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RESEARCH ARTICLE

Food demand estimation from consumption and expenditure data: Meat demand in Nigeria

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Abstract
Hidden consumption is a potential problem when consumers' expenditure data from household surveys are used in demand analyses. A solution is to collect and use actual consumption data. This study compares demand estimation using consumption and expenditure data and evaluates meat demand in Nigeria. Data are from a nationally representative panel from Nigeria. The results show the elasticities estimated across both datasets were very similar; thus, if the only objective of data collection is to estimate elasticity using a demand system framework, collection of both types of data (consumption and expenditures) may be unnecessary. The elasticity estimates classify poultry, beef, and processed seafood as luxuries, while other meat and unprocessed seafood are classified as necessities. Own-price elasticities from both datasets indicated that poultry, beef, and processed seafood were price-elastic, and poultry was the most price-elastic.

Keywords: Data quality; EASI demand system; hidden consumption; Nigeria

JEL classification: D12

Introduction

Demand analysis has multiple applications in agribusiness analyses, including studies of consumer preferences status and dynamics and evaluations of agricultural and food policies. Applied demand analyses require three main components: a demand model derived from economic theory (e.g., The Almost Ideal Demand System); a dataset to estimate the model parameters, and an econometric estimation procedure. While an extensive literature has developed and compared demand models (e.g., Piggott 2003; Lewbel and Pendakur 2009) and estimation procedures (e.g., Shonkwiler and Yen 1999), analyses of the effects of data on demand estimation results are very limited.

One data issue prevalent when using consumers' expenditures data obtained from household surveys is the problem of hidden consumption, which gives rise to measurement error problems (e.g., Gibson and Kim 2011). This problem arises if households consume food stocks purchased in the market or food they produce themselves and do not report expenditures on the goods during the survey period (e.g., commonly one or two weeks). The problem of hidden consumption is likely more prevalent in developing countries where more households rely on their production. Why are measurement errors such as those due to hidden consumption relevant for food demand estimation (i.e., estimation of income and price elasticities)? The source of the problem is measurement error. Although classical measurement errors in the dependent variable do not cause any bias, measurement errors correlated with the values of the dependent variable or other explanatory variables can induce biases in demand parameters and elasticity estimates (e.g., Gibson 2002; Gibson et al. 2015).

Some "solutions" to the hidden data problem proposed in the literature involve estimating special econometric procedures that attempt to consider hidden consumption but require additional assumptions (e.g., Deaton and Irish 1984). Another solution to the hidden consumption problem is the collection of actual consumption data in addition to, or as a substitute for, expenditure/acquired consumption data. This study's main contribution is that it estimates and compares demand estimation results using consumption and expenditure data collected from the same individuals.[1] The data for this study was derived from the 2010–2015 Nigerian General Household Survey Panel component of the annual General Household Survey (GHS).

The analyses focus only on demand for meat products: poultry, beef, other meats, and unprocessed and processed seafood; thus, another contribution is evaluating meat demand in Nigeria. Meat consumption is increasing globally, and sub-Saharan African countries are set to reap considerable economic and health benefits from meat production and consumption (The Economist 2019). Nigeria is the most populous country in Africa and one of the largest meat consumers on the continent. Beef is the dominant and traditional meat in Nigeria (Solomon and Nazemzadeh 2004). With a population of approximately 190 million, Nigerians consume more than 360,000 tons of beef per year, and this amount is expected to increase to about 1.3 million tons by 2050 (Premium Times Nigeria 2014; Saumell 2014). Comparing meat consumption with other food commodities shows that meat, fish, and other animal products are the fourth food group consumed most commonly in Nigerian households (88.9%) (National Bureau of Statistics and Living Standards Measurement Study 2016).

Few previous studies have investigated household food demand in Nigeria, and even fewer have examined meat consumption and expenditure patterns. For example, Ezedinma, Kormawa, and Chianu (2006) studied 960 households' consumption and expenditures on beef, chicken, mutton, fish, eggs, and milk in three major cities in Nigeria – Abuja, Kaduna, and Kano. Studies such as this are no longer current, were limited to only several states and regions, and used cross-sectional data. In contrast, we evaluate meat demand in Nigeria using a nationally representative panel data sample. Demand analysis results (e.g., price and income elasticities) are helpful for the design and analysis of public policies and business strategies.

Literature review

The literature review is divided into two sections. First, we review the literature that has analyzed differences in estimates obtained using consumption versus expenditure (sometimes called acquisition surveys), while the second section reviews the literature on estimating meat demand in Nigeria.

A body of literature has already evaluated differences in estimates of nutritional status (caloric counts) using consumption versus acquisition surveys (e.g., Smith, Alderman, and

[1]We acknowledge, as suggested by a reviewer, that self-reported data are also subject to measurement error. However, if correctly measured, consumption data does solve the hidden consumption problem.

Aduayom 2006; Kaara and Ramasawmy 2008; Conforti, Grunberger, and Troubat 2017; Fiedler and Mwangi 2016). These studies focus on population-wide estimates of per capita Dietary Energy Consumption (DEC) and their variability. For example, Conforti, Grunberger, and Troubat (2017) compared DEC estimates from consumption versus acquisition data using 81 surveys from several countries. They found that acquisition surveys provided higher estimates (about 10% larger) of DEC than consumption surveys with larger relative variability (i.e., coefficient of variation).

In addition to population-wide estimates of nutritional status, food and policy analyses also require other information generated from survey data, such as income and price elasticities of demand (Piggot and Marsh 2011). Two groups of studies evaluate the effect of measurement error on demand estimation. The first group compares demand estimates obtained using alternative survey designs (Gibson 2002; Gibson et al. 2015; Gibson and Kim 2007). The second group evaluates econometric procedures that account for the measurement error problem due to infrequency of purchases (e.g., Deaton and Irish 1984; Kay, Keen, and Morris 1984; Keen 1986; Blundell and Meghir 1987).

For example, within the first group of studies, Gibson et al. (2015) assess the effect of alternative consumption survey designs on Engel demand estimation. The survey designs differed by the method of data capturing (diary versus recall), respondent type (individual versus household reporting), recall period (7-day, 14-day, and one month), and the number of items in the recall list. The authors find that the survey design affects estimated income effects, but not household size effects. However, studies comparing estimates obtained from consumption and expenditure data from the same household are less common (e.g., Gibson and Kim 2011).

Gibson and Kim (2011) measured hidden consumption from food stocks using an unusual household survey that observed food stock changes during the survey period directly. Based upon the bounded recall methodology used in the 1996 Papua New Guinea Household Survey, the authors identified hidden consumption. During the first interview, enumerators weighed household food stocks of 18 major foods and reweighed the stocks of the same foods again in the second interview. This made it possible to measure starting and ending food stocks and observe their hidden consumption. They compared parameter estimates obtained directly from measuring consumption of pre-existing food stocks (i.e., hidden consumption) with estimates obtained from infrequent purchase models (IPM) – models that attempt to account for this hidden consumption indirectly through statistical analysis.[2] The authors found that IPMs produced substantially biased income elasticity estimates. In contrast to their approach to testing the IPMs' performance using acquired consumption relative to a model that uses measured consumption, we compare demand estimation results using the same econometric procedure but two different data sources: consumption and expenditures. Moreover, Gibson and Kim's (2011) study focused only on estimating income elasticity, while we studied both price and expenditure elasticities.

