Discussion Papers
Department of Economics
University of Copenhagen

No. 07-15

Regional Differences in Food Consumption in Urban Mozambique: A Censored Demand System Approach

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ISSN: 0902-6452 (print) ISSN: 1601-2461 (online)

Regional differences in food consumption in urban Mozambique: A censored demand system approach

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August 2007

Abstract

A nationwide household survey for Mozambique is used to estimate a large censored food demand system with 12 food groups for the sample of urban households. Using the translog indirect utility approach, the censored nature of the data is addressed by estimating a system of Tobit equations with a recently suggested quasi maximum likelihood estimator. Augmenting the system with demographic and geographical variables in a theoretically consistent way, I find that differences in elasticities between regions are significant. The results show that regional variation has to be taken into account when evaluating policies or employing CGE models. Further, the approach employed here can be applied to a number of developing countries with varying geographic conditions.

JEL classification: D12, O12, O18

Keywords – Censored demand system, Elasticities, Mozambique, Food demand, Regional differences.

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1. Introduction

Over the last ten years Mozambique has enjoyed a good spell of macroeconomic growth and – measured by a consumption metric – the level of poverty has fallen steadily from 69 percent in 1996 to 54 percent in 2002 (MPD, 2004). Other poverty indicators show similar improvements. Despite these achievements which had broad geographic coverage Mozambique is still a poor country with limited integrated markets and a strong need for further poverty reduction policies (Fox et al., 2005). The task of policy formulation is complicated by the geography of Mozambique. The two main centres of economic activity (Maputo, the capital in the south, and Beira in the central part of the country) are separated by more than a 1,000 kilometres. Further to the north of Beira the Zambezi River cuts off the northern part of the country and only poor infrastructure link the two parts, limiting economic integration.

Detailed knowledge of households' preference structure is a valuable tool for improving policy advice and evaluating the effects of existing policies. Important policy areas where such knowledge can improve policy advice span a range from tax reform and transfers to public goods provision. In poor countries, such as Mozambique with a per capita income of 1,300 USD (PPP) in 2005, where the bulk of expenditures are directed towards food consumption, studying food demand is important. This is so both as a goal in itself to allow policy makers to study the effect of policies directly affecting food demand (i.e. price subsidies) and as an essential building block in economy wide models, such as general equilibrium models (e.g. Jensen & Tarp, 2004).

Not surprisingly, given the importance of price and income response parameters, identifying and estimating these have a long tradition in applied economics. Because price variation is inherently necessary for any successful attempt at identifying consumers' responses to price changes, estimation of price and income elasticities in developed countries has usually relied on aggregate time series data. Since prices normally vary little within developed countries at any given point in time, time series data is essential to identify price variation. However, in developing countries where markets are less integrated and transportation is often burdensome in terms of both monetary and time costs, prices can be expected to vary considerably between locations. If nationally representative (or regionally representative but dispersed) cross sectional household survey data is available the price differences between different locations can be exploited to obtain estimates of price response parameters. This was first exploited by Deaton (1987) to estimate own and cross price elasticities from a cross section of households from Cote d'Ivoire.[1] An additional benefit from using household survey data is the availability of demographic variables at the household level. This makes it possible to (partly) control for household heterogeneity in the parameters. In addition, household surveys usually have a sample size which permits estimation of a large number of parameters.

This paper attempts to shed light on households' response to relative price changes in food products in urban areas in Mozambique, a geographically weakly integrated country.[2] The contribution of the present paper is twofold. First, I use the most recent national representative household survey conducted in Mozambique in 2002/03 (IAF02) to estimate a large complete demand system for 12 food groups augmented with demographic and locational variables using the urban household sample. This is done using a translog demand system approach. Using survey data at the household level both poses challenges and yields benefits. A recurring problem when estimating demand systems using micro data is the likely wide presence of households reporting zero consumption of one or more of the commodities analyzed. As will be evident, the problem of censoring is severe in the sample of urban Mozambican households considered here. Ignoring it would bias our estimates. The approach taken in the present paper accounts for censoring by estimating a system of Tobit equations as proposed by Yen, Lin and Smallwood (2003).

Second, location dummy variables for households living in the southern, central and northern part of the country are utilized in the demand system (together with demographic

[1] See Kedir (2005) for a recent application to Ethiopia.
[2] While the majority of Mozambican household reside in rural areas the urban definition applied in this study is quite broad covering some 30 percent of the population of households.

variables) to focus on differences in elasticities between these regions. In particular, the paper investigates to what extent differences are due to preferences (i.e. differences in parameters) or whether they are attributable to regional price differences. Given the geography of Mozambique, location is likely to be an important determinant of demand patterns and elasticities. The results are interesting in themselves and should be a valuable input into ongoing efforts at the Mozambican Ministry of Planning and Rural Development to construct both national and regional applied general equilibrium models. Further, the methodology used here can be applied to other countries where regions differ in geography.

For the purposes of this paper I am fortunate to use a data set which is both nationally representative and have a spatial time dimension in the way the data was collected. Because it was collected throughout a full year there is ample price variation over and above what exists between villages as a result of lack of market integration. Thus, elasticities are expected to be estimated with a better precision than is usually obtainable from cross-sectional data.

The remainder of the paper is structured as follows: in section 2 the data together with some descriptive statistics are presented. This is followed by an outline of the methodology employed in section 3, while section 4 presents the results. Finally, section 5 concludes.

2. Data and descriptive statistics

The data source for this study is the 2002/03 nationally representative household survey of Mozambican households (IAF). It contains detailed information on food consumption for a random sample of 8,700 households in Mozambique, as well as information on general characteristics of the household, daily expenses and consumption from home production, possession of durable goods, gifts and transfers received. All aspects of survey implementation and a set of summary statistics are available from the National Institute of Statistics (INE 2004). The interviewers were in the enumeration area for a week, during which three household visits were programmed in order to administer questionnaires and assist households in keeping track of daily consumption. Thus, to the extent it is possible food consumption should be very well covered within the survey period.

The survey was designed with an explicit view to be representative in time as well as space. Data collection was done over the space of one year divided into quarters. For each sub-group of the population, the survey was designed to represent, one quarter of the households were interviewed in each period.

