150

Source: Authors Estimation based on World Bank International Comparison Programme

As countries shift from low to high income, the item becomes own-price elastic. As income levels decline, there is an increase in the absolute value of the Frisch unconditional own-price elasticities. The negative unconditional Slutsky own-price elasticity values rise as countries shift from low to high income. Meat has the highest price elasticities, while cereals and bread have the lowest unconditional Slutsky elasticity.

As income levels fall, meat becomes an own-price elastic item. The unconditional Slutsky elasticities for other foods shift as income levels decline. The unconditional Frisch and Cournot elasticities are situated between the unconditional Slutsky elasticities.

When a country's income decreases, the absolute value of the unconditional Cournot elasticity increases. The unconditional Cournot elasticities are smaller than own-price elasticities of unconditional Frisch and Slutsky. Lower-income countries have higher unconditional Cournot elasticities than higher-income ones, indicating that countries with less income are more sensitive to price changes.

Table 11: Unconditional Slutsky own-price elasticities for food subgroups

Country	Year	Real Income per capita	Bread and cereals	Meat	Fish and seafood	Milk, cheese and eggs	Oils and fats	Fruit	Vegetables	Sugar, jam, honey, chocolate and confectionery	other food products
Russia	2017	24.05	-0.060	-0.142	-0.098	-0.147	-0.089	-0.145	-0.084	-0.114	-0.134
India	2017	20.64	-0.053	-0.160	-0.106	-0.160	-0.090	-0.156	-0.087	-0.122	-0.148
Russia	2011	18.44	-0.056	-0.152	-0.102	-0.154	-0.090	-0.151	-0.085	-0.118	-0.141
India	2011	15.54	-0.016	-0.254	-0.142	-0.227	-0.098	-0.213	-0.100	-0.161	-0.222
S. Africa	2017	6.42	-0.072	-0.114	-0.087	-0.127	-0.087	-0.128	-0.080	-0.102	-0.112
S. Africa	2011	4.77	-0.073	-0.112	-0.087	-0.126	-0.087	-0.128	-0.079	-0.102	-0.111
China	2017	4.18	-0.011	-0.267	-0.146	-0.236	-0.099	-0.221	-0.102	-0.167	-0.231
China	2011	3.52	0.023	-0.350	-0.178	-0.296	-0.106	-0.272	-0.115	-0.202	-0.297
Brazil	2017	2.18	-0.053	-0.160	-0.105	-0.160	-0.090	-0.156	-0.087	-0.121	-0.148
Brazil	2011	1.47	-0.052	-0.163	-0.107	-0.162	-0.091	-0.157	-0.087	-0.123	-0.150

Source: Authors Estimation based on World Bank International Comparison Programme

Table 12: Unconditional Cournot own-price elasticities for food subgroups

Country	Year	Real Income per capita	Bread and cereals	Meat	Fish and seafood	Milk, cheese and eggs	Oils and fats	Fruit	Vegetables	Sugar, jam, honey, chocolate and confectionery	other food products
Russia	2017	24.05	-0.060	-0.141	-0.098	-0.147	-0.089	-0.145	-0.084	-0.114	-0.133
India	2017	20.64	-0.053	-0.160	-0.105	-0.160	-0.090	-0.156	-0.087	-0.122	-0.148
Russia	2011	18.44	-0.056	-0.151	-0.102	-0.154	-0.090	-0.151	-0.085	-0.118	-0.141
India	2011	15.54	-0.015	-0.253	-0.141	-0.227	-0.098	-0.214	-0.100	-0.161	-0.221
S. Africa	2017	6.42	-0.072	-0.113	-0.087	-0.128	-0.087	-0.129	-0.079	-0.102	-0.112
S. Africa	2011	4.77	-0.072	-0.112	-0.087	-0.127	-0.087	-0.128	-0.079	-0.102	-0.110
China	2017	4.18	-0.010	-0.266	-0.146	-0.236	-0.099	-0.221	-0.102	-0.167	-0.231
China	2011	3.52	0.023	-0.349	-0.178	-0.296	-0.106	-0.273	-0.115	-0.202	-0.297
Brazil	2017	2.18	-0.053	-0.159	-0.105	-0.160	-0.090	-0.156	-0.086	-0.122	-0.148
Brazil	2011	1.47	-0.052	-0.162	-0.106	-0.162	-0.091	-0.158	-0.087	-0.123	-0.150

Source: Authors Estimation based on World Bank International Comparison Programme

6. Conclusion

This paper adopts Tayebi's (2019) CBS demand model, which builds on the foundational work of Keller and Van Driel (1985). Tayebi introduces two new versions: the CBS level model and the CBS-PI level model. These models are better suited for demand analysis involving cross-country comparisons and single-country time-series analysis.