A related literature has evaluated data quality and focused on assessing the quality of Homescan datasets versus Consumer Expenditure Survey datasets (e.g., Boonsaeng and Carpio 2019; Sweitzer et al. 2017). In contrast, our study evaluates the demand estimation results using consumption and expenditure data from the same survey.

The literature review identified only a small number of studies that examined Nigerian consumers' demand for meat products; however, none used nationally representative country samples, and most used small cross-sectional samples (Igwe and Onyekwere 2007;

[2]Gibson and Kim (2011) can also be seen both as a comparison of demand estimation results using different datasets and an assessment of econometric procedures used to account for infrequency of purchases.

Alimi 2013; Ogundari 2012). The most extensive study was conducted using data from urban households in 3 cities in Northern Nigeria (Ezedinma, Kormawa, and Chianu 2006), in which 960 households' expenditures on beef, mutton/goat, chicken, fish, eggs, and milk were evaluated. The authors found that urban households' meat demand increased as their income increased. More affluent households consumed primarily chicken, eggs, and milk, while poorer households consumed more fish and beef. Beef was found to be the meat product mainly consumed by 77% of households, followed by fish (68%), milk (47%), eggs (45%), chicken (22%), and mutton and goat meat (15%). Own-price elasticities indicated that beef, mutton/goat, chicken, fish, eggs, and milk are highly elastic, and all the meat products were found to be complements. Relative to the previous studies that have analyzed meat demand in Nigeria, this study uses a sample of households observed during several periods and drawn from around the country.

Data

The data for this study was derived from the 2010–2015 Nigerian General Household Survey Panel component of the annual GHS. The survey began in 2010/2011 and resulted from a partnership between local and international organizations (National Bureau of Statistics 2016).

Sample and sampling design

The GHS-Panel consists of three waves: Wave 1 (conducted in 2010/2011)[3], Wave 2 (in 2012/2013)[4], and Wave 3 (in 2014/2015)[5]. The sample was designed to represent the national and zonal levels. The selection of households in the sample was made in two stages. The first involved the selection of Enumeration Areas (EAs). These EAs were the Primary Sampling Units and were selected based on a probability proportional to the size and the total number of households in each EA. A total of 500 EAs were chosen in this first stage. The second stage involved the random selection of ten households per EA, and 5,000 households were selected in total (National Bureau of Statistics 2016). Only 4,407 of these households completed all of the interviews across the three waves and because of incorrect or missing information, the final sample used in this study was 3,013 households.

Food consumption and expenditures

During each wave, households in the sample were visited twice – a post-planting visit (between September and November) and a post-harvest visit (between February and April). Information on household food consumption and expenditures was obtained in each visit. The household member most familiar with the household's food purchases and consumption was asked the following questions[6]: (1) How much in total did your household consume of this [ITEM] in the past 7 days? (2) How much did the household purchase of this [ITEM] during the past 7 days? (3) How much did your household spend on this [ITEM] during the past 7 days? The analysis was based on these consumption and expenditure data.

[3]Data availaility at General Household Survey, Panel 2010–2011, Wave 1, Nigeria, 2010–2011. See: https://microdata.worldbank.org/index.php/catalog/1002

[4]Data availability at General Household Survey, Panel 2012–2013, Wave 2, Nigeria, 2012–2013. See: https://microdata.worldbank.org/index.php/catalog/1952

[5]Data availability at General Household Survey, Panel 2015–2016, Wave 3, Nigeria, 2015–2016. See: https://microdata.worldbank.org/index.php/catalog/2734

[6]See: https://microdata.worldbank.org/index.php/catalog/2734/related-materials

We considered only five meat products in this study because there were no conversion factors for the remaining food groups in the data. The meat groups (and subgroups) considered are poultry (chicken and other poultry), beef (beef), other meats (mutton, pork, goat, and others- excluding poultry), unprocessed seafood (fresh-fish, frozen-fish, and other unprocessed seafood), and processed seafood (smoked-fish, dried fish, and canned fish).

Fisher ideal price index

We constructed Fisher-price indices for the demand model using a three-step procedure: (1) the unit values for each meat product are determined; (2) quality-corrected prices are specified; and (3) price indices for the commodity groups are constructed.

Following Boonsaeng and Carpio (2019), the first step involved defining a single unit value $\left(UV_{si}^{h}\right)$[7] for each product s in meat group i (Table 1) for household h as:

$$UV_{si}^{h} = \frac{m_s}{q_s} \tag{1}$$

in which m_s is the household's expenditure on meat product s in the past 7 days (household's response to question (3) above), and q_s is the amount of meat product s purchased (household's response to question (2) above).

In the second step, we specified quality-corrected prices[8] to derive an approximation of prices that accounted for quality and measurement error (Alfonzo and Peterson 2006). The first stage of this quality correction involved an OLS regression of the form:

$$lnUV_{si}^{h} = \alpha_s + \beta_s lnx + \sum_{l=1}^{L} \theta_{sl} z_l + \sum_{c=1}^{C-1} \varphi_{sc} D_c + \varepsilon_s \tag{2}$$

in which UV_{si}^{h} is the unit value of product s in meat group i for household h, x is household income, z corresponds to household characteristics, D_c, $c = 1, \ldots, C$, are dummy variables that indicate the enumeration areas (clusters) to which the household belongs, α_s, β_s, θ_{sl}, and φ_{sc} are parameters, and ε_s is a vector of error terms. Note that these individual regressions only use data from individuals with observed purchases. In the second stage, we define an approximation of the price as:

$$ln\hat{P}_{si} = \hat{\alpha}_s + \sum_{c=1}^{C-1} \hat{\varphi}_{sc} D_c \tag{3}$$

in which $\hat{P}_{si}$ is the approximated price of meat product s in meat group i, and $\hat{\alpha}_s$ and $\hat{\varphi}_s$ are OLS estimates of α_s and φ_s, respectively. This price approximation is independent of household-specific choices, reflects region, time, and seasonal variations, and allows us to estimate price-quantity relations accurately. Moreover, this procedure enables the estimation of prices for households, even if they do not report expenditures (Alfonzo and Peterson 2006; Meghir and Robin 1992; Zhen et al. 2011).

In the third step, we combined quality-corrected meat product prices, $\hat{P}_{si}$, into an index that represented the meat group price. The Fisher-price index for household h's meat group i is:

[7]The single unit value is deflated by the Nigerian composite consumer price index (National Bureau of Statistics 2022). We selected month and year of the Nigerian composite consumer price index associated to the time the survey was conducted.

[8]The quality-corrected prices were estimated for each time period of survey.