The geography of Mozambique and the fact that 'around the year' price information is available should allow sufficient price variation to identify price elasticities with good precision. This is an exercise which is often difficult when only cross section data is available. It is natural to divide the 11 provinces of Mozambique into three distinct regions; south, central and north. The south is made up of the provinces Maputo City, Maputo province, Gaza and Inhambane. The provinces of Sofala, Manica, Tete and Zambezia constitute the central part of Mozambique. Lastly, the north includes Nampula, Niassa and Cabo Delgado.[3]

The food demand system estimated includes all expenditures on food products – divided into 11 separate food groups and a residual category; vegetables, maize flour, fish, bread, rice, meat, oil & fats, fruits, sugar, beans, other staples and the residual group other foods. Other staples consist of cassava and potatoes and the residual group includes beverages, spices and meals eaten outside the house. Maize, bread and rice are the main staples of Mozambican households in urban areas, with some also consuming cassava and potatoes (other staples). As an artefact of the geography of Mozambique fish is also widely consumed. Meat is composed of beef, pork and chicken meat. In nutritional terms beans are an important protein substitute for meat and fish. Fruits are consumed throughout Mozambique. A large component of oil and fats is cooking oil, but a limited number of households also consume butter.

[3] In the following the regions are simply referred to as: south, central and north.

To avoid the problems inherent in evaluating the value of home produced goods the scope is limited to the urban part of the sample.[4] This sample consists of 4,005 urban households interviewed in 335 clusters. However, households were removed where the unit price and expenditure information looked dubious or were missing, very large households, and households which had zero purchases for more than eight goods. Specifically, deleted households were those with more than 10 members, households with logarithmic income and prices more than four standard deviations from the mean sample value. Unit prices were obtained by averaging over all consuming households in each enumeration area. If no households in the enumeration area consumed the good the average over households interviewed in the same quarter in the same region (north, central or south) was used. Unit prices for bundles of goods are obtained by weighting individual good prices with the expenditure share. The final sample includes 3,543 households.

[Table 1 about here]

The first part of Table 1 presents expenditure shares on the 12 food groups for the south, central and the north separately. Expenditure shares clearly differ between regions. Vegetables are much more widely consumed in the south, with the highest expenditure share there, compared with central and north. On the other hand, maize flour which makes up around 24 percent of the budget in the central region is less important in the north and only accounts for 3 percent of expenditure in the south. Fish and other staples – mostly cassava and potatoes – are the most important food product for households located in the north, whereas these food groups are less important elsewhere, although fish is widely consumed. In the north sorghum is a significant part of the other staple category. Overall, it is clear that there are large regional differences in food consumption patterns which need to be accounted for in the estimation. In addition, Table 1 indicates the need for estimating a large demand system with many goods when the focus is on regional differences. Aggregating some of the categories further risks blurring regional differences in food

[4] Excluding rural household to some extent limits the usefulness of the elasticity estimates obtained here for nationwide policy analysis. However, including rural households would add further complications without adding much value to the analysis of regional differences.

consumption. Thus, the approach of limiting the number of demographic variables in favour of more food groups seems warranted.

The two last columns of the both the upper and lower part of Table 1 illustrate the need for a censored approach to estimate food demand for urban Mozambican households. While two food groups (vegetables and fish) are consumed by more than 90 percent of the households, most food groups have a substantial number of households with zero-purchases. Looking at the second half of Table 1 reveals that only around 3 percent of the households consume all 12 goods; again highlighting the relevance of taking zero consumption explicitly into account.

Apart from the dummy variables for location, south and north (central is the base specification), household size is also included as an additional explanatory variable to account for economies of scale in food preparation. There are other potential demographic variables which could be included, but their inclusion would add limited value to the focus of this analysis, and at the same time expand the already large number of parameters to be estimated.

[Table 2 about here]

Table 2 lists some summary statistics for the demographic and location dummy variables. The mode of the distribution of household size is five members, which constitutes 16 percent of all households. The sample is roughly equally divided between the three geographical areas.

3. Methodology

3.1 The translog demand system

The theoretical point of departure is the *n*-good indirect translog demand system proposed by Christensen, Jorgensen & Lau (1975)[5]. The flexible indirect utility function is logarithmic quadratic in normalized prices and has the form

$$\log\ V(p,x) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \log \frac{p_i}{x} + 1/2 \sum_{i}^{n} \sum_{j}^{n} \gamma_{ij} \log \frac{p_i}{x} \log \frac{p_j}{x} \tag{1}$$

where *x,* p_j is total expenditure and the price of good *j,* respectively. The unknown parameters are α_0, α_i and $\gamma_{ij}, i, j = 1,.....,n$. Since all prices are normalized by income, homogeneity of degree zero in prices and income is guaranteed. Share equations can be obtained by applying a logarithmic version of Roy's identity

$$w_i = \frac{\alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log\left(p_j / x\right)}{1 + \sum_{k}^{n} \sum_{j}^{n} \gamma_{kj} \log\left(p_j / x\right)}, \quad i = 1,.....,n. \tag{2}$$

The normalisation $\sum_{j=1}^{n} \alpha_j = 1$, ensuring that the budget shares sum to one, has been imposed. The theoretical restriction of Slutsky symmetry can be implemented by the restriction $\gamma_{ij} = \gamma_{ji}$ for all *i,j*. Demographic and locational variables are incorporated through the α-parameters. Specifically, let z^h denote a *1xL* vector of household demographic and location dummy variables for household *h* with the elements denoted by z_l^h. The α-parameters can then be specified as $\alpha_i(z^h) = \alpha_{i0} + \sum_{l=1}^{L} \alpha_{il} z_l^h$. To maintain the adding-up property the following restrictions must be satisfied: $\sum_{i=1}^{n} \alpha_{i0} = 1, \quad \sum_{i=1}^{n} \alpha_{il} = 0, l = 1...L$.

[5] For recent applications of the indirect translog demand system see Yen, Fang & Su (2004) and Yen, Lin & Smallwood (2003).

Adding an error term, ε_i, and denote by Λ the set of all parameters, latent share equations can be written in the form

$$\bar{w}_i = w_i(p, x; \Lambda) + \varepsilon_i, \quad i = 1, \ldots\ldots, n,$$

where $w_i(p, x; \Lambda)$ is the deterministic component given by (2).

3.2 Accounting for censoring

Without restrictions on the error term the system of latent share equations cannot be a valid representation of observed behaviour since nothing constrains the shares to be non-negative. In particular, if a substantial number of households have zero consumption of some goods, the distribution of the error terms should allow for a positive probability of observing zero consumption. A number of methods have been proposed to deal with the issue of censoring. Wales and Woodland (1983) suggest a Kuhn-Tucker approach, whereby a utility function is maximized subject to non-negativity constraints on quantities. Lee and Pitt (1986) start from a random indirect utility function and use a dual approach related to the literature on rationing based on reservation prices, where demand for all goods depends on market prices for positively consumed goods and reservation prices for non-consumed goods. Because the rationed quantity is zero it is sometimes possible to solve for reservation prices explicitly. While theoretically appealing, these approaches suffer from the drawbacks that in the case of many non-consumed goods for some households, evaluation of multiple integrals is necessary. Further, as illustrated by Van Soest and Kooreman (1990), the issue of coherency of the solution has also to be addressed. Since the set of reservation (and market) prices that supports the observed behaviour may not be unique. In addition, for some flexible forms neither the Wales and Woodland nor the Lee and Pitt approaches are feasible.