Balanced panel data and random effects methods are used to estimate demand for eleven broad goods groups and nine food subgroups. The findings show that countries with lower per capita income are more responsive to changes in income and prices than those with higher per capita income, aligning with theoretical expectations.

The study pools cross-sectional and time-series country data for accurate demand estimation. Panel data analysis is used to reflect structural changes in consumption and spending patterns. The study uses geometric mean prices and quantities as deflators to generate changes in log prices and quantities.

Tayebi's (2019) multistage budgeting is adopted to estimate the demand model and associated income and price elasticities for eleven consumption categories and nine food subgroups. The CBS-PI levels and CBS levels models are used for estimation, using maximum likelihood and random effects.

Data on consumption, expenditure, and prices are collected from three ICP phases (2005, 2011, and 2017) for BRICS countries. Income and own-price elasticities are calculated using estimated coefficients.

The results show that both the CBS-PI levels and CBS levels models work well for BRICS countries. The estimated demand coefficients and price and income elasticities align with other studies in this area.

In BRICS countries, significant spending is observed on necessities like food and non-alcoholic drinks, which have income elasticities less than one. High expenditure is also seen on health and education. High-income countries spend a large portion of their income on alcoholic beverages, tobacco, and narcotics, with India having an income elasticity of 3.13 in 2017 and China 5.55 in 2005.

Other consumption categories, including housing, water, power supply, cooking, and other fuels; furniture; maintenance and repair of home items; transport and communication; leisure; and culture, are income elastic and their prices increase as income levels fall. As income increased in India, so did the demand for services, leading to more people working in services. Services have become a necessity with income elastic and price inelastic demand, highlighting the importance of services for growth in India (Kothe, 2019).

In BRICS countries, expenditure and own-price elasticities for food subgroups decrease as income increases, except for bread and cereals, which are considered necessities due to their elasticity being less than one. Low-income countries like South Africa and China are more responsive to income and price changes, leading to larger adjustments in their food consumption patterns. This holds true for various food items, some of which have elasticities greater than two, indicating they are luxury items.

Low-income countries spend more of their food budget on low-value foods like bread and cereal, while high-income countries like India spend more on high-value foods. For certain food subgroups, estimates show income elasticities, while others show inelastic unconditional income. In BRICS nations, meat, fruits, and other foods are becoming luxury goods. Changes in the prices of certain food items have a greater effect on lower-income countries.

Overall, the demand for food categories is responsive to changes in their own prices as income declines. The estimated elasticities could help predict future food demand and simulate the effects of government policies. This information can assist in creating effective food policies for low-income countries. The paper highlights the importance of considering income levels when assessing how changes in food prices will affect consumption patterns. It emphasizes the significance of demand-side influences on long-term economic structure (Clements & Vo, 2021).

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Annexure 1: Pooled parameter estimates for Broad Consumption Groups using SUR

Consumption categories	Parameters	Model	
		SUR	Standard Errors
Food and non-alcoholic drinks	Beta (β)	0.126*	(0.0558)
Alcoholic drink, tobacco and narcotics		0.135***	(0.0388)
clothing and footwear		-0.0276	(0.0253)
Housing, water, electricity, gas and other fuels		0.144*	(0.0562)
Furniture, home equipment and maintenance		0.0947***	(0.0256)
Health		0.100	(0.100)
Transport		0.108**	(0.0419)
Communication		0.0321	(0.0281)
Recreation and Culture		0.0274	(0.0254)
Education		0.240***	(0.0611)
Restaurants and hotels		0.0195	(0.0299)
Food and non-alcoholic drinks	Income Flexibility ϕ	0.0488	(0.0720)
Alcoholic drink, tobacco and narcotics		0.0269	(0.0501)
clothing and footwear		0.0701*	(0.0326)
Housing, water, electricity, gas and other fuels		0.123	(0.0724)
Furniture, home equipment and maintenance		-0.0476	(0.0331)
Health		-0.149	(0.130)
Transport		-0.00152	(0.0540)
Communication		-0.0379	(0.0363)
Recreation and Culture		0.00431	(0.0328)
Education		0.0164	(0.0788)
Restaurants and hotels		-0.0532	(0.0386)