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Table 1. Average budget shares, amounts and expenditures, and percentage differences (consumption data–expenditures data)

		Budget share		Quantities (kg)		Expenditures (₦)[b]		% Difference		
Meat groups	Sub-group (products)	Consume (St. Dev.)[a]	Purchase (St. Dev.)[a]	Consume (St. Dev.)[a]	Purchase (St. Dev.)[a]	Consume (St. Dev.)[a]	Purchase (St. Dev.)[a]	Shares[c] (*P*-value)[g]	Quantities[d] (*P*-value)[g]	Expenditure[f] (*P*-value)[g]
Poultry	1) Chicken, Other poultry	0.061 (0.186)	0.041 (0.152)	0.249 (1.509)	0.162 (1.477)	188.58 (719.52)	117.14 (546.59)	48.78 (<.001)	53.70 (<.001)	60.99 (<.001)
Beef	1) Beef	0.300 (0.312)	0.311 (0.324)	0.789 (1.936)	0.772 (1.917)	522.41 (1206.75)	501.72 (750.57)	−3.54 (<.001)	2.20 (<.001)	4.12 (0.050)
Other meats	1) Mutton 2) Pork 3) Goat 4) Others (excluding poultry)	0.110 (0.249)	0.102 (0.246)	0.307 (1.155)	0.244 (0.997)	211.02 (674.52)	160.75 (484.53)	7.84 (<.001)	25.82 (<.001)	31.27 (<.001)
Unprocessed Seafood	1) Fresh-fish 2) Frozen fish 3) Other unprocessed seafood	0.307 (0.327)	0.300 (0.332)	1.075 (3.077)	0.934 (2.977)	532.93 (6072.81)	382.81 (637.82)	2.33 (0.008)	15.10 (<.001)	39.22 (0.023)
Processed seafood	1) Smoked-fish 2) Dried fish and canned fish	0.218 (0.296)	0.209 (0.302)	0.455 (1.638)	0.398 (1.271)	342.65 (1137.51)	283.06 (637.71)	4.31 (<.001)	14.32 (<.001)	21.05 (<.001)

[a]St. Dev. denotes standard deviation.
[b]1 US$ = 415.42 ₦, March 19, 2022.
[c][(average share consumption data – average share expenditures data)/average share expenditures data]*100%.
[d][(average quantity consumption data – average quantity expenditures data)/average quantity expenditures data]*100%.
[f][average expenditure consumption data – average expenditure expenditures data)/average expenditure expenditures data]*100%.
[g]*p*-values reported correspond to paired t-tests of the variables.

$$p_i^h = \sqrt{P_{Pi}^h P_{Li}^h} \tag{4}$$

in which $P_{Pi}^h = \frac{\sum \hat{p}_{si}^h q_{si}^h}{\sum \hat{\bar{P}}_{si} q_{si}^h}$; $P_{Li}^h = \frac{\sum \hat{p}_{si}^h q_{si}}{\sum \hat{\bar{P}}_{si} q_{si}}$, P_{Pi}^h and P_{Li}^h are household h's Paasche and Laspeyres indices for meat group i, respectively, q_{si}^h is the amount of product s in meat group i that household h purchased, q_{si} is the average amount of product s in meat group i, $\hat{p}_{si}^h$ is the price of product s in meat group i for household h, and $\hat{\bar{P}}_{si}$ is the average price of product s in meat group i. The Fisher-price index obtained using expenditure data was also used for the demand models of consumption data. Thus, we assume that the value per unit (i.e., price) of households' consumption is the same as the price of goods purchased. In other words, the price of food consumed is the same as its estimated market price.

Model for unbalanced panel demand system

The demand model used in this study is the Exact Affine Stone Index (EASI) demand system (Lewbel and Pendakur 2009). We use the EASI model's approximate linear version, which has been shown to provide similar results (Lewbel and Pendakur 2009). Further, we use a more parsimonious version of the original EASI model that excludes the interaction terms between prices and demographic characteristics and between prices and actual total expenditures. The EASI budget share demand for commodity i for household h can be modified as:

$$w_i^h = \sum\nolimits_{r=0}^{4} b_{ri}\left(lnx^h\right)^r + \sum\nolimits_{j=1} A_{ji} lnp_j^h + \sum\nolimits_{k=1} C_{ki} z_k^h + \varepsilon_{it},\ i = 1, 2, \ldots, n \tag{5}$$

in which w_i^h is the budget share allocated to the ih meat group for household h (i.e. $w_i^h = p_i^h q_i^h / Y^h$), Y^h is the total expenditures in meats for household h, p_j^h is the Fisher-price index of meat group j for household h, and lnx^h is the natural log of household h's actual total expenditures on all meats ($lnx^h = lnY^h - \sum_{i=1}^{n} lnp_i^h \bar{w}_i$, in which $\bar{w}_i$ is all households' average budget (Lewbel and Pendakur 2009)). The explanatory variables in this model include K different demographic characteristics ($z_k's$). The estimated model used a fourth order polynomial in lnx^h (see Lewbel and Pendakur 2009).

For the demand system that used expenditure data, the w_i^h variable was constructed using the reported expenditures on each meat group ($E_i^h = p_i^h q_i^h$). For the demand system that used consumption data, the w_i^h variable was constructed using the q_i^h reported and the price predicted in Equation (3). Compensated, uncompensated, and expenditure elasticities were calculated using the parameters in Equation (5) (Lewbel and Pendakur 2009; Boonsaeng and Carpio 2020). The demand system was estimated by imposing homogeneity and symmetry restrictions. The last equation is dropped from the demand system, and its parameters are recovered using the adding-up constraint (Lewbel and Pendakur 2009). Whereas there are several recommended approaches to account for censoring issues in demand estimation (e.g., Shonkwiler and Yen 1999; Meyerhoefer, Ranney, and Sahn 2005; McCullough et al. 2022), we used simple linear regression models, as the main objective of this study is to estimate prices and income effects on average demand (Deaton 1997, p. 92).

The Wooldridge-Chamberlain-Mundlak approach (Wooldridge 2019) to estimate fixed effects models in unbalanced panel data is used for econometric estimation. The fixed effects estimator is chosen since it is robust to potential endogeneity due to the correlation between explanatory variables and unobserved time-invariant factors (Wooldridge 2002). Following this approach, the fixed effects demand system can be computed as the original demand system with the covariates' time averages added as additional explanatory variables. Hence, the econometric model for the EASI demand system in Equation (5) for meat group i for household h and time period t is as follows:

$$w_{it}^{h} = \sum_{r=0}^{4} b_{ri}\left(lnx_{t}^{h}\right)^{r} + \sum_{j=1} A_{ji} lnp_{jt}^{h} + \sum_{k=1} C_{ki} z_{kt}^{h} + \sum_{r=0}^{4} f_{ri}\left(\overline{lnx_{t}^{h}}\right)^{r} + \sum_{j=1} B_{ji} \overline{lnp_{jt}^{h}} + \varepsilon_{it}$$

$$i = 1, 2, \ldots, n, t = 1, 2, \ldots, \; T, \text{and } h = 1, 2, \; \ldots, \; H \tag{6}$$

in which n is the total number of meat groups, H is the total number of households, and T is the total number of time periods. The $\overline{lnx_{t}^{h}}$ and $\overline{lnp_{jt}^{h}}$ are additional explanatory variables, in which $\overline{lnx_{t}^{h}} = T_{h}^{-1}\sum_{t=1}^{T_h} lnx_{t}^{h}$ and $\overline{lnp_{jt}^{h}} = T_{h}^{-1}\sum_{t=1}^{T_h} lnp_{jt}^{h}$. T_h is the number of times that household h is observed in the unbalanced panel data, $\overline{lnx_{t}^{h}}$ is the average of the natural log of actual total expenditures on n goods for household h, and $\overline{lnp_{jt}^{h}}$ is the average price of meat group j for household h. The model does not include average values of the z_{kt}^{h}, as there is little or no variability over time (see Table 2). Income and all expenditure values (including unit values) were deflated using the Nigerian composite consumer price index reported by the National Bureau of Statistics (2022).