An alternative solution, the Amemiya-Tobin approach, is inspired by Amemiya's (1974) multivariate regression with truncated normal distributions. Here the consumer is implicitly seen as maximizing a deterministic utility function and deviations from the corresponding deterministic shares are interpreted as random errors in the optimization process, measurement errors in the shares or random disturbances which influence the consumption decision (Wales and Woodland, 1983). However, like the Kuhn-Tucker approach, the implementation of Amemiya-Tobin type estimators is complicated by the need for evaluating multiple integrals in cases where censoring is severe. To circumvent the computational difficulties involved in the procedures described above, Shonkwiler and Yen (1999) suggested a two-step estimation procedure, where a probit regression is run in the first step for each equation to determine the pattern of censoring.[6] Using the estimated parameters in the second step, each latent share equation is augmented so as to take into account the censored nature of the data. The augmented system can then be estimated consistently with the (transformed) errors being normally distributed. The two-step nature of the estimator makes inference complicated by the need to adjust the covariance matrix as devised by Murphy and Topel (1985). Even so, the technique has been widely used in empirical applications (e.g. Yen, Kan and Su 2002).[7]

In this paper I follow the Amemiya-Tobin approach and specify the system of expenditure shares as a system of Tobit equations (see Yen, Lin and Smallwood 2003, Dong, Gould and Kaiser 2004, Yen and Lin 2002).[8] The method has the advantage of having potential fewer parameters for a given number of share equations than for example the two-step approach. For the study of regional difference in Mozambique a large (in terms of different food groups) demand system is essential in order to avoid that the aggregation of food groups is not obscuring possible differences among regions. To overcome the computational burden of simulating multiple integrals, a quasi maximum likelihood estimation technique recommended by Yen, Lin and Smallwood (2003) is employed.

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[6] Alternatively, a multivariate probit can be run to facilitate cross equation correlation between the errors in the censoring mechanism, however, multivariate probit estimation requires evaluation of multiple integrals (or simulations hereof).

[7] The three approaches considered here have received much attention. However, other methods have recently been suggested in the literature, see Golan, Perloff and Shen (2001) and Perali and Chavas (2000).

[8] This treatment is not entirely innocuous. In particular, the Tobit formulation suffers the well-known limitation that the same process determines both the probability of censoring and the size of the expenditure share. Thus, a variable is constrained to influence the probability of censoring and the expenditure share in the same direction. Even with its drawbacks, this set-up has the advantage of saving on parameters.

3.3 Quasi maximum likelihood estimation

Write the observed shares, w_i^*, as a system of Tobit equations where joint normality of the error term, ε_i, is assumed

$$w_i^* = \max(w_i(p,x;\Lambda) + \varepsilon_i, 0), \quad i = 1,..,n \tag{3}$$

Even if the adding up condition is imposed on the deterministic shares, it may not hold for the observed shares in the model. To overcome this Pudney (1989) suggests treating the n'th good as a residual good and then obtain the elasticities from the following identity,[9]

$$w_n^* = 1 - \sum_{i=1}^{n-1} w_i^* .$$

To construct the likelihood function for the *n-1* estimated share equations, let the first k goods be the ones which are consumed in positive quantities by household h, and partition the *(n-1)x1* error vector into

$$\left[e_1 : e_2\right] \equiv \left[\varepsilon_1, \varepsilon_2, .., \varepsilon_k : \varepsilon_{k+1}, \varepsilon_{k+2}, ... \varepsilon_{n-1}\right]$$

and assume they are normally distributed with covariance matrix

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

where Σ_{11} is a *kxk* matrix, Σ_{21} is a *(n-1-k)xk* matrix and Σ_{22} is a *(n-1-k)x(n-1-k)* matrix. The joint probability density function (pdf) of the errors can be written in terms of the joint marginal pdf for the first k errors and the pdf of the last *n-1-k* errors conditional on the first k errors, i.e.

$$f(e_1, e_2) = g(e_1) \times h(e_2 \mid e_1) .$$

where $g(e_1)$ is the joint marginal pdf for the first k errors, distributed k-dimensional normal with zero mean and covariance matrix Σ_{11}. The joint pdf of e_2 conditional on e_1, $h(e_2 \mid e_1)$, can be shown to be *(n-1-k)*-dimensional normal with mean and covariance matrix given by (Greene, 2000)

$$\mu_{2.1} = \Sigma_{21}\Sigma_{11}^{-1}e_1$$
$$\Sigma_{22.1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{21}'$$

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[9] This has the consequence that the estimated parameters are not invariant to which good is excluded.

The likelihood contribution of household *h*, being in consumption regime *c*, i.e. where the first *k* goods are consumed, can be stated as

$$L_c^h = g(e_1) \int_{-\infty}^{-w_{n-1}(\Lambda)} \cdots \int_{-\infty}^{-w_{l+2}(\Lambda)} \int_{-\infty}^{-w_{l+1}(\Lambda)} h(u_{k+1}, u_{k+2}, .., u_{n-1} \mid e_1) du_{k+1} du_{k+2} .. du_{n-1}$$

Using the expressions for the mean and covariance matrix given above, it is possible to evaluate the multiple integral as a standard *(n-k-1)*-dimensional normal pdf. Define the indicator function I_c^h as being one if household *h* is in consumption regime *c* and zero otherwise. The likelihood function for the sample of *N* households can now be written as

$$L = \prod_{h=1}^{N} \prod_{c} L_c^h (w_h(\Lambda))^{I_c^h} \tag{4}$$

Where $w_h(\Lambda)$ denotes the *(n-1)x1* vector of deterministic shares for household *h*.