Source: World Bank International Comparison Programme

Annexure 2: Pooled parameter estimates for food subgroups using SUR

Consumption categories	Parameters	Model	
		SUR	Standard Errors
Cereals and bread	Beta (β)	0.131***	(0.0164)
Meat		0.324***	(0.0250)
Fish and seafood		0.0652***	(0.0123)
Milk, cheese and eggs		0.164***	(0.0129)
Oils and fats		0.0319***	(0.00193)
Fruit		0.0625***	(0.0145)
Vegetables		0.109***	(0.0180)
Sugar, jam, honey, chocolate and confectionery		0.112***	(0.0107)
other food products		0.00444	(0.0224)
Cereals and bread	π_{ij}	-0.00256	(0.00175)
Meat		-0.00986***	(0.00207)
Fish and seafood		0.00240	(0.00124)
Milk, cheese and eggs		0.00375**	(0.00121)
Oils and fats		-0.000219	(0.000216)
Fruit		0.00319*	(0.00157)
Vegetables		0.00307	(0.00182)
Sugar, jam, honey, chocolate and confectionery		0.000800	(0.00106)
other food products		-0.000139	(0.00241)

Source: World Bank International Comparison Programme

Annexure 3: Hausman test between FE and SUR (OLS) estimators of CBS-PI level model (Equation14)

	food	beverages	clothing & footwear	hsgwater electgas	furnish household equipment	health	transport	commu-nication	recreation & culture	education	restau-rants & hotels
main											
d(logQc)	0.126*	0.135***	-0.0276	0.144*	0.0947***	0.100	0.108**	0.0321	0.0274	0.240***	0.0195
	(0.0558)	(0.0388)	(0.0253)	(0.0562)	(0.0256)	(0.100)	(0.0419)	(0.0281)	(0.0254)	(0.0611)	(0.0299)
log(pict/pit)	0.0488	0.0269	0.0701*	0.123	-0.0476	-0.149	-0.00152	-0.0379	0.00431	0.0164	0.0532
	(0.0720)	(0.0501)	(0.0326)	(0.0724)	(0.0331)	(0.130)	(0.0540)	(0.0363)	(0.0328)	(0.0788)	(0.0386)
Constant	0.0242	-0.135**	0.0868**	0.0427	-0.0751*	0.124	-0.0498	0.00534	0.00699	-0.0437	0.0134
	(0.0742)	(0.0516)	(0.0337)	(0.0747)	(0.0341)	(0.134)	(0.0556)	(0.0374)	(0.0338)	(0.0813)	(0.0398
Hausman test between FE and SUR (OLS) estimators											
chi2(2)	0.67	11.53**	18.00***	11.73**	2.06	47.52***	2.70	23.26***	2.28	9.46**	11.76**
Prob>chi2	0.7145	0.0031	0.0001	0.0028	0.357	0.0000	0.2596	.0000	0.3205	0.0088	0.0028
N	15	15	15	15	15	15	15	15	15	15	15

Annexure 4: Hausman test between FE and RE estimators of CBS-PI level model (14)

	food	beverages	clothing & footwear	hsgwater electgas	furnish household equipment	health	transport	commu-nication	recreation & culture	education	restau-rants & hotels
main											
d(logQc)	0.171*	0.00636	-0.132**	-0.245	-0.0209	0.930***	-0.0273	-0.0741	0.00755	0.438*	-.0532
	(-0.0635)	(-0.054)	(-0.0352)	(-0.131)	(-0.0435)	(-0.154)	(-0.0944)	(0.057)	(-0.0215)	(-0.149)	(-0.0328)
log(pict/pit)	0.0192	-0.0231	0.0581*	0.217*	0.0116	-0.195	0.025	-0.0571	0.0344*	-0.159	0.0689*
	(-0.0415)	(-0.0353)	(-0.023)	(-0.086)	(-0.0285)	(-0.101)	(-0.0618)	(-0.0371)	(-0.014)	(-0.0977)	(-0.0215)
Constant	-0.0357	0.0442	0.231**	0.567*	0.0782	-1.004**	0.133	0.152	0.0318	-0.3	0.103*
	(-0.0857)	(-0.0729)	(-0.0475)	(-0.177)	(-0.05870	(-0.208)	(-0.127)	(-0.0765)	(-0.029)	(-0.201)	(-0.0443)
Hausman test between FE and RE estimators											
chi2(2)	0.14	3.76	3.87	6.76*	4.07	9.73**	1.66	3.27	0.36	5.3	9.89**
Prob>chi2	0.9302	0.1526	0.1445	0.034	0.1307	0.0077	0.4369	0.1945	0.8369	0.0705	0.0071
N	15	15	15	15	15	15	15	15	15	15	15