An additional problem with the demand system estimation of Equation (6) is the potential endogeneity of total expenditures. To account for this problem, we used Blundell and Robin's (2000) control function approach. The procedure involves two steps. The first step requires the estimation of a linear regression model with lnx_{t}^{h} as the dependent variable, and as explanatory variables, all the other explanatory variables included in the share models $lnp_{jt}^{h'}s$ and $z_{kt}^{h'}s$ as well as the natural log of household income, its square, cube, and fourth power (these serve as instruments). Similar to the budget share models, model estimation used the Wooldridge-Chamberlain-Mundlak approach, with the average values of explanatory variables across time for each household included as controls. In the second step, the predicted errors of the first-step regression model are used as an explanatory variable in Equation (6) to account for endogeneity Blundell and Robin (2000).

Comparison of elasticities between consumption and expenditure data

In addition to the comparison of the magnitudes of the elasticities obtained using consumption and expenditure data, the null hypothesis of no differences between these elasticities was tested using a two-sample T^2 statistic (Gupta et al., 1996):

$$T^2 = \frac{N_1 N_2}{(N_1 + N_2)}\left(\hat{E}_1 - \hat{E}_2\right)\hat{W}^{-1}\left(\hat{E}_1 - \hat{E}_2\right)', \tag{7}$$

in which $\hat{W}$ is the pooled covariance matrix obtained from the two covariance matrices, N_1 and N_2 are the number of observations, and $\hat{E}_1$ and $\hat{E}_2$ are the vectors of estimated elasticities of Models 1 and 2, respectively. The test has an F distribution, with degrees of freedom p and $N_1 + N_2 - p - 1$:

$$F = \frac{N_1 + N_2 - p - 1}{(N_1 + N_2 - 2)p} T^2 \tag{8}$$

in which p is the size of the elasticity vectors $\left(\hat{E}_1 \text{ and } \hat{E}_2\right)$.

Table 2. Household composition variables and demographic characteristics

Variable	Definition	Mean
Continuous variables		
Age	Age of the household head (in years)	49.57
Household size	Number of household members	6.60
Income[a]	Median household monthly income (₦)	22,000.00
Dummy variables (yes = 1, no = 0)		
Male	1 if household head is male, 0 otherwise	0.880
Religion:		
1 Christian	1 if Christian, 0 otherwise	0.648
2 Islam	1 if Islam, 0 otherwise	0.336
3 Other	1 if household head does not self-identify as Christian or Muslim, 0 otherwise	0.016
Married	1 if household head is married, 0 otherwise	0.842
Education		
1 Primary	1 if household head finished primary education, 0 otherwise	0.411
2 Secondary	1 if household head finished secondary education, 0 otherwise	0.303
3 College	1 if household head finished college education, 0 otherwise	0.195
4 Religions	1 if household head finished religious education, 0 otherwise	0.081
Region:		
1 North-Central	1 if household is located in the North-Central, 0 otherwise	0.168
2 North-East	1 if household is located in the North-East, 0 otherwise	0.122
3 North-West	1 if household is located in the North-West, 0 otherwise	0.117
4 South-East	1 if household is located in the South-East, 0 otherwise	0.205
5 South-South	1 if household is located in the South-South, 0 otherwise	0.225
6 South-West	1 if household is located in the South-West, 0 otherwise	0.162
Survey time periods		
Y2010_2	1 if year is 2010 and post-harvest season, 0 otherwise	0.264
Y2012_1	1 if year is 2012 and post-planting season, 0 otherwise	0.246
Y2012_2	1 if year is 2012 and post-harvest season, 0 otherwise	0.230
Y2015_1	1 if year is 2015 and post-planting season, 0 otherwise	0.260

[a]This value corresponds to the median household income, as income has a highly skewed distribution. Mean household income was ₦225,648.20 (1 US$ = 415.42 ₦, March 19, 2022).

Results and discussion

Summary statistics

Table 1 presents the budget shares, amounts consumed, and expenditures obtained from consumption and purchase data over a 7-day period. Poultry had the lowest share and accounted for less than 7% of total household meat expenditures, on average. Unprocessed seafood and beef had the largest budget shares and accounted for approximately 30% of total household meat expenditures. In general, the budget shares estimated from consumption data were very similar to those estimated from purchase data. The largest difference in budget shares was poultry, and the difference was 48.78%. The last three columns in Table 1 show the relative average difference (in %) in shares, expenditures, and quantities calculated using consumption and purchased data (see Appendix 1 for censoring levels across datasets).

The meat groups' ranking in descending order of consumption and purchase amounts was the same: unprocessed seafood, beef, processed seafood, other meats, and poultry. However, consumption amounts were in every case larger than purchase amounts (22.23% greater, on average), thus, providing evidence of the hidden consumption problem. The differences in quantities were all statistically significant ($\alpha < 0.05$). The largest difference was for poultry (53.70%), meat more likely to derive from households' own production.

Table 1 also shows households' average weekly meat expenditures. Overall, average expenditures calculated using consumption data were also consistently higher (31.33%, on average) than the corresponding purchase data values, again providing some evidence of hidden consumption. Four of the five differences in expenditure values were also statistically significant ($\alpha < 0.05$). The largest difference in expenditure values also corresponded to poultry. The average weekly household expenditures on poultry estimated using consumption data were ₦188.58, while average expenditures using the purchase data were ₦117.14 (1 US\$ = ₦415.42, as of March 19, 2022; Trading Economics 2022). Thus, average expenditures on poultry using consumption data were 60.99% higher than the value obtained from purchase data.

The ranking of meats based on expenditures differs when consumption or purchase data are used (Table 1). When consumption data are used, unprocessed seafood ranked as the meat category with the highest expenses, while it is beef when purchase data are used. Moreover, there is a larger difference in expenditure values between these two meat categories (unprocessed seafood and beef) when purchase data (unprocessed seafood: ₦382.81, beef: ₦501.72) rather than when consumption data are used (unprocessed seafood: ₦532.93, beef: ₦522.41). These differences reflect dissimilarities in the "meat group" composition across data types because the unit values for meat subgroups were the same in both data types.