While methods exist to simulate the likelihood function derived above (see Yen, Lin & Smallwood (2003) for a simulated maximum likelihood approach), they are computationally intensive when the number of non-consumed goods are large for a sizable part of the sample, as is the case for the present sample. Instead I adopt the quasi maximum likelihood (QML) procedure where the true likelihood function is approximated by linking bivariate Tobit models across the equations. More explicitly, the likelihood function given by (4) is approximated by multiplying all possible pair-wise combinations of bivariate Tobit likelihood functions. Define for household *h* and equation *i* and *j* the normalized errors; $u_{ih} = \left(w_{ih}^* - w_i(\Lambda)\right)/\sigma_i$ and $u_{jh} = \left(w_{jh}^* - w_j(\Lambda)\right)/\sigma_j$ where w_{ih}^* is the observed share for good *i* and σ_i is the standard deviation of the *i*'th error term. The likelihood contribution from the joint share equations *i,j* of household *h* takes the form of a bivariate Tobit likelihood function

$$L_{ij}^{h}=\left[\Psi(u_{ih},u_{jh},\rho_{ij})\right]^{I(w_{ih}^{*}=0,w_{jh}^{*}=0)}\times\left[\sigma_{j}^{-1}\sigma_{i}^{-1}\psi(u_{ih},u_{jh},\rho_{ij})\right]^{I(w_{ih}^{*}>0,w_{jh}^{*}>0)}\times$$
$$\left[\sigma_{j}^{-1}\phi(u_{jh})\Phi\left((u_{ih}-\rho_{ij}u_{jh})/(1-\rho_{ij}^{2})^{1/2}\right)\right]^{I(w_{ih}^{*}=0,w_{jh}^{*}>0)}\times$$
$$\left[\sigma_{i}^{-1}\phi(u_{ih})\Phi\left((u_{jh}-\rho_{ij}u_{ih})/(1-\rho_{ij}^{2})^{1/2}\right)\right]^{I(w_{ih}^{*}>0,w_{jh}^{*}=0)}$$

I(.) is an indicator function taking the value one if it evaluates to true, ϕ,Φ, are the standard normal pdf and standard normal cumulative distribution function (cdf), respectively. Similar, the bivariate standard normal pdf and cdf are denoted ψ and Ψ. The quasi likelihood function for the *N* households over all pair wise bivariate Tobits is given by

$$L=\prod_{h=1}^{N}\prod_{i=1}^{n-2}\prod_{j=i+1}^{n-1}L_{ij}^{h} \tag{5}$$

Cross-equation parameter restrictions on the demand system are easily accommodated via the linking of the pair wise Tobit likelihoods. Estimation proceeds by maximizing (5). The parameters obtained are consistent but will be less efficient than full information maximum likelihood estimation. In Monte Carlo simulations, Barslund (2006a) shows that the quasi maximum likelihood estimator yields parameter estimates very close to those of a simulation based full information maximum likelihood method.

3.4 Elasticities and decomposition of demographic effects

As pointed out by Lazaridis (2004), in a system of censored demand equations, price and expenditure elasticities should take into account not only the direct effect on the latent share but also the indirect effect from a possible change in the nature of censoring. The unconditional mean of observed shares is given by (Wooldridge 2002)

$$E(w_{i}^{*})=\Phi\left[w_{i}(\Lambda)/\sigma_{i}\right]w_{i}(\Lambda)+\sigma_{i}\phi\left[w_{i}(\Lambda)/\sigma_{i}\right]$$

Income and uncompensated price elasticities for the system of equations can be written as

$$\eta_i^X = \frac{1}{Ew_i^*}\hat{\Phi}_i \cdot \frac{-\sum_{j=1}^{n}\hat{\gamma}_{ij} + w_i(\hat{\Lambda})\cdot\sum_{i=1}^{n}\sum_{j=1}^{n}\hat{\gamma}_{ij}}{1+\sum_{i=1}^{n}\sum_{j=1}^{n}\hat{\gamma}_{ij}\overline{\log}\left(p_j/x\right)} + 1 \text{ and } e_{ij}^M = \frac{1}{Ew_i^*}\hat{\Phi}_i \frac{\hat{\gamma}_{ij} - w_i(\hat{\Lambda})\cdot\sum_{k=1}^{n}\hat{\gamma}_{kj}}{1+\sum_{i=1}^{n}\sum_{j=1}^{n}\hat{\gamma}_{ij}\overline{\log}\left(p_j/x\right)} - \delta_{ij}$$

where a hat denotes estimated parameters and $\hat{\Phi}_i = \Phi\left[w_i(\hat{\Lambda})/\hat{\sigma}_i\right]$. δ_{ij} is the kronecker delta taking the value one if $i=j$ and zero otherwise. A bar indicates that the logarithm is evaluated at the mean price and income for the location and demographic group in question and the superscript M denotes uncompensated (Marshallian) elasticities. Compensated price elasticities, ε_{ij}^C, can be calculated using the Slutsky equation $\varepsilon_{ij}^C = \varepsilon_{ij} + \eta_i^X Ew_i^*$, for all $i, j = 1,...,n.$

Differences in elasticities between demographic and geographical groups can be obtained by utilizing the augmentation of the α_i parameter (as described above). Let superscript r and a signify a reference and alternative demographic group, respectively, and make the convenient normalization of prices and incomes such that $\overline{\log}^r\left(p_j/x\right) = 0$ for the reference group. The difference in expenditure elasticities for good i is then

$$\partial\eta_i^{X,r,a} = \eta_i^{X,r} - \eta_i^{X,a}$$

$$= \frac{1}{Ew_i^{*,r}}\hat{\Phi}_i^r \cdot \left[-\sum_{j=1}^{n}\hat{\gamma}_{ij} + w_i^r(\hat{\Lambda})\cdot\sum_{i=1}^{n}\sum_{j=1}^{n}\hat{\gamma}_{ij}\right] - \frac{1}{Ew_i^{*,a}}\hat{\Phi}_i^a \cdot \frac{-\sum_{j=1}^{n}\hat{\gamma}_{ij} + w_i^a(\hat{\Lambda})\cdot\sum_{i=1}^{n}\sum_{j=1}^{n}\hat{\gamma}_{ij}}{1+\sum_{i=1}^{n}\sum_{j=1}^{n}\hat{\gamma}_{ij}\overline{\log}^a\left(p_j/x\right)} \quad (6)$$

Analogous for own- and cross price elasticities. Confidence intervals facilitating statistical inference are obtained by the delta method.[10]

It is possible to decompose the elasticity differences into two components; a part stemming from demographic price differences and a part due to differences in α parameters. The relative importance of the first part can be judged by taking the difference between the

[10] An alternative method to get standard errors for the elasticities and their differences is to use a bootstrap approach. However, given the computational burden in estimating the system, this is not feasible here.

elasticity for the reference demographic group and the elasticity for the alternative demographic group evaluated at the parameters pertaining to the reference group and prices for the alternative group. Similarly, the difference associated with differences in α parameters is calculated by taking the difference in (6), but with the elasticity for the alternative demographic group evaluated at reference group prices. Because the elasticities are non-linear the two components will not in general sum to the total difference defined by equation 6 above. However, the ratio of the two components will illustrate their relative importance in contributing to the total difference. The results will focus on differences in elasticities with respect to geographical location, but differences between any two demographic groups can be analysed using the framework presented here.