Annexure 5: Hausman test between RE and ML estimators of CBS-PI level model (14)

	food	beverages	clothing & footwear	hsgwater electgas	furnish household equipment	health	transport	commu-nication	recreation & culture	education	restau-rants & hotels
main											
d(logQc)	0.126*	0.135***	-0.0276	0.144*	0.0947***	0.1	0.108**	0.0321	0.0274	0.240***	0.0195
	(-0.0558)	(-0.0388)	(0.0253)	(-0.0562)	(-0.0256)	(-0.1)	(-0.0419)	(-0.0281)	(-0.0254)	(-0.0611)	(-0.0299)
log(pict/pit)	0.0488	0.0269	0.0701*	0.123	-0.0476	-0.149	-0.00152	-0.0379	0.00431	0.0164	-0.0532
	(-0.072)	(-0.0501)	(-0.0326)	(-0.0724)	(-0.0331)	(-0.13)	(-0.054)	(-0.0363)	(-0.0328)	(-0.0788)	(-0.0386)
Constant	0.0242	-0.135**	0.0868**	0.0427	-0.0751*	0.124	-0.0498	0.00534	0.00699	-0.0437	0.0134
	(-0.0742)	(-0.0516)	(-0.0337)	(-0.0747)	(-0.0341)	(-0.134)	(-0.0556)	(-0.0374)	(-0.0338)	(-0.0813)	(-0.0398)
Hausman test between RE and MLE estimators											
chi2(2)	2.86	5.57	9.84**	0.00	6.41*	0.00	1.41	9.43**	1.27	0.00	23.27***
Prob>chi2	0.2391	0.0616	0.0073	1.00	0.0406	1.00	0.4939	0.009	0.5303	1.00	0.0000
sigma_e											
Constant	0.0423***	0.0294***	0.0192***	0.0425***	0.0194***	0.0760***	0.0317***	0.0213***	0.0192***	0.0463***	0.0227***
	-0.00772	-0.00537	-0.0035	-0.00776	-0.00354	-0.0139	-0.00578	-0.00389	-0.00351	-0.00845	-0.00414
N	15	15	15	15	15	15	15	15	15	15	15

Standard errors in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Annexure 6: Hausman test between FE and MLE estimators of CBS-PI level model (Equation 14)

	food	beverages	clothing & footwear	hsgwater electgas	furnish household equipment	health	transport	commu-nication	recreation & culture	education	restau-rants & hotels
main											
d(logQc)	0.171*	0.00636	-0.132**	-0.245	-0.0209	0.930***	-0.0273	-0.0741	0.00755	0.438*	-.0532
	(-0.0635)	(-0.054)	(-0.0352)	(-0.131)	(-0.0435)	(-0.154)	(-0.0944)	(0.057)	(-0.0215)	(-0.149)	(-0.0328)
log(pict/pit)	0.0192	-0.0231	0.0581*	0.217*	0.0116	-0.195	0.025	-0.0571	0.0344*	-0.159	0.0689*
	(-0.0415)	(-0.0353)	(-0.023)	(-0.086)	(-0.0285)	(-0.101)	(-0.0618)	(-0.0371)	(-0.014)	(-0.0977)	(-0.0215)
Constant	-0.0357	0.0442	0.231**	0.567*	0.0782	-1.004**	0.133	0.152	0.0318	-0.3	0.103*
	(-0.0857)	(-0.0729)	(-0.0475)	(-0.177)	(-0.05870	(-0.208)	(-0.127)	(-0.0765)	(-0.029)	(-0.201)	(-0.0443)
Hausman test between FE and MLE estimators											
chi2(2)	0.67	11.53	18	11.73	2.06	47.52	2.7	23.26	2.28	9.46	11.76
Prob>chi2	0.7145	0.0031	0.0001	0.0028	0.357	0	0.2596	0	0.3205	0.0088	0.0028

Annexure 7: Hausman test between FE and SUR estimators of the CBS level model (Equation 13)