Table 2 presents the household composition variables and demographic characteristics. The average age of the household head in the data was 50 years and most households (88%) had a male head. Households in the sample had 7 members on average and a median income of ₦22,000 (\$US 52.96). Concerning the level of education completed, 41% of household heads had completed primary education, 30% had a secondary education, and 19% had completed a college education. Religious education is commonplace in Nigeria and 8% of household heads in the sample had completed some form of religious education. Households in the sample were distributed across the six geographical regions of the country, but the majority are in the South-South (22.5%) while the North-West had the lowest percentage of households (11.7%).

Demand estimation results

Elasticities-purchases based model

We present two sets of estimation results for the EASI demand system. The first is based on purchase data (Table 3) while the second is based on consumption data (Table 4). Table 3 presents the results of the compensated and uncompensated price elasticities as well as the expenditure elasticities derived from the purchase data. The price elasticities show that the own-price elasticities were negative and statistically significant at the 5% level for all the meat groups. The top section of Table 3 shows that own-price Marshallian elasticities of

Table 3. Compensated and uncompensated price elasticities from the Exact Affine Stone Index demand panel estimates (based upon purchase data)

		Change in quantity				
Price change	Meat groups	Poultry	Beef	Other meats	Unprocessed seafood	Processed seafood
		Marshallian/uncompensated elasticities				
	Poultry	−1.078** (0.286)	−0.231 (0.311)	−0.171 (0.155)	0.184 (0.174)	0.080 (0.206)
	Beef	−0.058 (0.056)	−1.052** (0.084)	−0.046 (0.037)	0.026 (0.039)	−0.037 (0.059)
	Other meats	−0.018 (0.074)	−0.006 (0.109)	−0.875** (0.083)	−0.068 (0.063)	0.131 (0.094)
	Unprocessed seafood	0.085** (0.041)	0.116 (0.052)	0.020 (0.032)	−0.964** (0.041)	0.014 (0.045)
	Processed seafood	0.014 (0.057)	−0.015 (0.087)	0.038 (0.044)	−0.067 (0.042)	−1.019** (0.086)
		Hicksian/compensated elasticities				
	Poultry	−0.994** (0.280)	−0.147 (0.306)	−0.087 (0.161)	0.268 (0.178)	0.164 (0.208)
	Beef	0.287** (0.040)	−0.707** (0.070)	0.298** (0.033)	0.371** (0.038)	0.307** (0.052)
	Other meats	0.052 (0.064)	0.063 (0.100)	−0.805** (0.090)	0.002 (0.067)	0.200** (0.090)
	Unprocessed seafood	0.331** (0.025)	0.362** (0.039)	0.266** (0.023)	−0.718** (0.039)	0.261** (0.030)
	Processed seafood	0.233** (0.040)	0.204** (0.076)	0.257** (0.044)	0.152** (0.044)	−0.800** (0.079)
		Expenditure elasticities				
	Expenditure	2.066** (0.475)	1.108** (0.102)	0.681** (0.215)	0.820** (0.095)	1.047** (0.143)

Note:
**Denotes significance at 5%, and
*denotes significance at 10%.

poultry (−1.078), beef (−1.052), and processed seafood (−1.019) were greater than one in absolute value and therefore price-elastic. This indicates that a 1% increase in their prices results in a more than proportionate decline in their demand, ceteris paribus. Poultry was the most price-elastic among the meat products, with an elasticity of −1.078. Other meats (−0.875) and unprocessed seafood (−0.964) were found to be price inelastic.

The lower section of Table 3 shows the compensated elasticities for the meat groups. Again, the own-price elasticities, shown on the main diagonal of the matrix, were all statistically significant at the 5% level. However, these own-price elasticities were less than one and smaller in magnitude (i.e., in absolute value) relative to own-price uncompensated elasticities. The compensated elasticities reflect changes in the demand for a meat product in response to price changes while they ignore the income effect.

Table 4. Compensated and uncompensated price elasticities from the Exact Affine Stone Index demand panel estimates (based upon consumption data)

Price change	Meat groups	Change in quantity				
		Poultry	Beef	Other meats	Unprocessed seafood	Processed seafood
		Marshallian/uncompensated elasticities				
	Poultry	−1.035** (0.107)	−0.200 (0.178)	−0.037 (0.096)	0.023 (0.106)	0.119 (0.183)
	Beef	−0.056 (0.039)	−1.036** (0.100)	−0.026 (0.053)	0.071 (0.049)	−0.057 (0.098)
	Other meats	0.010 (0.048)	0.001 (0.110)	−0.942** (0.085)	−0.092 (0.064)	0.102 (0.109)
	Unprocessed seafood	0.052 (0.034)	0.132** (0.060)	0.004 (0.037)	−0.986** (0.047)	0.011 (0.063)
	Processed seafood	0.029 (0.047)	−0.061 (0.115)	0.032 (0.062)	−0.056 (0.062)	−1.001** (0.147)
		Hicksian/compensated elasticities				
	Poultry	−0.948** (0.116)	−0.113 (0.176)	0.050 (0.094)	0.111 (0.106)	0.206 (0.176)
	Beef	0.265** (0.036)	−0.714** (0.093)	0.295** (0.039)	0.392** (0.047)	0.264** (0.084)
	Other meats	0.104** (0.052)	0.095 (0.105)	−0.847** (0.083)	0.002 (0.067)	0.196** (0.100)
	Unprocessed seafood	0.317** (0.021)	0.397** (0.046)	0.269** (0.024)	−0.721** (0.052)	0.275** (0.047)
	Processed seafood	0.258** (0.050)	0.168 (0.115)	0.261** (0.051)	0.173** (0.066)	−0.772** (0.128)
		Expenditure elasticities				
	Expenditure	1.428** (0.293)	1.070** (0.115)	0.856** (0.198)	0.862** (0.095)	1.052** (0.161)

Note: **Denotes significance at 5% and *denotes significance at 10%.

The uncompensated cross-price elasticities in Table 3 were largely insignificant (at 10% or greater) and 10 of the 20 cross-pairs were negative. Moreover, all the uncompensated cross-price elasticities were inelastic, implying that a percent change in one good's price index will result in a less than proportionate change in the other good's quantity demanded, while other prices are held constant.

A larger number of compensated cross-price elasticities (13 out of 20) were significant ($\alpha = 0.10$) and only two were negative (poultry-beef and poultry-other-meat), although both were insignificant. Cross-pairs with negative algebraic signs indicate complementarity (e.g., poultry and beef) while positively signed cross-pairs indicate substitutability (e.g., unprocessed seafood and poultry). The difference in values between uncompensated and compensated cross-price elasticities indicates that cross-price changes' income effect in the compensated elasticities tends to dominate the (uncompensated) cross-price effects (i.e., compensated elasticity = uncompensated elasticity + share x expenditure elasticity).

The expenditure elasticities[9] for the meat groups were all positive and significant ($\alpha = 0.05$), indicating that they were normal goods (Table 3). The expenditure elasticities for poultry (2.066), beef (1.108), and processed seafood (1.047) were greater than one and suggest that households consider them luxuries, while other meat (0.681) and unprocessed seafood (0.820) are considered necessities because they had elasticities less than one.