An obvious alternative to analysing regional differences in elasticities would be to estimate three models separately and compare the estimated elasticities. An advantage is that it would not be necessary to restrict the price response parameters, γ_{ij}'s, in (2) to be equal over regions.[11] Although attractive, this would reduce the sample considerably for each region and, contrary to the method pursued here, it would not allow for a statistical test of difference between the regions.

4. Results

4.1 Elasticities for central Mozambique

All estimations are carried out using household weights provided by the National Statistical Office in Mozambique. Standard errors are robust to clustering at the enumeration area, and stratification of the sample.[12] In total, 188 parameters were estimated. A full list of coefficients is relegated to appendix B.

[11] In principle it is possible to augment each γ_{ij} in (2) with regional dummy variables but the number of parameters to estimate would be unmanageable in practical terms.

[12] All estimations were done in the software package Stata 9.2 using the command qmldemand_tl.ado (see appendix A).

The reference household considered in the following has five members and comes from the central part of the country. I compare the elasticities from this group of households with two households with an equal number of members in respectively the south and north of the country. Income and all prices are normalised such that the average over the households in the reference group is one (i.e. the logarithm of income, prices and prices over income are zero).

As expected, a substantial number of parameters are estimated with good precision. In total 111 of the 188 (56 %) estimated parameters are significant at the five percent level. Of the 78 price response parameters (γ's) 35 (45 %) are significant at the five percent level, and 45 out of 66 estimated covariance parameters (ρ's and σ's) are significant. Inclusion of the demographic variables is also warranted from the results; 20 out of 33 are significant. All but one of the 11 α_{i0}'s are significant at 5 percent. Table 3 shows the size and significance of the demographic variables.

[Table 3 about here]

Each column shows the effect from the demographic variable on the deterministic share (see equation 2) relative to a reference household.[13] Looking horizontally across the table it is clear that inclusion of household size and the dummy variables for location is warranted. Only the meat food group is unaffected by any of the three variables (none of them enters significantly). Focusing on the differences between the central part and the north and south of Mozambique the table illustrates some striking differences. For vegetables and fish both the north and south dummy variable are significant and with opposite signs, reflecting the observations in Table 1 and signifying that there are significant differences in consumption shares between the three regions for these food items even when possible price differences have been accounted for. The expenditure share for oil and fats, fruits, and beans in the north and south is significantly different from the central part of Mozambique, but since

[13] Recall from (3) that an increase in the deterministic share (and as a result the latent share) has two effects; it increases the probability of the household consuming the good (non-censoring) and it increases the expenditure share given consumption of the good.

they have the same sign it is not possible to assess if they also differ between the north and south. In the south all other food groups except meat and other staples have significantly different expenditure shares relative to the central part. The results listed in Table 3 point in the direction of different elasticities between the regions in Mozambique. This is explored further below.

The precision with which the coefficients are estimated is expected to carry over to small standard errors around the estimated elasticities. Table 4, which shows estimated elasticities and their standard errors for a reference household in central Mozambique, confirms this.

[Table 4 about here]

Of the 121 estimated price elasticities 52 are significant at the 5 percent level and a further 11 are significant at the 10 percent level.[14] All 11 expenditure elasticities are significantly different from zero. However, more interestingly; seven are different from one at the 5 percent significance level.

Looking at the estimated uncompensated own price elasticities, bread, oil and fats, sugar, beans, fish, meat and fruits are price elastic – with the first four food groups significantly greater than minus one in absolute terms – while fruits, fish and meat have uncompensated own prices around minus one. Vegetables and maize flour are both significantly price inelastic. While the point estimate for rice and other staples suggest they are price inelastic, although the confidence interval is too large to say so significantly. The cross price elasticities are generally smaller than own price elasticities in absolute value. However, for some goods there are sizeable cross price effects. This is especially valid for maize flour, rice, beans and other staples, which all have relatively large and significant cross price effects. A majority of food groups are gross complements as is often found in food demand

[14] Since focus is exclusively on food consumption all elasticities are conditional elasticities and, thus, expenditure elasticities are measured with respect to total food expenditures.

studies (see Yen, Lin & Smallwood 2003, Dong, Gould & Kaiser 2004) and the absolute size also conforms well to these studies.

Most food groups have one or more gross substitutes except for maize flour and sugar. That might be expected given the importance of this ingredient in the food basket for households located in the central part of the country, cf. Table 1. Sugar has in general few natural substitutes. Notable significant gross substitutes are found between vegetables and bread and fish. Fish and beans together with rice and other stables are also gross substitutable. There is no evidence of meat and fish being (significant) gross substitutes as might be expected by these two important sources of protein. The other main protein source, beans is a gross substitute for both fish and meat.

The food expenditure elasticities reveal four food groups, namely vegetables, fish, fruits and beans to be necessities and the remaining seven, maize flour, bread, rice, meat, oil and fats, sugar and other staples to be luxury food items. As noted earlier seven of these pass significance tests (in terms of luxuries and necessities) at five percent. These findings conform reasonably well to prior expectations. The fact that maize flour and rice come out as luxuries reflect the small incomes which, despite the good economic performance of the Mozambique economy recently, many urban families still have to get by on (MPD 2004). It is surprising that the category other staples, containing mainly cassava and potatoes, is not a necessity. It might be that the category is so broad that items are used for food variety by wealthier households. It also reflects to some extent the choice of the central part of the country as the reference location. Table 1 revealed that other staples is a much bigger category in the northern part of Mozambique and Table 3 showed a large significant coefficient on the northern location dummy for the food category of other staples.

[Table 5 about here]

Turning to the compensated price elasticities, these are displayed in Table 5 for completeness. The compensated own price effects are all negative and smaller (in absolute value) than their uncompensated counterpart as would be expected from demand theory. While most food products are gross complements Table 5 shows that if households are compensated for price changes most products become net substitutes.

4.2 Regional differences in elasticities

I now proceed to evaluate the impact of geography on food demand elasticities. As noted above for a majority of food groups the dummy variables for location (North and South) are significant, and therefore expenditure shares differ between regions once possible relative price differences have been accounted for. Thus, given the utility function, the estimated parameters can be used for partial welfare analysis of relative price changes and the effects are allowed to differ between the demographic groups included in the estimation. However, for policy analysis in general and for equilibrium analysis in CGE models in particular, the parameters of interest are often the elasticities. It therefore becomes of interest to investigate to what extent the share differences carry over to differences in regional elasticities and whether these differences are significant. This is pursued here using the methodology discussed in section 3.3.