		Bread & cereals	Meat	Fish	milk&eggs	oils&fats	fruit	vegetables	Sugarjam	otherfood
main										
d(logQc)		0.131***	0.324***	0.0652***	0.164***	0.0319***	0.0625***	0.109***	0.112***	0.00444
		(0.0164)	(0.0250)	(0.0123)	(0.0129)	(0.00193)	(0.0145)	(0.0180)	(0.0107)	(0.0224)
breadcereals		-0.00256								
		(0.00175)								
Meat			-0.00986***							
			(0.00207)							
Fish				0.00240						
				(0.00124)						
milk&eggs					0.00375**					
					(0.00121)					
oils&fats						-0.000219				
						(0.000216)				
fruit							0.00319*			
							(0.00157)			
vegetables								0.00307		
								(0.00182)		
ex2Sugarjam									0.000800	
									(0.00106)	
otherfood										-0.000139
										(0.00241)
Constant	0.0158***	0.00943	-0.00532	-0.0167***	-0.000263	-0.00253	-0.000244	-0.00893**	0.00867	
	(0.00441)	(0.00604)	(0.00289)	(0.00369)	(0.000557)	(0.00375)	(0.00428)	(0.00292)	(0.00635)	
Hausman Test bet FE and SUR										
chi2(2)	98.49	3.00	4.16	0.60	1.47	3.50	0.78	6.63	6.21	
Prob>chi2	0.00	0.2235	0.1249	0.7414	0.4800	0.1741	0.6775	0.0363	0.0448	
N	10	10		10	10	10	10	10	10	

Standard errors in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Annexure 8: Hausman test between FE and RE estimators of the CBS level model (13)

		Bread & cereals	Meat	Fish	milk&eggs	oils&fats	fruit	vegetables	Sugarjam	otherfood
d(logQc)		-0.186**	1.122	0.0955	0.0614	0.0278	0.141	0.0752	-0.0373	0.0831
		(0.0307)	(0.500)	(0.114)	(0.211)	(0.0310)	(0.190)	(0.207)	(0.0391)	(0.0302)
breadcereals		-0.0114**								
		(0.00131)								
Meat			0.000341							
			(0.0175)							
Fish				-0.00196						
				(0.00390)						
demilk&eggs					0.00365					
					(0.00386)					
oils&fats						-0.00280				
						(0.00216)				
fruit							-0.0102			
							(0.0102)			
vegetables								-0.000548		
								(0.0124)		
Sugarjam									-0.00224	
									(0.00117)	
otherfood										-0.00324
										(0.00163)
Constant	0.0907***	-0.155	-0.00199	0.00159	0.00614	0.0114	0.0133	0.0244	0.00178	
	(0.00568)	(0.120)	(0.0142)	(0.0449)	(0.00718)	(0.0196)	(0.0196)	(0.00837)	(0.00654)	
Hausman Test bet FE and RE										
chi2(2)	6.58	3.07	1.46	0.54	1.67	2.45	0.71	4.96	1.98	
Prob>chi2	0.0372	0.2155	0.4811	0.7637	0.4349	0.294	0.6996	0.0837	0.3714	
N	10	10	10	10	10	10	10	10	10	
r2_a	0.934	0.246	-1.342	-1.095	-0.651	-1.235	-1.650	-0.346	0.399	

Standard errors in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Annexure 9: Hausman test between FE and ML estimators of the CBS level model (13)

		Bread & cereals	Meat	Fish	milk&eggs	oils&fats	fruit	vegetables	Sugarjam	otherfood
main										
d(logQc)		0.131***	0.324***	0.0652***	0.164***	0.0319***	0.0625***	0.109***	0.112***	0.00444
		(0.0164)	(0.0250)	(0.0123)	(0.0129)	(0.00193)	(0.0145)	(0.0180)	(0.0107)	(0.0224)
breadcereals		-0.00256								
		(0.00175)								
Meat			-0.00986***							
			(0.00207)							
Fish				0.00240						
				(0.00124)						
milk&eggs					0.00375**					
					(0.00121)					
oils&fats						-0.000219				
						(0.000216)				
fruit							0.00319*			
							(0.00157)			
vegetables								0.00307		
								(0.00182)		
Sugarjam									0.000800	
									(0.00106)	
otherfood										-0.000139
										(0.00241)
Constant	0.0158***	0.00943	-0.00532	-0.0167***	-0.000263	-0.00253	-0.000244	-0.00893**	0.00867	
	(0.00441)	(0.00604)	(0.00289)	(0.00369)	(0.000557)	(0.00375)	(0.00428)	(0.00292)	(0.00635)	
Hausman Test bet FE and ML										
chi2(2)	98.49	3.00	4.16	0.60	23.42	3.5	0.78	6.63	6.21	
Prob>chi2	0.0000	0.2235	0.1249	0.7414	0.0000	0.1741	0.6775	0.0363	0.0448	
sigma										
Constant	0.00499***	0.00757***	0.00365***	0.00401***	0.000598***	0.00439***	0.00530***	0.00329***	0.00692***	
	(0.00112)	(0.00169)	(0.000816)	(0.000896)	(0.000134)	(0.000981)	(0.00119)	(0.000735)	(0.00155)	
N	10	10	10	10	10	10	10	10	10	