Elasticities–consumption-based model

Table 4 provides the results of the uncompensated, compensated, and expenditure elasticities derived from the consumption data. The own-price uncompensated elasticities in Table 4 were all negative and significant at the 5% level. In addition, poultry, beef, and processed seafood were price-elastic (greater than 1 in absolute value). Other meats and unprocessed seafood were price inelastic. The top section of Table 4 shows that poultry and beef were the most price-elastic, with an elasticity estimate of −1.035 and −1.036, respectively. With respect to compensated own-price elasticity estimates, in terms of absolute value, they were smaller in magnitude than the corresponding own-price uncompensated elasticities.

Like the uncompensated cross-price elasticities obtained using purchase data, all cross-price elasticities using consumption data were inelastic and only one was significant ($\alpha = 0.10$). The cross-price compensated elasticities were larger than their uncompensated counterparts in terms of absolute value, except for the poultry-beef and other-meats-unprocessed seafood cross-pairs. For these, the compensated cross-price elasticity of −0.113 and 0.002 are less (in absolute value) than their uncompensated cross-price elasticity of −0.200 and −0.092, respectively. Most compensated cross-price elasticities were statistically significant ($\alpha = 0.10$) and indicated that meats are substitutes. Moreover, compensated cross-price elasticity values suggest that income effects are larger relative to uncompensated cross-price effects.

All meat groups' expenditure elasticities were positive and significant at the 5 percent level (Table 4). Poultry (1.428), beef (1.070), and processed seafood (1.052) were identified as luxuries because their expenditure elasticities were greater than one, while other meats (0.856) and unprocessed seafood (0.862) were identified as necessities because their elasticities were less than one. Analogous to the results obtained from purchase data (Table 3), changes in expenditures affected the other meat group the least.

Comparison of elasticities: consumption versus purchase-based models

The results of the F-tests using the two-sample T^2 statistic led to the null hypothesis of no difference between price elasticities and expenditure elasticities to be rejected ($p<0.01$) in the three tests conducted: one each for Marshallian, Hicksian, and expenditure elasticities. The direct comparison of own-price and expenditure elasticities obtained from consumption and purchase data is provided in Table 5. Although there is evidence of statistically significant differences, with few exceptions, none of the elasticity values differ from an economic perspective.

The Hicksian own-price elasticities obtained from both purchase and consumption data were all significant and inelastic. The percentage difference ranged from −4.63% to 5.22%, with an average absolute difference of only 2.95%. Marshallian demand elasticities obtained from purchase and consumption also identified the same meats as inelastic or elastic/unitary elastic.

[9]These expenditures elasticities can be interpreted as income elasticities (i.e., unconditional expenditure elasticities). According to Carpentier and Guyomard (2001), unconditional expenditure elasticities can be obtained by multiplying the conditional expenditure elasticities (i.e., the expenditures elasticities reported in this study for each meat type) times the expenditure elasticity for the commodity (i.e., the meat commodity). Panel data models estimated using meat share of income as the dependent variable and log income, and individual and time fixed effects as explanatory variables, resulted in meat expenditure elasticities that did not differ statistically from 1.

Table 5. Panel demand system-percentage differences in Hicksian own-price, Marshallian own-price, and expenditure elasticities using data on purchases and consumption

Meat groups	Hicksian own-price elasticities			Marshallian own-price elasticities			Expenditure elasticities		
	Consumption	Purchases	% change	Consumption	Purchases	% change	Consumption	Purchases	% change
Poultry	−0.948**	−0.994**	−4.63	−1.035**	−1.078**	−3.99	1.428**	2.066**	−30.88
Beef	−0.714**	−0.707**	0.99	−1.036**	−1.052**	−1.52	1.070**	1.108**	−3.43
Other meats	−0.847**	−0.805**	5.22	−0.942**	−0.875**	7.66	0.856**	0.681**	25.70
Unprocessed seafood	−0.721**	−0.718**	0.42	−0.986**	−0.964**	2.28	0.862**	0.820**	5.12
Processed seafood	−0.772**	−0.800**	−3.50	−1.001**	−1.019**	−1.77	1.052**	1.047**	0.48
Average absolute difference			2.95			3.44			13.12

Note: **Denotes significance at 5%.

Poultry, beef, and processed seafood were identified as price-elastic or unitary inelastic, and other meats and unprocessed seafood as price inelastic. The percentage difference ranged from −3.99% to 7.66% with an average absolute difference of 3.44%.

With respect to the differences between the expenditure elasticities, their magnitudes were similar except for poultry. The percentage differences ranged from −30.88% to 25.70%, with an absolute mean of 13.12%, while the percentage difference for poultry was 30.88%. Moreover, the same classification as luxury (poultry, beef, and processed foods) or normal goods (other meats and unprocessed seafood) based on expenditure elasticity values was obtained using consumption or expenditure data.

Further, we also compared the statistical significance of the cross-price elasticities obtained using both datasets. Using the purchase data, only one of twenty uncompensated price elasticities was significant ($\alpha = 0.10$); one uncompensated elasticity was also significant using consumption data, but none was significant in both sets of results. Thirteen compensated cross elasticities were significant ($\alpha = 0.10$) in the purchase data model and thirteen in the consumption data model, while twelve were significant in both models. All the significant elasticities had similar values and indicated that meat products were substitutes. Only the sign of one non-significant compensated cross-price elasticity (poultry–other meat) differed across consumption and purchased demand results.

The only previous study that has evaluated hidden consumption's effect on elasticity estimation is Gibson and Kim (2011). However, their study is not directly comparable to this study. They evaluated the use of econometric procedures that account for "hidden consumption," i.e., the infrequency of purchase model (IPM). They found that the IPM model results in smaller income elasticities. In contrast, we use the same econometric procedures but evaluate them using different datasets. We do not find that the use of purchase or consumption data has a major influence on meat expenditure elasticities unless the differences in amounts consumed are substantial (more than 33%). Still, even in that case, we find no evidence that expenditure elasticities based on consumption data are significantly greater than those based on purchase data. In addition, price elasticities were very similar in both datasets. However, it is important to highlight the fact that consumption data is not necessarily "the gold standard" as it is also subject to measurement errors. Thus, elasticity estimates across datasets may be similar not because measurement errors in expenditure data are not severe but because the effects of measurement errors in both datasets are comparable.

How do this study's elasticity results compare to previous studies? Ezedinma, Kormawa, and Chianu (2006) found elastic own-price elasticities for all types of meats. This study found that price elasticities were inelastic for other meat and unprocessed seafood, and those for poultry, beef, and processed seafood were equal. Ezedinma, Koramawa, and Chianu (2006) also reported that all meat products were complements, contrasting with a more complex pattern of substitutability/complementarity found in this study. With respect to expenditure elasticities, Ezedinma, Kormawa, and Chianu (2006) found that poultry and mutton/goat were elastic, while this study finds that poultry, beef, and processed seafood are expenditure elastic. However, as mentioned before, the differences may be attributable to the studies' geographic coverage, the time the data were collected, and the methods used (e.g., demand system, group composition, etc.).