[Table 6 about here]

Table 6 shows expenditure and own price elasticities for central and southern Mozambique measured for a reference household (i.e. with five household members), their differences and the standard error of the differences. The difference is calculated by (6) and associated standard errors are obtained by the delta method. Looking first at expenditure elasticities (the five first columns), note that roughly the same goods are necessities and luxuries in both areas – with the exception of beans and possibly bread. Neither bread nor beans are estimated with enough precision in the south to reject that bread is a luxury and beans a necessity as is the case in central Mozambique. There are sizeable differences in elasticities (absolutely greater than 0.1) for maize flour, bread, fruits, beans and oil and fats. However, only for bread is the difference significant at 5 percent. In the south the point estimate of the expenditure elasticity of maize flour is very high at 2.03 – but the confidence interval around this estimate is correspondingly large (not shown) implying no significant difference between the central and southern estimates. For vegetables, meat and fish the differences are small and insignificant. Note though, that the point estimates for vegetables still differ with around 6 percent between central and south. For maize flour, bread, oil and fats, fruits and beans the point estimates differ with 10 percent or more, making it clear that policies aimed at or implying price changes for these food groups will have different impact in the two regions.

The last two columns of the first part of Table 6 attempt to separate the total differences in expenditure elasticities into respectively a price effect and a parameter effect as described in section 3.3. Informally, the price effect can be interpreted as the difference that would have been observed had the equations been estimated without the location dummy variables.[15] It is the effect of households being at different points on the same demand curve due to price differences alone. Although the two effects do not add to the total differences – as expected because of the non-linearities in the system – they nonetheless seem sensible in size and direction. As an example take sugar, where the price effect suggests that the expenditure elasticity should have been higher in the central than in the southern part of the country. The observed difference is negative and to reconcile that with the positive price effect the parameter effect must be large and negative relative to the price effect – as is indeed the case. In general the parameter effects are much larger than the price effects suggesting that differences in expenditure elasticities are due to differences in parameters rather than to differences in prices. For bread and other staples this is not the case, though. Here relative price differences play a role.

The second part of Table 6 concentrates on own price elasticities. While the same exercise has been done for cross price elasticities only differences in own price elasticities are

[15] Estimating the model without location dummy variables would have resulted in another set of parameter estimates, possibly, with differences of another magnitude, thus clearly, one has to be cautious in interpreting the reported differences. On the other hand as argued in section 3.3, the relative sizes of the price effects and the parameter effects still convey useful information as to the source of the observed differences.

reported to keep the focus and to have a manageable amount of output. Price elastic and inelastic food groups do not differ between the two regions. In general the size of the differences is smaller than for expenditure elasticities and for fish, rice, meat, fruits, sugar and other staples there are virtually no differences between elasticities. However, for two food groups, bread and oil and fats, differences are sizeable and significant. For beans the difference is small, but estimated with good precision so that the difference in own price elasticities is significant at 5 percent. Parameter effects explain most of the differences. Only for bread and oil and fats is the magnitude of the price effect non-negligible. Since own price elasticities constitute a combined substitution and income (expenditure in the terminology here) effect it would be preferable to observe large price effects in the differences between own price elasticities where large price effects were observed for expenditure elasticities; at least for some goods. This to some extent is the case as illustrated by the food groups of bread and oil and fats. However, for maize flour and other staples the price effect fail to show up in the differences in own price elasticities. This could be because the substitution and income effects cancel out the price effect difference.

To sum up, differences in expenditure and own price elasticities between south and central Mozambique are generally small in absolute size. For a few goods, notably vegetables and bread, the size and significance of the absolute differences warrant the use of different elasticities for the two regions.

[Table 7 about here]

Table 7 is equivalent to Table 6 and shows differences between central and northern Mozambique. Luxuries and necessities do not differ between the two regions – except for other staples, where the point estimate shows it to be a necessity in the north. With a point estimate of 0.98 and a standard error of 0.13 this is a borderline case. There are sizeable differences in expenditure elasticities for oil and fats and other staples (respectively, -0.18 and 0.20), although the confidence intervals surrounding them are too large to make them significant at any level. This to some extent reflects the rather strong data requirement to estimate differences with precision. Even when they are not significant the size of the differences in point estimates are worth taking into account when analysing regional changes in food consumption – whether it is by using different regional expenditure elasticities or as part of a sensitivity analysis. The price effect is of relative importance for maize flour, meat and beans, whereas to the extent there are differences in expenditure elasticities for the other food groups these are driven by parameter effects. As for own price elasticities, the size of the differences resemble those found between the central and southern part of Mozambique. For maize flour, bread and oil and fats the differences are significant. The price effects are small for all food groups and nowhere larger than 0.03 in absolute sizes. Except for vegetables (where the total difference is not significant) and oil and fats the parameter effects are equally quite small.

5. Conclusion

Even though Mozambique has managed to reduce poverty considerably during the past decade, it is still a poor country where around 50 percent of expenditures are directed towards food consumption. Therefore food prices, food demand and nutrition are among the key elements when discussing household welfare, and in particular changes herein. However, little is known about demand elasticities for core food groups in Mozambique. In this paper a large food demand system has been estimated for a nationally representative sample of urban Mozambican households. The issue of censoring of the expenditure shares has been addressed by a recently suggested maximum likelihood estimator. Because of Mozambique's varied geography and limited economic integration across regions the focus is on regional differences. The novel estimates illuminate some interesting differences in expenditure shares between demographic and geographic groups. Further, expenditure and own price elasticities are presented for respectively northern, central and southern Mozambique, and a test for statistical significance between regions is developed. In particular for own price elasticities there are significant – both in a statistical and a quantitative sense – differences between the central and the south and north of Mozambique. Apart from being the first estimates using micro data for Mozambique the findings are useful for developers of CGE models with a regional aspect and for the evaluation of policies that alter relative food prices.

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Tables

Table 1. Food consumption for urban Mozambican households.