Summary and conclusions

This study estimates and compares meat demand estimation results using consumption and expenditure data obtained from a nationally representative sample from Nigeria. The comparison of elasticities estimated across both datasets did not reflect major differences in the results, which suggests that if the only objective of data collection is to estimate elasticity using a standard demand system framework, collection of both types of data may be unnecessary, even when the observation period is only 7 days, as was the case in the Nigerian survey used in this study. However, we need to be very careful about making general conclusions based on a particular study, and more research is needed to evaluate data quality characteristics' effect on demand estimation results.

The estimation results reveal that expenditures on beef were the highest, while those on poultry were the lowest. Expenditure elasticities were positive for all the meat products, indicating that they were normal goods. The results derived from both the consumption and expenditure datasets indicated that poultry, beef, and processed seafood are luxuries, while other meat and unprocessed seafood are necessities. Among the luxury products, poultry was the most expenditure elastic. Among the meat products considered to be necessities, changes in total meat expenditures affected the other meat group the least. Own-price elasticities from both datasets indicate that poultry, beef, and processed seafood were price-elastic, and poultry had the greatest price elasticity.

Current population growth estimates suggest that Nigeria will become the third most populous country in the world, and its population will increase from approximately 191 million to 411 million by 2050. As the population increases, a strong growth in household demand for meat products is expected, particularly poultry products. Producers, industry stakeholders, and the government have a role to play in accelerating the production of meat products to meet the increased demand. Factors such as transformation from low-yielding to high-yielding breeds of animals, transportation and marketing infrastructures, pest and disease control, storage facilities, and trade strategies are important factors that need to be addressed urgently to ensure that there is a chance for domestic production growth to keep pace with the projected demand increase. Hence, demand estimation results provide important information for analyses of policies and strategies.

The study has several limitations. First, although the comparison between expenditure and consumption reflects some evidence of hidden consumption, consumption data are also subject to measurement errors since it is also self-reported in the surveys. More research is needed to quantify and compare the measurement error levels in both self-reported data types, for example, using modern technologies (e.g., scanner data, pictures of receipts or meals, etc.). Another limitation of this study is the use of a price index and a unit price generated using only household-level expenditure data. Future work should include the use of prices collected separately. Finally, our analyses only evaluate the effects of variables from both datasets on average demand. An extension of the study will consider evaluating the separate effects of explanatory variables (e.g., prices and income) on the probability of purchases and consumption and on the quantities purchased and consumed using censored panel demand system, and using models that account for the large percentage of zeros in some of the share equations (e.g., McCullough et al. 2022; Meyerhoefer, Ranney, and Sahn 2005).[10,11]

[10]Most estimation models proposed in the literature for censored demand systems can be characterized as statistical fixes to economic consumer models that result only on interior solutions (i.e., do not allow corner solutions). Thus, the majority of these models provide approximations to the results of the consumer model that work under certain conditions (e.g., they required censored normality in the case of Tobit models). Linear regression models provide another approximation to these models (Deaton 1997, p. 92.).

[11]We explored the sensitivity of our analyses to using a censored panel estimation approach. We combined the Shonkwiler and Yen (1999) method with the Wooldridge-Chamberlain-Mundlak approach to estimate non-linear panel data models (Wooldridge 2019). Overall, elasticity estimates were robust to the method used. On average, own price elasticity estimates between censored and uncensored estimation procedures differed by no more than 1.4%. Higher differences were observed for expenditure elasticity estimates, which, on average, differed by no more than 15%. We only present the uncensored model's results since they rely on fewer assumptions.

Data availability statement. General Household Survey, Panel 2010–2011, Wave 1, Nigeria, 2010–2011 https://microdata.worldbank.org/index.php/catalog/1002

General Household Survey, Panel 2012–2013, Wave 2, Nigeria, 2012–2013 https://microdata.worldbank.org/index.php/catalog/1952

General Household Survey, Panel 2015–2016, Wave 3, Nigeria, 2015–2016 https://microdata.worldbank.org/index.php/catalog/2734

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References

Alfonzo, L., and H.H. Peterson 2006. "Estimating food demand in Paraguay from household survey data." *Agricultural Economics* **34** (3): 243–257. https://doi.org/10.1111/j.1574-0864.2006.00122.x

Alimi, S.R. 2013. "An analysis of meat demand in Akungba-Akoko, Nigeria." *Nigerian Journal of Applied Behavioural Sciences* **1**: 96–104.

Blundell, R., and C. Meghir 1987. Bivariate alternatives to the Tobit model. *Journal of Econometrics* **34** (1–2): 179–200. https://doi.org/10.1016/0304-4076(87)90072-8

Blundell, R., and J.M. Robin 2000. "Latent separability: Grouping goods without weak separability." *Econometrica* **68** (1): 53–84.

Boonsaeng, T., and C.E. Carpio 2019. "A Comparison of food demand estimation from homescan and consumer expenditure survey data." *Journal of Agricultural and Resource Economics* **44** (1): 117–140. https://www.jstor.org/stable/26797546

Boonsaeng, T., and C.E. Carpio 2020. "Budget allocation patterns of U.S. households across income levels in the 21st century." *Journal of Consumer Affairs* **54** (1): 342–387. https://doi.org/10.1111/joca.12273

Carpentier, A., and H. Guyomard 2001. "Unconditional elasticities in two-stage demand systems: An approximate solution." *American Journal of Agricultural Economics* **83** (1): 222–229. https://www.jstor.org/stable/1244312

Conforti, P., K. Grünberger, and N. Troubat 2017. "The impact of survey characteristics on the measurement of food consumption." *Food Policy* **72**: 43–52. https://doi.org/10.1016/j.foodpol.2017.08.011

Deaton, A. 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Baltimore, MA: World Bank.

Deaton, A., and M. Irish 1984. "Statistical models for zero expenditures in household budgets." *Journal of Public Economics* **23** (1–2): 59–80. https://doi.org/10.1016/0047-2727(84)90067-7

Ezedinma, C.I., P.M. Kormawa, and J. Chianu 2006. "Urban household demand for meat and meat products in Nigeria: An almost ideal demand system analysis." *Paper prepared or presentation at the Farm Management Association of Nigeria Conference*. Jos, Nigeria. Available at https://core.ac.uk/download/pdf/6833387.pdf

Fiedler, J.L., and D.M. Mwangi 2016. *Improving Household Consumption and Expenditure Surveys' Food Consumption Metrics: Developing a Strategic Approach to the Unfinished Agenda* (Vol. **1570**). Washington, D.C.: International Food Policy Research Institute. https://www.ifpri.org/publication/improving-household-consumption-and-expenditure-surveys%E2%80%99-food-consumption-metrics

Gibson, J. 2002. "Why does the Engel method work? Food demand, economies of size and household survey methods." *Oxford Bulletin of Economics and Statistics* **64** (4): 341–359. https://doi.org/10.1111/1468-0084.00023

Gibson, J., K. Beegle., J. De Weerdt, and J. Friedman 2015. "What does variation in survey design reveal about the nature of measurement errors in household consumption?" *Oxford Bulletin of Economics and Statistics* **77** (3): 466–474. https://doi.org/10.1111/obes.12066