Food group	South	Central	North	Full Sample: Households consuming (%)	Full Sample: Mean expenditure share (%)
	Share in total food expenditure (%)				
Vegetables	19.4	10.7	5.3	91.7	11.9
Maize flour	3.1	23.6	15.5	52.9	13.4
Fish	11.5	13.2	20.5	90.1	15.2
Bread	13.0	5.0	3.9	65.9	7.5
Rice	8.6	9.8	7.0	50.2	8.4
Meat	9.1	6.6	4.9	33.7	6.9
Oil & fats	3.6	5.4	2.6	58.8	3.8
Fruits	12.0	3.9	5.3	83.3	7.3
Sugar	3.5	3.3	3.4	52.1	3.4
Beans	3.6	5.7	4.6	54.8	4.6
Other staples	4.7	6.1	21.1	66.0	10.9
Other food	8.0	6.5	6.0	72.4	6.8
No. Obs. (N)	1720	1102	721	3543	3543

Number of goods consumed	Number of household consuming (full sample)	Share of household consuming (%) (full sample)
4	227	6.4
5	334	9.4
6	520	14.7
7	606	17.1
8	594	16.8
9	526	14.9
10	370	10.4
11	268	7.6
12	98	2.8

Source: IAF2002/03. Sample as explained in the main text.
Note: Shares in columns with the heading 'Share in total food expenditure' and 'Mean expenditure share' may not sum to 100 due to rounding.

Table 2. Sample means of demographic variables.

Variable	Description	Mean	Min	Max
Household size	Household size normalized at the mode of the sample distribution	5.06	1	10
South	Household located in south (omitted category)	0.36	0	1
Center	Household located in center (=1)	0.29	0	1
North	Household located in north (=1)	0.35	0	1

Source: IAF2002/03. Sample as explained in the main text.

Table 3. Size and significance of demographic and geographic variables.

Equation	Household size	South	North
Vegetables	0.005***	0.078***	-0.063***
	(0.001)	(0.008)	(0.010)
Maize flour	-0.003	-0.296***	-0.041
	(0.004)	(0.029)	(0.026)
Fish	0.005***	-0.062***	0.072***
	(0.002)	(0.011)	(0.015)
Bread	0.004***	0.049***	-0.009
	(0.001)	(0.011)	(0.014)
Rice	-0.005*	-0.049*	-0.023
	(0.003)	(0.026)	(0.024)
Meat	0.011	0.043	-0.074
	(0.008)	(0.026)	(0.050)
Oil & fats	0.001	-0.056***	-0.040***
	(0.001)	(0.008)	(0.007)
Fruits	0.002***	0.086***	0.033***
	(0.001)	(0.011)	(0.008)
Sugar	-0.001	-0.024***	0.002
	(0.001)	(0.001)	(0.008)
Beans	0.004***	-0.036***	-0.037***
	(0.001)	(0.010)	(0.012)
Other staples	-0.010***	0.010	0.132***
	(0.003)	(0.021)	(0.029)

Note:
*, **,*** denotes significance at 10, 5 and 1 percent level. Standard errors in parenthesis. Household size normalised at 5 members (the mode of the distribution). That is, effects of household size are calculated relative to a household with 5 members. Effects are on the deterministic shares (equation 2).

Table 4. Estimated uncompensated elasticities for a reference household.[a)]

	Vegetables	Maize flour	Fish	Bread	Rice	Meat	Oil & fats	Fruits	Sugar	Beans	Other staples
Vegetables	-0.84***	-0.08	0.12***	0.23***	-0.10	0.02	0.02	0.03	0.00	-0.03	-0.04
Maize flour	-0.09***	-0.59***	-0.02	-0.04	-0.10*	0.06*	-0.04	0.01	-0.07***	-0.17***	-0.15***
Fish	0.07***	0.05	-1.05***	0.05	-0.18***	0.01	0.04	-0.04**	-0.03	0.17***	-0.06
Bread	0.28***	-0.15	0.05	-1.37***	-0.54***	-0.10*	0.02	-0.03	-0.01	0.12	0.35***
Rice	-0.11**	-0.20**	-0.21***	-0.27***	-0.82***	0.12***	-0.08	-0.09**	0.07	0.06	0.16***
Meat	0.03	0.01	0.01	-0.06**	0.07**	-1.10***	0.00	0.03	0.01	0.05*	-0.15***
Oil & fats	0.01	-0.10	0.06	0.03	-0.16	0.03	-1.34***	0.09**	0.02	0.11*	0.11***
Fruits	0.05	0.08	-0.09**	-0.03	-0.22**	0.07	0.11***	-1.00***	0.05	0.15***	-0.16***
Sugar	-0.03	-0.34***	-0.10*	-0.01	0.17	0.06	0.01	0.04	-1.29***	-0.03	0.11*
Beans	-0.05	-0.45***	0.29***	0.11*	0.14	0.09**	0.09*	0.11***	-0.02	-1.22***	0.04
Other staples	-0.05	-0.33***	-0.10*	0.22***	0.21***	-0.20***	0.05**	-0.09***	0.05*	0.02	-0.91***
Expenditure elasticities	0.66***	1.31***	0.86**	1.23***	1.30***	1.10	1.07	0.92	1.29***	0.89**	1.18

[a)] Reference household: 5 household members, located in central Mozambique.
Notes:
The table show percentage points change in demand for the row good when the price of the column good changes by 1 percent.
*, **,*** denotes significance at 10, 5 and 1 percent level. For price elasticities the significance is with respect to difference from 0.
For expenditure elasticities the significance is with respect to differences from 1. All expenditure elasticities are significantly different from zero at any conventional level.
All standard errors calculated by the delta method. They are not reported but available from the author.

Table 5. Estimated compensated elasticities for a reference household.[a)]

	Vegetables	Maize flour	Fish	Bread	Rice	Meat	Oil & fats	Fruits	Sugar	Beans	Other staples
Vegetables	-0.77	0.07	0.21	0.27	-0.04	0.07	0.06	0.06	0.03	0.01	0.01
Maize flour	0.05	-0.30	0.15	0.03	0.03	0.15	0.04	0.06	-0.02	-0.09	-0.05
Fish	0.17	0.24	-0.93	0.09	-0.10	0.07	0.09	0.00	0.01	0.23	0.00
Bread	0.42	0.12	0.22	-1.30	-0.42	-0.02	0.09	0.02	0.04	0.19	0.44
Rice	0.03	0.09	-0.03	-0.20	-0.69	0.21	-0.01	-0.04	0.12	0.14	0.26
Meat	0.15	0.25	0.16	0.00	0.18	-1.03	0.07	0.07	0.05	0.12	-0.07
Oil & fats	0.12	0.14	0.20	0.09	-0.05	0.10	-1.27	0.14	0.06	0.18	0.19
Fruits	0.15	0.28	0.04	0.02	-0.12	0.13	0.16	-0.96	0.08	0.21	-0.09
Sugar	0.11	-0.06	0.07	0.06	0.30	0.15	0.08	0.10	-1.24	0.05	0.20
Beans	0.05	-0.25	0.41	0.16	0.23	0.15	0.14	0.15	0.02	-1.17	0.11
Other staples	0.07	-0.08	0.06	0.28	0.33	-0.11	0.12	-0.04	0.10	0.10	-0.82

[a)] Reference household: 5 household members, located in central Mozambique.
Notes:
The table show percentage points change in compensated demand for the row good when the price of the column good changes by 1 percent.