Gibson, J., and B. Kim 2007. "Measurement error in recall surveys and the relationship between household size and food demand." *American Journal of Agricultural Economics* **89** (2): 473–489. https://doi.org/10.1111/j.1467-8276.2007.00978.x

Gibson, J., and B. Kim 2011. "Testing the infrequent purchases model using direct measurement of hidden consumption from food stocks." *American Journal of Agricultural Economics* **94** (1): 257–270. https://doi.org/10.1093/ajae/aar135

Gupta, S., P. Chintagunta, A. Kaul., and D.R. Wittink 1996. "Do household scanner data provide representative inferences from brand choices: A comparison with store data." *Journal of Marketing Research* **33** (4): 383–398. https://doi.org/10.2307/3152210

Igwe, K.C., and O.N. Onyekwere 2007. "Meat demand analysis in Umuahia Metropolis Abia State, Nigeria." *Agricultural Journal* **2** (5): 550–554. https://medwelljournals.com/abstract/?doi=aj.2007.550.554

Kaara, J., and S. Ramasawmy 2008. "Food data collected using acquisition and consumption approaches with a seven-day recall method in Kenya's KIHBS 2005/2006." In R. Sibrian (Ed.), *Deriving Food Security Information from National Household Budget Survey: Experiences, Achievements, Challenges*. Rome: Food and Agriculture Organization, pp. 69–79.

Kay, J.A., M.J. Keen, and C.N. Morris 1984. "Estimating consumption from expenditure data." *Journal of Public Economics* **23** (1–2): 169–181. https://doi.org/10.1016/0047-2727(84)90071-9

Keen, M. 1986. "Zero expenditures and the estimation of Engel curves." *Journal of Applied Econometrics* **1** (3): 277–286. https://doi.org/10.1002/jae.3950010305

Lewbel, A., and K. Pendakur 2009. "Tricks with hicks: The EASI demand system." *American Economic Review* **99** (3): 827–863. https://www.jstor.org/stable/25592484

McCullough, E., C. Zhen, S. Shin, M. Lu, and J. Arsenault 2022. "The role of food preferences in determining diet quality for Tanzanian consumers." *Journal of Development Economics* **155**, 102789. https://doi.org/10.1016/j.jdeveco.2021.102789

Meghir, C., and J.M. Robin 1992. "Frequency of purchase and the estimation of demand systems." *Journal of Econometrics* **53** (1–3): 53–85. https://doi.org/10.1016/0304-4076(92)90080-B

Meyerhoefer C.D., C.K. Ranney, and D.E. Sahn 2005. "Consistent estimation of censored demand systems using panel data." *American Journal of Agricultural Economics* **87**: 660–672. https://doi.org/10.1111/j.1467-8276.2005.00754.x

National Bureau of Statistics 2016. *LSMS – Integrated Surveys on Agriculture General Household Survey Panel 2015/2016*. Washington, DC: Nigerian National Bureau of Statistics.

National Bureau of Statistics 2022. CPI and Inflation Report December 2022. Available at https://nigerianstat.gov.ng/elibrary/read/1241274#

National Bureau of Statistics and Living Standards Measurement Study 2016. "Basic Information Document: Nigeria General Household Survey Panel 2015/16." Accessed 2018.

Ogundari, K. 2012. "Demand for quantity versus quality in beef, chicken and fish consumption in Nigeria." *Revista de Economica e Agronegocio* **10** (1): 29–50. https://doi.org/10.22004/ag.econ.141140

Piggott, N.E. 2003. "The nested PIGLOG model: An application to U.S. food demand." *American Journal of Agricultural Economics* **85** (1): 1–15. https://doi.org/10.1111/1467-8276.00099

Piggott, N.E., and T.L. Marsh 2011. Constrained utility maximization and demand system estimation. In J.L. Lusk, J.Roosen, and J.F. Shogren (Eds)., *The Oxford Handbook of the Economics of Food Consumption and Policy*. Oxford, New York: Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199569441.013.0002

Premium Times Nigeria 2014. "Nigeria to Increase Beef Consumption to 1.3 Million Tonnes by 2050." May. Accessed 2019. https://www.premiumtimesng.com/news/160843-nigeria-increase-beef-consumption-1-3-million-tonnes-2050-adesina.html.

Saumell, C. 2014. "Food Alert: Demand for Beef in Nigeria is on the Increase." *Bord Bia*. September 12. Accessed 2019. https://www.bordbia.ie/industry/manufacturers/insight/alerts/pages/demandforbeefinnigeriaisontheincrease.aspx.

Shonkwiler, J., and S.T. Yen 1999. "Two-step estimation of a censored system of equations." *American Journal of Agricultural Economics* **81** (4): 972–982. https://doi.org/10.2307/1244339

Smith, L.C., H. Alderman, and D. Aduayom 2006. *Food Insecurity in Sub-Saharan Africa: New Estimates from Household Expenditure Surveys* (Vol. **146**). Washington, DC: International Food Policy Research Institute. https://doi.org/10.2499/0896291502

Solomon, O.G., and A. Nazemzadeh 2004. "Consumerism: statistical estimation of Nigeria meat demand." Allied Academies International Conference. Academy for Studies in International Business. Proceedings. 47–56. https://search.proquest.com/docview/192411205/fulltextPDF/17B7CA7ACEFB4BCBPQ/1?accountid=7098.

Sweitzer, M., D. Brown, S. Karns, M.K. Muth, P. Siegel, and C. Zhen 2017. "*Food-at-home expenditures: Comparing commercial household scanner data from IRI and government survey data.*" Technical Bulletin No. (TB-1946), Economic Research Service (ERS), U.S. Department of Agriculture (USDA). Accessed March 10, 2022. https://www.ers.usda.gov/webdocs/publications/85252/tb-1946.pdf?v=1755.1

The Economist 2019. "International." *Global Meat- Eating is on the Rise, Bringing Surprising Benefits.* May 4. Accessed 2019. https://www.economist.com/international/2019/05/04/global-meat-eating-is-on-the-rise-bringing-surprising-benefits.

Trading Economics 2022. Nigerian Naira, Currencies, Trading Economics Website: Accessed March 19, 2022. https://tradingeconomics.com/currencies

Wooldridge, J.M. 2002. "*Econometric Analysis of Cross Section and Panel Data.*" Cambridge, MA: The MIT Press.

Wooldridge, J.M. 2019. "Correlated random effects models with unbalanced panels." *Journal of Econometrics* **211** (1): 137–150. https://doi.org/10.1016/j.jeconom.2018.12.010

Zhen, C., M.K. Wohlgenant, S. Karns, and P. Kaufman 2011. "Habit formation and demand for sugar-sweetened beverages." *American Journal of Agricultural Economics* **93** (1): 175–193. https://doi.org/10.1093/ajae/aaq155

Appendix

Table A1. Levels of censoring in meat groups' budget shares

Groups	Levels of censoring (%) Consumption	Purchases	Difference (purchases – consumption) % points
Poultry	87.92	91.62	3.70
Beef	42.79	43.83	1.04
Other meats	79.11	81.31	2.20
Unprocessed seafood	37.30	40.46	3.16
Processed seafood	50.45	55.35	4.90

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