Table 6. Elasticity differences between the central and southern part of Mozambique.[a)]

	Expenditure elasticities					Own price elasticities				
	Central	South	Difference (Total)	Difference (Price effect)	Difference (Parameter effect)	Central	South	Difference (Total)	Difference (Price effect)	Difference (Parameter effect)
Vegetables	0.66*** (0.04)	0.70*** (0.08)	-0.04 (0.11)	0.00	-0.03	-0.84*** (0.04)	-0.91*** (0.03)	0.07 (0.13)	0.01	0.07
Maize flour	1.31*** (0.05)	2.03 (1.09)	-0.72 (1.09)	-0.08	-0.58	-0.59*** (0.09)	-0.53*** (0.16)	-0.06 (0.08)	-0.02	-0.07
Fish	0.86** (0.06)	0.88 (0.11)	-0.02 (0.17)	0.02	-0.06	-1.05 (0.05)	-1.05 (0.05)	0.01 (0.01)	-0.01	0.02
Bread	1.23*** (0.05)	1.00 (0.06)	0.23** (0.11)	0.15	0.14	-1.37** (0.17)	-1.20** (0.10)	-0.17** (0.07)	-0.10	-0.09
Rice	1.30*** (0.05)	1.36*** (0.06)	-0.06 (0.10)	0.03	-0.10	-0.82 (0.15)	-0.82 (0.15)	-0.00 (0.01)	0.00	-0.00
Meat	1.10 (0.24)	1.08 (0.30)	0.02 (0.53)	-0.02	0.05	-1.10 (0.09)	-1.10 (0.08)	-0.00 (0.01)	0.00	-0.00
Oil & fats	1.07 (0.04)	1.19** (0.08)	-0.12 (0.11)	0.06	-0.25	-1.34*** (0.09)	-1.42*** (0.11)	0.09*** (0.03)	-0.06	0.16
Fruits	0.92 (0.08)	0.80*** (0.07)	0.12 (0.14)	0.03	0.12	-1.00 (0.09)	-1.00 (0.04)	0.00 (0.04)	0.00	0.00
Sugar	1.29*** (0.05)	1.35*** (0.07)	-0.06 (0.12)	0.05	-0.13	-1.29*** (0.11)	-1.31*** (0.11)	0.02 (0.02)	-0.02	0.05
Beans	0.89** (0.05)	1.01 (0.06)	-0.12 (0.11)	-0.04	-0.07	-1.22*** (0.08)	-1.28*** (0.10)	0.06** (0.03)	0.02	0.04
Other staples	1.18 (0.13)	1.25* (0.13)	-0.07 (0.13)	-0.09	0.02	-0.91 (0.07)	-0.90 (0.08)	-0.00 (0.01)	-0.00	0.00

[a)] Measured at the reference household, i.e. for each region a household with: 5 household members.
Notes:
Standard errors are calculated by the delta method and shown in parenthesis. *, **,*** denotes significant different from zero at 10, 5 and 1 percent level. For price elasticities the significance is with respect to difference from 0. For expenditure and own price elasticities the significance is with respect to differences from 1. All expenditure and own price elasticities are significantly different from zero at any conventional level.

Table 7. Elasticity differences between the central and northern part of Mozambique.[a)]

	Expenditure elasticities					Own price elasticities				
	Central	North	Difference (Total)	Difference (Price effect)	Difference (Parameter effect)	Central	North	Difference (Total)	Difference (Price effect)	Difference (Parameter effect)
Vegetables	0.66*** (0.04)	0.63*** (0.09)	0.03 (0.11)	0.01	0.00	-0.84*** (0.04)	-0.74*** (0.06)	-0.10 (0.14)	0.01	-0.09
Maize flour	1.31*** (0.05)	1.43*** (0.08)	-0.12 (0.13)	-0.08	-0.06	-0.59*** (0.09)	-0.54*** (0.11)	-0.05** (0.02)	-0.03	-0.01
Fish	0.86** (0.06)	0.82* (0.11)	0.04 (0.16)	0.00	0.04	-1.05 (0.05)	-1.04 (0.04)	-0.01 (0.01)	0.01	-0.01
Bread	1.23*** (0.05)	1.31*** (0.08)	-0.08 (0.12)	-0.01	-0.03	-1.37** (0.17)	-1.43** (0.18)	0.06** (0.03)	0.02	0.02
Rice	1.30*** (0.05)	1.40*** (0.06)	-0.10 (0.10)	-0.04	-0.05	-0.82 (0.15)	-0.81 (0.17)	-0.01 (0.02)	0.00	0.00
Meat	1.10 (0.24)	1.23 (0.34)	-0.12 (0.58)	-0.06	-0.09	-1.10 (0.09)	-1.12 (0.13)	0.02 (0.04)	0.02	0.01
Oil & fats	1.07 (0.04)	1.25*** (0.07)	-0.18 (0.11)	0.00	-0.16	-1.34*** (0.09)	-1.48*** (0.13)	0.14*** (0.04)	0.02	0.11
Fruits	0.92 (0.08)	0.86 (0.09)	0.07 (0.17)	0.00	0.07	-1.00 (0.09)	-1.00 (0.08)	0.00 (0.01)	0.00	0.00
Sugar	1.29*** (0.05)	1.32*** (0.09)	-0.03 (0.13)	-0.02	0.01	-1.29*** (0.11)	-1.31*** (0.11)	0.02 (0.02)	0.01	0.00
Beans	0.89** (0.05)	0.93 (0.06)	-0.03 (0.11)	0.05	-0.07	-1.22*** (0.08)	-1.26*** (0.10)	0.04 (0.03)	-0.02	0.04
Other staples	1.18 (0.13)	0.98 (0.13)	0.20 (0.17)	0.00	0.19	-0.91 (0.07)	-0.91* (0.05)	0.01 (0.02)	-0.01	0.01

[a)] Measured at the reference household, i.e. for each region a household with: 5 household members.

Notes:

Standard errors are calculated by the delta method and shown in parenthesis. *, **,*** denotes significant different from zero at 10, 5 and 1 percent level. For price elasticities the significance is with respect to difference from 0. For expenditure and own price elasticities the significance is with respect to differences from 1. All expenditure and own price elasticities are significantly different from zero at any conventional level.